An applied approach to multi-criteria humanitarian supply chain planning for pandemic response

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Abstract

Purpose – When a large-scale outbreak such as the COVID-19 pandemic happens, organizations that are responsible for delivering relief may face a lack of both provisions and human resources. Governments are the primary source for the humanitarian supplies required during such a crisis; however, coordination with humanitarian NGOs in handling such pandemics is a vital form of public-private partnership (PPP). Aid organizations have to consider not only the total degree of demand satisfaction in such cases but also the obligation that relief goods such as medicine and foods should be distributed as equitably as possible within the affected areas (AAs).

Design/methodology/approach – Given the challenges of acquiring real data associated with procuring relief items during the COVID-19 outbreak, a comprehensive simulation-based plan is used to generate 243 small, medium and large-sized problems with uncertain demand, and these problems are solved to optimality using GAMS. Finally, post-optimality analyses are conducted, and some useful managerial insights are presented.

Findings – The results imply that given a reasonable measure of deprivation costs, it can be important for managers to focus less on the logistical costs of delivering resources and more on the value associated with quickly and effectively reducing the overall suffering of the affected individuals. It is also important for managers to recognize that even though deprivation costs and transportation costs are both increasing as the time horizon increases, the actual growth rate of the deprivation costs decreases over time.

Originality/value – In this paper, a novel mathematical model is presented to minimize the total costs of delivering humanitarian aid for pandemic relief. With a focus on sustainability of operations, the model incorporates total transportation and delivery costs, the cost of utilizing the transportation fleet (transportation mode cost), and equity and deprivation costs. Taking social costs such as deprivation and equity costs into account, in addition to other important classic cost terms, enables managers to organize the best possible response when such outbreaks happen.

Keywords Humanitarian, COVID-19, Deprivation cost, Equity, NGO

Paper type Research paper

1. Introduction

COVID-19, which has been classified as a pandemic by the World Health Organization (WHO), hit the world in late 2019 and has involved about 213 countries so far, affecting about 7 million people and taking the lives of about 420,000 people by June 11, 2020 (WHO, 2020). The COVID-19 pandemic has added an extra load to many health systems of different countries all around the globe, and the various costs of controlling the infections have led to an economic crisis. While many other former crises have hit humankind in a short time span and in a particular region (e.g. hurricanes such as Katrina in 2005) or have developed over a longer time period with worldwide effects (e.g. the 2008 financial crisis), the COVID-19 pandemic has quickly impacted much of the world, and the large-scale countermeasures put in place have rapidly hurt economies (Kuckertz *et al.*, 2020). The protective measures imposed by countries around the world to avoid increasing the spread rate of COVID-19 include prohibiting large congregations of people, limiting unnecessary travel, and extensive social

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distancing. Self-isolation has also been advised for those who had contact with suspected individuals. Taken together, these actions have significantly mitigated the infection rate of COVID-19.

The use of Personal Protective Equipment (PPE), such as face masks and face shields, is important for protecting healthcare workers, as well as other individuals who cannot always self-isolate. Other related practices for controlling infection include using alcohol-based hand sanitizers and hand washing, as well as covering coughs and sneezes in order to minimize the infection spread from one individual to another (Pallister-Wilkins, 2016). Both ethically and practically, it is necessary for governments to arrange for the reasonable dissemination of PPE to clinicians during situations such as the COVID-19 pandemic (Binkley and Kemp, 2020). Although the lack of a vaccine and antiviral medicines, as well as ventilators, was predicted early on during the crisis, the shortage of sufficient PPE for healthcare suppliers was not. Owing to increasing worldwide demand, current projections continue to indicate an insufficient number of PPE resources to defend clinicians against pandemics (Binkley and Kemp, 2020). Given the rapid decision-making needed regarding the fair allocation of such rare resources, hospitals must carefully define their policies on PPE allocation to vulnerable hospitals and affected areas (AAs). These policies must be ethical and scientifically based, and the actual distribution of the resources should conform to the notion of equity in humanitarian logistics. With this in mind, we specifically incorporate a focus on equity in the model below.

The concept of sustainability in a disaster context is still in its infancy, as compared to its use in commercial supply chains (Najjartabar *et al.*, 2018), and it has not yet been explored well by researchers in the literature (Cao *et al.*, 2018). Following Klumpp *et al.* (2015), the goal of sustainable humanitarian logistics is to guarantee every human being a level of comfort sufficient for the health and welfare of him or herself and of their family, particularly in disaster situations and emergency circumstances. This comprises providing food, medical care, housing, clothing and essential social services by preparing, executing and controlling the efficient, effective flow and storing of relief commodities, services and correlated information through the entire supply chain, in order to satisfy current requirements. Unfortunately, the frequent absence of organized planning processes, and actual sustainability measurement instruments, endanger the improvement of sustainable processes (Laguna-Salvadó *et al.*, 2019). The incorporation of sustainability into humanitarian supply chains ensures acquiring a standard of living for the affected individuals as part of the social dimension, using the donated resources in an ethical and efficient manner as part of the economic dimension, and finally decreasing the environmental influence of relief operations as part of the environmental dimension (Klumpp, 2013). In this paper, we specifically focus on the social and economic dimensions of sustainability.

Disasters disrupt the working of communities and societies and negatively impact people's lives and property. Effective and efficient humanitarian relief operations, however, can alleviate casualties and reduce damages (Leiras *et al.*, 2014). According to the WHO, humanitarian relief operations are designed to provide essential resources such as water, fuel, food, and medical supplies, and to distribute them among affected areas to alleviate the suffering of people (Committee, 2000). Logistics operations and relief chain performance play essential roles in achieving successful emergency responses and account for about 80% of all disaster relief activities (Van Wassenhove, 2006). The relief supply chain includes many key players that are engaged aftermath of a disaster, including local and regional relief organizations, military, governments, international relief organizations and non-governmental organizations (NGOs). Each of these players may have different capacities, limitations, obligations, and logistics expertise associated with managing flows of materials, storage of goods and associated information resources (Balcik *et al.*, 2010).

The World Bank's Support Plan is an example of a complementary intervention to reinforce health systems and diminish damage to people and to the economy of countries using donations and low-interest loans to governments and support to the private sector (United Nations, 2020). Accordingly, one can say that governments are the primary source for the required humanitarian supplies during a crisis such as COVID-19. However, the coordination between government and humanitarian NGOs in handling such pandemics is also vital, particularly in North Africa and some countries in the Middle East, where NGOs deliver humanitarian supplies. Due to the dynamic nature of a disaster and the increasing number of disasters in the last decade, no single organization has enough potential to provide all the required resources in the relief chain (Bui *et al.*, 2000).

With this in mind, the following paper presents a novel relief supply chain approach for crises such as COVID-19. The approach adopts a sustainability perspective with a focus on social and economic concepts and engages key relief chain factors by considering two important entities in humanitarian supply chains: governments and NGOs. In particular, the role of NGOs in humanitarian activities highlights the social aspect of sustainability.

The contributions of the paper can be summarized as follows:

(1) It proposes a multi-criteria sustainable humanitarian supply chain planning model to optimize total imposed costs to the entire supply chain, including delivery costs of humanitarian aid for pandemic relief.

(2) It takes deprivation and equity costs into account simultaneously in the proposed mathematical model, accompanied by other real-world limitations associated with the social aspects of sustainability.

(3) It considers uncertainty in the planning process and incorporates it by generating stochastic demand.

(4) It uses a simulation-based process for generating data and applies the proposed mathematical model over the numerous generated sample problems.

(5) It provides a comprehensive plan (comprehensive insights), including sensitivity analyses over the obtained results, and discusses important parameters that enable governmental or NGOs' managers to organize the best possible response when any similar crisis occurs.

The results of the analysis below demonstrate that although more frequently dispatching relief items to the affected areas will increase the transportation and utilization costs of vehicles, it will also more effectively achieve the more important goal of decreasing deprivation costs. Nevertheless, they show that even though deprivation and transportation costs increase as the time horizon increases, the actual growth rate of the deprivation costs decreases over time.

The rest of the paper is organized as follows: In Section 2, the related literature is discussed in detail, including a summarized table showing different studies with their features. Section 3 presents the proposed mathematical model, including the imposed constraints to such a system. Section 4 comprises how extensive data are generated for different problem sizes. In Section 5, the computational results are presented, including some sensitivity analysis and managerial implications. Finally, Section 6 presents the conclusion and some future streams of research.

2. Literature review

The primary objective of relief logistics and humanitarian supply chain management is to save human lives, mitigate suffering, and keep human dignity (Habib *et al.*, 2016). These goals have been addressed through the definition and formulation of many objective functions in the context of relief operation management. For example, minimizing total logistical cost (Zokaee *et al.*, 2016), minimizing response time (Yi and Kumar, 2007) and maximizing population coverage (Viswanath and Peeta, 2003), are among the objective functions surveyed by scholars. However, since humanitarian logistics operations directly contribute to mitigating loss of life, social principles should be explicitly incorporated into the logistics modeling to make sure that delivery strategies result in acceptable service levels for the maximum number of individuals. Motivated by this insight, Holguín-Veras *et al.* (2013) analyzed the use of social costs as additional criteria for disaster planning and operations for executing and controlling the efficient flow of emergency items. In their study, the concept of deprivation cost was suggested as a means for economically measuring the human suffering related to the absence of access to an appropriate service or relief commodity. The use of such a deprivation cost is able to cover many concerns related to an imbalanced supply of urgent goods, but a question still remains open: how directly does it investigate the criterion of equity (fairness)? If relief goods are to be supplied to the affected areas (AAs), then organizations who are in charge of this responsibility have to worry not only about demand satisfaction but also about the prerequisite that relief commodities should be disseminated among the affected individuals as equitably as possible (Gutjahr *et al.*, 2018).

Ensuring equity is very important since it is one of the three key measures, accompanied by effectiveness and efficiency, which are normally related to specifying suitable locations for public service facilities (Marsh and Schilling, 1994; Savas, 1978; Attari *et al.*, 2020). The concept of equity in public policy and healthcare literature is generally divided into two concepts: horizontal and vertical equity (Joseph *et al.*, 2016). Horizontal equity is defined to be “the equal treatment of equals,” signifying that every in-need person or group of people has access to the same amount of resources with the goal of meeting that requirement (Joseph *et al.*, 2016). Based on this definition, horizontal equity can be applied in humanitarian problems through “equity constraints” that make sure that an assured quantity of demand is met in each AA (Davis *et al.*, 2013; Noyan *et al.*, 2016; Yan and Shih, 2009). On the other hand, vertical equity can be defined as “the unequal, but equitable, treatment of unequals.” In this type of equity, the emphasis is on providing a quantity of resources, which is proportional to need (Joseph *et al.*, 2016). Vertical equity can be applied through an objective function that incorporates a measure of human welfare, such as “deprivation costs” (Holguín-Veras *et al.*, 2013), or one that specifically targets need, such as a function based on risk (Arnette *et al.*, 2019). As an example of the latter, Arnette and Zobel (2019) created a mixed-integer linear programming (MILP) model for the American Red Cross, with the goal of helping to more effectively pre-position required resources to open emergency shelters. This model included a risk-based objective function that focused on reducing the exposure of vulnerable populations in an equitable manner.

Over the past few decades, optimization techniques have proven their ability to tackle emergency logistics and relief supply chain problems. There are many review studies that survey operations research (OR) oriented papers and categorize them into classes based on some defined criteria. For example, Altay and Green (2006) analyze 109 papers published in OR and management-related journals and separate them into groups based on the disaster lifecycle stage (mitigation, preparedness, response, or recovery) with which they are associated. Natarajarathinam *et al.* (2009), in turn, follows a research approach in which all the studies prior to 2008 that discuss the problem of emergency supply chain management are classified as conceptual, analytical, empirical, or applied.

Optimization techniques associated with disaster operations management are generally classified into relief distribution and transportation models, facility location models, and multi-commodity network flow models (Caunhye *et al.*, 2012). According to Duran *et al.* (2011), one specific type of humanitarian relief model focuses on exploring the optimal location of facilities, such as warehouses, to effectively manage the relief chain. The locations of such critical facilities have a direct impact on the response time, cost, and service quality. A second type of model identified by Duran *et al.* (2011) focuses on estimating demand and supply requirements at the various nodes of a relief chain. Finally, a third type of model focuses on the delivery of emergency items and the sequence of activities, given decisions regarding the facility locations (Ghaffarinasab *et al.*, 2020) and demand management (Goli and Malmir, 2020). This current research effort focuses on the third type of optimization model that arises in the context of relief network flow management.

Table 1 provides a summary of the literature that addresses the problem of relief distribution, emergency logistics, and relief supply chain management. The key characteristics of relief supply chain management that were considered in each paper are indicated in the table in order to show the differences in the contributions of each study.

Because of the need to consider not just the economic impacts of a disaster but also its social and environmental impacts, multi-criteria optimization can be an important tool in solving problems associated with delivering humanitarian aid. Such applications of multi-criteria optimization to the management of natural disasters, epidemics, and other forms of humanitarian crises is reviewed in Gutjahr and Nolz (2016). The authors discuss multi-criteria decision-making approaches in addition to the different optimization criteria that have been employed and tested in this area.

In the context of pandemics and COVID-19, in particular, Ivanov (2020) recently conducted a simulation study and illustrated some new research issues associated with the impact of COVID-19. He first explained the specific characteristics relating to a pandemic crisis. Then, he showed how a simulation-based methodology could be employed so as to test and predict the influences of the pandemic crisis on the supply chain performance by means of the example of COVID-19. In addition, there are other papers in the literature dealing with a pandemic crisis from the humanitarian logistics perspective that present a mature body of knowledge. These include Altay *et al.* (2018), Anparasan and Lejeune (2018), Altay and Pal (2014), and Dubey *et al.* (2019).

Given the key characteristics of the papers outlined in Table 1, the research contributions of this current paper are threefold. First, it attempts to directly quantify human suffering by including social costs (both deprivation and equity costs) in the objective function, in addition to transportation costs and selection of the vehicle fleet. Second, the current study considers multiple types of suppliers and designs a new humanitarian supply chain network based on a practical point of view. Unlike the papers shown in Table 1, it focuses specifically on the role of governments and NGOs and highlights their critical activities in the aftermath of a disaster from the perspective of centralized operations planning. Third, several different means of transportation are evaluated in distributing the relief items, which leads to a more realistic relief supply chain model.

In addition to the above, this research effort also focuses directly on the context of the COVID-19 pandemic, which has not been investigated so far in the literature.

3. Problem statement

In the humanitarian problem being considered in this research effort, there are entities, including governments and third-party logistics providers (3PLs), that each play an important role in terms of joint cooperation. A variety of responsibilities could be handled by 3PLs, such as inventory management (including warehousing), shipping, etc.

Table 1. Summary of the literature related to relief distribution and network optimizations

Author/year	Research method	Objective(s)	Mathematical modeling	Optimization type	Coordination perspective (inventory management)	Transportation modes	Stakeholder perspective	Solution approach
Zokaee *et al.* (2016)	Applied	Minimizing total cost, maximizing people's satisfaction level	MILP	Robust	Decentralized	Not considered	Single type supplier	Exact (lingo)
Tavana *et al.* (2018)	Analytical	Minimizing total cost and time	MILP	Deterministic	Centralized	Not considered	Single type supplier	Epsilon-constraint method and a modified NSGA-II
Ben-tal *et al.* (2011)	Analytical	Minimizing total travel cost	MILP	Robust	Decentralized	Not considered	Only flow of good in the network	Simulation
Li *et al.* (2018)	Analytical	Maximizing the total expected appeal coverage	ILP	Stochastic	Decentralized	Not considered	Only distribution centers are considered	Exact scenario generating
Noham and Tzur (2018)	Analytical	Maximizing the ratio of number of units to total response time as an equity criterion	MINLP	Deterministic	Decentralized	Not considered	Single type supplier	Tabu search
Özdamar *et al.* (2004)	Applied	Minimizing the amount of unsatisfied demand	ILP	Deterministic	Decentralized	Considered	Single type supplier	Exact (gams)-scenario generating
Liu and Jiang (2015)	Applied	Minimizing the total (weighted) unsatisfied demands, the total cost	ILP	Robust	Decentralized	Only helicopters	Only considering temporary facilities	Exact (CPLEX)

(*continued*)

Author/year	Research method	Objective(s)	Mathematical modeling	Optimization type	Coordination perspective (inventory management)	Transportation modes	Stakeholder perspective	Solution approach
Chong *et al.* (2019)	Applied	Minimizing the number of open warehouses, demand, safety stock fulfillment, and total cost	Goal programming	Deterministic	Centralized	Not considered	Single type supplier	Exact (lingo)
Sheu (2010)	Conceptual	Quickly responding	Dynamic programming	Stochastic	Centralized	Not considered	Single type supplier	Simulation
Zhang *et al.* (2012)	Applied	Minimizing the total cost of allocating resources to a primary and secondary disaster	MILP	Deterministic	Decentralized	Not considered	Single type supplier	Heuristic
Current research	Analytical	Minimizing total transportation costs, equity cost, and deprivation cost	MINLP	Deterministic	Centralized	Considered	Multiple suppliers	Exact (GAMS)

Table 1.

(Kayvanfar *et al.*, 2017). The transportation network model being considered in this study includes distribution centers (DCs), which are assumed to be responsible for inventory and distribution management by a 3PL. Because warehousing and distribution management play critical roles in responding to emergencies, it's beneficial to have them be performed by an independent organization. Providing the required resources for the DCs and backing them up are assumed to be done jointly by governments and NGOs. In the context of their responsibility for logistics and inventory management, the DCs play an essential role in reducing social and economic impacts in the aftermath of a disaster. In some cases, NGOs cooperatively bid on relief commodities to support longstanding preparedness activities and to decrease expenditures (Li *et al.*, 2018).

Three important entities: the private sector, which plays the role of business/the market, the government, and the NGOs who deliver the actual aid, are a significant part of modern disaster risk reduction ecosystems. A good example of collaboration between such entities in this context can be found in the COVID-19 response in Malaysia (Shah *et al.*, 2020). In general, there is a reciprocal dependency between NGOs and Governments (Hashemi *et al.*, 2019), with the NGOs providing specific services and the governments enabling operations and offering financial support (Asad and Kay, 2014).

These three types of entities have been progressively converting collaborations to employ more proactive disaster response strategies (Li *et al.*, 2018). These strategies utilize an expert workforce and are equipped with an understanding of humanitarian and social needs in order to alleviate the risks of crises. Although the role of government has traditionally gotten more attention in the context of emergency management research, and specifically in crises, the more recent attention being paid to stimulating bolder cooperation of both NGOs and business entities in risk reduction can be observed as a prerequisite for the future resilience of societies (Lassa, 2018).

In many countries, such as in Africa and the Middle East, governments are the main source of providing the required resources during a crisis (Fathalikhani *et al.*, 2020). In the recent COVID-19 pandemic, however, it is often NGOs that have been serving the affected populations by directly providing food, money, and temporary accommodations (Shah *et al.*, 2020). This indicates that in order to handle such crises appropriately, it can be important to connect governments to other organizations. NGOs often play a significant role by emphasizing the operational aspects of emergency planning through human resource management within a short time after the occurrence of a disaster (Ben-tal *et al.*, 2011; Zokaee *et al.*, 2016). The purpose of engaging and defining these roles clearly for governments, NGOs, and 3PLs who may manage DCs, is to reflect the stages of informing, consulting, involving, collaborating, and empowering. Wilson *et al.* (2018) examined relief supply chain management from an operational point of view and used interviews with 12 key informants to develop a best practice matrix for appropriate logistics and resource management. They concluded that a key challenge facing logisticians in emergency response management is the acquisition and storage of critical resources in advance of a crisis and the use of a just-in-time (JIT) approach. Also, most respondents answered that the levels of inter-agency collaboration could and must be further developed in order to have better community outcomes.

In this paper, we propose that having mutual communication between governments and NGOs, along with outsourcing logistics management to 3PL companies, will improve the level of collaborations and effectiveness of relief activities. Such an arrangement has not yet been investigated so far in this context. Moreover, considering the important concepts of equity and deprivation costs within this arrangement will highlight the social aspect of sustainability in the humanitarian supply chain under consideration. The kind of resource sharing between the governments and NGOs (in general and for distributing PPEs) that we explicitly consider as the basis for our modeling effort is based on Mubah (2013), Joe Duke and Edet (2012), Mondal *et al.* (2016), Werker and Ahmed (2008) and Hershey (2013). Specific examples of such resource sharing behavior are provided in Table 2.

All the tasks mentioned above are assumed to be performed cooperatively by NGOs and governments, such as what was observed in Malaysia in response to COVID-19 (Cheong, 2020). However, depending on the circumstances of a given country, either local or national governments, or NGOs, or both could be involved.

With this as the context, the following operational assumptions are used to construct the proposed mathematical model.

(1) Delivery vehicles are always filled to capacity, i.e. it will be assumed that a visit to affected area k always is carried out via full trucks or full truck loads (TL).

(2) Governments and/or NGOs act as the sole suppliers in the model (i.e. any other sources of relief commodities must be processed through these official channels).

(3) Suppliers can provide more than one type of relief commodity.

(4) There is a set of predefined locations for the DCs.

(5) Each DC can serve more than one AA.

(6) Each supplier can serve more than one DC.

(7) The suppliers have capacity limitations for providing each type of relief commodity. Both of them can play this role, however, NGOs are helping governments in doing so.

(8) Relief commodity flow is allowed from suppliers to DCs, from DCs to the AAs, and directly from governments to AAs. In other words, we assume that direct relief commodity flows cannot exist from one government to another government or from one DC to another DC.

Table 2. Examples of resource sharing between governments and NGOs from the literature

Resource sharing behavior	Reference
A collaboration could be formed between governments and NGOs in the pre-disaster/pre-crisis phase in terms of awareness enhancement about the crises	Bazeghi and Baradaran (2010)
NGOs are to be supported financially by the governments	Fathalikhani *et al.* (2020)
Providing information about the transportation infrastructure should be done by the governments because the governments are responsible for inviting international aid, monitoring, and coordinating external assistance such as with the Red Cross	Bazeghi and Baradaran (2010)
Governments usually arrange/set the regulatory and legal frameworks governing relief assistance	Zokaee *et al.* (2016)
Governments should increase public awareness of the situation	Shah *et al.* (2020)
By providing food, medical masks, respiratory equipment, alcohol-based hand sanitizers, and other health care, NGOs not only help governments in crisis response and mitigation, but they also help to build local capacity to withstand future disasters/crises	Shah *et al.* (2020); Bernama (2020)
Understanding the traditions, culture, and activities of affected people is important for addressing problems that occur in a disaster, and this task can be done by NGOs. For example, some NGOs are helping to educate citizens on COVID-19	The Star (2020)
Several NGOs and public figures have also helped to sew PPE for medical front liners, including several Malaysian fashion designers associated with the Malaysian Official Designers Association (Moda) that have produced PPE for local medical staff	Cheong (2020)
UNICEF asked suppliers for the PPEs to cover the predicted requirements for COVID-19 response from UN agencies and NGOs	UNICEF (2020)

(9) No limitation is assumed for the number of transportation vehicles available, and the devastated areas are considered to be accessible through the current road network.

(10) The DCs are each managed by a 3PL, so alternative transportation modes (such as trucks and railroad) are available.

(11) A minimum demand satisfaction rate is defined for each type of relief commodity, giving the minimum service level in the affected areas with the goal of satisfying equity.

(12) The daily demand in each AA is uncertain.

(13) The inventory of DCs should be balanced (inventory balance of warehouse).

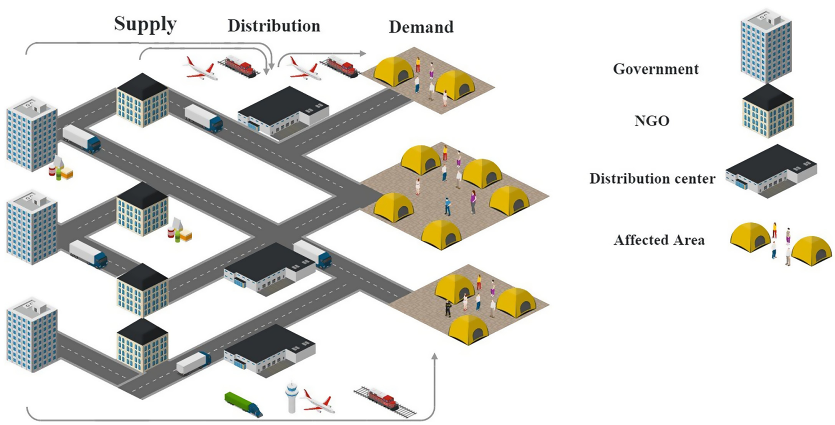
(14) The planning horizon for the intervention is limited and known.

Figure 1 provides a general overview of the possible interactions between the different entities in a relief supply chain. As discussed above, however, our model makes some additional assumptions about the specific supply chain being considered. For example, although there can, in theory, be a direct connection between governments and AAs (represented by the arrow at the bottom of the figure), we assume that relief commodities are generally transported from NGOs to DCs and, after that, to the AAs. In other words, we assume that NGOs do not directly assist AAs. In an emergency situation, governments can play a critical role in providing important resources such as the financial and transportation infrastructure. Therefore, future consideration of direct flow between governments and AAs could improve the effectiveness of delivering relief services (and thus increase the comprehensiveness of the model).

3.1 Sets

G-Index for governments ($g = 1, 2, \ldots, G$);

I-Index for humanitarian NGOs ($i = 1, 2, \ldots, I$);



Note(s): G: Government, NGO: Non-Governmental Organization, DC: Distribution Center, and AA: Affected Area

Figure 1. Designed transportation network

J-Index for distribution centers (j =1, 2, . . ., J);

K-Index for AAs (k = 1, 2, . . ., K);

M-Index for the relief commodity type (m = 1, 2, . . ., M);

V-Index for vehicle type (v = 1, 2, . . ., V);

T-Index for period (t = 1, 2, . . ., T); T signifies the planning horizon.

3.2 Parameters

D^{t}_{mk}-The demand for relief commodity m in the affected area of k in period t.

ω_t-The minimum percentage of demand for relief commodities in AAs that should be satisfied in period t;

α_v-The fixed cost of using vehicle v;

Bud_t-The available budget in period t.

B-A big positive arbitrary number;

Cost^{v}_{gi}-Transportation cost per unit of relief commodity by vehicle v from government g to ith NGO;

Cost^{v}_{ij}-Transportation cost per unit of relief commodity by vehicle v from ith NGO to jth DC.

Cost^{v}_{jk}-Transportation cost per unit of relief commodity by vehicle v from jth DC to kth AA;

Cost^{v}_{gk}-Transportation cost per unit of relief commodity by vehicle v from government g to kth AA.

Cap_{mj}-The capacity of jth DC to supply relief commodity m;

Scap_{mg}-The supply capacity of government g to supply relief commodity type m;

Scap_{mi}-The supply capacity of ith NGO to supply relief commodity type m;

inv^{t}_{mj}-Inventory level of relief commodity type m in the jth distribution center at the end of period t.

δ_m-Holding cost of relief commodity (relief item) type m.

η_k-Delivery costs of relief commodities to AA_k.

c_k-The fixed part of the delivery cost to AA_k.

θ_f-The weight of parts of the objective function.

3.3 Decision variables

x^{vt}_{mgi}-Amount of relief commodity m that is transferred by vehicle v from government g to ith NGO in planning horizon t;

x^{vt}_{mij}-Amount of relief commodity m that is transferred by vehicle v from ith NGO to jth DC in planning horizon t;

x^{vt}_{mjk}-Amount of relief commodity m that is transferred by vehicle v from jth DC to kth AA in planning horizon t;

x^{vt}_{mgk}-Amount of relief commodity m that is directly transferred by vehicle v from government g to kth AA in planning horizon t;

y^{t}_{mk}-A binary variable that is 1 if the kth AAs is supplied in planning horizon t by relief item type m; 0, otherwise;

σ_k-The average number of deliveries to AA$_k$.

z^{t}_{v}-A binary variable that is 1 if the vehicle type v is used for delivering in planning horizon t; 0, otherwise;

The proposed nonlinear mathematical model is formulated as follows:

3.4 The mathematical model

$$\min z = \theta_1 P_1 + \theta_2 P_2 + \theta_3 P_3 \tag{1}$$

$$\begin{aligned} P_1 = &\left(\sum_{m,g,i,v,t} \mathrm{Cost}^{v}_{gi} x^{vt}_{mgi} + \sum_{m,i,j,v,t} \mathrm{Cost}^{v}_{ij} x^{vt}_{mij} + \sum_{m,j,k,v,t} \mathrm{Cost}^{v}_{jk} x^{vt}_{mjk} + \sum_{m,g,k,v,t} \mathrm{Cost}^{v}_{gk} x^{vt}_{mgk} \right) \\ &+ \sum_{k} \eta_k \sigma_k + \sum_{m,j,t} \delta_m \mathrm{Inv}^{t}_{mj} \end{aligned} \tag{2}$$

$$P_2 = \sum_{v,t} z^{t}_{v} \alpha_v \tag{3}$$

$$P_3 = \sum_{t} r(t).\left\{ D^{t}_{mk}. \sum_{m,k} (1 - y^{t}_{mk}) + \sum_{m,k} \left[y^{t}_{mk}. \left(D^{t}_{mk} - \left(\sum_{g,v} x^{vt}_{mgk} + \sum_{j,v} x^{vt}_{mjk} \right) \right) \right] \right\} \tag{4}$$

The proposed objective function, Eq. (1), includes four terms of the imposed costs to such a system which should be minimized as follows: the first part (P_1) includes total transportation cost in the predefined network, total delivery costs of all periods, as well as holding costs of relief items, as shown in Eq. (2); the second part (P_2) shows the cost of utilizing the transportation fleet (transportation mode) based on their corresponding fixed cost (Eq. (3)); the third part (P_3) gives total deprivation costs, as denoted by Eq. (4). In other words, when the corresponding demand of a particular relief item in a given time period is not completely satisfied, then the deprivation cost is computed for the unmet demand. As previously mentioned, minimizing deprivation costs can be used as an approach for ensuring vertical equity.

It should also be pointed out that θ_1, θ_2, and θ_3 are the weight/importance of the first, second, and third parts of the objective function, respectively. In order to reflect the relative importance of the social component in the humanitarian context, our preliminary analysis below adopts the specific values $\theta_1 = 0.3$, $\theta_2 = 0.1$, and $\theta_3 = 0.6$.

The variable cost for vehicles is incorporated into the model in two places. First of all the transportation cost per unit of relief commodity is included in the cost parameters: Cost^{v}_{gi}, Cost^{v}_{ij}, Cost^{v}_{jk} and Cost^{v}_{gk}. In addition, the variable costs of the different commodities also incorporate the relative ease/difficulty of carrying the commodities in the different vehicle types and the ease/difficulty of destination accessibility.

Supposing λ_k (according to day) is the time interval at which demands are supplied to AA$_k$ (i.e. the delivery interval), one can represent the increase in deprivation cost through the deprivation intensity function, $r(t)$. We then have $\sum_0^t r(t)$ as the deprivation cost accrued between two deliveries (Gutjahr and Fischer, 2018). It should be pointed out that $r(t)$, which is defined as $r(t) = 3t$ in this research effort, drops down to 0 when sufficient supply is delivered to an affected area. In other words, it starts again after any delivery to AAs. This particular form of the $r(t)$ function was chosen as a simple linear approximation of the quadratic function used by Gutjahr and Fischer (2018). Adopting this simpler form allows for limiting the relative complexity of the third part of the objective function (P_3) while still capturing the underlying nature of deprivation costs over time. Although alternate forms of the function were also considered during model development, this particular function provided the most straightforward and reasonable results in terms of the rate of change from one period to the next. A more detailed consideration of alternate forms of this function, and of the associated impacts on system performance and managerial decision making, is intended as future research.

The constraints related to the flow of relief commodities are considered in Eqs. (5) and (6):

$$\sum_{g} x_{mgi}^{vt} = \sum_{j} x_{mij}^{vt} \qquad \forall v, i, m, t \tag{5}$$

$$\sum_{i} x_{mij}^{vt} = \sum_{k} x_{mjk}^{vt} \qquad \forall v, j, m, t \tag{6}$$

The capacity of distribution centers is limited, so constraint (4) presents the capacity restriction for all types of utilized resources.

$$\sum\nolimits_{m} \mathrm{inv}_{mj}^{t} \leq \mathrm{cap}_{j}^{t} \quad \forall j, t \tag{7}$$

The limited supply capacity of the gth government could be stated as in constraint (5).

$$\sum_{i,v} x_{mgi}^{vt} + \sum_{k,v} x_{mgk}^{vt} \leq \mathrm{Scap}_{mg}^{t} \quad \forall m, g, t \tag{8}$$

The constraint related to the limited supply capacity of the ith NGO could be stated in terms of constraint (6).

$$\sum_{j,v} x_{mij}^{vt} \leq \mathrm{Scap}_{mi}^{t} \quad \forall m, i, t \tag{9}$$

The relief commodities can be delivered if a vehicle is selected to do so. Eqs. (10–13) indicate such constraints.

$$\sum_{m,g,i} x_{mgi}^{vt} \leq Bz_{v}^{t} \;\; \forall v, t \tag{10}$$

$$\sum_{m,i,j} x_{mij}^{vt} \leq Bz_{v}^{t} \;\; \forall v, t \tag{11}$$

$$\sum_{m,j,k} x_{mjk}^{vt} \leq Bz_{v}^{t} \;\; \forall v, t \tag{12}$$

$$\sum_{m,g,k} x_{mgk}^{vt} \leq Bz_{v}^{t} \;\; \forall v, t \tag{13}$$

The inventory balance can then be established through Eq. (14) as:

$$\sum_{i,v} x_{mij}^{vt} + \mathrm{inv}_{mj}^{t-1} - \sum_{k,v} x_{mjk}^{vt} = \mathrm{inv}_{mj}^{t} \quad \forall j, t, m \tag{14}$$

According to the assumptions considered in this study, the minimum rate of demand should be satisfied. Therefore, Eqs. (15) and (16) capture the relative fairness of sending relief commodities to the individual AAs. Actually, Eqs. (15) and (16) ensure that if AA_k is not supplied in period t, no stocks from neither government nor DC should be transferred, but if AA_k is supplied in period t from either a government or a DC, then the minimum rate of demand should be satisfied, shown by Eq. (16).

$$\sum_{g,v} x^{vt}_{mgk} + \sum_{j,v} x^{vt}_{mjk} \leq \mathrm{B}y^{t}_{mk} \qquad \forall m,k,t \tag{15}$$

$$\sum_{g,v} x^{vt}_{mgk} + \sum_{j,v} x^{vt}_{mjk} \geq \omega_t D^{t}_{mk} y^{t}_{mk} \qquad \forall m,k,t \tag{16}$$

Constraint (14) is a budget constraint that assumes the cost of total deliveries in period t should be at most Bud_t. This is equal to the running amount that is left once previous periods have drawn on the available overall budget. Eq. (19) shows that the budget in each period (Bud_t) should be less than the remaining amount of the total budget up to that period, where Bud is the total available budget at the beginning of the planning process.

$$\sum_{k} \eta_k . \sigma_k \leq \mathrm{Bud}_t \qquad \forall\ t \tag{17}$$

$$\mathrm{Bud}_t \leq \mathrm{Bud} - \sum_{i=1}^{t-1} \mathrm{Bud}_i \qquad \forall t \tag{18}$$

Eq. (19) gives the delivery cost of relief commodities to AA_k per time period, which includes a fixed cost (c_k) and variable cost ($x^{vt}_{m,g,k}.\phi^{v}_{m}$ and $x^{vt}_{m,j,k}.\phi^{v}_{m}$) that is assumed to be a linear function ϕ^{v}_{m} of the amount delivered. The parameter c_k, and possibly also the function ϕ^{v}_{m}, depends on the accessibility of AA_k. Also, the function ϕ^{v}_{m} changes according to each product type and transportation vehicle type.

$$\eta_k = c_k + \sum_{m,v} \phi^{v}_{m} \left(\sum_{j,t} x^{vt}_{mjk} + \sum_{g,t} x^{vt}_{mgk} \right) \quad \forall k \tag{19}$$

If a given AA is remote from the DC or difficult to reach due to geographical barriers, c_k will have a higher value than in the case where AA_k is near and easy to reach.

Eq. (20) is defined to update the value of D^{t}_{mk}, where D'^{t}_{mk} is the randomly generated value using the corresponding discrete uniform distribution, and the phrase written within the bracket is the unmet demand corresponding to the previous period. Eq. (21) signifies how σ_k is calculated.

$$D^{t}_{mk} = D'^{t}_{mk} + \left[D^{t-1}_{mk} - \left(\sum_{g,v} x^{vt-1}_{mgk} + \sum_{j,v} x^{vt-1}_{mjk} \right) \right] \qquad \forall m,k,t \tag{20}$$

$$\sigma_k = \frac{1}{T} \sum_{m,t} y^{t}_{mk} \qquad \forall k \tag{21}$$

Constraint (19) then requires that different affected areas have the most similar possible rates of demand satisfaction.

$$\left| \frac{\left(\sum_{g,v} x_{mgk}^{vt} + \sum_{j,v} x_{mjk}^{vt} \right)}{D_{mk}^{t}} - \frac{\left(\sum_{g,v} x_{mgk'}^{vt} + \sum_{j,v} x_{mjk'}^{vt} \right)}{D_{mk'}^{t}} \right| \leq \zeta \qquad \forall m, t, k, k', (k \neq k') \tag{22}$$

This is, in effect, an equity constraint. As already pointed out, horizontal equity can be applied in humanitarian problems through equity constraints, which guarantees that an assured amount of demand is met in each AA (Davis *et al.*, 2013; Noyan *et al.*, 2016).

Equity constraints are intended to ensure the fair and equitable distribution of resources. We may represent the amount of demand met in a given AA by calculating the ratio between the total amount of relief received by each AA and the corresponding demand in that location. To apply the constraint we then ensure that the difference in this ratio between any two AAs is less or equal than a threshold, ζ. This particular form of the constraint was chosen because it guarantees that all AAs receive the same relative proportion of relief (within a tolerance) for their particular demand level, which reduces the possibility that any particular area will suffer much higher relative losses than other areas.

4. Data generation

Since accessibility to real data about the procurement of relief items for COVID-19 in affected areas is limited, a comprehensive simulation-based plan is conducted in this section to explore the effectiveness of the model above. In this regard, numerous replications of the model are conducted in order to demonstrate how our proposed humanitarian supply chain network works. The model was constructed to be general enough to be applied in a large number of different situations, and the parameters chosen for the testing below are intended to be representative of a straightforward real-world situation in order to illustrate how the model works.

The problems to be considered are categorized into small, medium, and large-sized instances. In the literature, in most cases, three datasets of relief commodities are considered (Zokaee *et al.*, 2016). Details about the most important parameter values assigned for the small, medium, and large-sized samples are reported in Tables 3–5, respectively.

The stochastic demand values are generated using a discrete uniform random variate generator within the ranges reported in Tables 3–5, respectively. In all samples, three of the most useful relief items in the COVID-19 pandemic are taken into account: medical masks, alcohol-based hand sanitizers, and respiratory equipment (ventilators). For the first item (masks: $m = 1$), the reported values are representative of "tens" of items (e.g. 600*100 = 6,000); for the second relief item (alcohol-based sanitizers: $m = 2$), the values signify "0.1 L" (e.g. 600*0.1 = 60 L); and for the last item (ventilators: $m = 3$), the values

No. of AAs (k)	Time horizon (T)	Demand for relief items	Demand interval	Demand class
5	5,10,15	D_{mk}^{t} $(m = 1)$	DU (600, 800)	1
			DU (700, 900)	2
			DU (800, 1,000)	3
		D_{mk}^{t} $(m = 2)$	DU (600, 800)	4
			DU (700, 900)	5
			DU (800, 1,000)	6
		D_{mk}^{t} $(m = 3)$	DU (600, 800)	7
			DU (700, 900)	8
			DU (800, 1,000)	9

Table 3.
Characteristics of test instances (small)

represent "units." The specific values used for the small-sized instances in Table 3 were estimated based on information given by several hospitals in Iran. The medium and large-sized instances in Tables 4 and 5 were then generated with respect to these base values, to reflect the greater demand rates that are likely occur with the spread of the COVID-19 pandemic. The time horizons that are being considered, i.e. $T = 5$, 10, and 15 days, provide an initial indication of how different decision periods impact the model's performance.

In each of Tables 3–5, and for each type of relief item, three different demand intervals are considered. These 9 distinct combinations of relief item and demand interval are each identified in the Tables as a specific *demand class*, and they are used to create the scenarios given in Table 6. For each of the individual demand intervals, three different demand values are generated with the goal of producing more robust data, yielding $3 \times 3 = 9$ cases for each relief item. Also, three different time horizons ($T = 5$, 10, and 15) for each of these 9 cases are considered, which means that $9 \times 3 = 27$ instances are generated. Thus, by taking the three individual relief items into account, a total of $27 \times 3 = 81$ problems are generated for each category (small, medium, and large). This gives $81 \times 3 = 243$ problems for different categories.

Based on these test instances, the demand classes are used to generate $3 \times 9 = 27$ different scenarios, as shown in Table 6, in order to combine the three types of relief items into a single problem instance. The first 9 scenarios belong to small-sized instances, the second 9 scenarios belongs to medium-sized instances, and the last 9 scenarios belong to large-sized instances. Since each scenario includes three levels of demand, and 3 values have been generated for each demand interval, it means that each row of Table 6 contains $3 \times 3 \times 3 = 27$ samples, with a total of $27 \times 27 = 729$ instances being generated and analyzed in this research effort.

For example, the sixth row of Table 6 (scenario #6) signifies that the first, fifth, and ninth rows (1-5-9) of Table 3 (for small instances) are taken into account for generating instances of

No. of AAs (k)	Time horizon (T)	Demand for relief items	Demand interval	Demand class
10	5,10,15	D^t_{mk} $(m = 1)$	DU (1,000, 4,000)	1
			DU (2,000, 5,000)	2
			DU (3,000, 6,000)	3
		D^t_{mk} $(m = 2)$	DU (1,000, 4,000)	4
			DU (2,000, 5,000)	5
			DU (3,000, 6,000)	6
		D^t_{mk} $(m = 3)$	DU (1,000, 4,000)	7
			DU (2,000, 5,000)	8
			DU (3,000, 6,000)	9

Table 4. Characteristics of test instances (medium)

No. of AAs (k)	Time horizon (T)	Demand for relief items	Demand interval	Demand class
15	5,10,15	D^t_{mk} $(m = 1)$	DU (6,000, 10,000)	1
			DU (8,000, 12,000)	2
			DU (10,000, 14,000)	3
		D^t_{mk} $(m = 2)$	DU (6,000, 10,000)	4
			DU (8,000, 12,000)	5
			DU (10,000, 14,000)	6
		D^t_{mk} $(m = 3)$	DU (6,000, 10,000)	7
			DU (8,000, 12,000)	8
			DU (10,000, 14,000)	9

Table 5. Characteristics of test instances (large)

Time horizon	Level of demand	No. of scenario
5	1-4-7	1
	1-4-8	2
	1-4-9	3
	1-5-7	4
	1-5-8	5
	1-5-9	6
	1-6-7	7
	1-6-8	8
	1-6-9	9
10	2-4-7	10
	2-4-8	11
	2-4-9	12
	2-5-7	13
	2-5-8	14
	2-5-9	15
	2-6-7	16
	2-6-8	17
	2-6-9	18
15	3-4-7	19
	3-4-8	20
	3-4-9	21
	3-5-7	22
	3-5-8	23
	3-5-9	24
	3-6-7	25
	3-6-8	26
	3-6-9	27

Table 6.
The scenarios considered for all small, medium, and large-sized problems

demand for the first, second, and third relief items, respectively. In other words, the demand range of the first, second, and third relief items in this case of small problems are DU(600, 800), DU(700, 900), and DU(800, 1,000), respectively. Also, in each scenario, and in each demand range, three numbers are randomly generated for demand.

The rest of the parameters used are reported in Table 7. It should be pointed out that the number of governments (G), number of NGOs (I), number of distribution centers (J), and number of relief items (M) are 2, 2, 3, and 3, respectively for all small, medium and large-sized instances. These values are simply chosen to illustrate how the proposed model and network works on a representative problem.

All of the values reported in Table 7 are obtained through the literature, depending on availability, and by trial-and-error, as necessary. They are intended to represent a reasonable estimate of conditions in the current context. As already mentioned, to the best of the authors' knowledge, this research is one of the first papers that investigates mutual communication between governments and NGOs (3PLs) in terms of humanitarian supply chain planning for COVID-19 situations. As such, the accessibility of real-world data during the actual crisis was limited.

5. Computational results

In this section, the obtained results of the 729 sample problems are presented, obtained from 3 (problem size) $\times$ 3 (demand level) $\times$ 3 (different values of each demand level) $\times$ 3 (time horizons) $\times$ 3 (number of relief items) factor levels. By considering different combinations of different demand levels for different relief commodities, altogether $243 \times 3 = 729$ samples are

Category	Value of parameters
Small (K = 5, Bud = 5,000)	$\text{Scap}_{mg} = (3,000,\ 6,000)$ $\text{Scap}_{mi} = (100,\ 300)$ $c_k = (30, 70)$ $\text{Cap}_{mj} = (200, 400)$ $\text{Cost}^v_{gk} = (100,\ 200)$ $\text{Cost}^v_{jk} = (20, 90)$ $\text{Cost}^v_{ij} = (30,\ 80)$ $\text{Cost}^v_{gi} = (20,\ 90)$ $\psi_k = (1,500,\ 3,500)$ $\alpha_v = (200,\ 320)$ $\omega_t = (0.5,\ 0.9)$
Medium (K = 10, Bud = 50,000)	$\text{Scap}_{mg} = (10,000,\ 20,000)$ $\text{Scap}_{mi} = (100,\ 300)$ $c_k = (30, 70)$ $\text{Cap}_{mj} = (200, 400)$ $\text{Cost}^v_{gk} = (100,\ 200)$ $\text{Cost}^v_{jk} = (20, 90)$ $\text{Cost}^v_{ij} = (30,\ 80)$ $\text{Cost}^v_{gi} = (20,\ 90)$ $\psi_k = (1,500,\ 3,500)$ $\alpha_v = (200,\ 320)$ $\omega_t = (0.5,\ 0.9)$
Large (K = 15, Bud = 500,000)	$\text{Scap}_{mg} = (50,000,\ 120,000)$ $\text{Scap}_{mi} = (100,\ 300)$ $c_k = (30, 70)$ $\text{Cap}_{mj} = (200, 400)$ $\text{Cost}^v_{gk} = (100,\ 200)$ $\text{Cost}^v_{jk} = (20, 90)$ $\text{Cost}^v_{ij} = (30,\ 80)$ $\text{Cost}^v_{gi} = (20,\ 90)$ $\psi_k = (1,500,\ 3,500)$ $\alpha_v = (200,\ 320)$ $\omega_t = (0.5,\ 0.9)$

Table 7. The rest of the parameter values for the test instances

generated and analyzed. All problems are coded in GAMS 24.1.2 and solved using the ILOG CPLEX on a PC with a 2.3 GHz Intel® Core™ i5-2410M CPU processor and 4 GB RAM memory.

5.1 Illustrative example

Figure 2 provides an example of a medium-sized problem that illustrates how the proposed model works schematically. As seen in Figure 2, we consider 2 governments, 2 NGOs, 3 DCs, and 10 AAs in total. This representation considers only one type of relief item since representing several types of items on a single depiction is visually too complicated. The parameters required to solve the optimization model are as given above.

Two types of vehicles (including ground and air transportation facilities) are presumed to be available for delivery of relief items, depending on the needs for different routes. Based on the optimal solution represented in Figure 2, the model uses both types of suppliers (i.e. governments and NGOs) to satisfy the total demand of all AAs, and it uses three DCs to distribute all of the relief items. This scenario is solved with a planning horizon of five periods

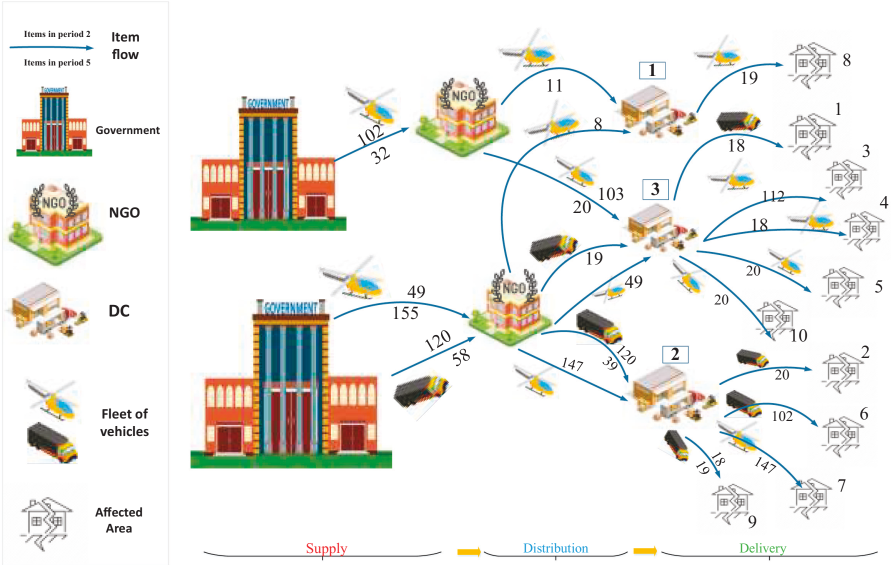


Figure 2.
The representation of the considered humanitarian network in a sample problem

(T = 5), and all of the required demands are supplied in two out of the five-time periods, i.e. t = 2 and t = 5. The numbers written above the arrows in Figure 2 signify the level of supply, distribution, and delivery in the second time period in this instance (t = 2), while the numbers written below the arrows indicate relief items supplied, distributed, and delivered in the fifth time period (t = 5). For example, the first government (the upper one) sends 102 items of one type of relief item in t = 2 and 32 items in t = 5 to the first NGO (a total of 134 items). The first NGO then supplies the first and third DCs, sending 11 items to the first DC at time t = 5, and 103 and 20 items to the third DC at times t = 2 and t = 5, respectively. The first DC, in turn, sends all of the received items from both NGOs in different time periods, i.e. 19 items (11 + 8 = 19), to the 8th AA in t = 5.

It should be pointed out that some factors affect the frequency of deliveries, such as budget, the capacity of the fleet, etc. In the proposed model, delivering supplies at time t = 2 addresses some of the demand, but new demand grows again, and the unmet demand incurs deprivation costs because individuals become subject to a higher probability of infection, therefore an additional delivery is also scheduled.

5.2 Comparative results

In this section, the average results obtained from running all scenarios for each combination of time horizon and problem category are presented. In particular, Table 8 provides the detailed results for each component of the objective function: P_1, P_2, P_3, along with P^* (the overall objective function value). According to these results, one can first observe that increasing the size of the problem leads to all parts of the objective function increasing quantitatively. This is directly caused by the corresponding increase in demand. There is an additional important insight in such a trend, however. When the problem size rises, the growth rate of P_1 increases, but the growth rate of P_3 actually decreases. This phenomenon could be interpreted as follows: Because of the increasing demand, the model tries to diminish the deprivation costs (P_3) by sending relief items to affected areas more frequently, thus yielding a significant increase in transportation costs (P_1). In other words, when more people

		t = 5	t = 10	t = 15	Avg
Small	P_1	378,000	446,000	449,887	424,629
	P_2	1,340	3,480	4,020	2,947
	P_3	790,000	1,650,000	2,136,500	1,525,500
	P^*	1,169,340	2,099,480	2,590,407	1,953,076
Medium	P_1	1,210,000	1,113,150	945,532	1,089,561
	P_2	2,180	4,360	6,420	4,320
	P_3	1,823,000	6,238,666	8,759,650	5,607,106
	P^*	3,035,180	7,356,176	9,711,602	6,700,987
Large	P_1	6,607,000	9,800,000	11,434,500	9,280,500
	P_2	1,090	2,180	4,050	2,440
	P_3	3,510,000	18,500,000	28,030,880	16,680,293
	P^*	10,118,090	28,302,180	39,469,430	25,963,233

Table 8. The average costs belonging to different parts of the objective function

are affected, as in the case of the COVID-19 pandemic, the minimization of deprivation cost takes precedence over the minimization of transportation costs. Since the population is increased by growing the problem size from one side (possibly increasing the deprivation costs), and the frequency of the supply is increased from the other side (likely decreasing the deprivation costs), altogether the output of the model shows that the growth rate of the deprivation costs is decreased.

The transportation cost of utilizing the fleet is also generally enlarged by increasing the time horizons in each problem size; however, its growth rate is also decreasing. The reason for this is that by lengthening the aid operations and enlarging their size, larger vehicles are employed. However, the utilization costs of these vehicles are not linearly increased, i.e. doubling the capacity corresponds to less than double the utilization costs. In other words, in large instances, the model prefers larger vehicles for this reason.

5.3 Sensitivity analysis

In this section, a sensitivity analysis is conducted in order to provide a better understanding of the obtained results.

5.3.1 Analyzing the effect of time period on deprivation cost. One of the most interesting and important factors applied in this research is the concept of *deprivation cost*. Figure 3 uses the results reported in Table 8 to show how this cost fluctuates by changing the problem size and time periods. As discussed above, when the problem size rises, the growth rate of the

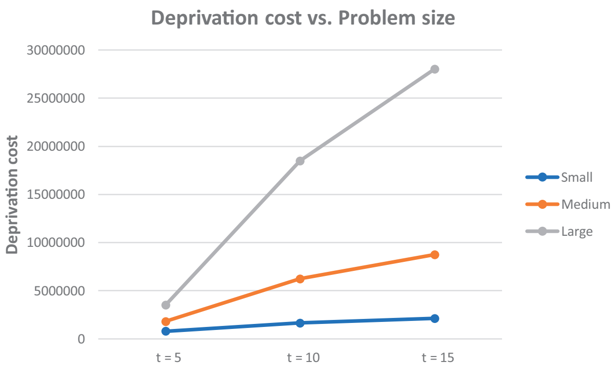


Figure 3. Fluctuations of deprivation cost for different problem sizes and time periods

deprivation costs decreases. When $t = 5$, this rate is changing from 2.3 to 1.92, while when $t = 10$, the growth rate of deprivation cost varies from 3.78 to 2.96, and finally, when $t = 15$, this rate changes from 4.1 to 3.2. This clearly shows that although deprivation costs are increasing quantitatively, the growth rate is decreasing due to the reasons mentioned above.

5.3.2 Analyzing the effect of equity on deprivation cost. Another important concept considered in this research is *equity,* which is applied through Eq. (23). When the right-hand side of this constraint increases, it allows for more variation in the level of demand satisfaction across different areas. Consequently, the problem space is expanded, and areas with higher accrued deprivation costs due to larger populations can better be targeted, thus decreasing the deprivation costs.

It should also be mentioned that all of the 729 sample problems in this research are run with $\zeta = 0.3$, however for conducting sensitivity analysis some different values of ζ are taken into account to have better insight about changing this important parameter's value. As can be seen from Figure 4, by decreasing ζ to 0.1 the deprivation cost is increased, while increasing the value of ζ to 0.5 will result in a lower deprivation cost.

5.4 Managerial insights

In this section, some important and applied managerial insights are extracted from the results obtained above. The intent is to provide decision support for managers at the governmental and NGO levels, as well as practitioners in the field so that they can cope with likely obstacles in this context and offer their best possible response when any similar crisis occurs.

The relevant implications are as follows, and they primarily revolve around deprivation cost, as one of the most important and interesting concepts in a sustainable humanitarian context.

(1) When the problem size and total demand both increase, it corresponds to more people being affected and needing help. In the context of humanitarian supply chain planning in general, and given the associated desire to ensure the sustainability of the relief efforts, human lives are considered to be relatively more important than any other imposed expenditures to the system. The proposed planning approach, therefore, tries to minimize the deprivation cost with respect to the other costs. In other words, more frequently dispatching relief items to the affected areas will increase transportation and utilization costs of vehicles but more effectively achieve the more important goal of decreasing deprivation costs.

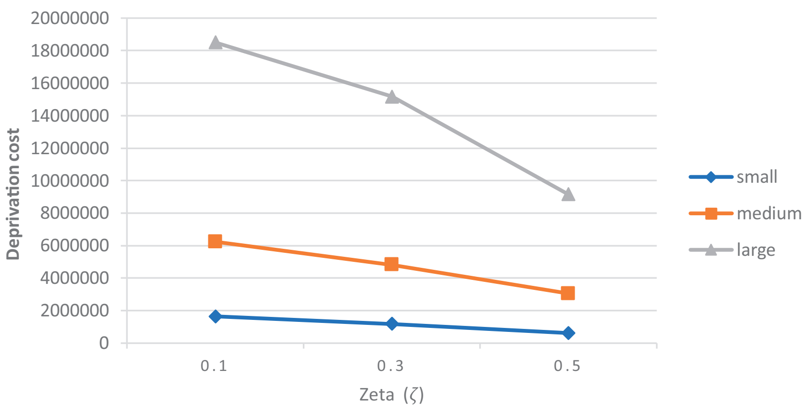


Figure 4.
Fluctuations of deprivation cost for different problem sizes and zeta values

This implies that given a reasonable measure of deprivation costs, it can be important for managers to focus less on the logistical costs of delivering resources and more on the value associated with quickly and effectively reducing the overall suffering of the affected individuals. It is also important for managers to recognize that even though deprivation costs and transportation costs are both increasing as the time horizon increases, the actual growth rate of the deprivation costs decreases over time.

(2) According to the results obtained above, relaxing the restriction that different areas must all satisfy very similar amounts of demand allows for more deliveries to be made to areas where the deprivation costs are higher. This is a good illustration of the difference between horizontal equity, where the same access to resources must be provided to each different affected group of individuals, and vertical equity, where the individuals with more need are provided with a correspondingly higher level of assistance. Including the deprivation costs in the calculation of "need" allows managers to make allocation decisions that formally address the nonlinear increase in demand over time due to previously unmet needs.

6. Conclusions, limitations and future research

The COVID-19 pandemic has enforced a new burden on the health systems of many countries around the world, and the control mechanisms used against the infections have often led to economic crises. Under these circumstances, non-governmental organizations (NGOs) can play a significant role in coping with the existing obstacles in such outbreaks through cooperation with governments in the form of public–private partnerships (PPP). The different aspects of sustainability, specifically the social and economic aspects of the crisis, can be addressed more sustainably by incorporating the NGO perspective into the process.

One of the biggest challenges in handling humanitarian issues is distributing relief items such as medicine and food as equitably as possible to the areas (AAs) impacted by a disruptive event like the COVID-19 pandemic. Alcohol-based hand sanitizers and masks, along with reusable respirators, are examples of Personal Protective Equipment (PPE) that must also be distributed during a pandemic. To measure the impact of not having access to such resources, we may adopt the notion of a "deprivation cost" as a form of economic measurement (social costs) of the human suffering associated with the absence of access to a suitable good or service.

In this research effort, a new sustainable humanitarian supply chain model was proposed that considers the COVID-19 outbreak and focuses on minimizing total incurred costs to the system, including transportation and delivery costs, deprivation costs, and utilization cost of the transportation fleet. Different types of vehicles and relief items were considered in this research to give more freedom to the managers with a greater number of scenarios to consider when such an outbreak happens. One of the main contributions of this research is that it considers both deprivation and equity, simultaneously, along with other cost terms in a sustainable manner.

In the example supply network that was used to illustrate the model, increasing the size of the problem corresponds to increasing the total amount of demand. In response, the model tries to minimize deprivation costs by dispatching relief items more frequently to the affected areas, which results in a noteworthy increase in transportation costs. In other words, when more people are infected in such an outbreak, the minimization of deprivation cost becomes more vital than minimizing other costs such as transportation costs. However, the growth rate of the deprivation costs decreases; as the size of the demand increases, because of the increased allocation of PPE to meet that demand with less delay. The initial test results also showed that the allocation of resources is more effective at reducing the deprivation costs if less effort is put towards strictly balancing the number of resources sent to each affected area. If the model is allowed to allocate more resources to areas with higher instances of deprivation costs, then it is able to address the overall need across the network much more effectively.

As is often true for research in the humanitarian realm, one of the limiting factors for this study was the limited accessibility of actual data for relief commodities, suppliers, warehouses, and the different costs associated with a real pandemic. Better access to such data would help to further validate and improve the usefulness of the results, and it would provide a better vision into the future and for similar disasters, particularly for managers within the relief supply chain. Such data restrictions make conducting sensitivity analyses very important, and further sensitivity analyses over other parameters would help in exploring other aspects of the problem.

Another limitation of the model, as presented above, is related to the use of uncertainty. A deterministic model was chosen in this initial analysis, in order to limit the complexity and aid in exposition. For future work, however, different types of uncertainty could be incorporated into the model, and robust or stochastic problem-solving approaches could be used to help it be more representative of real-world conditions. For example, one could apply such uncertainty-based approaches to the supply chain context similar to what was done in Kayvanfar *et al.* (2018). Furthermore, it is also important to recognize that the single-objective model introduced above could be expanded into a multi-objective context, and analyzed in greater detail with respect to the Pareto optimality of the results.

For future research, one could also conduct a more in-depth analysis of the form of the deprivation cost function, particularly as it applies to different types of resources and the relative extent to which lack of access to those resources has a negative impact over time. One could also look closely at the trade-offs between deprivation costs and other types of costs, such as inventory costs. Because deprivation costs are not expenditures in the same sense as logistic costs, developing a better understanding of how to incorporate them in the context of budget restrictions could be very useful for helping managers to better understand the relative impact of their decisions in handling such outbreaks.

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