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A Two-Stage Stochastic Post-Disaster Humanitarian Supply Chain Network Design Problem

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Abstract. The design and operation of humanitarian supply chain networks (HSCN) after natural disasters have progressively attracted interest from academia over recent years. We propose an optimization methodology to solve the HSCN planning problem occurring after a natural disaster. Considering the crucial role accurate modeling of the operations plays in the decision-making process, we aim to analyze the effect of unmet demand accumulating over the planning horizon in order to better understand and respond to natural disasters. To this end, we explicitly consider the impact of unmet demand through time under uncertain conditions by introducing a spread factor. We develop a two-stage stochastic model that retains the uncertainty pertaining to the demand along with the transportation and storage capacities of the HSCN. Then, we address a case study with real-world data from the 2018 earthquake in Indonesia. Various aspects of the problem are studied over a set of experiments, including the importance of modeling uncertainty, the effect of the budget on the solution performance, and the role of the spread factor in the accurate understanding of the crisis. The results obtained from the designed experiments verify the importance of considering uncertainty in the HSCN design problem. Furthermore, according to the obtained results, considering lower values for the spread factor parameter can irreparably misguide the decision-makers by an inaccurate presentation of the crisis' depth and consequently increase the damage caused to people's health.

Keywords: Stochastic programming, humanitarian relief network, tactical planning, humanitarian supply chain, post-disaster.

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1 Introduction

The United Nations Office for Coordination of Humanitarian Affairs (OCHA) annually reports the global appeals and the annual funding for disasters and emergencies. The global appeals present the financial requests of humanitarian organizations around the world each year. As for the annual funding, it refers to the overall value of the appeals that are fulfilled. The highest percentage of covered appeals in the last decade has been 65 percent (OCHA, 2021b). Furthermore, OCHA reports that the total amount of annual appeals has increased from 8.9 billion US dollars in 2011 to 38.5 billion US dollars in 2020 (OCHA, 2021b) thus indicating that humanitarian organizations are facing serious challenges regarding their budget to prepare and respond to natural disasters. Moreover, it has been observed that 75 percent of the available funding to perform disaster response is allocated to the design and the management of relief supply chains (Besiou and Van Wassenhove, 2020; Van Wassenhove, 2006; Stegemann and Stumpf, 2018). Therefore, improving the overall planning processes that define how the limited resources available to humanitarian organizations (e.g. budget, staff, means of transportation) are used to provide relief to affected populations after a natural disaster occurs is an important and pressing issue.

Emergency Management. Emergency Management (EM) is a field of study that has received an ever-increasing amount of attention from scientists, motivated by the desire to improve the efficiency of relief efforts provided to affected populations following natural disasters. EM is a multidisciplinary field that focuses on how humanitarian organizations should prepare for and respond to disasters to distribute the required aid (Anaya-Arenas et al., 2014). EM activities can be divided into two groups: pre-disaster and post-disaster. Pre-disaster activities include mitigation and preparedness. The goal of pre-disaster activities is to reduce the negative impacts of a possible disaster by pre-positioning critical supplies (i.e., mitigation) and developing response plans in advance of the events happening (i.e., preparedness). As for post-disaster activities, they include three different phases: response, short-term recovery, and long-term recovery (Holguín-Veras et al., 2012). The response phase occurs in the first 72 hours that follow the occurrence of a natural disaster (OCHA, 2021a). During this phase, the necessary equipment, critical supplies, and material necessary for both the search-and-rescue operations and the emergency repairs to be performed on critical infrastructure are transported to the affected region. The short-term recovery activities include damage and impact assessments, debris removal, distribution of critical supplies, restoration of critical infrastructure, and managing both the donations received and the work performed by volunteers (Holguín-Veras et al., 2012). These activities must be coordinated, which makes the short-term recovery a challenging phase in the post-disaster period. For example, the design of a network to distribute the critical supplies requires the information obtained from the damage and impact assessments performed. Furthermore, the priority choices made regarding debris removal must be coordinated with the selection of specific routes to be used for the distribution of critical supplies. Planning all of these activities in an integrated manner thus defines important challenges to be resolved. As for the activities performed in the long-term recovery phase, they include restoring infrastructure, providing psychological counseling to the affected population, and delivering overall humanitarian assistance to the region that may be ongoing for multiple years.

Distribution of critical supplies. In this study, our focus is on the short-term recovery phase, which is conducted at a crucial point in the overall timeline of the humanitarian activities performed post-disaster. It is important to note that the short-term recovery phase occurs in an emergency state during which critical supplies are not sufficiently available to satisfy the demand, critical infrastructure is not fully operational and the demand is at its extreme point (i.e., the affected population's demand for aid will peak following a natural disaster) (Holguín-Veras et al., 2013). The choices made by humanitarian organizations regarding how the available resources are used to perform this phase are paramount to the ultimate success and positive impact of the aid that will be provided.

Once a natural disaster occurs, the distribution of critical supplies to vulnerable populations defines some of the most challenging, vital, and complex operations that are conducted by humanitarian organizations. First, the management of such operations is particularly challenging because it involves various stakeholders, whose actions need to be coordinated to successfully perform the required critical supply distribution. The stakeholders include governments, military, humanitarian organizations, donors, media, and volunteers (both local and international). Coordination among stakeholders occurs at different levels. For example, when a disaster happens, the affected region is oftentimes divided into subregions where different humanitarian organizations will operate, thus enabling the overall affected region to be better covered in terms of the aid provided. For security reasons, military personnel are often called upon to protect humanitarian organizations, their staff, and volunteers when they are deployed in the field to distribute the aid. Communication and coordination between the military and humanitarian organizations is thus a pivotal part of the distribution of critical supplies. Lastly, a coordinated effort between humanitarian organizations and the media is also required to bring attention to the crisis that occurred which, in turn, can be helpful to fundraise and collect the required budget for the necessary operations to be performed. Second, the distribution of critical supplies is also vital to the health conditions of the affected population post-disaster. Critical supplies may include, for example, medical supplies, which are required to treat life-threatening injuries that directly occurred following the natural disaster. Finally, distribution planning is particularly complex in post-disaster humanitarian settings. The complexity stems from the fact that decisions related to the investments in the required infrastructure, the selection of logistical services, and the use of such services to perform the necessary distribution need to be made in an informational environment that involves a high level of uncertainty.

Humanitarian Supply Chain Network. The distribution of critical supplies is performed via the use of a Humanitarian Supply Chain Network (HSCN) (Tavana et al., 2018; Hong and Jeong, 2019). An HSCN consists of a physical network of hubs that are used to store, transport, and distribute critical supplies among the vulnerable population post-disaster. In an HSCN, hubs are physical locations that receive and store critical supplies in the network. Critical supplies are then transported between the hubs using transportation services. For brevity, we refer to these as services from now on. In this paper, we are interested in solving the problem of designing an HSCN in the short-term recovery phase that will operate (i.e., receive, store and distribute critical supplies) over a given planning horizon. Specifically, our aim is to design such a network, while explicitly considering the various sources of uncertainty that directly affect the informational context in which these relief operations are planned and executed. Sources of uncertainty may include a lack of information regarding the needs assessments of the affected population (e.g. uncertainty regarding the demography in the affected zone preventing an exact evaluation of the demand for specific critical supplies), damage levels to the infrastructure (e.g. road conditions, available vehicles, etc.) and overall effects of possible secondary impacts (e.g. landslides following floods, aftershocks following an earthquake, etc.).

Contributions. In this paper, we propose a two-stage stochastic post-disaster HSCN design model, that enables the uncertainty related both to the demand for aid and the available capacities for the chosen infrastructure and services to be formulated. Moreover, in the short-term recovery phase, it is paramount to service the demand for critical supplies quickly. The reason being to limit the harm that may spread and cumulate over the affected population. Our model thus proposes a novel formulation to account for the effects that unmet demands have over time. Our model also expresses the correlated effects of unmet demands for different critical supplies which to the best of our knowledge has not been considered in the existing literature of network design, facility location, and other supply chain related planning problems. The goal is then to design an HSCN that minimizes the expected total harm caused by the unmet demands for the considered critical supplies over the planning horizon. To assess the efficiency of our proposed stochastic model, we develop a dataset linked to the 2018 Indonesia earthquake and conduct a thorough numerical analysis. First, the importance of considering uncertainty in the HSCN design problem is investigated by comparing the solutions obtained by solving the proposed stochastic model when compared to its deterministic counterpart. Then, the effects of explicitly incorporating the residual demands over the planning horizon into our stochastic HSCN design model are evaluated in terms of the overall performance of the humanitarian relief operations conducted. Finally, to study the impacts that restrictive budgets may have on the performance of the designed HSCN, a series of experiments are conducted where the stochastic model is solved using different budget levels.

Outline. The remainder of this paper is structured as follows. In Section 2, we provide a literature review on the topic. In Section 3, we describe the problem setting. Section 4 details the two-stage stochastic post-disaster HSCN design model that is developed. The numerical experiments and analyses are presented in Section 5. Finally, we close the paper with the conclusion in Section 6.

2 Literature review

We now position our study within the existing literature. We review the related work on both the considered problem and the optimization method that is proposed to solve it. Thus, the focus of Subsection 2.1 is on supply chain network design for humanitarian relief, where we review what aspects of the problem have been studied in the context of designing and operating a supply chain to receive and distribute humanitarian relief to an affected population. In Subsection 2.2, we review the studies dedicated to the development of Service Network Design (SND) optimization methods. Specifically, we present the literature on both deterministic SND models and SND models under uncertainty, which present the formulations previously proposed to model and solve similar problems.

2.1 Humanitarian Supply Chain Network

Early attempts to solve HSCN design problems focused on directly applying the optimization methods originally developed for commercial supply chain applications (Van Wassenhove, 2019). However, these two general settings have significant differences (Balcik and Beamon, 2008). For instance, the aims and objectives of the supply chains can be quite different. In a humanitarian setting, the goal is to lessen the harm to people's health by reducing the delivery time (Diabat et al., 2019), expanding the coverage of the relief network (Hasani and Mokhtari, 2019), and optimizing the usage of budget in the design and operation of HSCN (Hasani and Mokhtari, 2018), as opposed to commercial supply chains, which aim to minimize the cost of distribution and delivery (Pishvaee and Razmi, 2012). Furthermore, as previously evoked, when planning post-disaster operations, humanitarian organizations are pressed for time and need to design the supply chain quickly, using limited available resources, while facing high levels of uncertainty in the informational planning context. Although these issues are also important in commercial settings, their intensity might not reach the same levels as observed when delivering humanitarian aid. Therefore, these differences have motivated a separate line of research specifically dedicated to solving humanitarian supply chain design problems (Anaya-Arenas et al., 2014; Campbell et al., 2008).

Various optimization methods have been developed to formulate and solve a wide gamut of humanitarian relief planning problems (e.g. Anaya-Arenas et al. (2014); Balcik et al. (2016); Behl and Dutta (2019)) to improve the performance of HSCNs. As previously mentioned, the scientific literature divides into two categories: optimization methods to solve problems related to either the pre-disaster or post-disaster planning phases (Anaya-Arenas et al., 2014). Most studies in the pre-disaster phase are dedicated to improving preparedness for possible catastrophic events that would require the deployment of humanitarian aid. In this phase, the main focus is on developing methods that support the decision-making processes involved in the location of warehouses and the stockpiling of critical supplies as a preventive measure to react in a more efficient manner whenever humanitarian organizations are called upon to provide aid (e.g. Yahyaei and Bozorgi-Amiri (2019); Bozorgi-Amiri et al. (2013, 2012); Alem et al. (2016)). In the post-disaster planning phase, candidate warehouses are assumed known (i.e., humanitarian organizations work with the existing infrastructure, which might have been, in part, designed in the pre-disaster phase). Hence, the main focus tends to support (via the use of optimization methods) the decision-making processes involved in the location of temporary facilities (e.g. distribution centers), determining the number of required vehicles to perform the distribution operations, the assignment of beneficiaries to the distribution centers, and the management of the flow of critical supplies (e.g. Afshar and Haghani (2012); Tzeng et al. (2007); Noyan et al. (2016)). In the post-disaster planning phase, when designing the HSCN, the overall goal is to distribute the aid in such a way as to alleviate the harmful effects of the catastrophic event on the affected people's health.

Network Structure and Parameter Uncertainty. The post-disaster HSCN design problem is both complex and challenging to solve, especially while facing various sources of uncertainty in the planning context. Its inherent complexity directly stems from the multiple decisions that need to be made at the different levels that define the distribution operations. A level being defined here as a set of locations with specific and similar infrastructure (e.g. comparable storage capacities, locations serving the same purpose in the supply chain, etc.) that are used for the storage and distribution of the critical supplies. When reviewing the literature, some studies propose models that integrate these decisions, while others only focus on one level. Afshar and Haghani (2012) proposed an integrated model for the HSCN that considers both the network design problem and the vehicle routing problem that needs to be solved to distribute the critical supplies to the affected population. The network design problem included the facility location decisions and the capacity constraints imposed on both the facilities and the transportation services performed between them. The proposed model is in compliance with the FEMA supply chain structure that consists of three layers of permanent facilities and four layers of temporary facilities. Furthermore, the vehicle routing component of the model includes both the routing and the pick-up and delivery schedules performed by the vehicles. One of the most challenging parts of planning an HSCN is the last-mile delivery (Balcik et al., 2008). In an attempt to model the last-mile relief network design problem, Noyan et al. (2016) proposed a two-stage stochastic model to select the locations and the capacities of the distribution centers with the overall aim to maximize the accessibility for the affected population while also considering distribution equity. The decisions regarding the location of the distribution centers and their capacities are made in the first stage. In the second stage, the allocation of the beneficiaries to the distribution centers, as well as the quantity of supplies sent to each distribution center are established. Tzeng et al. (2007) proposed a model to design a three-layer HSCN using three objective functions to consider the financial, effectiveness, and fairness aspects of the problem. The first objective function aims to minimize the total cost, including the setup and operational costs of the distribution centers and the transportation services. The goal of the second objective function is to improve the effectiveness of the designed network by minimizing the total travel time by the vehicles from the distribution centers to the demand points. Finally, the third objective function maximizes the worst satisfaction level (i.e., the ratio of satisfied demand to total demand) for each critical supply at each period. Indeed, fairness and equity in the distribution of critical supplies to a vulnerable population are important aspects when solving an HSCN design problem. Anaya-Arenas et al. (2018) discussed the importance of fairness and equity in the context of humanitarian relief and proposed four measures to quantify the fairness both across and within operational periods. The first two measures calculate the average gap between the minimum and maximum levels of unsatisfied demand over both points (i.e., locations) and periods, while the last two measures evaluate the dispersion of the aid provided using the overall variance of unsatisfied demand computed over the periods and points considered.

HSCN design problems are also challenging to solve, given that they naturally appear in settings that involve a high level of uncertainty. Thus, different aspects of the informational context (i.e., parameters) have been considered uncertain in the literature on HSCN design problems. Adıvar and Mert (2010) considered the procurement costs of critical supplies and the delays in the delivery times to be uncertain and then formulated them as fuzzy parameters. In another paper, Vitoriano et al. (2011) studied the relief distribution problem while considering the uncertainty in the level of damage to the infrastructure. The authors used reliability analysis to model uncertainty. They defined reliability parameters as the probability of successfully crossing each arc in the relief network. They then model the problem using goal programming. However, considering demand level uncertainty is most common. Here, Balcik et al. (2016); Behl and Dutta (2019) both provide a survey and classification of the different studies dedicated to such problem variant.

Demand satisfaction. Two approaches have been employed in the literature to model demand satisfaction. The first approach requires all demands to be fully satisfied (e.g. Balcik and Beamon (2008); Jabbarzadeh et al. (2014); Berkoune et al. (2012)). In these studies, which considered pre-disaster planning problems, the need to meet the expressed demands is formulated as hard constraints in the optimization models. Berkoune et al. (2012) studied the last-mile delivery problem in the humanitarian relief setting. They proposed a model that minimizes the total transportation time by selecting both the best route for each vehicle and the proportion of delivered critical supplies to each demand point. They also defined demand satisfaction as a constraint that needs to be fully satisfied in their model. Balcik and Beamon (2008) studied the facility location for humanitarian relief problems. They proposed a stochastic optimization model that maximizes the expected covered demand over the defined set of scenarios. The decisions in this model are the location of the warehouses, the quantity of stockpiled critical supplies, and the allocation of critical supplies from each selected warehouse to the points of demand. Again, proposed model enforces each warehouse to have enough critical supplies to fully satisfy the demand of the assigned points. Jabbarzadeh et al. (2014) used robust optimization to model the supply of blood both during and after disasters in a multi-period setting. The model seeks to establish the locations and the required quantities of blood at facilities for each period in the considered horizon. The authors include a control constraint in their model that leads to infeasibility if the total level of provided supply is less than the level of demand.

In a post-disaster planning phase, the high level of uncertainty in the affected region, the elevated levels of the demands, and the limited resources may make it difficult to ensure the satisfaction of the entire demand. Thus, the second approach to model demand satisfaction relies on the use of soft constraints that apply a penalty for the unmet demands (e.g. Ahmadi et al. (2015)). When used in a multi-period setting, the unmet demands at a current period may be carried over to the next period (e.g. Lin et al. (2011)).

In the existing literature, the effects of unmet demand for one critical supply on the level of demand for other critical supplies have not been explicitly studied. However, such effects are clearly important considering the nature and urgency of the demand that is considered when solving the HSCN design problem in the post-disaster planning phase. In particular, insufficient treatment of a disease in one time period may cause a spread of the disease in the subsequent time periods. Therefore, we propose to explicitly model such cumulative effects, solving the problem in a multi-period setting. Furthermore, when generally formulating the limited resources that are available to humanitarian organizations to distribute aid post-disaster, either fixed budget limits are added as hard constraints in the models, or, the objective function simply aims to minimize the costs incurred by the operations conducted (thus assuming that a sufficient budget is available). We are not aware of studies that explicitly consider the effects that varying donations received over time have on the considered design problem. In this study, we thus formulate the pattern of receiving varying donations to define the available budget over multiple time periods and their overall effect on both the design and distribution decisions to be made. Finally, we consider the combined effects of solving the HSCN design problem when facing both demand and capacity uncertainty. Depending on the nature and intensity of the catastrophic event, these sources of uncertainty can certainly be simultaneously observed when planning the aid in the post-disaster phase.

2.2 Service Network Design

SND problems refer to a general class of network design problems that focus on the supply-related resources and activities of transportation systems (Crainic and Hewitt, 2021). A wide range of decisions are involved in SND optimization models. These decisions can be grouped in two general categories: the design and the flow decisions (Crainic and Hewitt, 2021). Design decisions involve: the selection of services, i.e., the routes connecting the origins and destinations of the commodities to be transported (which may either be direct links or paths involving the use of intermediary terminals) and their schedules, which are either fixed based on the service itself or, decided upon (i.e., frequency, timing, etc.). As for the flow decisions, they involve setting the itineraries for the different commodities, which establish how and when they are transported from their respective origins to their final destinations. Typically, the objective is to design a service network that is efficient and profitable while satisfying the demand. The literature on SND models can be classified in two classes: deterministic (all relevant parameters assumed known) or under uncertainty (at least one parameter being assumed to randomly vary). In the following, we briefly review the literature on these two classes of SNDs.

2.3 Deterministic Service Network Design

In the present Subsection, we review the different proposed modelling approaches that properly formulate SND problems that appear in deterministic settings. These include: static, time-dependent, dynamic, frequency, and time-space SNDs (Crainic and Hewitt, 2021). Static SND models seek to design a service network in a static setting where the problem characteristics remain fixed and, therefore, the time dimension is not explicitly considered in the formulation (Chouman and Crainic, 2021). The school bus service network is an example of a static SND where all problem characteristics remain the same for each day of operation. In a time-dependent SND, the quantity of available supply, the level of demand, and other problem characteristics can change over time. For instance, the demand for transporting agricultural goods will increase during the harvest season compared to the rest of the year. Thus, the time dimension needs to be explicitly considered (see, e.g. Andersen et al. (2009)).

It should also be noted that SND problems can appear at all planning levels (i.e., strategic, tactical, and operational). Strategic planning defines a general guide for the management of an organization based on stakeholders' long-term priorities and goals. Tactical planning focuses on shorter periods of time (i.e., yearly or monthly) and provides an action plan to achieve the organization's objectives in the defined planning horizon. Finally, operational planning is performed on the short-term (i.e., weekly or day-to-day). In (Crainic, 2000), SND problems are divided according to their planning level and grouped into frequency or dynamic models. The strategic and tactical SND problems are the topic of study in frequency formulations, e.g. Duan et al. (2019); Rothenbächer et al. (2016). Frequency SND problems seek to find the best type of service and their frequencies for the considered planning horizon, the itineraries, and the workload and policies to be implemented at the terminals involved (Crainic, 2000). In contrast, dynamic SND models are applied at the operational level (see, e.g. Wieberneit (2008)), where the focus is on the scheduling of the services and their departure times (Crainic, 2000). Lastly, in some applications, the explicit management of resources may be an integral part of the SND problems. Resources to perform the services, such as vehicles or workforce, can be located in different geographical points at different time periods throughout the considered planning horizon. Thus, services that are selected and need to be performed on a given schedule, must also include the required resources. To efficiently formulate both the flow of the commodities and the management of the resources, a time-space representation of the network, e.g. as developed in Andersen et al. (2009); Crainic et al. (1984, 2016b)), is required.

2.4 Service Network Design under Uncertainty

Researchers have investigated the importance of considering uncertainty when formulating and solving SND problems (see, e.g. Crainic and Hewitt (2021); Lanza et al. (2021); Lium et al. (2009, 2007)). The problem variant most studied in the literature assumes that demands are uncertain (see, e.g. Lium et al. (2007); Bai et al. (2014); Crainic et al. (2016a); Ng and Lo (2016)). For this problem variant, Lium et al. (2007) compared the solutions obtained by solving a deterministic SND model when compared to its stochastic variant. This study clearly showed that by applying an optimization approach that explicitly considers uncertainty in demand, the designed networks included characteristics that improved their overall adaptability to varying demand realizations. Specifically, it was observed that networks obtained by solving a stochastic model included the options of: 1) alternative paths to connect the origins and destinations of commodities and 2) consolidation options for multiple commodities over specific arcs, which better hedged against random demand variations (i.e., commodity volumes).

Lanza et al. (2021) studied the importance of considering travel time uncertainty when solving an SND problem involving service quality targets. Again, solution differences were observed when comparing the networks obtained by applying deterministic optimization versus stochastic optimization. Specifically, it was observed that the solutions obtained by solving the deterministic model prioritized the one-stop services over the non-stop (or direct) services in an effort to lower the fixed costs incurred. In contrast, when the stochastic model was solved, the solutions obtained would select direct services as a means to reduce the risk of paying additional costs due to possible operational delays. Overall, the use of the stochastic optimization approach produced networks that were more cost-efficient (i.e., reducing the sum of both the set-up costs and the penalties incurred due to delays in the deliveries) when compared to their deterministic counterparts.

Both stochastic programming and robust optimization have been applied to model and solve SND problems that involve uncertainty (Bai et al., 2014; Wang and Qi, 2020). Considering that our problem setting assumes that a set of scenarios (that capture how the uncertain parameters may randomly vary) is available, the selected approach is stochastic programming. When formulating stochastic SND problems that appear at the tactical planning level, as highlighted in the scientific literature, two-stage formulations are the approach of choice, e.g. Bai et al. (2014); Crainic et al. (2016a). Thus, the process by which uncertain parameters become known is approximated by assuming that the values of all stochastic parameters are observed in a single stage (i.e., the second). Such an approach results in a model that is easier to solve, when compared to a multi-stage formulation, while still providing the means to find a tactical planning solution (i.e., network) that efficiently performs in the context of a randomly changing informational context.

3 Problem description

In this section, we present the here considered HSCN design problem that we will solve. First, Subsection 3.1 describes the general characteristics of the problem, including the network structure, uncertain parameters, and both the tactical and operational decisions involved. Then, Subsection 3.2 explains how budget requirements are imposed in the present setting and how they affect the HSCN design problem. Furthermore, this section also presents the various costs that are incurred from the different decisions made in the problem. Finally, Subsection 3.3 defines the concept of demand, which includes the cumulative effect of unmet demand over time, and its correlated effects on the critical supplies.

3.1 HSCN Design Problem

We study a multi-period HSCN design problem that involves tactical planning decisions made by organizations in the short-term recovery phase of EM. We consider a three-layer structure, as exemplified in Figure 1, which is a common structure for real-world HSCNs (Séguin, 2019). Each layer consists of a set of hubs with different characteristics, including the ports of entry, the warehouses, and the Distribution Centers (DCs). A port of entry is the physical location where the organization receives critical supplies, e.g. an airport, a seaport, or a train station. A warehouse is a hub that relies on storage resources that can hold critical supplies over several time periods. For instance, storage resources could be classrooms in a school or a set of containers located on land. The warehouses are more numerous than the ports of entry and are located closer to the affected region. Finally, a DC is a physical location within walking distance from beneficiary groups (i.e., a group of people relocated to a temporary site that could be a school, a temporary camp, or any other building) that is used to hand over the critical supplies to beneficiaries. We assume that each beneficiary group is assigned to a single DC that is dedicated to the transfer of all the critical supplies to satisfy (as much as possible) the expressed demand. The critical supplies are transported between consecutive layers using services. We assume there are no services connecting the hubs in the same layer (i.e., no transhipments are allowed). In addition, it is assumed that there are no direct services between the ports of entry and the DCs.

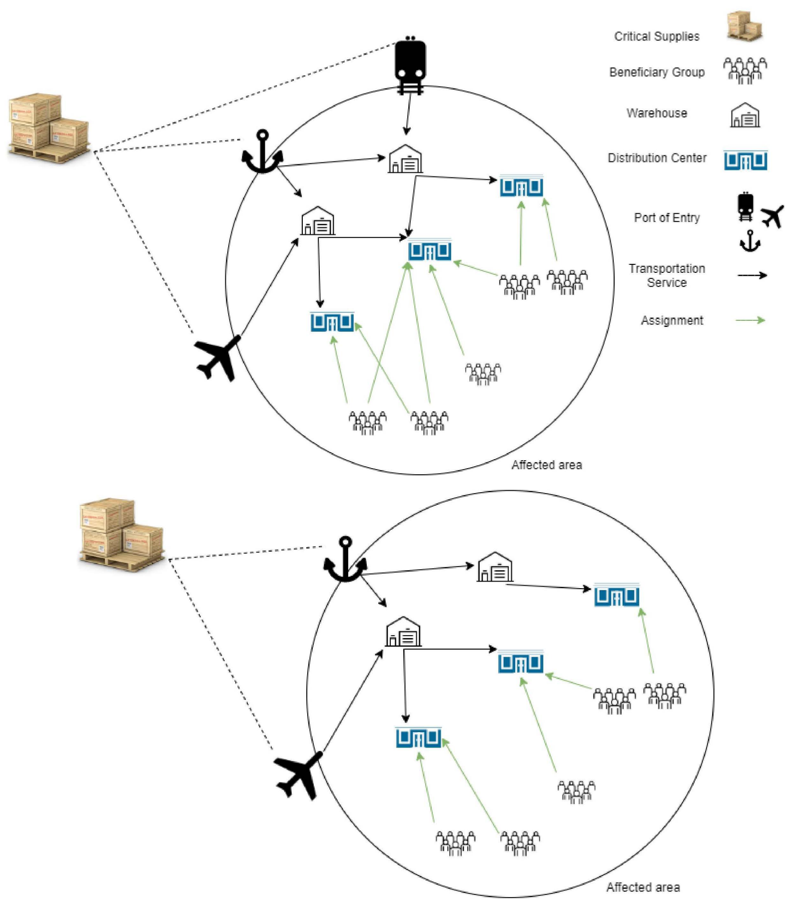

Figure 1: top: all available hubs, services, and assignments. bottom: selected hubs, services, and assignments in an example HSCN.

The planning of the considered HSCN involves making a series of decisions that determine the capacities of the network (i.e., the design decisions) and the use of these capacities to perform the required humanitarian aid (i.e., the operational decisions). To design the HSCN, one needs to select hubs and services capable of transporting the critical supplies from the ports of entry to the DCs, select resources for warehouses and services, and assign beneficiary groups to the DCs. Specifically, we first select a set of hubs and a set of services to connect them that will be available for the considered time horizon. We then assign transportation resources to the selected services (e.g. number of vehicles) and the storage resources for the selected warehouses (e.g. available space to be used or the number of containers). Thus, the storage capacity of a warehouse is a decision made by choosing the number of units of storage resources to be made available. Likewise, the transportation capacity of a service is a decision made by selecting the number of transportation resource units that define the operational capabilities of the service (i.e., how much quantity of critical supplies can be transported). Each transportation resource unit provides a fixed amount of capacity, and it is possible to assign multiple transportation resources to each selected service. However, it is assumed that there is a limit on the total number of resources available for each service (i.e., the locally available transportation supply is not infinite). Each service has a pair of hubs as origin and destination. Furthermore, performing a service entails loading the critical supplies at the origin hub, transporting them to the destination hub, and then returning to the origin hub to be able to repeat the process. Finally, we assign each beneficiary group to a single DC to ensure that the beneficiaries are able to pick up their critical supplies and know exactly where to do so. A DC should be within a predefined walking distance from a beneficiary group to be considered as a possible assignment to it. It is thus assumed that at least one DC is within walking distance from each beneficiary group. While each beneficiary group must be assigned to a single DC, each DC can provide the critical supplies for multiple beneficiary groups. We assume the design of the HSCN remains unchanged throughout the planning horizon. We next define the operational decisions made over the considered horizon.

To properly characterize the relief operations, we first define the concept of a time period in the HSCN design problem. Specifically, a time period is defined as the time required to perform the following operations: 1) receive a shipment of critical supplies into the port of entry hubs, 2) transport these critical supplies through the network until they reach the DCs, and 3) transfer the critical supplies to the beneficiary groups to satisfy demand. Therefore, a period is assumed to be the required time (e.g. a full week) to distribute the received shipment from the entry points of the HSCN to the final destinations, which are the beneficiary groups. Using this definition, the time horizon is discretized to produce a set of periods that span the planning context. Therefore, the operational decisions made at each time period include selecting the quantity of critical supplies transferred through the selected services, the desired inventory levels of the warehouses, and the quantity of the critical supplies allocated to the beneficiary groups at the DCs.

The decision-making process requires access to the value of a series of parameters, including the demands for the critical supplies, the locations of the beneficiary groups, the available budget, the set of available hubs, available services, and their resources. While some of these parameters are known in advance (e.g. the locations of the beneficiary groups, the available hubs, the available budget, etc.) and thus are deterministic, the values of other parameters (e.g. the demands) are uncertain at the moment the HSCN is designed. Vitoriano et al. (2011) highlighted the importance of considering the damage to the infrastructure after the main event caused by the secondary impacts (e.g. fires, landslides, and aftershocks). The occurrence of secondary impacts increases the levels of uncertainty on different aspects of the HSCN design problem. Specifically, the selected warehouses and their storage capacities might not be fully available (i.e., due to damages) in subsequent periods. A similar observation can be made regarding the selected transportation services and their capacities. Therefore, in this problem, we consider these three sets of parameters as uncertain (i.e., the demands, the available inventory resource of warehouses, and the available transport resource of services). In this case, an efficient HSCN should ideally provide a higher level of flexibility (i.e., scheduled or planned adaption of the distribution operation to possible external circumstances affecting the influential components of the problem) in light of the secondary impacts that may occur in the affected region (Sahebjamnia et al., 2017). In addition to the decrease of available warehouse capacity due to secondary impacts, the damaged resources may also lose critical supplies stored in the damaged part of the warehouses. Naturally, at each period, the total amount of critical supplies stored at a warehouse cannot be greater than the remaining capacity of that warehouse. This clearly motivates the need to explicitly consider the usable inventories of critical supplies that are available, both at the beginning and end of each period, over the considered horizon.

3.2 Budget

In this subsection, we first introduce the costs related to the decisions made in both the design and the operations conducted through the HSCN. We then discuss how the overall budget requirements are imposed in the present problem. In this case, there are two general types of costs, the fixed-costs, and the flow-costs. The fixed-costs include those associated with the selection decisions: a) of hubs (e.g. accounting for staff salary and maintenance), b) inventory resources (e.g. security guards and rent), and c) transportation resources (e.g. drivers, staff for loading and unloading the vehicles and security guards). The fixed-costs are assumed to be paid only once at the moment when the selection decisions are made. Regarding the transportation services, some expenses occur every time they are used and are proportional to the quantity of critical supplies that are transported (e.g. fuel cost). These expenses are referred to as the flow-costs of the services.

As for the budget involved in the HSCN design problem, it is assumed to include two general parts: a) the initial budget and b) donations. The initial budget is the amount available at the beginning of the planning horizon. It is often made up of the amount that was planned in the preparedness phase of the pre-disaster planning performed by the humanitarian organization. As for donations, they represent the financial support that is received over the subsequent time periods considered on the horizon. These will vary according to different aspects related to the specific disaster (i.e., how much journalistic coverage it receives, the severity of the event, the fund-raising activities of the organization, etc.). The amount of donations received following a given disaster could be considered an uncertain parameter. However, we assume that humanitarian organizations are realistically able to estimate this amount using historical data. In all cases, our proposed optimization model easily enables scenario analyses to be performed on the budget parameters (as illustrated in Subsection 5.2.4). To impose the budget constraints, it should first be observed that the amount of available budget is dependent on the specific time period considered. Thus, the budget requirements and the limits that they impose should directly apply to the decisions made at each time period. Following this principle, the incurred fixed-costs are limited by the initial budget, while the incurred flow-costs in each period are limited by the remaining budget from the previous period and the donations received at the current period.

3.3 Demand

We now define how the level of demand is calculated over the considered horizon. The demands of each beneficiary group for specific critical supplies are assessed based on the population in the considered zone, which is oftentimes uncertain at the time when the design decisions are made (Council, 2007). However, these numbers can be estimated based on various data sources, such as the number of residences, the number of beneficiaries, the intensity of the natural disaster, and the overall resistance of the urban or rural infrastructure (Council, 2007). A distinctive feature of our proposed model, when compared to those developed in the related scientific literature, is how the cumulative adverse effects of unmet demand of beneficiary groups are evaluated. Specifically, while operating the HSCN, we might not be able to fully satisfy the demand of the beneficiary groups at each considered time period. In turn, this may negatively affect the population's health for the beneficiary groups involved. For example, mosquito nets are pivotal items in controlling malaria epidemics. If the demand for mosquito nets is not fully satisfied, the epidemic spreads, and in turn the subsequent demand for mosquito nets is further increased. Additionally, one may observe an increase in the demand for malaria tests and medication. Therefore, unmet demands for a given critical supply will cumulate and possibly worsen overtime, but they are also likely to affect the demand for other critical supplies (i.e., there are correlated adverse effects).

To evaluate the adverse effects of unmet demands, we first assume that each unit of unmet demand for a given critical supply carries over to the following time period along with a negative penalty representing its negative effects. Furthermore, we introduce a series of spread factor parameters to measure how one unit of unmet demand for a specific critical supply negatively affects the demand for the other items in the following period. Specifically, let $s^{k'k}$ represent the effect of one unit of unmet demand of critical supply k' on the demand for the critical supply k in the subsequent time period. To formulate the effects of unmet demands on the demand level at the beginning of period t, we define the total demand, represented by $\hat{d}_l^{kt}$, for the critical supply k and for the beneficiary group l, as the sum of the base demand and the residual demand carried over from $t-1$. The base demand, formulated as parameter $\tilde{d}_l^{kt}$, represents the demand for the critical supply k, at period t, expressed by the beneficiary group l, and it is considered uncertain. As for the residual demand, it captures the negative effects on the level of demand in the current period that are directly linked to the unmet demands carried over from the previous period. Therefore, to obtain the total demand value, the following formula is applied in the case of the critical supply k, at period t and for the beneficiary group l:

$$\hat{d}_l^{kt} = \tilde{d}_l^{kt} + \sum_{k' \in K} s^{k'k} (\hat{d}_l^{k't-1} - \sum_{i \in V_{DC}} \bar{a}_{il}^{k't-1}). \tag{1}$$

As defined in Equation (1), $\hat{d}_l^{k't-1}$ represents the total demand of the beneficiary group l at period $t-1$ and $\bar{a}_{il}^{k't-1}$ defines the decision prescribing the amount of critical supply k' that is delivered to the beneficiary group l from the DC i at period $t-1$. Therefore, the spread factor $s^{k'k}$ is proportionally applied to the amount of unmet demand of critical supply k' at period $t-1$. Finally, the overall objective pursued is to design an HSCN that minimizes the total expected penalties of unmet demands over the defined planning horizon.

4 Optimization model

We begin this section by explaining our reasoning for choosing a two-stage model to formulate the HSCN design problem. We then present the proposed mathematical model. A stage refers to a specific moment within the time horizon at which decisions are made while considering the informational context of that point of time, i.e., the known parameters and the parameters that still remain uncertain (stochastic). When formulating a tactical planning problem, it is common to apply an approximation of the informational process by considering a two-stage setting. The reasoning behind this choice being that one is primarily interested in determining what should be the tactical plan (i.e., the a priori or first-stage decisions), while the operational decisions (i.e., the recourse or second-stage decisions) are used to evaluate how the tactical plan can be implemented. The latter can thus be defined as an approximation of the operators occurring in practice (i.e., decisions in the second stage being made under the assumption that all stochastic parameters become known). Moreover, in humanitarian relief planning, one typically cannot assume that all information will be perfectly revealed at the end (i.e., the exact value of some parameters can remain unknown). This further justifies the use of an approximation regarding how operations are conducted.

In the considered HSCN design problem, the value associated with the uncertain parameters will be revealed as time elapses (e.g. demands become known as more information arrives from the field). However, organizations cannot wait to obtain all the contextual information before designing the HSCN, e.g. services may not remain available if they are not booked in advance. Furthermore, the cost of booking the hubs and the services may increase if their booking is delayed. On the other hand, postponing the operational decision-making process will result in better decisions being made considering that there will be less uncertainty regarding the parameter values. Therefore, as advocated in the related literature (Grass and Fischer, 2016), we use a two-stage model where, in the first stage, the design decisions of the model are made whereas, in the second stage, we include the operational decisions for all periods.

We propose a model to design an HSCN that receives, stores and distributes critical supplies, i.e., set K, among the beneficiary groups, i.e., set L, over a given planning horizon, i.e., set T. We design the HSCN by selecting a set of hubs that are represented by set V, and a set of services, represented by set A. The designed HSCN is then used to transport the critical supplies from ports of entry to DCs over a known number of periods (i.e., $t \in T$). To model the uncertain parameters, we use a set, Ψ, of scenarios. Each scenario is a realization of random events associated with uncertain parameters. Table 1 introduces the sets used to define the model.

Set	Definition
V_I	Set of ports of entry $i \in V_I$.
V_W	Set of warehouses $i \in V_W$.
V_{DC}	Set of DCs $i \in V_{DC}$.
V	Set of all hubs $i \in V$, where $V = V_I \bigcup V_W \bigcup V_{DC}$.
A	Set of all services $(i, j) \in A$.
L	Set of beneficiary groups $l \in L$.
K	Set of critical supplies $k \in K$.
Ψ	Set of scenarios $\psi \in \Psi$.
T	Set of periods $t \in T$.

Table 1: Sets used in the optimization model.

Deterministic Parameters	
Parameter	Definition
$\tilde{f}_{ij}$	Cost of selecting one unit of transportation resource of service $(i, j) \in A$.
$\hat{f}_i$	Cost of selecting one unit of inventory resource for warehouse $i \in V$.
f_i	Cost of selecting a hub $i \in V$.
c_{ij}^k	Cost of transporting one unit of critical supplies $k \in K$, by service $(i, j) \in A$.
u_{ij}	Capacity of one unit of transportation resource of service $(i, j) \in A$.
u_i	Capacity of one unit of inventory resource of warehouse $i \in V_W$.
m_i	Maximum number of inventory resources available for warehouse $i \in V_W$.
m_{ij}	Maximum number of transportation resources available for service $(i, j) \in A$.
n_i^{kt}	Maximum quantity of critical supplies $k \in K$ that can be delivered to the port of entry $i \in V_I$ at period $t \in T$.
b^k	The penalty for one unit of unmet demand of critical supply $k \in K$.
z^0	The initial budget.
z^t	The received donation amount at the beginning of period $t \in T$.
$s^{kk'}$	Spread factor of one unit of unmet demand of critical supply $k \in K$ on critical supply $k' \in K$.
Parameters of the scenario-based stochastic model	
Parameter	Definition
p_ψ	Probability of scenario $\psi \in \Psi$.
$g_{i\psi}^t$	Percentage of available inventory resources of hub $i \in V$, at period $t \in T$, in scenario $\psi \in \Psi$.
$g_{ij\psi}^t$	Percentage of available transport resources of service $(i, j) \in A$, at period $t \in T$, in scenario $\psi \in \Psi$.
$d_{l\psi}^{kt}$	The base demand of beneficiary group $l \in L$, for critical supplies $k \in K$, at period $t \in T$, in scenario $\psi \in \Psi$.
$\hat{d}_{l\psi}^{kt}$	Total demand of beneficiary group $l \in L$, for critical supplies $k \in K$, at period $t \in T$, in scenario $\psi \in \Psi$.

Table 2: Model input parameters.

The input parameters of our model are presented in Table 2. The total demand for supply $k \in K$ for the beneficiary group $l \in L$ in period $t \in T$ in the scenario $\psi \in \Psi$ is given by parameter $d_{l\psi}^{kt}$. The total demand value, as defined by Equation (1), consists of the sum of the uncertain base demand, $\tilde{d}_{l\psi}^{kt}$, and the unmet demand from the previous period. Parameter $s^{kk'}$ represents the spread factor, indicating the impact of one unit of unmet demand of critical supply k on the demand of critical supply k' in the subsequent time period. We define a penalty parameter b^k that indicates the penalty for one unit of unmet demand of critical supply k. The penalty for each critical supply needs to be adjusted with regard to the specific catastrophic event that occurred, the geographical characteristics of the affected region, the current weather, and other components affecting the demands. For instance, the penalty for food is more than shelter in the dry season, but this balance may change during the rainy season as shelter becomes more valuable when compared to the dry season. The model then minimizes the total expected penalty for all beneficiary groups over all time periods, computed using the defined scenarios.

As shown in Table 1 the set of all hubs V is divided into three subsets: the set of the ports of entry V_I, the set of warehouses V_W and the set of DCs V_{DC}. There is a fixed cost f_i for selecting a hub. Furthermore, there is a fixed-cost $\hat{f}_i$ to select each unit of inventory capacity resources for each hub. The capacity of one unit of inventory in the warehouse $i \in V_W$ is represented by u_i. The effects associated with the secondary impacts on the hubs are modelled as uncertain capacity parameters. Specifically, the uncertain parameter $\tilde{g}_{i\psi}^t$ represents the percentage of the available storage resources of the warehouse $i \in V_W$, at period $t \in T$, in scenario $\psi \in \Psi$. At the beginning of each time period, damaged inventory capacity is discarded, given that it is not usable anymore. To consider this change in the inventory level, we use two inventory variables:

one at the beginning and the other at the end of each time period. The inventory level of a warehouse at the beginning of period t is denoted by variable $\hat{r}^{kt}_{i_\psi}$ and the inventory level of a warehouse at the end of the period is given by variable $r^{kt}_{i_\psi}$. We represent the import capacity of each port of entry by the parameters $n^{kt}_i, \forall i \in V_I, k \in K, t \in T$, which limits the output flow of each port of entry, for each critical supply at each time period. In addition, the parameter z^t denotes the financial donations received in period $t \in T$, with z^0 representing the initial budget.

Parameter $\hat{f}_{ij}$ is the fixed-cost for selecting one unit of transportation capacity resource for service $(i, j) \in A$. Parameter u_{ij} indicates the capacity of one unit of transportation resource for service $(i, j) \in A$. In addition, parameter c^k_{ij} indicates the flow-cost of the service $(i, j) \in A$ for a unit of critical supply k.

The list of decision variables are presented in Table 3. In the first stage, we model tactical decisions including the selection of hubs, represented by the binary decision variables $y_i, i \in V$, and the selection of services, represented by the binary decision variables $x_{ij}, (i, j) \in A$. We also select the capacity of warehouses and services, represented by the integer decision variables $\hat{y}_i, i \in V_W$ and $\hat{x}_{ij}, (i, j) \in A$, respectively. Furthermore, the binary decision variable a_{il} represents the assignment of beneficiary group $l \in L$ to DC $i \in V_{DC}$. In the second stage, three groups of continuous decision variables are used. The flow decision variables, $\bar{x}^{kt}_{ij_\psi}, (i, j) \in A, \psi \in \Psi$ indicate the quantity of critical supplies $k \in K$ transported through each service in each period $t \in T$, and the allocation decision variables $\bar{a}^{kt}_{il_\psi}, i \in V_{DC}, l \in L, k \in K, t \in T, \psi \in \Psi$ determine the amount of each critical supply that will be delivered to each beneficiary group. The continuous decision variables $\hat{r}^{kt}_{i_\psi}$ and $r^{kt}_{i_\psi}$ indicate the inventory level of warehouse $i \in V_W$ for critical supply $k \in K$ in scenario $\psi \in \Psi$ at the beginning and end of period $t \in T$, respectively.

In the following, the first and second stage (i.e., recourse) models are introduced. The first stage model seeks to design an HSCN minimizing the expected penalty of the recourse function over the set of scenarios Ψ. The recourse function, represented by $Q_\psi(\hat{x}, \hat{y}, a)$, defines the second stage that selects the operational decisions for a specific scenario $\psi \in \Psi$ to minimize the penalty of unmet demand over the planning horizon.

First Stage	
Variable	Definition
$x_{ij} \in \{0, 1\}$	1 if service $(i, j) \in A$ is selected to be part of the HSCN; 0 otherwise.
$y_i \in \{0, 1\}$	1 if hub $i \in V$ is selected to be part of the HSCN; 0 otherwise.
$\hat{x}_{ij} \in \mathbb{N}^0$	Number of units of transport resources selected for service $(i, j) \in A$.
$\hat{y}_i \in \mathbb{N}^0$	Number of units of inventory resources selected for hub $i \in V_W$.
$a_{il} \in \{0, 1\}$	1 if beneficiary group $l \in L$ is assigned to DC $i \in V_{DC}$; 0 otherwise.
Second Stage	
Variable	Definition
$\bar{x}^{kt}_{ij_\psi} \geq 0$	Quantity of critical supply $k \in K$ transferred through service $(i, j) \in A$ at period $t \in T$ in scenario $\psi \in \Psi$.
$\bar{a}^{kt}_{il_\psi} \geq 0$	Quantity of critical supply $k \in K$ at period $t \in T$ allocated to beneficiary group $l \in L$ from DC $i \in V_{DC}$ in scenario $\psi \in \Psi$.
$r^{kt}_{i_\psi} \geq 0$	Inventory level (in number of units) of critical supply $k \in K$ at warehouse $i \in V_W$ at the end of period $t \in T$ in scenario $\psi \in \Psi$.
$\hat{r}^{kt}_{i_\psi} \geq 0$	Inventory level (in number of units) of critical supply $k \in K$ at warehouse $i \in V_W$ at the beginning of period $t \in T$ in scenario $\psi \in \Psi$.

Table 3: Decision variables of the two-stage stochastic model.

$$\min \sum_{\psi \in \Psi} p_\psi Q_\psi(\hat{x}, \hat{y}, a) \tag{2}$$

s.t.

$$2x_{ij} \leq y_i + y_j \quad \forall (i, j) \in A, \tag{3}$$

$$\hat{y}_i \leq m_i y_i \quad \forall i \in V_W, \tag{4}$$

$$\hat{x}_{ij} \leq m_{ij} x_{ij} \quad \forall (i, j) \in A, \tag{5}$$

$$\sum_{i \in V} f_i y_i + \sum_{i \in W} \hat{f}_i \hat{y}_i + \sum_{(i,j) \in A} \hat{f}_{ij} \hat{x}_{ij} \leq z^0, \tag{6}$$

$$\sum_{i \in V_{DC}} a_{il} = 1 \quad \forall l \in L, \tag{7}$$

$$a_{il} \leq y_i \;\; \forall i \in V_{DC},\; \forall l \in L, \tag{8}$$

$$\begin{aligned}&\hat{x}_{ij} \in \mathbb{N}^0,\; \hat{y}_i \in \mathbb{N}^0,\; x_{ij} \in \{0,1\},\; y_i \in \{0,1\},\\ &a_{il} \in \{0,1\},\; \forall i \in V,\; \forall (i,j) \in A.\end{aligned} \tag{9}$$

Where $Q_\psi(\hat{x}, \hat{y}, a)$ is defined as follows:

$$Q_\psi(\hat{x}, \hat{y}, a) := min \sum_{t \in T} \sum_{k \in K} b^k \sum_{l \in L} (\hat{d}^{kt}_{l\psi} - \sum_{i \in V_{DC}} \bar{a}^{kt}_{il_\psi}) \tag{10}$$

s.t.

$$\sum_{k \in K} \bar{x}^{kt}_{ij_\psi} \leq u_{ij} g^t_{ij_\psi} \hat{x}_{ij}, \quad \forall (i,j) \in A,\; \forall t \in T, \tag{11}$$

$$\bar{a}^{kt}_{il_\psi} \leq \sum_{(j,i) \in A} u_{ji} g^t_{ji_\psi} m_{ji} a_{il}, \quad \forall i \in V_{DC},\; \forall l \in L,\; \forall k \in K,\; \forall t \in T, \tag{12}$$

$$\bar{a}^{kt}_{il_\psi} \leq \hat{d}^{kt}_{l\psi}, \quad \forall i \in V_{DC},\; \forall l \in L,\; \forall k \in K,\; \forall t \in T, \tag{13}$$

$$\sum_{l \in L} \bar{a}^{kt}_{il_\psi} \leq \sum_{j \in W} \bar{x}^{kt}_{ji_\psi}, \quad \forall i \in V_{DC}, \forall k \in K,\; \forall t \in T, \tag{14}$$

$$\hat{d}^{kt}_{l\psi} = d^{kt}_{l\psi} + \sum_{k' \in K} s^{k'k} (\hat{d}^{k't-1}_{l\psi} - \sum_{i \in V_{DC}} \bar{a}^{k't-1}_{il_\psi}), \quad \forall l \in L,\; \forall k \in K,\; \forall t \in T, \tag{15}$$

$$\begin{aligned}&\sum_{i \in V} f_i y_i + \sum_{i \in W} \hat{f}_i \hat{y}_i + \sum_{(i,j) \in A} \hat{f}_{ij} \hat{x}_{ij} + \sum_{t'=1}^{t} \sum_{(i,j) \in A} \sum_{k \in K} c^k_{ij} \bar{x}^{kt'}_{ij_\psi} \leq \\ &z^0 + \sum_{t'=1}^{t} z^{t'}, \quad \forall t \in T,\end{aligned} \tag{16}$$

$$\hat{r}^{kt}_{j_\psi} \leq r^{kt-1}_{j_\psi} \quad \forall j \in V_W,\; \forall k \in K,\; \forall t \in T, \tag{17}$$

$$\sum_{k \in K} \hat{r}^{kt}_{j_\psi} \leq u_j g^t_{j_\psi} \hat{y}_j \quad \forall j \in V_W,\; \forall t \in T, \tag{18}$$

$$\sum_{k \in K} r^{kt}_{j_\psi} \leq u_j g^t_{j_\psi} \hat{y}_j \quad \forall j \in V_W,\; \forall t \in T, \tag{19}$$

$$r^{kt}_{j_\psi} = \hat{r}^{kt}_{j_\psi} + \sum_{(i,j) \in A} \bar{x}^{kt}_{ij_\psi} - \sum_{(j,i) \in A} \bar{x}^{kt}_{ji_\psi}, \quad \forall j \in V_W,\; \forall k \in K,\; \forall t \in T, \tag{20}$$

$$\sum_{(i,j) \in A} \bar{x}^{kt}_{ij_\psi} \leq n^{kt}_i \quad \forall i \in V_I,\;\; \forall k \in K,\; \forall t \in T, \tag{21}$$

$$\begin{aligned}&\bar{x}^{kt}_{ij_\psi} \geq 0,\; \bar{a}^{kt}_{il_\psi} \geq 0,\; r^{kt}_{i_\psi} \geq 0,\; \hat{r}^{kt}_{i_\psi} \geq 0,\; \forall (i,j) \in A,\\ &\forall i \in V,\; \forall k \in K,\; \forall t \in T.\end{aligned} \tag{22}$$

The Objective Function (2) minimizes the expected recourse value (i.e., the expected total penalty for unmet demands). Constraints (3) ensure that a service can only be selected if its origin and destination hubs are part of the HSCN. Constraints (4) indicate that inventory resources at a warehouse can only be selected if that warehouse is also part of the HSCN. Similarly, Constraints (5) indicate that the selection of transportation resources for a service is conditional to it being included in the HSCN. The initial budget, which limits the total cost incurred for the selected hubs and services and their resources in the first stage, is imposed by Constraints (6). Constraints (7) indicate that each beneficiary group should be assigned to a single DC, whereas Constraints (8) prohibit assigning beneficiary groups to DCs that are not part of the HSCN. Finally, the necessary integrality requirements and bounds imposed on the first stage decision variables are included by Constraints (9).

In the second stage, the operational decisions are made. The Objective Function (10) minimizes the total penalty associated with the unmet demands for all beneficiary groups over the entire planning horizon. Constraints (11) are the service capacity Constraints, ensuring that, at each period, the quantity of critical supplies transported by each service is limited to its assigned transportation capacity. After transferring the critical supplies to the DCs, they are allocated to the beneficiary groups. Constraints (12) impose the critical supply limits that are available at each DC to serve the beneficiary groups that are assigned to it. To impose the non-anticipativity requirements in each period, the allocated quantity of critical supplies to each beneficiary group is limited by its demand at that period which is enforced by Constraints (13). Constraints (14) ensure that in each DC, the total quantity of allocated critical supplies is limited by the quantity that is available at that DC. Constraints (15) compute the total demand at each period as the summation of the base demand and the residual demand multiplied by the spread factor. Constraints (16) are the budget Constraints that limit the cumulative expenses at a given time period to be less than equal to the sum of the initial budget and the donations received up to that time period.

Constraints (17) indicate that the inventory level at the beginning of each period is limited by the inventory level at the end of the previous time period. At each period, the inventory level for a warehouse cannot exceed its inventory capacity. These limits are imposed by Constraints (18) and (19). The inventory level for a hub at the end of a period is computed based on its inventory level at the beginning of the period plus the quantity of critical supply that is received at the hub minus the quantity of critical supply that is delivered from it. Constraints (20) calculate the inventory level for each warehouse at the end of each period. The ports of entry do not have inventory capacity, therefore all received critical supplies at a period must be sent to the warehouses. Since we have a limit on the maximum level of critical supplies that can be received at each port of entry from international humanitarian organizations and other donors, the output flow of critical supplies at each port of entry must not exceed such level. Constraints (21) ensure that these limits are imposed in all periods. Finally, Constraints (22) define the bounds of the variables used in the second stage.

5 Experimental results

In this section, we design and apply a series of numerical experiments to study the performance of the proposed model on a practical HSCN design problem (derived using a particular case study). Subection 5.1 introduces the considered case study, obtained using real-world data from Indonesia's 2018 earthquake. In Subsection 5.2 we present the numerical experiments that are conducted and the detailed results obtained on the case study. Subsection 5.2 reports lower and upper bounds when the introduced optimization model is used to solve the considered problem instances, as well as stability results related to the size of the used scenario samples. This subsection also investigates the importance of explicitly considering the uncertainty when solving the problems, as well as the impact of the available budget and the spread-factor on the performance of the designed HSCN over the planning horizon.

5.1 Data generation for the case study

Our case study focuses on the 2018 earthquakes in Indonesia. On the 29th of July 2018, a 6.4 magnitude earthquake occurred on the island of Lombok. This earthquake had more than 1,500 aftershocks, three of which were particularly strong: a 7.0 magnitude earthquake on the 5th of August 2018, a 5.9 magnitude earthquake on the 9th of August 2018, and a 6.4 magnitude earthquake on the 26th of August 2018. These earthquakes caused 564 deaths, 1,584 injured, and 445,343 people displaced into more than 2,700 camps (i.e., beneficiary groups) (IFRC, 2021a). Immediately after the earthquakes, Indonesia's government announced a state of emergency, which ended on the 26th of August 2018, by declaring the transition to the long-term recovery phase. We here consider this period of 28 days as the short-term recovery phase of our planning problem. The planning horizon is then divided into four periods, each period being one week-long. To model the demands associated with the locations of the beneficiary groups, we used a data set made available by the International Organization for Migration (IOM, 2019), which indicates the number of individuals and households associated with the beneficiary group locations. Our study focuses on a specific part of the island of Lombok (Pringgabaja, Suela, and south of Aikmel), where 13,177 individuals were displaced into 71 beneficiary groups.

The International Federation of Red Cross and Red Crescent Societies (IFRC) and its local partner Palang Merah Indonesia (PMI) are among the active humanitarian organizations in the region. We analyzed the "Emergency Plan of Action Operation" reports and "Operation Update" provided by the IFRC (IFRC, 2021a) to better understand the region's state and the challenges it faced regarding the humanitarian operations after the earthquake. Based on these reports, we located the ports of entry and the warehouse locations that IFRC and PMI used in their HSCN. Furthermore, we also learned that PMI signed agreements with third-party logistics companies to use their fleets to transport critical supplies over their HSCN (IFRC, 2021a). The airport on the island was damaged, which allowed only small airplanes to land. Hence, the larger aircrafts transporting supplies would land at the Surabaya airport, located on the Java island (IFRC, 2021a), and most of the critical supplies were then shipped to Lombok by boats. The IFRC used four points of entry, including: Serang port, Gresik port, and Juanda International Airport on Java island, and Lombok airport on the Lombok island. It further had six warehouses on Lombok. According to the IFRC reports, water was provided to beneficiaries via 21 water trucks operated from a single location on the island. Considering that the water supply came from a different relief network (which did not share resources with the rest), this study focuses on the following critical supplies: shelter, food, and hygiene items (e.g. soap, toilet paper, and sanitary pad) (IFRC, 2021a).

In order to standardize and harmonize the critical supplies in emergency operations, the International Federation and the International Committee of the IFRC have published the standard products catalog (IFRC, 2021b). This catalog presents the details regarding all critical supplies, including weight, volume, and the number of beneficiaries each unit can support during a given time frame (if applicable). Using this catalog, we were able to calculate the amount of critical supplies required for each individual or household during each period.

Although we extracted the values of multiple parameters from the IFRC reports, accurate values for some parameters were missing. Additional sources were thus needed to complete our data set. To evaluate the service capacities and associated costs, we consulted local vehicle rental websites. We first chose two types of trucks (i.e., medium duty trucks for services between ports of entry and warehouses and pick-up trucks for services between warehouses and DCs) from the available trucks and calculated the fixed-cost and the flow-cost for renting the trucks using the pricing information from the website. However, since the reported costs on the website were priced for one delivery between each origin and destination, we defined a service resource between an origin and destination pair to operate only one delivery per period. Specifically, for the flow-cost, we multiplied the per kilometer cost of transporting the critical supplies obtained from the local website by the distance between the hubs. To calculate the distances between the different locations, we used an online routing engine (Luxen and Vetter, 2011) that operates on the OpenStreetMap data. We were thus able to evaluate both the walking and the driving distances between the different geographical locations (i.e., the driving distance between the ports of entry and warehouses, the driving distance between warehouses and DCs, and the walking distance between the DCs and beneficiary groups).

Another set of parameters that were not mentioned in the IFRC reports are the locations of the DCs. Hence, we generated a set of possible DC locations to complete our data set as follows. It is first assumed that beneficiaries will, most likely, have to walk to the DCs to acquire their critical supplies. Therefore, the best candidate locations for the DCs are those that are close to the beneficiary groups. Hakimi (1964) showed that in a given graph if one is interested in finding the specific location that minimizes the total distance between the selected location and all nodes in the graph then the location will necessarily be one of the nodes. When applying this result to the present case, the location that minimizes the total distance from all beneficiary groups is necessarily among the beneficiary group's location. Therefore, all beneficiary group locations are potential candidates for the DC locations. In order to reduce the number of candidate locations for the DCs, we clustered the beneficiary groups using the DBSCAN algorithm (Ester et al., 1996). DBSCAN is a density-based clustering algorithm that clusters the beneficiary groups based on two parameters: a parameter indicating the neighbourhood radius for the DCs to be included in the same cluster and a parameter specifying the minimum number of neighbours within each cluster, impacting the cluster's density. Different values for these two parameters result in different clusters. As typical in clustering analysis, a domain expert then selects the cluster most useful in practice (Mendes and Cardoso, 2006). Figure 2 presents the locations of the beneficiary groups and the four candidate locations for the DCs that were obtained following the cluster analysis that was performed using the DBSCAN algorithm.

Scenario generation

In order to approximate the two-stage stochastic programming and, to study the performance of the obtained solution, we require a set of scenarios that properly captures the probable variations of the uncertain parameters' values. Since each natural disaster is a unique event that is often different from previous ones (Chen et al., 2011), relying on experts' opinions is a common approach to formulate the uncertainty that humanitarian organizations face when planning operations (Karimi and Hüllermeier, 2007). The experts' opinions are obtained based on the damage assessments conducted after a natural disaster occurs. Since the damage assessments are time-consuming, the affected region is often divided into smaller sub-regions where the assessments are conducted in a sample set of locations (Balcik and Yanıkoğlu, 2020; Balcik, 2017). Considering that we did not have access to specific assessments, we decided to simulate the experts' opinions to characterize the parameter uncertainties. Specifically, we simulated the experts' predictions regarding the values of the uncertain parameters using the three-point estimating technique (Hakimifar et al., 2021). Following this technique, the experts are asked to provide three values for each uncertain parameter: an optimistic value, a pessimistic value, and a most likely value, i.e., a triangular probability distribution (Benini et al., 2017). To generate scenarios for this problem, we thus considered that a total of three experts would provide their assessments for each uncertain parameter (thus providing a specific triangular probability distribution for each stochastic parameter assessed by each expert). The explicit values provided by each expert were randomly generated using the available dataset. Specifically, we assume that the available dataset of the uncertain parameters obtained from the humanitarian organizations' websites is a realization of the triangular distributions provided by the experts. Therefore, while the characteristics of the triangular distributions are chosen randomly, the minimum and maximum values of distributions embrace this realization. Finally, we assume that the same confidence level was associated to each expert's assessments. We thus generated an equal number of scenarios from the expert-specific distributions.

Ground Truth

A total of 1000 scenarios sampled from the triangular distributions provided by the three experts (334 first expert, 333 second expert, 333 third expert) were used to represent the ground truth (i.e., an accurate approximation of how the stochastic parameters can randomly vary). However, given the complexity of the proposed model, solving it using all the scenarios that define the ground truth is not computationally tractable. Therefore, we use the Sample Average Approximation (SAA) (Kleywegt et al., 2002) method to generate more manageable scenario sets which can be used to efficiently solve the two-stage stochastic model.

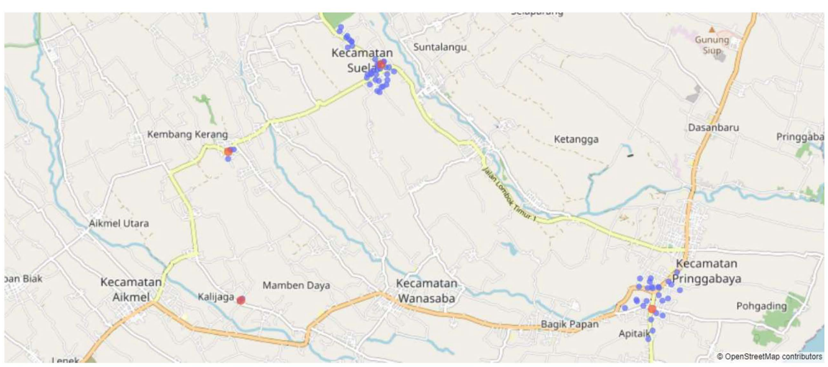

Figure 2: Original beneficiary groups and their respective clusters presented on the OpenStreetMap (OpenStreetMap contributors, 2022). The blue circles represent the beneficiary groups and the red circles indicate the distribution centers.

Yet, it is crucial to assess the effects of the sample size on the in-sample stability and out-of-sample stability of the solutions obtained (Kaut and Wallace, 2003). After choosing an appropriate sample size (i.e., one that provides a satisfactory level of stability), the problem can be solved by generating a scenario set with the prescribed size and then evaluating the obtained solution using the ground truth to assess its expected performance in practice.

5.2 Computational Results

In this subsection, we report the numerical results for the two-stage stochastic model in the context of the considered case study. We start by studying the effects of varying the number of scenarios on the solutions obtained by solving the two-stage model by performing in-sample stability and out-of-sample stability analyses (Kaut and Wallace, 2003) in Subsection 5.2.1. Then in Subsection 5.2.2, we obtain lower and upper bounds for the planning solution over the considered ground truth. Since that capacity and demand are the uncertain parameters, we separately study the effects of each of these parameters on the obtained solution. In Subsection 5.2.3, we compare the performance of the solution obtained from our two-stage model with its counterpart models in which the uncertain parameters are replaced with their deterministic counterparts. In our problem, we assume that the available budget is known beforehand. In Subsection 5.2.4, we evaluate the effects of the available budget. Finally, in Subsection 5.2.5, we study the effects of the spread factor and compare the different solutions induced by changing the values of the spread factor. The implementations are done using the Pyomo software package (Hart et al., 2017, 2011) on a machine with Intel e5-2630 v4 2.2 GHz CPU and 256 GB of memory.

5.2.1 In- and Out-of-Sample Stability

In this subsection, we explore the impact of the number of scenarios used to solve the HSCN problem on the obtained solution. When solving a two-stage model, increasing the number of scenarios obtained using an appropriate sampling method improves the approximation of the uncertain parameters. However, in practice, the resulting optimization problem should remain solvable in a reasonable amount of time. Solving an optimization problem with distinct sets of scenarios (even of the same size) may lead to different solutions. We now consider both the in-sample and out-of-sample stability to analyze the effect of sample size on the final solution quality. An in-sample stability test evaluates the stability of the obtained solutions over different scenario sizes in terms of their reported objective function value. Likewise, an out-of-sample stability test evaluates the stability of the expected objective function value of the obtained solutions over the ground truth.

To evaluate the in-sample stability, we solve our two-stage model with a specific number of scenarios with 15 different randomly generated scenario sets. Then, we calculate the average and standard deviation of the objective function values. By repeating this process for different scenario numbers, we study the effect of the number of scenarios on the in-sample stability of the studied problem. Table 4 represents the results obtained, indicating that, as the number of scenarios increases, the standard deviation significantly decreases, which translates as an increase in the in-sample stability. As the number of scenarios increases from 10 to 50, the Coefficient of Variation (CV) (i.e., the ratio of the standard deviation to the average) is reduced from 5.72% to 3.36%. However, as the number of scenarios increases from 50 to 200, the CV decreases to 2.03%. Considering the computational cost of using 200 scenarios compared to 50 and the slight reduction over the CV value, 50 is the best candidate for the following experiments. Since the average objective function values in this table are calculated over small scenario sets (not the ground truth), they are not indicative of the quality of the obtained solutions. The abbreviation O.F. in the following tables stands for the objective function.

number of scenarios	average of O.F. value	standard deviation of O.F. value
10	7,168.60	410.70
20	7,210.70	439.40
30	7,315.50	370.34
50	7,138.60	240.25
100	7,466.50	285.35
200	7,258.90	147.73

Table 4: The in-sample stability analysis results.

In addition to the in-sample stability, we also study the out-of-sample stability of the problem over different scenario sizes. In a similar process, we apply the first-stage solutions obtained from the in-sample stability test on the entire ground truth and calculate the average value and the standard deviation of the objective function over all 15 solutions obtained for each scenario size. Table 5 presents the results obtained by repeating this process for different scenarios sizes. Here the objective function value refers to the entire ground truth and therefore indicates the quality of the solutions. According to the presented data in Table 5, by increasing the scenario size from 10 to 50, CV decreases from 2.34% to 0.03%. However, by increasing the scenario size to 200, CV decreases to 0.00%, which is negligible compared to the computational cost of using 200 scenarios. Based on the results of these two tables, we select 50 as the number of scenarios for our problem and use it in all following experiments, given its acceptable standard deviation both in in-sample and out-of-sample stability tests.

number of scenarios	average of O.F. value	standard deviation of O.F. value
10	7,419.40	173.92
20	7,303.57	7.55
30	7,302.88	8.50
50	7,299.70	2.33
100	7,299.09	0.42
200	7,298.76	0.19

Table 5: The out-of-sample stability analysis results.

5.2.2 Bounds and Value of Stochastic Information

We now compute both an upper and a lower bound for the HSCN problem. To obtain a lower bound, the Wait-and-See (WS) variant of the problem is solved (Tintner, 1955; Madansky, 1960). In the WS, the value of the uncertain parameters is considered known (i.e., the implicit assumption being applied here is that one can wait until all uncertain parameters become known before optimization is applied). We therefore obtain the WS objective function value by solving each scenario of the ground truth individually and then averaging over their optimal solution values.

As an upper bound, we solve the deterministic version of the problem by replacing the uncertain parameters with their expected values (Madansky, 1960; Dantzig, 1955). Then we apply the solution to the ground truth scenarios to calculate the expected objective function value of the deterministic solution, represented by EEV. Table 6 indicates the calculated upper and lower bounds over the ground truth.

Concept	Value
EEV (upper bound)	7,954.42
WS (lower bound)	7,298.36

Table 6: Upper and lower bounds for our problem.

We now calculate the Expected Value of Perfect Information (EVPI) (Birge and Louveaux, 2011), representing the possible improvement of the objective function value if the exact realizations of the uncertain parameters were known. We use the objective function value obtained in Subsection 5.2.1, on the ground truth as follows:

$$EVPI = RP - WS = 7299.70 - 7298.36 = 1.34.$$

Such a small value of EVPI indicates that the two-stage stochastic problem optimized on the 50 considered scenarios finds a solution that performs quite well on average, and having access to perfect information only marginally reduces the penalty in the objective function. Next, we investigate whether it is worth solving the stochastic problem instead of its deterministic counterpart. We therefore calculate the Value of Stochastic Solution (VSS) (Birge and Louveaux, 2011), representing the objective function gain by explicitly considering the uncertainty in the model:

$$VSS = EEV - RP = 7954.42 - 7299.70 = 654.72.$$

Such a high VSS value suggests that solving the stochastic variant may significantly improve the solution quality and is certainly worthwhile, considering that the objective function value is linked to population health.

5.2.3 Importance of modeling uncertainty

To study the effects of the considered uncertain parameters on the solutions, we now solve our two-stage model under three different settings. The first setting replaces the uncertain capacity parameters with their expected values. Therefore, the only remaining uncertain parameters in the model are the demands. In the second setting, we replace the uncertain demand parameters with their expected values, but the capacity parameters remain uncertain. In the third setting, both parameters are considered uncertain. Table 7 presents the average objective function values and their standard deviations over 15 runs for each setting. Analyzing the objective function column, the best results are obtained on the setting where both the capacity and demand parameters are uncertain. Particularly, considering the capacities as uncertain parameters leads to a considerable improvement in the average value of the objective function. Next, by comparing the standard deviation of these three settings, we conclude that considering the uncertainty of demand and capacity in the optimization model considerably improves the out-of-sample stability of the solution.

Capacity	Demand	Average Value of O.F.	Standard Deviation of O.F.
uncertain	expected value	7,319.49	29.21
expected value	uncertain	7,730.76	194.69
uncertain	uncertain	7,299.70	2.33

Table 7: Effect of modeling uncertainty on the optimal solution of the stochastic model (using 50 scenarios over 15 runs).

5.2.4 Impact of available budget

It is expected that the available budget plays a pivotal role in the quality of the final solution obtained as it limits the design and operational costs that are paid for each stage and time period. As we mentioned in the introduction, the final amount of donations received is often less than the amount initially requested. Therefore, we now analyze the impact of a possible budget shortage on the performance of the designed HSCN. Such analysis helps decision-makers to evaluate the robustness of the designed HSCN. To this end, we define two parameters for the budget: the amount the decision-makers anticipate, which is denoted z_{exp} (i.e., the expected budget), which we distinguished from the actual budget z_{act} (i.e., the amount actually received). The questions that we are investigating through this experiment are: (1) How does a HSCN perform if we expect a budget of z_{exp}, but the actual budget turns out to be z_{act}? (2) How would the HSCN perform if we knew the actual budget value at the design time and the HSCN is thus designed using z_{act}?

To answer the first question, we investigate the case where we design the HSCN using z_{exp}, but the available budget in practice is z_{act}. In this part of the experiments, we first solve the two-stage model using the z_{exp} as the budget. We then update the budget to z_{act} and apply the designed HSCN on the ground truth. Table 8 summarizes the results obtained in this experiment. In order to be able to track the expected penalty over the planning horizon, it is calculated separately for each time period. In the first row of Table 8, the value of the expected budget is equal to the actual budget (i.e., the expected budget at design time is received during the operation). As represented in the per period penalty column, unlike in other periods, the second period has a very low penalty, indicating that almost all the demand in this period is satisfied. In the second row, the actual budget is set to 80 percent of the expected budget leading to an increase in the expected penalty over all periods. The per-period penalty for this budget has a similar pattern as in the first row. When comparing the total penalty of the first two rows, one observes that: when the actual budget is reduced by 20 percent the increase in the overall penalty is only marginal. This observation proves very useful to decision-makers in the present setting. For example, in the context of our specific case study, this amount (corresponding to 20 percent of the original budget) may find a more effective use in other operations of the short-term recovery phase not considered in this planning problem. In the third row, the actual budget is reduced to 60 percent of the expected budget, resulting in a high increase in the expected penalty of the HSCN. It is also observed that most of this increase belongs to the first two periods. In order to reduce the impact of the spread factor on subsequent periods, the planning solution prefers to satisfy the demand in the early periods as much as possible, when the budget is limited. Finally, in the last row, with an actual budget equal to 40 percent of the expected budget, there is an even higher increase in the expected penalty on the HSCN performance.

actual budget z_{act}	O.F. value z_{exp} per period				total O.F. value z_{exp}
	First Period	Second Period	Third Period	Fourth Period	
z_{exp}	2, 116.92	10.30	2, 850.16	2, 322.78	7, 300.16
$0.8z_{exp}$	2, 147.75	10.57	2, 871.15	2, 333.28	7, 362.75
$0.6z_{exp}$	13, 903.64	6, 042.45	2, 986.34	2, 608.43	25, 540.86
$0.4z_{exp}$	134, 238.84	134, 843.53	3, 065.40	3, 330.40	275, 478.17

Table 8: Effect of budget on the optimum solution of the stochastic model (average over 15 runs using 50 scenarios).

In the second part of the experiment, the value of the actual budget at the design time is assumed known. Therefore, we solve the two-stage model using different values of z_{act} and apply the obtained HSCN to the ground truth. Figure 3 compares the obtained results of the two parts of the experiment. The impact of using z_{exp} at design time on the objective function value is negligible compared to the effect of the budget deficit indicating that a lack of budget cannot be compensated by a more prudent planning.

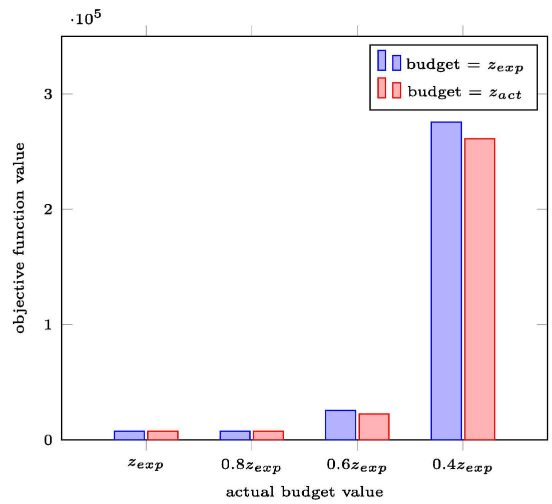

Figure 3: Penalty (objective function value) of the designed HSCN using z_{exp} as budget (blue) and using z_{act} as budget (red) over the ground truth with budget z_{act}.

5.2.5 Impact of the spread factor

In this subsection, the effects of the spread factor value (representing, e.g. the contagion level of diseases) on the performance of the obtained solution are studied.

We consider two different budget values, z and $2z$. For each budget level we evaluate three values for the spread factor: 0 (i.e., no spread), the identity matrix (represented by I), and $2I$. For the sake of the experiment, we assume that the unmet demand of each critical supply only impacts itself (but not other supplies) in the subsequent time periods (as represented by the identity matrix).

Table 9 represents the results of this experiment. To better analyze the effect of the spread factor on the HSCN's performance, we present the expected penalty separately per period and in total. An interesting pattern in the results is that, as the spread factor increases, the expected penalty shifts from early time periods to the end of the planning horizon. This is explained by the model's effort to avoid unmet demand early in order to avoid excessive spread over time. The results of this experiment are also visualized in Figure 4. As the spread factor increases, the impact of a higher budget on improving the objective function value decreases. An important observation in this experiment is that considering a lower value for the spread factor parameter can irreparably misguide the decision-makers on the performance of the designed HSCN.

Spread Factor	Budget	Objective Function Value(Total)	Objective Function Value (per period)			
			First Period	Second Period	Third Period	Fourth Period
0	z	2, 093.54	2, 085.57	7.97	0.00	0.00
0	2z	0.90	0.90	0.00	0.00	0.00
I	z	7, 300.16	2, 116.92	10.30	2, 850.16	2, 322.78
I	2z	3, 881.29	0.00	0.00	1, 989.06	1, 892.23
$2I$	z	14, 858.83	7.32	0.00	5, 078.27	9, 773.23
$2I$	2z	13, 540.26	0.15	0.00	4, 516.25	9, 023.86

Table 9: Effect of spread factor on the performance of the HSCN performance (average over 15 runs using 50 scenarios).

Spread Factor	Budget	First Stage Expenses	Second Stage Expenses (per period)			
			First Period	Second Period	Third Period	Fourth Period
0	z	60, 098.44	12, 682.30	10, 896.03	10, 913.85	10, 809.37
I	z	58, 628.16	12, 428.91	11, 500.73	11, 417.99	11, 424.22
$2I$	z	57, 794.27	12, 428.92	11, 521.51	11, 909.61	11, 745.70

Table 10: Effect of spread factor on the expenses of the optimized HSCN (average over 15 runs using 50 scenarios).

Table 10 represents the expenses in each stage in this experiment. The first stage expenses represent the HSCN design costs and the second stage expenses represent the operational costs in each period. The results indicate the importance of the spread factor as the first stage expenses of the designed HSCN with a spread factor value of 0 are considerably higher than models with a non-zero spread factor parameter. In other words, while the model can afford to spend more on the HSCN design when the spread is low, it tends to spend more on controlling disease (i.e., unmet demand) when the spread is high.

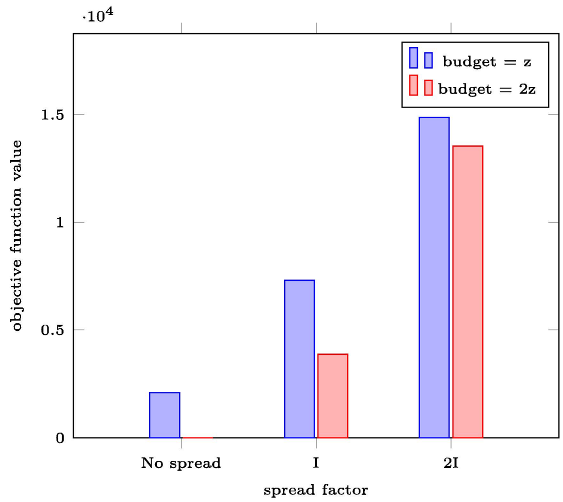

Figure 4: Impact of spread factor and available budget on the performance of the HSCN.

Finally, Table 11 characterize the best HSCNs obtained using different values for the spread factors. As the spread factor increases, the number of selected hubs and services reduces. The same holds true for the number of inventory and transport resources as the spread factor increases. These results support the previous conclusion obtained from Table 10, showing a decrease in the first stage expenses as the spread factor values increase. However, as represented in Figure 4, the changes in the obtained solution cannot fully compensate for the increase in the expected penalty caused by the increase of the spread factor values.

spread factor	point of entry	warehouse	warehouse resources	DC	service	service resources
0	3	3	17	4	15	116
I	2	3	14	4	12	106
$2I$	2	3	14	4	12	100

Table 11: Characteristics of the best HSCNs obtained by different spread factor values.

6 Conclusion

A fast and effective humanitarian response post-disaster is essential to avoid lasting negative effects on the affected communities. Effective use of the available response budget is therefore of the utmost importance. In this work, we have proposed a two-stage stochastic model to solve the HSCN design problem after a natural disaster to cover the aid provided over a given planning horizon. We propose a new approach to model the demand in a multi-period HSCN design problem setting that is more realistic. Our approach introduces a spread factor, which addresses the effects of each critical supply's unmet demand on all critical supplies' demand in the subsequent time periods.

The proposed two-stage stochastic optimization model was numerically evaluated in a case study based on the 2018 earthquake that occurred in Indonesia. The instances used for this case study were derived using real-world data gathered from the grey literature published by IFRC and PMI following this catastrophic event. This data was further complemented by information collected via local commercial websites to estimate the missing parts of the dataset. The stochastic optimization model was then used to formulate the considered problem while explicitly accounting for both demand and available capacity (both logistical infrastructure and transportation services) uncertainty. In order to provide an accurate representation of the uncertainty, we generated a ground truth consisting of 1000 scenarios sampled from the distributions of the uncertain parameters.

Multiple experiments were designed and conducted using the proposed model. The results demonstrate the importance of considering uncertainty and the proposed spread factor in the HSCN design problem.

Compared to its deterministic counterpart, the proposed stochastic model provided improved solution quality in terms of the objective function value as evaluated on the ground truth and its out-of-sample stability. The experiments also highlight the benefits of using the spread factor to provide decision-makers with insights regarding the crisis' depth and potential development over time in the affected region.

Furthermore, we studied the effect of budget shortages on the expected performance of the designed HSCN. In the investigated case study, the results suggest that the designed HSCN may be able to resist a certain level of budget shortage. However, as the shortage level increases the HSCN's expected performance may quickly decrease to an unacceptable level. Such experiments may help decision-makers to identify a more appropriate amount for the budget. The additional budget, which does not lead to a noticeable reduction in the unmet demand penalties considered, may therefore be allocated to other operations for more efficient use. The methodology introduced in this paper can thus assist the decision-makers by providing them with a better understanding of the crisis and how aid can be efficiently distributed.

In future work, one may extend the proposed methodology by considering other relevant aspects of the problem setting. Specifically, introducing concepts of fairness and equity when formulating the objective function would appear as a particularly impactful and challenging avenue of research to pursue. Additionally, investigating how ambiguity, which may affect the formulation of the uncertain parameters, would also appear as a relevant path of investigation.

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