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Résumé

Les organisations humanitaires jouent un rôle crucial en menant des opérations telles que la distribution rapide et efficace de produits essentiels aux populations vulnérables touchées par une catastrophe naturelle. Les retards ou les échecs dans la livraison de ces produits peuvent avoir des conséquences graves sur la santé et le bien-être des personnes sinistrées. Cette thèse se concentre sur la conception de Réseaux de Chaîne d'Approvisionnement Humanitaire (RCAH) après une catastrophe naturelle, dans un contexte où les ressources sont limitées et où une grande incertitude concernant les conditions dans les zones affectées ainsi que la gravité de la crise complique la planification. Trois articles scientifiques sont présentés traitant des enjeux décisionnels importants pour cette planification.

Dans le premier article, nous formulons et résolvons le problème de conception du RCAH en tenant compte de différentes sources d'incertitude. Plus précisément, nous proposons une méthodologie d'optimisation permettant de concevoir un RCAH destiné à stocker et distribuer des produits critiques à une population affectée sur un horizon temporel donné. Un modèle stochastique à deux étapes est développé pour traiter l'incertitude liée à la demande, ainsi qu'aux capacités de transport et de stockage au sein du réseau. Dans la première étape, des décisions de conception, telles que la sélection des hubs, des services, des stocks et des ressources de transport, sont prises, définissant ainsi la structure du RCAH pour toute la durée de l'horizon de planification. Dans la deuxième étape, des décisions opérationnelles liées au transport, au stockage et à l'allocation des produits sont prises. Le modèle intègre également les impacts cumulatifs de la demande non satisfaite en produits critiques au fil du temps.

Le deuxième article traite de l'ambiguïté concernant les distributions probabilistes inhérentes au contexte de planification du problème de conception d'un RCAH.

Après une catastrophe naturelle, les décideurs s'appuient sur des estimations de paramètres incertains issues de diverses sources de données (par exemple, enquêtes, images satellites, rapports gouvernementaux ou médias) pour planifier les efforts de secours humanitaires. Cependant, ces estimations peuvent entraîner des divergences significatives dans la manière dont les paramètres incertains sont formulés en tant que variables aléatoires, générant ainsi une ambiguïté dans le processus de planification. Cet article propose plusieurs approches d'optimisation permettant de résoudre ce problème en prenant explicitement en compte cette ambiguïté dans la conception du RCAH.

Les deux premiers articles supposent que la structure du RCAH reste inchangée pendant l'horizon de planification, en raison de la complexité de la coordination avec d'autres opérations humanitaires en cours (par exemple, l'enlèvement des débris) et du coût élevé d'acquisition de nouvelles ressources. Cela dit, certains ajustements peuvent néanmoins être envisagés par les organisations humanitaires pour réajuster les plans établis et les rendre plus efficients lorsque de nouvelles informations deviennent disponibles.

Par conséquent, dans le troisième article, nous proposons un modèle de conception d'un RCAH à plusieurs étapes permettant le transfert des ressources de transport (par exemple, les camions) entre les services sélectionnés au sein du RCAH conçu. De plus, le modèle autorise la sélection de services de transport supplémentaires à chaque étape de l'horizon de planification et repose sur une formulation du processus de divulgation d'informations qui reflète de manière plus réaliste ce qui est observé sur le terrain.

Dans l'ensemble, cette thèse met en lumière l'importance de considérer divers facteurs dans le problème de conception du RCAH. Un accent particulier est mis sur la modélisation de la propagation de la demande non satisfaite, étant donné qu'un manque des commodités essentielles peut entraîner une propagation de maladies. Le premier article souligne le rôle crucial du facteur de propagation dans l'optimisation de l'efficacité du réseau. Le deuxième article met en avant la nécessité de prendre en compte l'ambiguïté dans le contexte informationnel lors de la planification des opérations humanitaires. Plus spécifiquement, les résultats obtenus suggèrent que des approches robustes de modélisation sont essentielles pour une prise de décision efficace. Enfin, le troisième article démontre la valeur d'un modèle à plusieurs étapes permettant d'adapter les ressources de transport au fil du temps, améliorant ainsi la flexibilité et la réactivité du RCAH.

Ensemble, ces contributions renforcent la capacité à résoudre les problèmes de conception d'un RCAH, permettant de concevoir des réseaux plus résilients et adaptables suite à une catastrophe naturelle, réduisant ainsi les impacts attendus sur les populations vulnérables des régions affectées.

Abstract

Humanitarian organizations conduct crucial operations, such as the efficient and timely distribution of critical supplies to vulnerable populations after a natural disaster. Delays or failures in supply delivery can severely harm public health. This thesis focuses on the design of a Humanitarian Supply Chain Network (HSCN) in the aftermath of a natural disaster in a setting with limited resources and uncertainty regarding regional conditions and the severity of the crisis.

In the first paper, we formulate and solve the HSCN design problem under various sources of uncertainty. Specifically, we design an HSCN storing and distributing critical supplies to an affected population over a given time horizon. A two-stage stochastic model is developed to address uncertainty related to demand, as well as transportation and storage capacities within the network. In the first stage, design decisions, such as selecting hubs, services, inventory, and transportation resources, are made, with the HSCN's structure remaining fixed for the duration of the planning horizon. In the second stage, operational decisions related to transportation, storage, and supply allocation are made. The model also accounts for the cumulative impacts of unmet demand for critical supplies over time.

The second paper addresses ambiguity concerning the probability distributions used in the HSCN design problem. After a natural disaster, decision-makers rely on estimates of uncertain parameters from various data sources (e.g., surveys, satellite imagery, governmental reports, or media) to plan humanitarian relief efforts. These estimates, however, may contain significant discrepancies, leading to ambiguity in the planning process. The second paper proposes multiple modeling approaches to handle this ambiguity in HSCN design.

The first two papers assume that the structure of the HSCN remains unchanged

over the planning horizon due to the complexity of coordinating with other ongoing humanitarian operations (e.g., debris removal) and the high cost of acquiring new resources. In the third paper, we propose a multi-stage HSCN design model that allows for the relocation of transportation resources (e.g., trucks) between selected services within the designed HSCN. Additionally, the model allows the selection of additional transportation services at each stage of the planning horizon.

This thesis demonstrates the importance of considering various factors in the HSCN design problem, including spreading the demand, ambiguity in estimating uncertainty and leveraging more complex multi-stage models. The spread of demand refers to the accumulation of unfulfilled demand over time, which can affect future demands of all critical supplies with different intensities. For instance, failing to deliver medication and preventing products necessary for infectious diseases will increase the demand for these items (cumulative effect) and other items, such as shelters to quarantine affected people (spreading effect). The first paper highlights the significance of considering spreading the demand by introducing the spread factor in optimizing the network's efficiency. The second paper emphasizes the need to account for ambiguity in the informational context of humanitarian operations, suggesting that robust modeling approaches are essential for effective decision-making. Finally, the third paper showcases the value of a multi-stage model that adapts the transportation resources over time, ultimately improving the HSCN's flexibility and responsiveness. Together, these contributions advance the design of a more resilient and adaptive HSCN in the aftermath of a natural disaster, reducing the expected harm to the vulnerable population in the affected region.

CHAPTER I

INTRODUCTION

The number of natural disaster occurrences has been increasing over recent years, leading to more demand for humanitarian relief operations over the globe. However, the financial resources of humanitarian organizations have not grown as much (UNOCHA, 2021b), resulting in significant challenges when prioritizing and allocating budgets. More than 75% of the humanitarian organizations expenses in the relief operations are related to the design and operation of the relief supply chain (Besiou & Van Wassenhove, 2020; Van Wassenhove, 2006; Stegemann & Stumpf, 2018). Therefore, efficient design and operation of relief distribution networks are crucial to the success of humanitarian operations in response to natural disasters. Besides the financial limitations, humanitarian organizations also lack other necessary resources, including staff and means of transport, increasing the importance of efficiency in the overall planning process.

In response to these challenges, a growing number of studies in recent years have focused on addressing relief distribution planning problems. Emergency Management (EM) is a multidisciplinary field that focuses on the planning and coordination of humanitarian operations to mitigate the impacts of natural disasters. EM encompasses operations conducted both before (i.e., pre-disaster activities) and after (i.e., post-disaster activities) the occurrence of such events. The pre-disaster activities are divided into two parts, including the mitigation phase and the preparedness phase. The mitigation phase activities focus on prepositioning the critical supplies, while the preparedness phase activities develop response plans for a possible natural disaster. The post-disaster activities are divided into three phases: response, short-term, and long-term. The response phase includes humanitarian operations that are conducted in the first 72 hours after the natural disaster occurs. Such operations include transferring the required search-and-rescue equipment, removing debris from vital transportation routes, and restoring critical infrastructure. The short-term recovery phase focuses on restoring the affected region to its pre-disaster state by removing debris from all roads and streets, restoring all infrastructure, and distributing critical supplies to the vulnerable population. Therefore, additional activities, including damage assessments, and budget and volunteer management, are also necessary for this phase. The long-term phase, which may last several years, includes psychological support and humanitarian assistance to the affected population.

This thesis focuses on the short-term recovery phase, specifically on the design and operation of a Humanitarian Supply Chain Network (HSCN). An HSCN is a physical network of hubs responsible for receiving, storing, and distributing critical supplies to vulnerable populations affected by a natural disaster over a defined planning horizon. Transportation services support the movement of these supplies between hubs, ensuring efficient operations. The designed HSCN ultimately facilitates the delivery of critical supplies to the affected population within the specified planning horizon.

This thesis comprises three scientific papers that address key issues related to the design and operation of HSCNs. In the first paper, we consider the HSCN design problem under uncertainty. Specifically, we consider uncertainty in the demands of the vulnerable population, as well as the capacity of both the transportation services and inventories of the designed network over the planning horizon. In this context, sources of uncertainty may include a lack of information to accurately assess the needs of the population, damage to infrastructure and its impact on the ability to carry out required operations (such as transportation and stock management), and the potential effects of secondary impacts, which can further exacerbate the consequences of the natural disaster. The first paper introduces a novel formulation to capture the cumulative effect of unmet demand across critical supplies, highlighting the importance of accounting for interdependent shortages of critical supplies in optimizing disaster relief operations.

The need and damage assessment procedures begin as soon as a natural disaster occurs to estimate the value of uncertain factors in the HSCN design problem. The value of uncertain parameters is calculated following a natural disaster utilizing a variety of data sources. These information sources include polls, satellite images, official documents, and the media. The derived estimations might differ, which can cause ambiguity in the informational framework that underlies the planning of humanitarian aid activities. The second paper examines different methods for modeling inconsistent estimations obtained from multiple data sources while formulating the HSCN design problem following a natural disaster. Four mathematical models are proposed that explicitly account for the uncertainty and ambiguity that influence both the population's needs and the network's capacity for storage and delivery. The findings highlight the necessity of using mathematical models capable of addressing uncertainty and ambiguity, ensuring that HSCNs remain resilient to both uncertainty and the ambiguity stemming from assessments performed on multiple data sources with varying estimations of demand and resources available.

One of the presumptions in the first two studies is that the planned HSCN structure will remain the same throughout the planning horizon. The complexity of coordinating such adjustments with ongoing humanitarian efforts (such as debris removal) and the higher expense of choosing new resources are the motivations for such assumptions.

The third paper examines the benefits of incorporating evolving information dynamics (where contextual information about the effects of the natural disaster becomes more accurate over time, reducing uncertainty) and demand spread into the HSCN design problem. Specifically, it considers a setting where transportation resources (e.g., trucks) can be relocated between HSCN services and additional transportation resources can be employed during the planning horizon. We propose a three-stage stochastic model to design an HSCN under these conditions and compare its performance with a two-stage counterpart. Additionally, we conduct experiments to evaluate the impact of varying spread factor values on the obtained networks.

1.1 Literature Review

This section reviews the literature related to the HSCN design problem. Specifically, we review the literature related to the problem settings in Subsection 1.1.1, which addresses the main issues related to planning and operating HSCNs. The literature on Service Network Design, one of the primary optimization methodologies used to formulate and solve HSCNs, is reviewed in Subsection 1.1.2. Subsections 1.1.1 and 1.1.2 provide a comprehensive overview of the methodologies proposed to address HSCNs and highlight the present thesis's unique contributions. Finally, Subsection 1.1.3 reviews the literature on the approaches to model and solve HSCN design problems, providing a general overview of how optimization methods can explicitly account for the uncertainty that may affect the informational contexts.

1.1.1 Humanitarian Supply Chain Network

The early attempts to solve the HSCN design problem adapted the existing methods for modeling and solving the commercial supply chain design models into the HSCN design problem (Van Wassenhove, 2019). However, because of the pivotal differences between commercial and humanitarian supply chains (Balcik & Beamon, 2008), including the objectives pursued, availability of budget and resources, and the level of uncertainty (Diabat et al., 2019; Hasani & Mokhtari, 2019, 2018; Pishvaee & Razmi, 2012), a distinct line of research formed around the HSCN design problem (Anaya-Arenas et al., 2014; Campbell et al., 2008).

As discussed by Anaya-Arenas et al. (2014); Balcik et al. (2016); Behl & Dutta (2019), various humanitarian relief planning problems have been studied in the literature. One can divide humanitarian relief planning problems into the planning optimization problems in pre-disaster and post-disaster phases (Anaya-Arenas et al., 2014). The studies in the pre-disaster phase mainly focus on preparedness activities, including locating warehouses and stockpiling critical supplies. These studies aim to support the decision-making process in establishing the proper response plans of humanitarian organizations concerning a probable natural disaster occurring in the future (e.g. Yahyaei & Bozorgi-Amiri (2019); Bozorgi-Amiri et al. (2013, 2012); Alem et al. (2016)). The location of the candidate warehouses is considered known in the post-disaster planning phase, and the humanitarian organizations use the existing infrastructure in the affected region. However, locating temporary facilities remains part of the decision-making process in the post-disaster phase. In addition, the number of transportation vehicles, the assignment of the beneficiaries to distribution centers, and the flow of critical supplies in the designed network over the planning horizon are the post-disaster phase decisions (e.g. Afshar & Haghani (2012); Tzeng et al. (2007); Noyan et al. (2016)). Post-disaster planning studies seek to diminish the harm done to people's health by optimizing the distribution of critical supplies among vulnerable populations.

The structure of an HSCN consists of multiple layers. Here, a layer is referred to as a collection of locations with comparable infrastructure, including storage and role in the supply chain. The decisions made in different layers of an HSCN are interrelated, increasing the complexity of the problem. The literature contains two approaches for dealing with this complexity, including integrating the decisions (e.g. Afshar & Haghani (2012)) and focusing on one layer of the HSCN (e.g. Noyan et al. (2016)).

Another challenging aspect of the post-disaster HSCN design problem is dealing with uncertainty. The uncertainty in the HSCN design problem has multiple sources, including the secondary impacts of the natural disaster and a lack of information regarding the assessments. When designing an HSCN, the additional damages to the infrastructure and people's health are unknown. For instance, earthquake aftershocks could damage the roads in the region and increase the number of deaths, injuries, and people relocated. Furthermore, gathering accurate data regarding the affected population in each geographical region to assess the demands is time-intensive. Therefore, the available demand data at the HSCN design time contains uncertainty (Balcik et al., 2016; Behl & Dutta, 2019). Finally, the information regarding the road conditions and available vehicles is limited at the design time, and, therefore, the capacity of the roads and available vehicles is also a source of uncertainty in the HSCN design problem (e.g., Adıvar & Mert, 2010; Vitoriano et al., 2011).

Satisfying the demands of the affected population is the goal of relief distribution planning. The literature identifies two approaches to addressing demand satisfaction: complete satisfaction of the demand and maximizing demand satisfaction.

The first approach is common in the pre-disaster phase studies, and the planning problem is solved with the aim of satisfying all the demands (Balcik & Beamon, 2008; Jabbarzadeh et al., 2014; Berkoune et al., 2012). The second approach is particularly relevant in situations where there are limitations on available resources and high levels of demand. The goal is to minimize unsatisfied demand among the affected populations by planning with the incorporation of a penalty parameter for unmet demand (e.g., Ahmadi et al. (2015)). Furthermore, in a multi-period planning setting, this approach allows unmet demand from a given period to be carried over to the next period for fulfillment (e.g., Lin et al. (2011)). In planning contexts where it may not be possible to satisfy the entire demand for critical supplies, the lack of the latter (e.g., medication and mosquito nets) may result in a spread of disease. This, in turn, increases demand for such supplies. While those dynamics have been ignored in the literature, in practice, they may have a severe effect on the performance of planning solutions. As such, this thesis puts a particular emphasis on correctly modeling the spread of unmet demand. This allows models to better capture the complexities of real-world disaster scenarios and enhance the HSCN's adaptability to changing conditions.

To estimate the uncertain parameters present in humanitarian planning models, two general approaches are commonly used in the literature. The first approach relies on the availability of historical data to provide estimates of the uncertainty, while the second involves directly assessing the uncertain parameters using relevant contextual information specific to the studied problem. Using historical data to estimate the uncertainties is the go-to approach in pre-disaster relief planning problems. However, in post-disaster planning problems, the uncertainties are estimated by assessments. This is due to the unique characteristics of each natural disaster (Chen et al., 2011). Assessments, which are obtained through a time-consuming process, are required for each potential location within the affected region. Therefore, it is often more efficient to divide the region into smaller sub-regions to facilitate the overall planning process. The assessments are then performed in a sample set of points in each sub-region (Balcik & Yanıkoğlu, 2020; Balcik, 2017). Finally, the estimated value for each uncertain parameter is generalized for the whole sub-region. Multiple data sources could be used in the assessment process. These may include surveys, satellite imagery, governmental reports, and media. However, the provided data by each data source requires expert interpretations, which is often done by the three-point estimating technique (Hakimifar et al., 2021). When applying this technique, a set of recognized experts (i.e., specific individuals or organizations knowledgeable about the affected region) are asked to provide three estimates for each uncertain parameter, considering the available data sources. These estimates define the minimum, most probable, and maximum values for the parameters, thereby constructing a triangular distribution for each case (Benini et al., 2017). These probability distributions are then used to estimate the possible values of the uncertain parameters.

Multiple experts assess uncertain parameters, relying on different data sources, and their conclusions regarding the assessments may differ, which, in turn, can lead to different probability distributions being defined for the parameters. Given that all experts are highly regarded (i.e., the same level of confidence is assigned to their perspectives), the inconsistent or conflicting estimates lead to ambiguity in the decision-making process (Grass et al., 2023; Hosseinnezhad & Saidi-mehrabad, 2018). Such ambiguity adds another layer of complexity to the uncertainty in HSCN design. The second study introduces four optimization models tailored for ambiguity, enabling humanitarian organizations to make robust decisions despite ambiguity in estimations.

1.1.2 Service Network Design

Service Network Design (SND) methods are the preferred approaches for solving the network design problems that naturally arise in the planning of transportation systems. Specifically, SND problems focus on managing supply-related transportation resources and defining the corresponding activities to design an efficient a cost-effective network that satisfies the demand (Crainic & Hewitt, 2021). The decisions involved in an SND problem are divided into two categories: the design and flow decisions. The design decisions establish the transportation services that are selected and their schedules. Here, services refer to routes connecting the origin and destination terminals associated with commodities, which represent the demand requests for shipments. Services can either be direct links between origin-destination pairs or paths involving intermediary terminals. Additionally, service schedules can be fixed, determined by a specific frequency, or defined based on given timing decisions. The flow decisions indicate the itineraries for the commodities, including the transportation time and path. Lastly, SND models can be classified into two categories: deterministic SND models and SND models under uncertainty.

In the deterministic setting, different modeling approaches have been proposed based on the characteristics of the problem, including static, time-dependent, dynamic, frequency, and time-space SNDs (Crainic & Hewitt, 2021). The static SND approach is suitable for addressing SND problems with fixed characteristics (Chouman & Crainic, 2021). In static SND problems, parameter values remain constant over time, and as a result, the time dimension is not considered. However, in time-dependent SND problems, the problem characteristics are subject to change over time. For instance, the demand and quantity of available supply could change over the planning horizon. Consequently, the time dimension is explicitly incorporated into the modeling of time-dependent SND problems; see, e.g., Andersen et al. (2009).

Crainic (2000) categorized SND problems based on their planning level into frequency-based and dynamic SND models. Frequency SND focuses on strategic and tactical level problems, e.g. Duan et al. (2019); Rothenbächer et al. (2016), whereas the dynamic SND models are applied to operational-level problems. In frequency SND problems, the objective is to determine the most appropriate services and their frequencies over the planning horizon. Additionally, itineraries and restrictions are established for the selected terminals in the designed network. In contrast, dynamic SND focuses on scheduling the chosen services (Crainic, 2000). Scheduling the services involves both service selection and the time interval a service is transferred on an itinerary.

Researchers have also studied the effects of uncertainty when solving SND problems, see, e.g. Crainic & Hewitt (2021); Lanza et al. (2021); Lium et al. (2009, 2007). Demand has been the most studied uncertain parameter in SND problems; see, e.g. Lium et al. (2007); Bai et al. (2014); Crainic et al. (2016a); Ng & Lo (2016). The literature includes both stochastic programming and robust optimization methods for modeling and solving SND problems under uncertainty (Bai et al., 2014; Wang & Qi, 2020).

1.1.3 Optimization Approaches Under Uncertainty

Two lines of research exist in the literature for modeling uncertainty in optimization problems, including stochastic programming and robust optimization. Stochastic programming requires the probability distribution of the possible realizations of uncertain parameters to be available. However, robust optimization is the method of choice when the information regarding the uncertain parameters is limited. In this approach, an uncertainty set is defined for all uncertain parameters involved in the problem. Then, the counterpart of the problem is defined as a min-max problem. In this min-max problem, a defined budget value limits the domain of the uncertain parameters (Bertsimas et al., 2011; Goerigk & Lendl, 2021). Finally, distributionally robust optimization has been specifically designed for planning contexts where the underlying probability distributions are ambiguous (Delage et al., 2018).

The research presented in this thesis assumes the availability of probability distributions to formulate the uncertain parameters, derived from the assessment and needs evaluation processes conducted by humanitarian organizations during the planning of post-disaster operations. These distributions are then used to generate scenarios, capturing the random variability of uncertain parameter values and enabling the formulation of solvable problems. The remainder of this section focuses on how sampling techniques can be applied in conjunction with optimization to address problems involving uncertainty, specifically through the techniques defined by stochastic programming.

Stochastic programming is the preferred method for modeling and solving optimization problems when the uncertainty in the problem settings can be represented using random variables. In the context of HSCN, uncertainty is often estimated through damage and demand assessments, which assess the impacts of a natural disaster on the affected region. These assessments provide the basis for generating probability distributions for the uncertain parameters. Scenario-based sampling techniques then employ the estimated probability distributions to approximate the variability of the uncertain parameters in the model. The size of the scenario set plays a critical role in the accuracy of the approximation. As the number of scenarios increases, the representation of uncertainty improves, leading to more precise solutions. However, in combinatorial optimization problems, the size of the scenario set is practically limited due to the exponential growth in computational complexity, which can make large scenario sets computationally intractable. The Sample Average Approximation (SAA) method (Kleywegt et al., 2002) offers a practical solution by producing high-quality approximations while keeping the computational effort manageable. Additionally, in-sample and out-of-sample stability tests (Kaut & Wallace, 2003), provide a means to evaluate the reliability of the solutions and assist in determining the optimal scenario set size for the SAA approach. These stability tests ensure that the scenario sets used for approximation provide accurate representation of the underlying uncertainty distributions, increasing confidence in the results.

1.2 Research Studies Conducted

This section presents the three studies addressing key challenges in solving the HSCN design problem, which constitute the core content of this thesis. Subsection 1.2.1 introduces the first study, which develops a two-stage stochastic model to address cascading unmet demands. Subsection 1.2.2 presents the second study, focusing on models to explicitly handle data ambiguity from conflicting sources. Finally, Subsection 1.2.3 presents the third study, which proposes a dynamic three-stage model integrating information updates and interdependent demand spread, validated with real-world disaster data.

1.2.1 First Study: A Two-Stage Stochastic Model for Humanitarian Supply Chain Network Design in Post-Disaster Recovery

The first paper of this thesis focuses on the design of a two-stage stochastic HSCN for post-disaster recovery. This research addresses the uncertainty in demand and capacity that arises in the aftermath of natural disasters. A key innovation in this study is incorporating spread factor in the mathematical model, which accounts for the cumulative impact of unmet demand for one critical supply on the demand for other critical supplies in subsequent periods. This feature captures the interdependencies between different critical supplies. In a post-disaster environment, unmet demand for critical supplies, such as shelter, food, and hygiene kits, not only increases the immediate need for those critical supplies in future periods but can also amplify the demand for other critical supplies. The spread factor represents these effects, improving demand estimation accuracy and resource allocation.

The paper presents a two-stage stochastic model to design and operate HSCNs under uncertain conditions, using real-world data from the 2018 Indonesia earthquake to validate the approach. The research highlights the importance of modeling uncertainty in both demand and capacity to ensure the efficiency and effectiveness of relief operations. It also introduces the spread factor as a novel approach to representing the impact of unmet demand across time periods, significantly affecting humanitarian aid planning.

The study also investigates the impact of budget uncertainty, revealing that while a slight reduction in the available budget does not significantly affect the network's performance, a substantial budget shortfall can drastically increase the harm to the affected population and reduce the overall effectiveness of the relief network.

This paper contributes to developing more resilient and efficient HSCNs by providing decision-makers with tools to improve the management of the relief distribution in post-disaster recovery. The model proposed in this paper helps humanitarian organizations optimize the allocation of limited resources, minimize harm to the affected population, and improve the overall coordination of aid distribution under uncertain conditions.

1.2.2 Second Study: Addressing Ambiguity in Humanitarian Supply Chain Network Design

The design of HSCN in the aftermath of natural disasters is a complex process influenced by numerous sources of uncertainty. Humanitarian organizations typically rely on multiple data sources, such as satellite imagery, surveys, and governmental reports, to assess damage and demand. These sources often provide inconsistent or incomplete information, leading to ambiguity when performing assessments to formulate the uncertain parameters that define the context in which the HSCN design problem is to be solved.

This paper presents four optimization models that explicitly address the ambiguity resulting from inconsistent estimates obtained from multiple data sources within the context of HSCN design. The proposed models include Minimization of Expected Opportunity Loss (MIN-OppLoss), Minimization of Maximum Data-Source Penalty (MIN-MaxDSPen), Minimization of Expected Data-Source Penalty (MIN-ExpDSPen), and Minimization of Maximum Scenario Penalty. Each model provides a different approach to managing ambiguity, varying in terms of conservatism in handling the uncertainty present in the data. Here, MIN-MaxDSPen corresponds to a special case of distributionally robust optimization. While the classical approach suggests to remain robust against any distribution that fits a prescribed mean and standard deviation, our approach uses a discrete set of such distributions, corresponding to the distributions of the multiple data sources.

The models are evaluated using a real-world dataset from the 2018 Indonesia earthquake, providing insights into their effectiveness in mitigating the challenges posed by ambiguity in post-disaster HSCN design problems.

The results indicate that MIN-ExpDSPen is particularly effective when the decision-maker places higher trust in the more pessimistic data source, while MIN-MaxDSPen is more appropriate when the optimistic data source is favored. In cases where the ambiguity pattern is unclear or when the decision-maker holds equal confidence in both data sources, MIN-MaxDSPen consistently provides a robust solution across various scenarios. The findings underscore the overall importance of explicitly accounting for ambiguity in HSCN design problems.

1.2.3 Third Study: Information Dynamics and Demand Spread

The design of HSCN is a critical operation in the context of post-disaster humanitarian logistics. Establishing an effective mechanism for the timely distribution of relief supplies to affected populations is essential. The dynamic nature of disaster situations, characterized by the rapid evolution of demand and resource availability, necessitates adopting a more flexible approach to HSCN design. This paper introduces a novel three-stage optimization model for HSCN design that integrates information dynamics and demand spread, addressing the inherent uncertainties in demand and transportation capacity that arise in post-disaster settings.

In the literature, two-stage optimization is often used to model and solve HSCN design problems, where the design decisions are made upfront, with little or no capacity to adjust based on evolving information. The three-stage model proposed in this study provides an enhanced framework by incorporating an additional decision-making stage that allows for adjustments to the transportation resources as more information becomes available. This additional stage ensures that decisions are not static but evolve as the disaster progresses, thereby improving the HSCN's operational efficiency.

The effectiveness of the proposed model is demonstrated through a series of experiments conducted on a real-world dataset derived from the 2018 Indonesia earthquake. These experiments reveal several key advantages of the three-stage model over the two-stage models. Notably, the three-stage model facilitates more informed decision-making by allowing updates to transportation resource allocations during the operational phase of the disaster response, which results in more efficient use of resources. The model's ability to adjust to new information during the early phases of disaster relief ensures that critical supplies are distributed more effectively, leading to better outcomes for the affected population.

Furthermore, the integration of the spread factor into the model enhances its capability to manage the interrelated nature of demand across multiple types of critical supplies. The ability to model the effects of unmet demand across different critical supplies allows the model to more accurately reflect the complexities of real-world disaster scenarios, where the demand for one resource can influence the availability and need for others. This feature not only improves the model's accuracy but also provides a strategic advantage in optimizing supply chain operations under uncertainty.

The experimental results confirm that the three-stage model outperforms the two-stage models, particularly in terms of decision-making flexibility and resource allocation efficiency. Although the three-stage model demands higher computational efforts due to its increased complexity, the benefits of improved resource management and adaptability to changing conditions outweigh the associated costs. This suggests that the model provides a valuable tool for humanitarian organizations tasked with coordinating disaster response efforts, where the ability to adjust to evolving conditions dynamically is crucial for ensuring the timely and equitable distribution of aid.

CHAPTER II

A TWO-STAGE STOCHASTIC POST-DISASTER HUMANITARIAN SUPPLY CHAIN NETWORK DESIGN PROBLEM

Chapter Information

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Abstract

We consider the planning problem of designing and operating humanitarian supply chain networks (HSCN) after natural disasters. Specifically, we focus on the design of a three-layer network under demand and capacity uncertainty to support short-term recovery, i.e., to distribute critical supplies to the affected population. 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 apply our model to a case study using 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. According to the results obtained, 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

2.1 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 (UNOCHA, 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 (UNOCHA, 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 & Van Wassenhove, 2020; Stegemann & Stumpf, 2018; Van Wassenhove, 2006). After a natural disaster, humanitarian operations ultimately aim at reducing harm to the affected population. Considering the limited available budget, the efficiency of humanitarian operations directly impacts the received aid by the affected population. This impact could be both on the level of satisfied demand and the temporal aspect of aid delivery. The designed relief network with budget constraints should deliver as many necessary goods as possible to the affected population. Furthermore, the demands of the affected population must be satisfied as soon as possible. The reason being the failure in delivery or delay in satisfying demand harms the population's health and spreads the demand (e.g., spreading disease). Therefore, improving the overall planning processes that define how the limited resources available to humanitarian organizations such as budget, staff, and means of transportation are used to provide relief to affected populations after a natural disaster occurs is an important and pressing issue. In order to implement their aid plans and perform the required operations, humanitarian organizations need to go through relief distribution networks. Given the complexity of the underlying decisions, manual planning is likely to be rather inefficient. In particular, taking into consideration the probabilistic information for uncertain parameters becomes a challenge for manual planners. Hence, there is an undeniable need for dedicated optimization methods that enable organizations to efficiently design and operate such networks.

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 (UNOCHA, 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) (Hong & Jeong, 2019; Tavana et al., 2018). 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 order to design an HSCN, humanitarian organizations have to make a set of decisions, including the location of the hubs, resource allocation both for hubs and services, and assignment of vulnerable populations to hubs. Furthermore, on the operational level, humanitarian organizations must take decisions related to both transportation and inventory levels Anaya-Arenas et al. (2014). 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, such as 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, such as landslides following floods, and aftershocks following an earthquake.

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. 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 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 on network design, facility location, and other supply chain related planning problems.

Even though the model here proposed uses a linear coefficient to adjust the penalty from one time-period to another, the use of spread factors results in a non-linear demand behaviour over the planning horizon. Specifically, we assume that unmet demand from one time-period is not only carried over to the next time-period, but can further be amplified through the spread factor. This emulates, for example, the spread of disease. Moreover, such spread factors are defined among all pairs of commodities. For example, a failure of meeting the demand for shelters may increase the future need for medical supplies.

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. As such, the research questions we are aiming to answer in this paper are as follows. How can the supply chain operations most efficiently be planned in the context of demand uncertainty and demand spread over time? How does the demand spread impact the planning solution and the level of unmet demand? How does a wrong estimate of the budget impact the planning solution and the level of unmet demand? 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 2.2, we provide a literature review on the topic. In Section 2.3, we describe the problem setting. Section 2.4 details the two-stage stochastic post-disaster HSCN design model that is developed. The numerical experiments and analyses are presented in Section 2.5. Finally, we close the paper with the conclusion in Section 2.6.

2.2 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 2.2.1 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 2.2.2, 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.

2.2.1 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 & Beamon, 2008). For instance, the purposes and objectives of these 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 & Mokhtari, 2019), and optimizing the usage of budget in the design and operation of HSCN (Hasani & Mokhtari, 2018), as opposed to commercial supply chains, which aim to minimize the cost of distribution and delivery (Pishvaee & 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, such as Anaya-Arenas et al. (2014); Balcik et al. (2016); Behl & 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, for example Alem et al. (2016); Bozorgi-Amiri et al. (2012, 2013); Yahyaei & Bozorgi-Amiri (2019). 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, such as 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 & Haghani (2012); Noyan et al. (2016); Tzeng et al. (2007)). 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.

The post-disaster HSCN design problem here considered is both complex and challenging to solve, mainly due to two reasons. First, the inherent complexity stemming from the multiple decisions regarding the multi-level distribution network. Here, a level is defined 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. Second, the explicit representation of the various sources of uncertainty faced in the planning context, which, in the literature, mostly concerns the demand levels for critical supplies (Balcik et al., 2016; Behl & Dutta, 2019).

It is worthwhile to note that several other aspects may be relevant in the modeling of certain HSCNs and impact their ideal network structure. Zeng et al. Tzeng et al. (2007) proposed a multi-objective three-layer HSCN, including aspects of costs, effectiveness, and fairness in the objective. Fairness and equity (see, e.g. Anaya-Arenas et al. (2018); Ismail (2021); Noyan et al. (2016)) regarding the distribution of critical supplies to a vulnerable population are also important in this application context. However, considering that these aspects are not the main focus of our work, we do not review the literature related to this branch.

Table 2.1 summarizes the approaches and key assumptions that were made in the studies from the literature most related to our problem. The effects of unmet demand for one critical supply on the level of demand for other critical supplies have not been explicitly studied in the existing literature. 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 the spread of the disease in 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). Although uncertainty regarding the total amount of received donations has been studied before Falasca & Zobel (2011), we are not aware of studies that explicitly consider the reception of donations distributed over the planning horizon and its effect 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.

Paper	Phase	Structure	Objective	Uncertainty	Demand satisfaction
Modeling integrated supply chain logistics in real-time large-scale disaster relief operations Afshar & Haghani (2012)	post-disaster	seven layers	minimize unmet demand	none	unmet demand transferred to next time period
A collaborative humanitarian relief chain design for disaster response (Shokr et al., 2022)	pre- and post-disaster	three layers	minimize design cost and penalty cost of unmet demand	transportation cost, demand, supplier capacity	unmet demand not transferred to next time period
Logistics service network design for humanitarian response in East Africa (Dufour et al., 2018)	post-disaster	four layers	minimize logistic costs	demand	ensures demand is fully satisfied
Multi-objective optimal planning for designing relief delivery systems (Tzeng et al., 2007)	post-disaster	three layers	Minimize cost, minimize travel time, maximize satisfaction	none	ensures demand is fully satisfied
International disaster relief planning with fuzzy credibility (Adıvar & Mert, 2010)	pre-disaster	three layers	minimize the cost and maximizing the credibility of satisfying the demand	fuzzy supply quantity and procurement cost	unmet demand not transferred to next time period
A multi-criteria optimization model for humanitarian aid distribution (Vitoriano et al., 2011)	post-disaster	last-mile distribution	minimizing multi-criteria objective, cost, time, security, reliability	availability of roads	satisfied as much demand as possible (single period)
Importance of fairness in humanitarian relief distribution (Anaya-Arenas et al., 2018)	post-disaster	three layers	minimize unsatisfied demand and travel time, and maximize fairness and equity	none	unmet demand not transferred to next time period
A possibilistic mathematical programming model to control the flow of relief commodities in humanitarian supply chains (Ismail, 2021)	post-disaster	two layers	minimize transportation and deprivation costs	fuzzy deprivation cost	unmet demand transferred to next time period
Transportation in disaster response operations (Berkoune et al., 2012)	post-disaster	last-mile distribution	minimize transportation time	none	ensures demand is fully satisfied
Dynamic supply chain network design for the supply of blood in disasters: A robust model with real world application (Jabbarzadeh et al., 2014)	post-disaster	two layers	minimize mean and variance of total costs	demand, supply, transportation cost and capacity	unmet demand not transferred to next time period
A logistics model for emergency supply of critical items in the aftermath of a disaster (Lin et al., 2011)	post-disaster	last-mile distribuiton	minimize unmet demand, travel time and satisfaction rate between points of demand	none	unmet demand transferred to next time period

Table 2.1: Summary of literature on humanitarian relief network design.

2.2.2 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 & 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 & 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.

2.2.2.1 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 & 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 &

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.

2.2.2.2 Service Network Design under Uncertainty

Researchers have investigated the importance of considering uncertainty when formulating and solving SND problems (see, for instance Crainic & Hewitt (2021); Lanza et al. (2021); Lium et al. (2007, 2009)). The problem variant most studied in the literature assumes that demands are uncertain (see, for example Bai et al. (2014); Crainic et al. (2016a); Lium et al. (2007); Ng & Lo (2016)). For this problem variant, Lium et al. 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. 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; Hoyos et al., 2015; Wang & 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, for example (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.

2.3 Problem description

In this section, we present the here considered HSCN design problem that we will solve. First, Subsection 2.3.1 describes the general characteristics of the problem, including the network structure, uncertain parameters, and both the tactical and operational decisions involved. Then, Subsection 2.3.2 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 2.3.3 defines the concept of demand, which includes the cumulative effect of unmet demand over time, and its correlated effects on the critical supplies.

2.3.1 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 2.1, 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, such as 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 transshipments are allowed). In addition, it is assumed that there are no direct services between the ports of entry and the DCs.

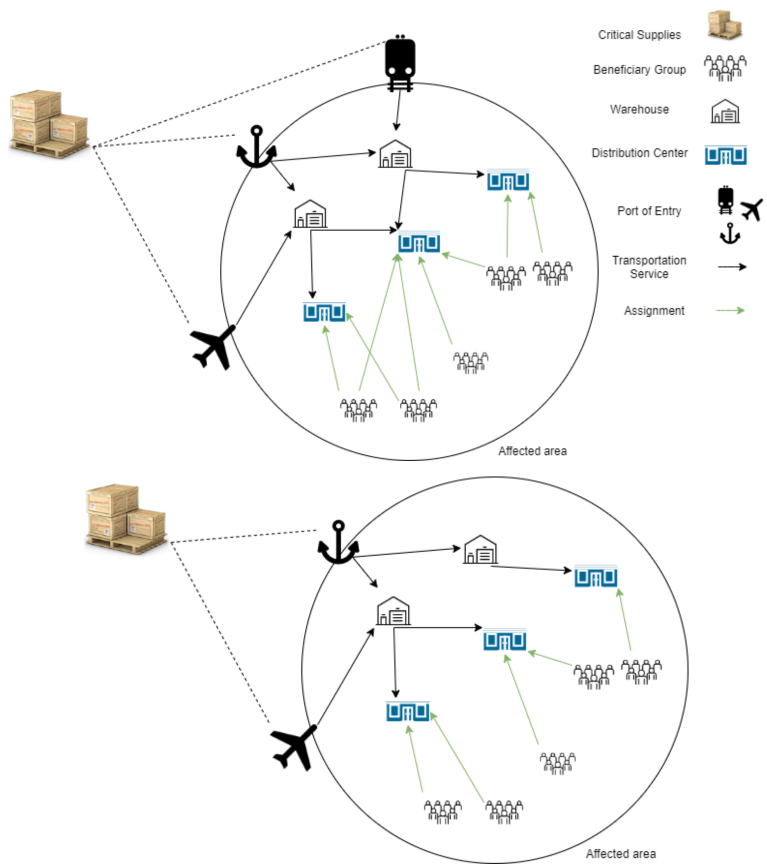


Figure 2.1: top: all available hubs, services, and assignments. bottom: selected hubs, services, and assignments in an example HSCN.

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, such as number of vehicles), and the storage resources for the selected warehouses, for instance 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, such as the locations of the beneficiary groups, the available hubs, the available budget, and thus are deterministic, the values of other parameters for instance the demands are uncertain at the moment the HSCN is designed. Vitoriano et al. 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.

2.3.2 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, such as security guards and rent, and c) transportation resources, for example 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 2.5.2.4). 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.

2.3.3 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:

$$\hat{d}_l^{kt} = \tilde{d}_l^{kt} + \sum_{k' \in K} s^{k'k} (\hat{d}_l^{k't-1} - \sum_{i \in V_{DC}} \bar{a}_{il}^{k't-1}). \tag{2.1}$$

As defined in Equation (2.1), $\hat{d}_l^{k't-1}$ 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.

2.4 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, such as 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 & Fischer, 2016b), 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 2.2 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 2.2: Sets used in the optimization model.

The input parameters of our model are presented in Table 2.3. 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 (2.1), 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. For example, a penalty unit for commodity “water” may refer to health related units, a penalty for the commodity of a certain “medication” the unit may refer to a sickness related unit and for a commodity “mosquito nets” the unit may be related to potential future infection risk. The values of the penalties for the critical supply need 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 may be higher than for shelter in the dry season, but this relation may change during the rain season as shelter becomes more valuable. The model then minimizes the total expected penalty for all beneficiary groups over all time periods, computed using the defined scenarios.

Deterministic Parameters	
Parameter	Definition
$\hat{f}_{ij}$	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 2.3: Model input parameters.

As shown in Table 2.2 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 $\tilde{g}^t_{i\psi}$ 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 2.4. 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.

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 2.4: Decision variables of the two-stage stochastic model.

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.

$$\min \sum_{\psi \in \Psi} p_\psi Q_\psi(\hat{x}, \hat{y}, a) \tag{2.2}$$

s.t.

$$2x_{ij} \leq y_i + y_j \quad \forall (i,j) \in A, \tag{2.3}$$

$$\hat{y}_i \leq m_i y_i \quad \forall i \in V_W, \tag{2.4}$$

$$\hat{x}_{ij} \leq m_{ij} x_{ij} \quad \forall (i,j) \in A, \tag{2.5}$$

$$\sum_{i \in V} f_i y_i + \sum_{i \in W} \hat{f}_i \hat{y}_i + \sum_{(i,j) \in A} \hat{f}_{ij} \hat{x}_{ij} \leq z^0, \tag{2.6}$$

$$\sum_{i \in V_{DC}} a_{il} = 1 \quad \forall l \in L, \tag{2.7}$$

$$a_{il} \leq y_i \ \ \forall i \in V_{DC}, \ \forall l \in L, \tag{2.8}$$

$$\begin{aligned} &\hat{x}_{ij} \in \mathbb{N}^0, \ \hat{y}_i \in \mathbb{N}^0, \ x_{ij} \in \{0,1\}, \ y_i \in \{0,1\}, \\ &a_{il} \in \{0,1\}, \ \forall i \in V, \ \forall (i,j) \in A. \end{aligned} \tag{2.9}$$

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

$$Q_\psi(\hat{x}, \hat{y}, a) := min \sum_{t \in T} \sum_{k \in K} b^k \sum_{l \in L} (\hat{d}^{kt}_{l\psi} - \sum_{i \in V_{DC}} \bar{a}^{kt}_{il_\psi}) \tag{2.10}$$

s.t.

$$\sum_{k \in K} \bar{x}^{kt}_{ij_\psi} \leq u_{ij} g^t_{ij_\psi} \hat{x}_{ij}, \quad \forall (i,j) \in A, \; \forall t \in T, \tag{2.11}$$

$$\bar{a}^{kt}_{il_\psi} \leq \sum_{(j,i) \in A} u_{ji} g^t_{ji_\psi} m_{ji} a_{il}, \quad \forall i \in V_{DC}, \; \forall l \in L, \; \forall k \in K, \; \forall t \in T, \tag{2.12}$$

$$\bar{a}^{kt}_{il_\psi} \leq \hat{d}^{kt}_{l\psi}, \quad \forall i \in V_{DC}, \; \forall l \in L, \; \forall k \in K, \; \forall t \in T, \tag{2.13}$$

$$\sum_{l \in L} \bar{a}^{kt}_{il_\psi} \leq \sum_{j \in W} \bar{x}^{kt}_{ji_\psi}, \quad \forall i \in V_{DC}, \forall k \in K, \; \forall t \in T, \tag{2.14}$$

$$\hat{d}^{kt}_{l\psi} = d^{kt}_{l\psi} + \sum_{k' \in K} s^{k'k} (\hat{d}^{k't-1}_{l\psi} - \sum_{i \in V_{DC}} \bar{a}^{k't-1}_{il_\psi}), \quad \forall l \in L, \; \forall k \in K, \; \forall t \in T, \tag{2.15}$$

$$\begin{aligned} &\sum_{i \in V} f_i y_i + \sum_{i \in W} \hat{f}_i \hat{y}_i + \sum_{(i,j) \in A} \hat{f}_{ij} \hat{x}_{ij} + \sum_{t'=1}^{t} \sum_{(i,j) \in A} \sum_{k \in K} c^k_{ij} \bar{x}^{kt'}_{ij_\psi} \leq \\ &z^0 + \sum_{t'=1}^{t} z^{t'}, \quad \forall t \in T, \end{aligned} \tag{2.16}$$

$$\hat{r}^{kt}_{j_\psi} \leq r^{kt-1}_{j_\psi} \quad \forall j \in V_W, \; \forall k \in K, \; \forall t \in T, \tag{2.17}$$

$$\sum_{k \in K} \hat{r}^{kt}_{j_\psi} \leq u_j g^t_{j_\psi} \hat{y}_j \quad \forall j \in V_W, \; \forall t \in T, \tag{2.18}$$

$$\sum_{k \in K} r^{kt}_{j_\psi} \leq u_j g^t_{j_\psi} \hat{y}_j \quad \forall j \in V_W, \; \forall t \in T, \tag{2.19}$$

$$r^{kt}_{j_\psi} = \hat{r}^{kt}_{j_\psi} + \sum_{(i,j) \in A} \bar{x}^{kt}_{ij_\psi} - \sum_{(j,i) \in A} \bar{x}^{kt}_{ji_\psi}, \quad \forall j \in V_W, \; \forall k \in K, \; \forall t \in T, \tag{2.20}$$

$$\sum_{(i,j) \in A} \bar{x}^{kt}_{ij_\psi} \leq n^{kt}_i \quad \forall i \in V_I, \;\; \forall k \in K, \; \forall t \in T, \tag{2.21}$$

$$\bar{x}^{kt}_{ij_\psi} \geq 0,\ \bar{a}^{kt}_{il_\psi} \geq 0,\ r^{kt}_{i_\psi} \geq 0,\ \hat{r}^{kt}_{i_\psi} \geq 0,\ \forall (i,j) \in A,$$
$$\forall i \in V,\ \forall k \in K,\ \forall t \in T. \tag{2.22}$$

The Objective Function (2.2) minimizes the expected recourse value (i.e., the expected total penalty for unmet demands). Constraints (2.3) ensure that a service can only be selected if its origin and destination hubs are part of the HSCN. Constraints (2.4) indicate that inventory resources at a warehouse can only be selected if that warehouse is also part of the HSCN. Similarly, Constraints (2.5) 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 (2.6). Constraints (2.7) indicate that each beneficiary group should be assigned to a single DC, whereas Constraints (2.8) 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 (2.9).

In the second stage, the operational decisions are made. The Objective Function (2.10) minimizes the total penalty associated with the unmet demands for all beneficiary groups over the entire planning horizon. Constraints (2.11) 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 (2.12) 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 (2.13). Constraints (2.14) ensure that in each DC, the total quantity of allocated critical supplies is limited by the quantity that is available at that DC. Constraints (2.15) compute the total demand at each period as the summation of the base demand and the residual demand multiplied by the spread factor. Constraints (2.16) 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 (2.17) 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 (2.18) and (2.19). 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 (2.20) 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 (2.21) ensure that these limits are imposed in all periods. Finally, Constraints (2.22) define the bounds of the variables used in the second stage.

2.5 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 2.5.1 introduces the considered case study, obtained using real-world data from Indonesia's 2018 earthquake. In Subsection 2.5.2 we present the numerical experiments that are conducted and the detailed results obtained on the case study. Subsection 2.5.2 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. Finally, Section 2.5.3 summarizes the managerial insights obtained from the experiments conducted in Section 2.5.2.

2.5.1 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) (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 types of critical supplies: shelter, food, and hygiene (e.g. soap, toilet paper, and sanitary pads) (IFRC, 2021a). For these three critical supplies, we consider unit penalty values of 5, 2 and 3, respectively. Each household has a demand of 1 unit for shelter and hygiene items, while their demand for food corresponds to a total of 28 units (which corresponds to 1 unit per day, given that the total planning horizon spans 28 days). As such, providing food has the highest priority in the objective function.

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 & 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 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 & Cardoso, 2006). Figure 2.2 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.

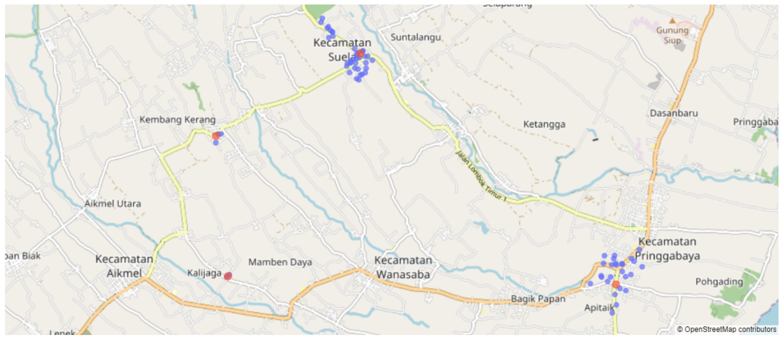


Figure 2.2: Original beneficiary groups and their respective clusters presented on the OpenStreetMap (OpenStreetMap contributors, 2022). The blue circles represent the beneficiary groups and the red circles indicate the distribution centers.

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 & 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, 2017; Balcik & Yanıkoğlu, 2020). Considering that we do not have access to specific assessments, we simulate the experts' opinions to characterize the parameter uncertainties. Expert estimations for humanitarian operations are commonly given by a triangular distribution for each uncertain parameter (Benini et al., 2017; Grass et al., 2023; Hakimifar et al., 2021), including an optimistic value, a pessimistic value, and a most likely value. We therefore simulate the experts' predictions for the values of the uncertain parameters using this three-point estimation technique. We consider a total of three experts, each of which provides 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. Furthermore, the probability of occurrences of the scenarios is assumed to be equal.

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. 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 & 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.

2.5.2 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 & Wallace, 2003) in Subsection 2.5.2.1. Then in Subsection 2.5.2.2, 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 2.5.2.3, 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 2.5.2.4, we evaluate the effects of the available budget. Finally, in Subsection 2.5.2.5, 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., 2011, 2017) on a machine with Intel e5-2630 v4 2.2 GHz CPU and 256 GB of memory.

2.5.2.1 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 2.5 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%. Furthermore, as the number of scenarios increases 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 2.5: 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 2.6 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 2.6, 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 2.6: The out-of-sample stability analysis results.

2.5.2.2 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 (Madansky, 1960; Tintner, 1955). 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 (Dantzig, 1955; Madansky, 1960). 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 2.7 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 2.7: Upper and lower bounds for our problem.

We now calculate the Expected Value of Perfect Information (EVPI) (Birge & 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 2.5.2.1, 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 & 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.

2.5.2.3 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 2.8 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 2.8: Effect of modeling uncertainty on the optimal solution of the stochastic model (using 50 scenarios over 15 runs).

2.5.2.4 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 2.9 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 2.9, 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	O.F. value z_{exp} per period				total O.F. value z_{exp}
z_{act}	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 2.9: 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 2.3

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.

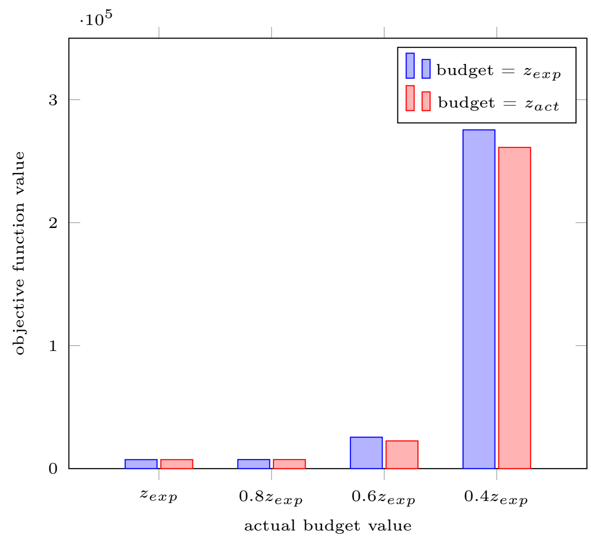


Figure 2.3: Penalty (objective function value) of the designed HSCN using z_{exp} as budget (blue) and using z_{act} as budget (red) over the ground truth with budget z_{act}.

2.5.2.5 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 2.10 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 2.4. 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 2.10: 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 2.11: Effect of spread factor on the expenses of the optimized HSCN (average over 15 runs using 50 scenarios).

Table 2.11 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.

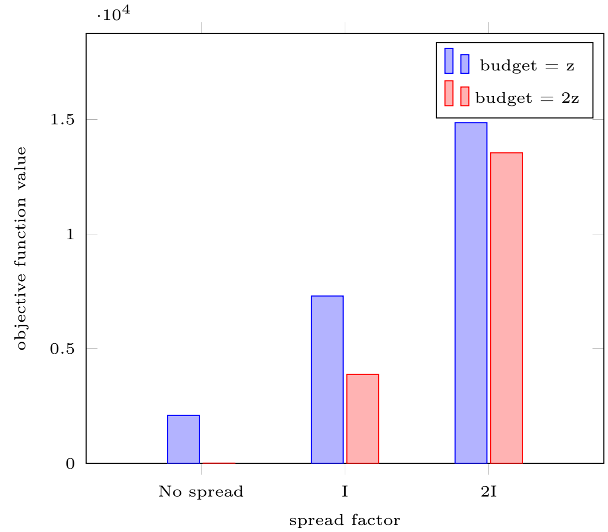
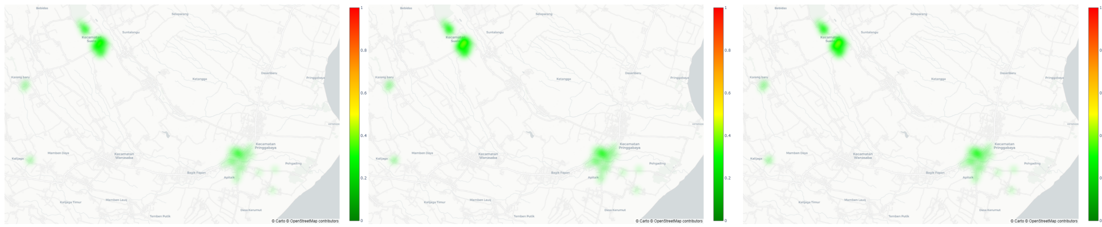
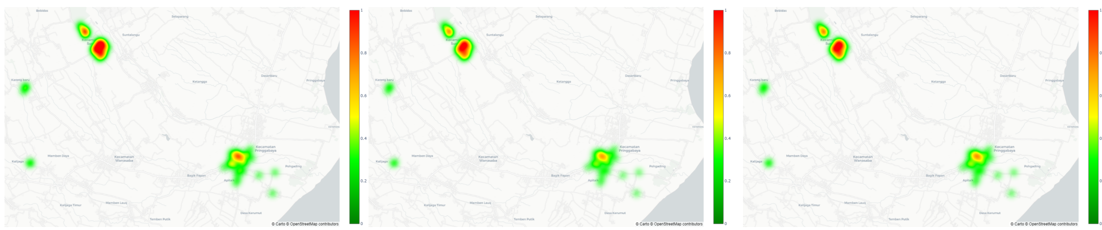


Figure 2.4: Impact of spread factor and available budget on the performance of the HSCN.

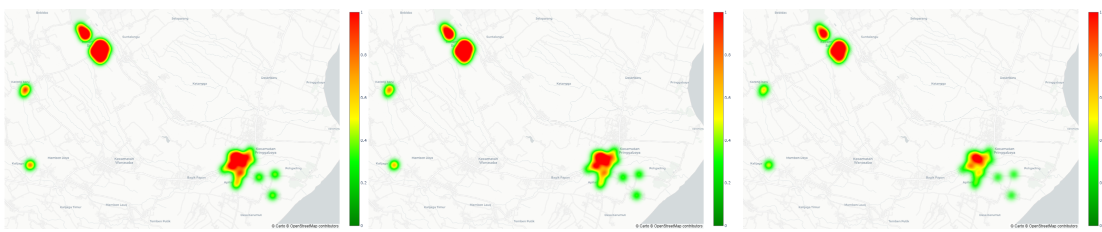
Given that the real spread-factor may not be known exactly to the planner, we now investigate the potential impact of under- or overestimating the spread factor on the performance of the designed network. To this end, we solved the problem assuming three different spread factor levels (0, I, and $2I$) and then evaluated the planning solutions under the assumption that any of those spread factors may occur in practice. Figure 2.5 visualizes the heatmaps and the total penalties obtained from this experiment. One observes that underestimating the spread factor can have a disastrous effect on the total penalty. In contrast, overestimating the spread factor seems to hold little risk, since it only marginally increases the penalty if, in reality, a smaller spread is present. This suggests that the planner should rather assume a high spread factor in the planning model, which holds a smaller down-side risk as doing the opposite (i.e., assuming a small spread factor).



((a)) $s' = 0, s = 0, p = 2093$ ((b)) $s' = 1, s = 0, p = 2105$ ((c)) $s' = 2, s = 0, p = 2115$



((d)) $s' = 0, s = 1, p = 8661$ ((e)) $s' = 1, s = 1, p = 7300$ ((f)) $s' = 2, s = 1, p = 7648$



((g)) $s' = 0, s = 2, p = 20256$ ((h)) $s' = 1, s = 2, p = 18718$ ((i)) $s' = 2, s = 2, p = 14858$

Figure 2.5: Heat-maps indicating the impact of overestimating or underestimating the spread factor value on the performance of the designed network. The spread factor value used to solve the model is represented by s', while the real spread factor used to evaluate the solution is s, resulting in expected penalty p.

Finally, Table 2.12 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 2.11, showing a decrease in the first stage expenses as the spread factor values increase. However, as represented in Figure 2.4, 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 2.12: Characteristics of the best HSCNs obtained by different spread factor values.

2.5.3 Managerial Insights

Based on the proposed model and the experimental results, we can derive several managerial insights for humanitarian organizations dealing with the here considered HSCN design problem:

1. As the HSCN design problem includes a high level of uncertainty, using an appropriate number of scenarios to analyze in-sample and out-of-sample stability is crucial to obtain a reliable and valid solution.

2. Although the stochastic model is more challenging to solve than its deterministic counterpart and, ultimately, requires higher computational times from the solver, the solution obtained using the stochastic model is more flexible and thus adaptable to the random fluctuations that lead to the different realizations of the uncertain parameters.

3. An overestimation of the available budget may have dire effects on the total penalty in the objective function (see Section 5.2.4., "Impact of available budget"). For example, while a 20% decrease of the budget has almost no

effect on the overall penalties within our case study, a 40% decrease more than triples the expected penalty, and a 60% decrease results in a more than 30-times higher penalty. This illustrates that the overall harm to the affected population exponentially increases as the budget decreases.

4. Underestimating the spread factor for unmet demand may severely compromise the health of the affected population (see Section 5.2.5., "Impact of the spread factor"). In our case study, ignoring or underestimating the spread factor results in unnecessary high penalties in certain regions. Specifically, assuming no spread factor (i.e., $S = 0$) in the optimization model, while, in fact, there is a high spread (i.e., $S = 2I$), results in a tenfold increase of the total penalty (from 2093 to 20256). In contrast, overestimating the spread factor seems to hold little risk. Assuming a high spread factor (i.e., $S = 2I$), while, in fact, there is no spread (i.e., $S = 0$) results in a marginal penalty increase (from 2093 to 2115).

2.6 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. Finally, one may also consider uncertainty in some of the parameters currently considered deterministic, for example, the total quantity of available critical supplies.

CHAPTER III

HANDLING AMBIGUITY IN STOCHASTIC HUMANITARIAN SUPPLY CHAIN NETWORK DESIGN

Chapter Information

An article based on this chapter has been submitted to a scientific journal.

Abstract

The design and operation of Humanitarian Supply Chain Networks after a natural disaster are among the most complex activities conducted by humanitarian organizations, involving different sources of uncertainty. Typically, the assessments of damage and the resulting demand for resources in the affected region are estimated using different data sources (e.g. surveys and satellite imagery). However, inconsistent estimates of uncertain parameters obtained from the use of multiple data sources may result in ambiguity, posing difficulties to define the planning problem. We here aim to mitigate such ambiguity by developing four mathematical models that deal with ambiguity with varying degrees of conservatism regarding the obtained estimations of the uncertainty. The performance of each proposed model is evaluated, considering two data sources across four ambiguity patterns and 20 problem instances generated using real-world data from the 2018 Indonesia earthquake. The results highlight the benefits of the Minimization of

Maximum Data-Source Penalty when the ambiguity pattern is unknown and the decision-maker has equally high confidence in all data sources.

Keywords: Humanitarian Supply Chain; Humanitarian Relief Network; Stochastic Programming; Ambiguity; post-disaster; Aid Planning

3.1 Introduction

In 2013, the total amount of funding requested by humanitarian organizations worldwide was 12.8 billion US dollars (UNOCHA, 2021b). However, the total amount of donations received by humanitarian organizations in the same year was 8.3 billion US dollars (UNOCHA, 2021b), accounting for only 65% of the requested funding. In all other years of the previous decade, the satisfaction rate of requested annual funding requested by humanitarian organizations was even lower. Since then, the total amount of funding requests of humanitarian organizations has increased to 51.6 billion US dollars (UNOCHA, 2021b) in 2022, from which only 29.7 billion US dollars was provided, covering 57.5% of the requested amount. These numbers indicate severe budget shortages for humanitarian organizations. Three-quarters of the expenses of humanitarian organizations are related to the logistics of humanitarian relief operations (Besiou & Van Wassenhove, 2020; Van Wassenhove, 2006; Stegemann & Stumpf, 2018). An efficient management of available resources for humanitarian relief operations is thus paramount for efficiently providing relief to the affected population. This includes allocating the available budget over time, the effective use of the available staff to perform and support the humanitarian operations, and the planning of the transportation operations to distribute critical supplies.

Effective distribution planning of critical supplies among vulnerable people after a natural disaster is crucial, given its direct impact on the population's health. The required planning is complex and mandates coordination among several stakeholders, while a series of crucial decisions need to be made to ensure operational success. A major complexity of the planning process stems from the high level of uncertainty in the informational environment in which tactical decisions, such as those related to infrastructure and logistics services, are made. Furthermore, a considerable multitude of stakeholders, including the governments, military, donors, and humanitarian organizations, require coordination at multiple levels. For example, when a disaster happens, the affected region is oftentimes divided into subregions where different humanitarian organizations will operate. This enables a better coverage of the affected region. For security reasons, military personnel are often called upon to protect humanitarian organizations, their staff, and volunteers when deployed in the field to distribute 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, helps to fundraise and collect the required budget for the necessary operations.

In this paper, we are specifically interested in the design and operation of a Humanitarian Supply Chain Network (HSCN) after the occurrence of a natural disaster over a defined planning horizon. An HSCN is defined as a physical network of hubs that are used to receive, store, and distribute critical supplies among the vulnerable population, where transportation services are planned to move the critical supplies. The design of an HSCN requires a comprehensive understanding of various parameters, including geographic and demographic data, financial constraints (e.g. the budget), and the availability of essential resources. While the values of some of these parameters are known at the design time, the values of others (e.g., demand, transportation, and storage capacities) are uncertain and estimated during the assessments of damages and needs. Such assessment of damages and needs starts immediately after the disaster, evaluating the damaged infrastructures and demand of affected populations (Balcik, 2017; Balcik & Yanıkoğlu, 2020). The assessment process must operate quickly to provide the required information to decision-makers. Given that on-site assessments of all impacted locations within a constrained timeframe are not feasible, supplementary data sources are employed to expedite the procurement of essential information. A data source (e.g. surveys, satellite imagery, governmental reports, and media) is a database from which data is collected or retrieved to help define probabilistic models accounting for uncertain components involved in the HSCN design problem. Hence, a finite set of probabilistic models is available to estimate the uncertain parameters in the HSCN design problem. Although a high level of confidence is observed for such obtained probabilistic models, they may have discrepancies, directly causing ambiguity in the informational context in which the planning process of humanitarian relief operations occurs. As such, ambiguity in the HSCN design problem is a problem setting in which inconsistent probability distributions are associated with the uncertain parameters (Langewisch & Choobineh, 1996). For instance, Grass et al. (2023) discuss a real-world humanitarian relief problem from Syria where two data sources provide estimations on the level of demand and in some demand points, the estimations barely overlap.

As a result, we are here interested in solving an HSCN design problem with discrepancies in the estimations of parameter uncertainty characterization obtained from various data sources. Specifically, we here consider uncertainty for parameters concerning demand and in both transportation and storage capacity. We propose four distinct optimization models with varying levels of conservatism, incorporating the inherent ambiguity in the HSCN design problem. This contribution advances the understanding and set of available tools for HSCN design by accounting for ambiguity in the studied problem. We are specifically interested in identifying the circumstances in which the proposed models are a superior choice to the commonly used two-stage stochastic model in the literature that does not explicitly account for such ambiguity. To this end, we conduct a comprehensive empirical evaluation, assessing the performance of the proposed optimization models. These experiments are performed with two different data sources and encompass four unique ambiguity patterns. Moreover, the utilized instances are generated from a 2018 Indonesian earthquake dataset, ensuring that the findings have practical relevance.

The remainder of the paper is structured as follows. Section 3.2 covers the literature on handling uncertainty in HSCN design problems and the modeling of uncertainty and ambiguity in general. Section 3.3 is dedicated to the problem definition. The proposed models are introduced in Section 3.4. The experiments and results are discussed in Section 3.5. Finally, we conclude in Section 3.6.

3.2 Literature review

In this section, we position our study within the existing literature. We review the literature on both the humanitarian relief problems under uncertainty and the optimization methods proposed to model and solve them. Subsection 3.2.1 presents a literature review on uncertainty in humanitarian relief studies, discussing the sources of uncertainty, the assessment process to obtain the required information after a disaster, and the ambiguity in estimating the uncertain parameters involved in humanitarian relief planning. Subsection 3.2.2 then reviews the relevant Operations Research literature on different approaches to model uncertainty, including Stochastic Programming and Robust Optimization.

3.2.1 Uncertainty in humanitarian relief

The design of an HSCN necessitates access to geographical and demographical data, as well as information regarding the availability of critical supplies and other essential resources (e.g. budget) for humanitarian relief distribution operations. While some information is known at the design phase (e.g. the available routes connecting hubs), some crucial information (e.g. the capacity of each route for transportation) becomes available over time. It is crucial to consider such uncertainty in the design process, providing adaptability to the changing circumstances (e.g. varying realizations of demand), allocating resources more effectively, and enhancing disaster response, ultimately saving lives and reducing the impact of the disaster on the affected populations.

Demand is the most common and often the most impactful uncertain component in humanitarian relief studies (Balcik & Beamon, 2008; Dönmez et al., 2021; Anaya-Arenas et al., 2014). Additional sources of uncertainty in humanitarian relief problems include a lack of information on the affected population, the urban or rural structure of the affected region, and the intensity of the natural disaster and its secondary impacts (e.g. landslide or aftershock). Further uncertain components in humanitarian relief studies are travel time, supply, network reliability, shipping cost, and shipping capacity (Anaya-Arenas et al., 2014; Tofighi et al., 2016; Daneshvar et al., 2023).

Damage and demand assessments are conducted after the natural disaster, providing probabilistic models that represent the uncertain components of the planning problem. Considering the limited time and a lack of resources available for the assessments, the affected region is divided into smaller subregions, and the assessments are taken by sampling sites in each subregion (Balcik & Yanıkoğlu, 2020; Balcik, 2017). In addition to the data obtained from on-site visits, other data sources are also available for the assessments. Data sources in humanitarian relief problems either need experts' interpretation (e.g. satellite imagery, media) or belong to previous natural disasters in the region (e.g. historical data) (Yáñez-Sandivari et al., 2021). Previous disasters' data sources are mostly used in pre-disaster studies (Balcik et al., 2019). However, since each natural disaster has unique characteristics (Chen et al., 2011), post-disaster studies rely more on the experts' interpreted data sources from the current natural disaster.

Benini et al. (2017) explain different types of responses provided by experts in assessments during humanitarian operations, including probability, continuous scale, and scalar quantity estimations. Probability estimation is a single-value estimation often used to estimate the likelihood of occurrences of an event. In continuous scale estimation, the expert indicates a range or a single value over a defined scale, estimating the uncertain components. Finally, scalar quantity is a three-point estimation method, including the minimum, maximum, and most probable values. The obtained data points form a triangular distribution representing the uncertain components (Hakimifar et al., 2021), providing higher accuracy than the former estimations. In this paper, we use the triangular distribution estimation method. A set of discrete scenarios is then generated from distributions estimating the value of uncertain components (Grass & Fischer, 2016a; Gutjahr & Nolz, 2016; Grass et al., 2023). Although the obtained estimations can be made with a high level of confidence, they might have discrepancies, resulting in ambiguity within the HSCN design problem. The common approach in the literature is to use stochastic programming to model the uncertainties. However, such an approach does not reflect the discrepancies between different data sources and could result in a sub-optimal solution based on each individual data source (Grass et al., 2023; Benini et al., 2017). To this end, Grass et al. (2023) propose a machine learning approach that leverages graph clustering and stochastic optimization techniques to address the challenges faced by humanitarian decision-makers in a shelter location problem with ambiguity affecting the demands. Specifically, their approach replaced the expectation function in the stochastic model with an aggregation function alongside scenario clustering, which enabled the ambiguity to be analyzed. However, the developed optimization method did not directly model the informational ambiguity but rather addressed it indirectly through the clustering analysis.

In contrast, our work is different at both the application and the methodological level. First, we focus on a different planning problem, i.e., HSCN design, for which we propose alternative optimization models that explicitly formulate and directly account for the ambiguity that is present. Second, we do not limit our models to stochastic programming, but rather require a combination along with robust optimization, and goal programming techniques, offering varying levels of ambiguity-averse perspectives to the decision-maker, depending on the chosen optimization approach that is used.

3.2.2 Uncertainty and ambiguity in operations research

We first review stochastic programming and robust optimization, both approaches are used to model and solve optimization problems with uncertainties. We then discuss goal programming, a mathematical optimization technique that can be used in optimization problems with multiple conflicting objectives.

Stochastic programming is the paradigm of choice for problems with uncertain components that can be formulated, with a high level of confidence, by probability distributions. In contrast, robust optimization is employed when the statistical information regarding the uncertain components of the problem is limited (e.g., only the upper bound and lower bounds of the probability distribution are available).

In stochastic programming problems (Birge & Louveaux, 2011), a set of scenarios (i.e., random realizations) generated from the probability distributions of the uncertain components represent the probabilistic outcomes of the uncertain parameters. However, probability distributions are not always available. Ben-Tal & Nemirovski (1998) introduce the concept of robust optimization, considering the possible realizations of uncertain parameters regardless of their probability distribution. To control the level of conservatism of the obtained solutions, the authors defined an uncertainty set (i.e., a predefined range of potential variations of uncertain parameters) that prevents all uncertain components from taking their worst-case values simultaneously, reducing the level of conservatism of the original max-min model introduced by Wald (1945). Further uncertainty sets are used in the literature, including polyhedral, norm-bounded, interval and chance-constrained uncertainty sets (Pluymers et al., 2005; Ben-Tal & Nemirovski, 2002; Abedor et al., 1995). The choice of uncertainty set depends on the nature of the problem and the level of conservatism or robustness desired in the optimization process. The polyhedral uncertainty set is defined by linear constraints, restricting the potential values of uncertain parameters (Pluymers et al., 2005). The norm-bounded uncertainty set is used where the magnitude of deviation is known but not the direction (Abedor et al., 1995). When only bounds on uncertain parameter values are known, the interval uncertainty set is used (Ben-Tal & Nemirovski, 2002). Using a chance-constrained probability set involves defining a probability distribution for uncertain parameters and setting constraints limiting the probability of violating the constraints below a specified threshold.

Finally, our work is also related to goal programming (Charnes & Cooper, 1957), a technique used to balance multiple conflicting objectives. Variations of goal programming have been used in the literature, including its combination with stochastic programming (Aouni et al., 2012) and robust goal programming (Ghahtarani & Najafi, 2013). In this study, we consider an HSCN design problem with the estimation of uncertain parameters obtained from multiple data sources, and optimizing the model based on each data source could be seen as a different goal. Hence, we use goal programming to propose a model that explicitly accounts for uncertainty and ambiguity in the HSCN design problem; see Minimization of expected opportunity loss approach in Section 3.4.2.

3.3 Problem description

In this section, we present the here-considered HSCN design problem. Specifically, this section introduces the general characteristics of the HSCN design problem under uncertainty, including the network structure, both deterministic and uncertain parameters, and the decisions involved.

An HSCN is a physical network of hubs connected by transportation services (Daneshvar et al., 2023). The designed HSCN receives, stores, transports, and distributes critical supplies to beneficiary groups over a defined planning horizon, aiming to minimize the harm to people's health caused by unmet demand. Here, we introduce the terminology used in the rest of the paper. The target population, called beneficiary groups, is the relocated people who live in temporary shelters such as camps, schools, and sports centers. We divide the planning horizon into operational time frames, referred to as time periods. A time period indicates the required amount of time during which a shipment is received, stored, and distributed in the affected region, plus the time that beneficiaries consume them.

Each beneficiary group needs a set of supplies that are called critical supplies. Some critical supplies are provided only once during the first period (e.g. tent and blanket), and others at every period (e.g. food). The beneficiary groups pick up the critical supplies from physical locations called Distribution Centers (DC). Failure to satisfy the demand for each critical supply causes a penalty. The required quantity of each critical supply for each individual or household is known (IFRC, 2021b), but the number of individuals in each beneficiary group is uncertain. The source of this uncertainty is due to both a lack of information and the possibility of change in the number of individuals in each group over time caused by secondary impacts (e.g. aftershocks following an earthquake, landslide following a flood). Therefore, the exact level of demand may never be available and is considered uncertain.

A high level of demand and limited resources typically prevent the HSCN from fully satisfying the demand of the beneficiary groups. The portion of demand that is not satisfied is denoted as unmet demand. Each unit of unmet demand negatively affects the level of demand in the next period, the degree of which can be accounted for by using the notion of a spread factor (Daneshvar et al., 2023). For instance, in the natural disasters that happen during pandemics, lack of access to face masks and alcohol-based disinfectants results in the spread of the epidemy and increases the demand for test kits and related medication (Sakamoto et al., 2020). The spread factor indicates the impact of one unit of unmet demand of a critical supply on the demand level for critical supplies in the next period. The demand in each period is therefore defined as the sum of a base demand calculated based on available estimations and a residual demand, which is the effect of unmet demand in the previous period. Equation (3.1) computes the total demand $\hat{d}_l^{kt}$ of beneficiary group l for critical supply k at period t. In this equation, $\tilde{d}_l^{kt}$ represents the base demand of beneficiary group l for critical supply k at period t, $s^{k'k}$ represents the spread factor of critical supply k' on supply k, and $\bar{a}_{il}^{k't-1}$ represents the allocated critical supply k' to beneficiary group l from DC i at period $t-1$.

$$\underbrace{\hat{d}_l^{kt}}_{\text{total demand}} = \underbrace{\tilde{d}_l^{kt}}_{\text{base demand}} + \underbrace{\sum_{k' \in K} s^{k'k} (\hat{d}_l^{k't-1} - \sum_{i \in V_{DC}} \bar{a}_{il}^{k't-1})}_{\text{residual demand}} \tag{3.1}$$

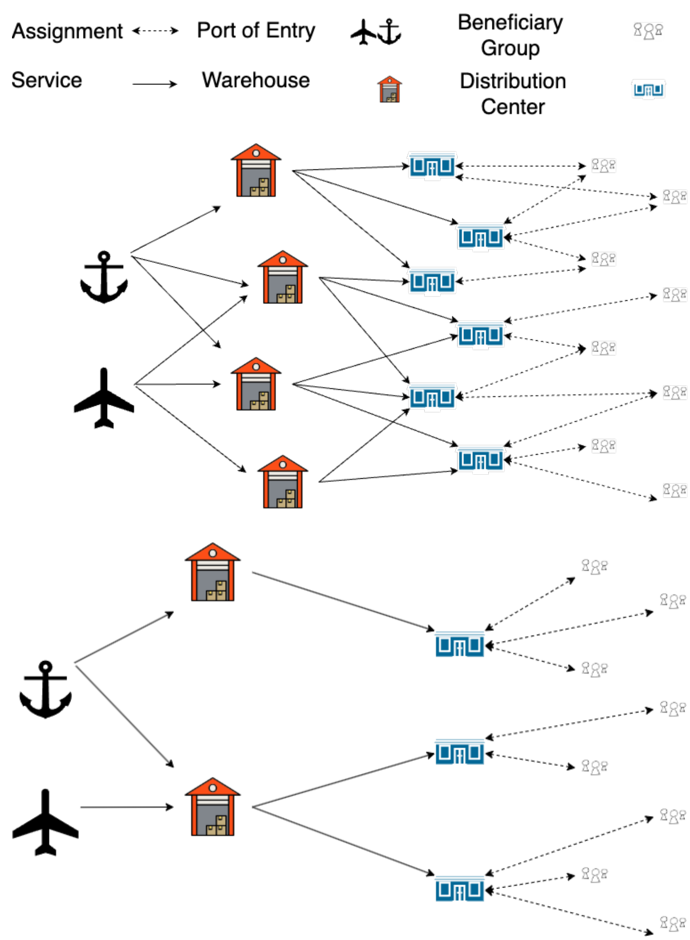


Figure 3.1: An HSCN illustration. Top: all available hubs, services, and assignments. Bottom: a designed HSCN, including the selected hubs, services, and assignments in an example HSCN planning solutions.

We consider a three-layer structure HSCN, as exemplified in Figure 1. The first layer of hubs consists of ports of entry that receive critical supplies from international humanitarian organizations. The second layer of hubs includes warehouses. A warehouse is a hub that receives critical supplies from ports of entry, stores them and sends them to the third layer of the HSCN, which consists of DCs. There is a fixed cost to use each selected hub for the considered planning horizon. In addition to the fixed cost of selecting a hub, there is an additional fixed cost for reserving the inventory resources available at selected warehouses. Inventory resources are only available at the warehouses, with the possibility to store critical supplies over the considered planning period. A unit of inventory resources could be a classroom in a school or a container located in a field used as a temporary warehouse. The fixed cost associated with utilizing inventory resources within warehouses is proportional to the requested capacity allocation at each respective warehouse, subject to the maximum available storage capacity of the warehouse. Each beneficiary group is assigned to a DC where it can pick up its allocated critical supplies at each time period. Transportation services move the critical supplies between selected hubs. We assume that each transportation resource commutes only between its origin and destination hubs, returning to its origin hub after delivering the critical supplies. The total transportation capacity between two hubs is given by the sum of the transportation services between these hubs. A unit of transportation resources could be a truck, a boat, a train wagon, or a helicopter. There is a fixed cost (e.g. for drivers, staff, and security escorts) for selecting each unit of transportation resources, as well as a variable flow cost (e.g. fuel) proportional to the travel distance of the transportation resources. The total costs incurred by the design decisions are limited by the initial budget available at the time of the design. Over the subsequent periods, the humanitarian organization receives donations for operational expenses (e.g. flow cost). Unused budget at any time period is carried over to the next period.

In the aftermath of a natural disaster, the extent of the impact of the event on the affected population (e.g. demand) and state of the region (e.g. transportation and inventory capacities) is uncertain. Over time, additional information may become available, reducing the contextual uncertainty (e.g. conducting direct observations in the affected region might enable a more accurate quantification of the needs of the affected population). However, humanitarian organizations cannot afford to wait for such information to plan and deploy the aid. Rapid responses are crucial to minimize harm in the affected region. Furthermore, the local resources necessary for the HSCN design might be notably scarce, and delaying the procurement of such resources could lead to an inflationary spiral (Holguín-Veras et al., 2012). Therefore, critical decisions regarding the structure and capacities of the HSCN need to be made amidst uncertainty, while other decisions concerning the allocation of the available resources can be made once additional information is obtained and uncertainty levels are diminished. We here consider a two-stage setting where the first decision stage occurs at the beginning of the planning horizon when the HSCN is designed under a rather high level of uncertainty. For the second stage (when the operational decisions are made), we assume that all stochastic parameters (e.g. demand and transportation capacity) become known.

The scenarios (i.e., realizations of the uncertain parameters) are generated using the probability distributions obtained from assessments conducted in the region. However, as multiple data sources (e.g. satellite imagery and governmental reports) are involved in the assessments, the probability distributions obtained might have inconsistencies, resulting in ambiguity. Specifically, when different assessments are performed using different data sources to quantify the same demands, they may yield different random distributions. Recalling that the same level of confidence is assigned to all assessments, the ambiguity arises from the uncertainty about which probabilities should be used during the planning process. In the next section, we present optimization models that explicitly account for such sources of ambiguity when solving the here-considered problem.

3.4 Optimization model

In this section, we propose a variety of optimization models that explicitly deal with the ambiguity that stems from inconsistent estimations of the uncertain components obtained from various data sources. Subsection 3.4.1 recalls how the HSCN problem is formulated as a two-stage stochastic optimization model under the general assumption that a single data source is used to generate a single scenario set Ψ. Then, in subsection 3.4.2, we introduce a series of optimization models that explicitly consider the ambiguity faced in the HSCN design problem under study.

3.4.1 HSCN design model

We model the HSCN design problem as a two-stage stochastic model, introduced in Daneshvar et al. (2023). In this model, the hubs and transportation services are selected from available hubs, represented by the set V, and services, represented by the set A. The set of hubs contains three subsets, including the port of entry hubs, V_I, the warehouse hubs, V_W, and the DC hubs, V_{DC}. The selected hubs and services will be part of the HSCN network over the entire planning horizon. The planning horizon consists of a sequence of time periods represented by the set T. The designed HSCN is used to distribute a set of critical supplies, represented by the set K, among the beneficiary groups which are represented by the set L, over the planning horizon. In order to model uncertain parameters, we use scenarios generated from estimations provided by data sources. In the HSCN design model, a set of scenarios are generated from a single data source, represented by Ψ.

There are some costs related to the design and some others for the operation of the HSCN. The former includes the cost of selecting hubs, represented by the parameter f_i, $i \in V$, the selection cost of the inventory resources assigned to warehouses, represented by the parameter $\hat{f}_i$, $i \in V_W$, and the cost of selecting transportation resources for services, represented by the parameter $\hat{f}_{ij}$, $(i, j) \in A$. We model the operational cost by the parameter c^k_{ij}, which represents the cost of transporting one unit of critical supply $k \in K$ by service $(i, j) \in A$. The parameter u_{ij} illustrates the capacity of one unit of transportation resource of the service $(i, j) \in A$, and the parameter u_i, $i \in V_W$ expresses the capacity of one unit of inventory resources. The parameter m_{ij} defines the maximum number of transportation resources available for the service $(i, j) \in A$, and the maximum number of inventory resources available for the warehouse $i \in V_W$ is indicated by the parameter m_i.

The parameter z^0 represents the initial budget, and the parameters z^t indicates the received donations at each period $t \in T$. The parameter n^{kt}_i demonstrates the maximum quantity of each critical supply $k \in K$ that can be made available at a point of entry hub $i \in V_I$ at period $t \in T$. The parameter $g^t_{i\psi}$ represents the percentage of available inventory resources of hub $i \in V_W$ at period $t \in T$, in scenario $\psi \in \Psi$. Furthermore, the parameter $g^t_{ij\psi}$ indicates the percentage of available transportation resources of service $(i, j) \in A$ at period $t \in T$. The base demand for critical supply $k \in K$ of a beneficiary group $l \in L$ at period $t \in T$ in scenario $\psi \in \Psi$ is represented by the parameter $d^{kt}_{l\psi}$. The parameter b^k specifies the penalty of unmet demand for the critical supply $k \in K$. The parameter $s^{k'k}$ represents the spread factor for one unit of the critical supply $k' \in K$ over the critical supply $k \in K$. Finally, the parameter $\hat{d}^{kt}_{l\psi}$ illustrates the total demand of the beneficiary group $l \in L$ for the critical supply $k \in K$ at period $t \in T$ in scenario $\psi \in \Psi$.

Table 3.1: Decision variables of the two-stage stochastic model.

First-stage	
$x_{ij} \in \{0,1\}$	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	
$\bar{x}^{kt}_{ij_\psi} \geq 0$	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 3.1 defines the decision variables of our model. Starting from the decision variables that are made in the first stage, the decision variable x_{ij} indicates if the service $(i,\ j) \in A$ is included in the HSCN, and the decision variable $\hat{x}_{ij}$ denotes the number of transport resources that are assigned to the service. Likewise, the decision variable y_i takes value 1 if the hub $i \in V$ is part of the network, and 0 otherwise. Decision variable $\hat{y}_i$ indicates the number of inventory resources assigned to the warehouse $i \in V_W$. Finally, decision variable a_{il} takes value 1 if the beneficiary group $l \in L$ is assigned to the DC $i \in V_{DC}$, and 0 otherwise.

The following are the second-stage decision variables of the model. The decision variable $\bar{x}^{kt}_{ij_\psi}$ indicates the quantity of the critical supply $k \in K$ transferred at period $t \in T$ on service $(i, j) \in A$ in scenario $\psi \in \Psi$. Furthermore, the decision variable $\bar{a}^{kt}_{il_\psi}$ indicates the quantity of critical supply $k \in K$ allocated to beneficiary group $l \in L$ at period $t \in T$ from DC $i \in V_{DC}$ in scenario $\psi \in \Psi$. $\hat{r}^{kt}_{i_\psi}$ represents the level of inventory of warehouse $i \in V_W$ for critical supply $k \in K$ at the beginning of period $t \in T$ in scenario $\psi \in \Psi$, and the decision variable $r^{kt}_{i_\psi}$ represents the inventory level at the end of that time period.

$$\min \sum_{\psi \in \Psi} p_\psi Q_\psi(\hat{x}, \hat{y}, a) \tag{3.2}$$

$$s.t. \quad 2x_{ij} \leq y_i + y_j \quad \forall (i, j) \in A, \tag{3.3}$$

$$\hat{y}_i \leq m_i y_i \quad \forall i \in V_W, \tag{3.4}$$

$$\hat{x}_{ij} \leq m_{ij} x_{ij} \quad \forall (i, j) \in A, \tag{3.5}$$

$$\sum_{i \in V} f_i y_i + \sum_{i \in W} \hat{f}_i \hat{y}_i + \sum_{(i,j) \in A} \hat{f}_{ij} \hat{x}_{ij} \leq z^0, \tag{3.6}$$

$$\sum_{i \in V_{DC}} a_{il} = 1 \quad \forall l \in L, \tag{3.7}$$

$$a_{il} \leq y_i \ \ \forall i \in V_{DC}, \ \forall l \in L, \tag{3.8}$$

$$\hat{x}_{ij} \in \mathbb{N}^0, \ \hat{y}_i \in \mathbb{N}^0, \ x_{ij} \in \{0, 1\}, \ y_i \in \{0, 1\}, a_{il} \in \{0, 1\}, \ \forall i \in V, \ \forall (i, j) \in A. \tag{3.9}$$

Where $Q_\psi(\hat{x}, \hat{y}, a)$ calculates the minimum penalty over the defined periods for the scenario $\psi \in \Psi$ with first stage decision variables values being fixed to $\hat{x}, \hat{y}, a$. $Q_\psi(\hat{x}, \hat{y}, a)$ is defined as follows:

$$Q_\psi(\hat{x}, \hat{y}, a) := min \sum_{t \in T} \sum_{k \in K} b^k \sum_{l \in L} (\hat{d}^{kt}_{l\psi} - \sum_{i \in V_{DC}} \bar{a}^{kt}_{il_\psi}), \tag{3.10}$$

$$s.t. \quad \sum_{k \in K} \bar{x}^{kt}_{ij_\psi} \leq u_{ij} g^t_{ij_\psi} \hat{x}_{ij} \quad \forall (i,j) \in A,\ \forall t \in T, \tag{3.11}$$

$$\bar{a}^{kt}_{il_\psi} \leq \sum_{(j,i) \in A} u_{ji} g^t_{ji_\psi} m_{ji} a_{il}, \quad \forall i \in V_{DC},\ \forall l \in L,\ \forall k \in K,\ \forall t \in T, \tag{3.12}$$

$$\bar{a}^{kt}_{il_\psi} \leq \hat{d}^{kt}_{l\psi}, \quad \forall i \in V_{DC},\ \forall l \in L,\ \forall k \in K,\ \forall t \in T, \tag{3.13}$$

$$\sum_{l \in L} \bar{a}^{kt}_{il_\psi} = \sum_{j \in W} \bar{x}^{kt}_{ji_\psi}, \quad \forall i \in V_{DC}, \forall k \in K,\ \forall t \in T, \tag{3.14}$$

$$\hat{d}^{kt}_{l\psi} = d^{kt}_{l\psi} + \sum_{k' \in K} s^{k'k} (\hat{d}^{k't-1}_{l\psi} - \sum_{i \in V_{DC}} \bar{a}^{k't-1}_{il_\psi}), \quad \forall l \in L,\ \forall k \in K,\ \forall t \in T, \tag{3.15}$$

$$\sum_{i \in V} f_i y_i + \sum_{i \in W} \hat{f}_i \hat{y}_i + \sum_{(i,j) \in A} \hat{f}_{ij} \hat{x}_{ij} + \sum_{t'=1}^{t} \sum_{(i,j) \in A} \sum_{k \in K} c^k_{ij} \bar{x}^{kt'}_{ij_\psi} \leq z^0 + \sum_{t'=1}^{t} z^{t'}, \quad \forall t \in T, \tag{3.16}$$

$$\hat{r}^{kt}_{j_\psi} \leq r^{kt-1}_{j_\psi} \quad \forall j \in V_W,\ \forall k \in K,\ \forall t \in T, \tag{3.17}$$

$$\sum_{k \in K} \hat{r}^{kt}_{j_\psi} \leq u_j g^t_{j_\psi} \hat{y}_j \quad \forall j \in V_W,\ \forall t \in T, \tag{3.18}$$

$$\sum_{k \in K} r^{kt}_{j_\psi} \leq u_j g^t_{j_\psi} \hat{y}_j \quad \forall j \in V_W,\ \forall t \in T, \tag{3.19}$$

$$r^{kt}_{j_\psi} = \hat{r}^{kt}_{j_\psi} + \sum_{(i,j) \in A} \bar{x}^{kt}_{ij_\psi} - \sum_{(j,i) \in A} \bar{x}^{kt}_{ji_\psi}, \quad \forall j \in V_W,\ \forall k \in K,\ \forall t \in T, \tag{3.20}$$

$$\sum_{(i,j) \in A} \bar{x}^{kt}_{ij_\psi} \leq n^{kt}_i \quad \forall i \in V_I,\ \ \forall k \in K,\ \forall t \in T, \tag{3.21}$$

$$\bar{x}^{kt}_{ij_\psi} \geq 0,\ \bar{a}^{kt}_{il_\psi} \geq 0,\ r^{kt}_{i_\psi} \geq 0,\ \hat{r}^{kt}_{i_\psi} \geq 0,\ \forall (i,j) \in A,\ \forall i \in V,\ \forall k \in K,\ \forall t \in T. \tag{3.22}$$

As a two-stage HSCN design model, the objective function (3.2) minimizes the expected penalty of unmet demand over the set of scenarios Ψ. Constraints (3.3) indicate that only services with selected hubs at their origin and destination are permitted for selection. Constraints (3.4) limit the number of inventory resources at each warehouse to the maximum available inventory resources at that warehouse. Similarly, constraints (3.5) limit the number of transportation resources for each transportation service to the maximum number of available transportation resources for that transportation service. Constraints (3.6) limit the total cost of selecting hubs and assigning resources to warehouses and transportation services to the initial budget. Constraints (3.7) ensure that each beneficiary group is assigned to exactly one DC. Constraints (3.8) limit the assignment of beneficiary groups to DCs that are selected to be part of the HSCN. Constraints (3.9) indicate the bounds of the decision variables.

The objective function (3.10) minimizes the total penalty of unmet demand over the planning horizon for a given scenario ψ. Constraints (3.11) limit the quantity of transported critical supplies over services to the available capacity of services at each time period. Constraints (3.12) ensure that the allocated amount of critical supplies to each beneficiary group from each DC are limited by the maximum amounts of the critical supplies received by the DC at each period. Constraints (3.13) limit the allocated critical supplies to each beneficiary group to the total demand of that beneficiary group at each period. Constraints (3.14) ensure that the total quantity of critical supplies that are delivered to each DC is equal to the total quantity of critical supplies allocated to beneficiary groups at each period. Constraints (3.15) formulate the total demand of each beneficiary group for each critical supply at each period as the summation of the base demand and the residual demand of that critical supply. Constraints (3.16) ensure that the amount for the overall costs of the first stage and first t periods that is paid, is limited by the summation of the initial budget and the received donation up to that period.

Constraints (3.17) restrict the inventory level of each critical supply at each warehouse at each period by its level at the end of the last period. Constraints (3.18) limit the inventory level of critical supplies at the beginning of each period to the available inventory capacity of that warehouse in that period. Similarly, Constraints (3.19) limit the inventory level of critical supplies at the end of each period to the available inventory capacity of that warehouse in that period. Constraints (3.20) indicate the inventory level of critical supplies at the end of each period as the sum of the inventory level at the beginning of that period and the received quantity of critical supplies at that period minus the quantity of shipped critical supplies to DCs at that period. Constraints (3.21) ensure that the quantity of shipped critical supplies from each port of entry is limited by the capacity of each port of entry at that period. Constraint (3.22) are the non-negativity requirements imposed on the all the second-stage decision variables.

3.4.2 Proposed HSCN design models

The HSCN design model ignores the ambiguity in the obtained estimates from multiple data sources. This subsection introduces the HSCN design models that explicitly handle the discussed ambiguity in the problem and provide alternative optimization methods for the HSCN design model.

Assume the decision-makers should make a series of decisions, represented here by $\boldsymbol{x} \in X$, X indicating the feasible set for the decisions while facing uncertainty represented here by parameter vector ξ. We further assume $F(\boldsymbol{x}, \xi)$ represents the function the decision makers seek to optimize and computes the penalty obtained by using the decision vector x when the uncertain parameters get the value ξ. Let there be e data sources with $\Psi_1, \Psi_2, ..., \Psi_e$ being their corresponding scenario sets.

The set containing all scenario sets obtained from available data sources is called the ambiguity set (Bayraksan & Love, 2015), represented by $\mathbb{P} := \{\Psi_1, \Psi_2, ..., \Psi_e\}$. We then define solution $\boldsymbol{x}_i^*$, $i \in \{1, 2, ..., e\}$ as the solution that obtains the minimum expected value of function $F(\boldsymbol{x}, \xi)$ for all possible values of $\xi \in \Psi_i$:

$$\boldsymbol{x}_i^* \in arg\min_{\boldsymbol{x} \in X} \mathbb{E}_{\xi \in \Psi_i}[F(\boldsymbol{x}, \xi)], \;\; \forall\, i \in \{1, 2, ..., e\} \tag{3.23}$$

Assuming $e = 1$, then (3.23) delivers a single solution $\boldsymbol{x}_1^*$. However, we have e data sources available, and we assume that:

$$\boldsymbol{x}_i^* \neq \boldsymbol{x}_j^* \quad \forall i \neq j \quad \text{and} \quad i, j \in \{1, 2, ..., e\}.$$

We define the opportunity loss of i'th data source when using solution $\boldsymbol{x}$, represented by $\epsilon_i(\boldsymbol{x})$, as the disparity between minimum expected value derived from the optimal solution $\boldsymbol{x}_i^*$ and the attained value when using solution $\boldsymbol{x}$, mathematically formulated as:

$$\epsilon_i(\boldsymbol{x}) := \mathbb{E}_{\xi \in \Psi_i}[F(\boldsymbol{x}, \xi)] - \mathbb{E}_{\xi \in \Psi_i}[F(\boldsymbol{x}_i^*, \xi)].$$

Then, we assume, employing the optimal solution $\boldsymbol{x}_j^*$, derived from considering scenario set Ψ_j, within the optimization function associated with the scenario set Ψ_i, results in a significant opportunity loss:

$$\epsilon_i(\boldsymbol{x}_j^*) >> \epsilon_i(\boldsymbol{x}_i^*) = 0 \quad \forall i, j \in \{1, 2, ..., e\}.$$

One then seeks to find a single solution $\boldsymbol{x}^*$ such that:

$$\boldsymbol{x}^* \in X \quad and \quad \epsilon_i(\boldsymbol{x}^*) \approx 0 \quad \forall i \in \{1, 2, ..., e\}.$$

Minimization of expected opportunity loss

We first present a goal programming (Charnes & Cooper, 1957) approach where minimizing data source-specific expected penalties are treated as distinct goals to reach. We refert this model to one of *Minimization of expected opportunity loss (MIN-OppLoss)*. Its objective (3.24) is defined as the total expected opportunity loss by associating the same weight to the deviations from each data source-specific target value.

$$\min_{\boldsymbol{x}} \sum_{i=1}^{e} \mathbb{E}_{\xi\in\Psi_i}[F(\boldsymbol{x},\xi)] - \mathbb{E}_{\xi\in\Psi_i}[F(x_i^*,\xi)] \tag{3.24}$$

The second part of the objective, $\mathbb{E}_{\xi\in\Psi_i}[F(x_i^*,\xi)]$, being a constant, can be removed from the formulation, making objectives (3.24) and (3.25) equivalent.

$$\min_{\boldsymbol{x}} \sum_{i=1}^{e} \mathbb{E}_{\xi\in\Psi_i}[F(\boldsymbol{x},\xi)] \tag{3.25}$$

This model is equivalent to the commonly used model in the literature (Daneshvar et al., 2023) that does not specifically consider ambiguity in the HSCN design problem. In other words, its considered distribution is defined as the union of the individual distributions of the various data sources.

In order to define the MIN-OppLoss model, one can replace the objective function (3.2) with the objective function (3.26). In an alternative view, Minimization of expected opportunity loss approach could be interpreted as the equivalent of the HSCN design model where Ψ is replaced by Ψ_{Total}. In (3.26), p_ξ represents the probability of scenario ξ if data source Ψ is providing the accurate estimation of uncertain parameters.

$$\min \sum_{i=1}^{e} \left[\sum_{\psi\in\Psi_i} p_\psi Q_\psi(\hat{x},\hat{y},a) \right] \tag{3.26}$$

subject to Constraints (3.3), (3.4), (3.5), (3.6), (3.7), (3.8), (3.9).

Minimization of Maximum Scenario Penalty

Using the classical robust optimization approach (Soyster, 1973), minimizing the worst-case scenario outcome using the scenario set $\Psi_{total} := \bigcup_{i=1}^{e} \Psi_i$. In other words, it provides a robust solution against uncertainties by considering the most adverse outcome while maintaining feasibility:

$$\min_{\boldsymbol{x}} \max_{\xi \in \Psi_{total}} F(\boldsymbol{x}, \xi). \tag{3.27}$$

We refer to this model as the *MIN-MaxScenPen* model by scenario. The obtained solution is expected to perform worse compared to other presented models on most of the realization of uncertain parameters while resulting in less harm in extreme scenarios.

Developing the Minimization of Maximum Scenario Penalty model is achieved by introducing an auxiliary decision variable, Θ, in the objective function, replacing the original objective function (3.2). Additionally, the constraint (3.29) is added to the first stage of the model, limiting the objective function value based on the penalties associated with each scenario in the scenario set Ψ_{Total}. Furthermore, constraint (3.30) indicates the bounds of the decision variable Θ.

$$\min \quad \Theta \tag{3.28}$$

subject to constraints (3.3), (3.4), (3.5), (3.6), (3.7), (3.8), (3.9), (3.29), and (3.30).

$$\Theta \geq Q_{\psi}(\hat{x}, \hat{y}, a), \quad \forall \psi \in \Psi_{total} \tag{3.29}$$

$$\Theta \geq 0. \tag{3.30}$$

Minimization of Expected Data-Source Penalty

The MIN-MaxScenPen model focuses on extreme cases, leading to overly cautious decisions and not capturing the full range of possible scenarios. To expand the number of scenarios involved in the solution using the concept of data source, we propose a model *Minimization of Expected Data-Source Penalty (MIN-ExpDSPen)*, which is based on robust optimization and aims to minimize data source level expected penalty. The MIN-ExpDSPen model defines an objective that minimizes the maximum expected penalty of data source-specific scenarios within the ambiguity set, as presented by objective (3.31):

$$\min_{\boldsymbol{x}} \max_{\Psi_i \in \mathbb{P}} \mathbb{E}_{\xi \in \Psi_i}[F(\boldsymbol{x}, \xi)] \tag{3.31}$$

The aim of this objective is to find a solution x that minimizes the highest level of expected penalty among the scenario sets in $\mathbb{P}$.

In this model, the objective function (3.32) replaces the objective function (3.2). Furthermore, we add the constraint (3.30) to the first stage of the model. Constraints (3.33) ensure that the objective function value of the first stage is more than the expected penalty of the designed HSCN over the scenario set generated from estimations obtained from each data source.

$$\min \quad \Theta \tag{3.32}$$

subject to constraints (3.3), (3.4), (3.5), (3.6), (3.7), (3.8), (3.9), (3.30) and:

$$\Theta \geq \sum_{\psi \in \Psi_i} p_\psi Q_\psi(\hat{x}, \hat{y}, a), \quad \forall i = 1, 2, ... e. \tag{3.33}$$

Minimization of Maximum Data-Source Penalty

While MIN-OppLoss approach minimizes the expected penalty over scenarios from all data sources, it does not consider the variance of the opportunity loss. In other words, the obtained HSCN may perform inadequately over some data sources and very well on others. In contrast, the here proposed model *Minimization of Maximum Data-Source Penalty (MIN-MaxDSPen)*, grounded in robust optimization, aims to address the variability in opportunity losses among scenario sets in $\mathbb{P}$. Consequently, this method minimizes the maximum opportunity loss within each data source's scenario set, as depicted in objective (3.34).

$$\min_{\boldsymbol{x}} \max_{\Psi_i \in \mathbb{P}} \mathbb{E}_{\xi \in \Psi_i}[F(\boldsymbol{x}, \xi)] - \mathbb{E}_{\xi \in \Psi_i}[F(\boldsymbol{x}_i^*, \xi)]. \tag{3.34}$$

Objective (3.34) provides a solution x with the minimum opportunity loss among all data sources.

To model this approach, the objective function (3.35) replaces the objective function (3.2). The range of the expected penalty in the HSCN design problem defines the domain of Θ. Therefore, the domain of the decision variable Θ defined by constraint (3.30) is in the range of positive real numbers. Constraints (3.36) in the first stage ensure that the value of auxiliary decision variable Θ is always more than the gap between the expected penalty of designed HSCN in this model and HSCNs designed by HSCN design model using Ψ_i, Where i could point to any data source from 1 to e.

$$\min \quad \Theta \tag{3.35}$$

subject to constraints (3.3), (3.4), (3.5), (3.6), (3.7), (3.8), (3.9) and:

$$\Theta \geq \sum_{\psi \in \Psi_i} p_\psi (Q_\psi(\hat{x}, \hat{y}, a) - Q_\psi(\hat{x}_i^*, \hat{y}_i^*, a_i^*)), \quad \forall i = 1, 2, ..., e. \tag{3.36}$$

3.5 Experimental results

In this section, we design and apply a set of experiments to study the performance of the proposed models for the HSCN design problem. Subsection 3.5.1 introduces the data set, including the characteristics of the natural disaster, the affected region, the sources used in the data preparation, and the scenario generation. Subsection 3.5.2 presents the experimental results, including a Pareto frontier analysis, a ranked-based analysis, and a comparative performance analysis over the solutions obtained by executing the proposed models on the introduced instances. Finally, managerial insights are presented.

3.5.1 Data set

We use a data set (Daneshvar et al., 2023) from the 2018 earthquake in Lombok island at Indonesia. More than 1500 aftershocks have been recorded in the region but most of them were weak shakes. The most important quakes in the region are presented in Table 3.2. The earthquake forced 445,343 individuals to relocate into 2,700 camps on Lombok and the neighboring islands. The Indonesian government announced a state of emergency from July 29th to August 26th, which is here considered as the planning horizon. We divide the planning horizon into 4 time periods, each presenting a week during the state of emergency. The International Organization for Migration (IOM) has published the list of all camps including the location and number of individuals in each camp (IOM, 2019). In this study, we consider 349 beneficiary groups on the island with a total population of 52,128 individuals in 15,993 households. Considering that clean water was distributed among beneficiary groups from local resources using 21 water trucks (IFRC, 2021a), we only consider shelter, food, and hygiene packs as the critical supplies that are brought in from outside the affected region and to be transported and distributed using the designed HSCN. We use the standard required quantity of each critical supply (IFRC, 2021b) per individual or per household that is calculated and published by the International Federation of Red Cross and Red Crescent Societies (IFRC).

Table 3.2: Most important earthquakes on Lombok island in 2018.

earthquake	date	strength
main earthquake	2018/07/29	6.4 Richter magnitude scale
first strong aftershock	2018/08/05	7.0 Richter magnitude scale
second strong aftershock	2018/08/09	5.9 Richter magnitude scale
third strong aftershock	2018/08/26	6.4 Richter magnitude scale

Palang Merah Indonesia (PMI) is the local branch of IFRC in Indonesia which was responsible for the distribution of critical supplies in the affected region. We used the published reports of IFRC and PMI to complete our data set (IFRC, 2021a). According to these reports, PMI used four ports of entry and six warehouses in their HSCN. Furthermore, PMI signed contracts with third-party companies to transport critical supplies among the hubs. However, since the details of the contracts are not included within the reports of the IFRC and PMI, we consulted the local transportation companies' websites for the cost and capacity of their services.

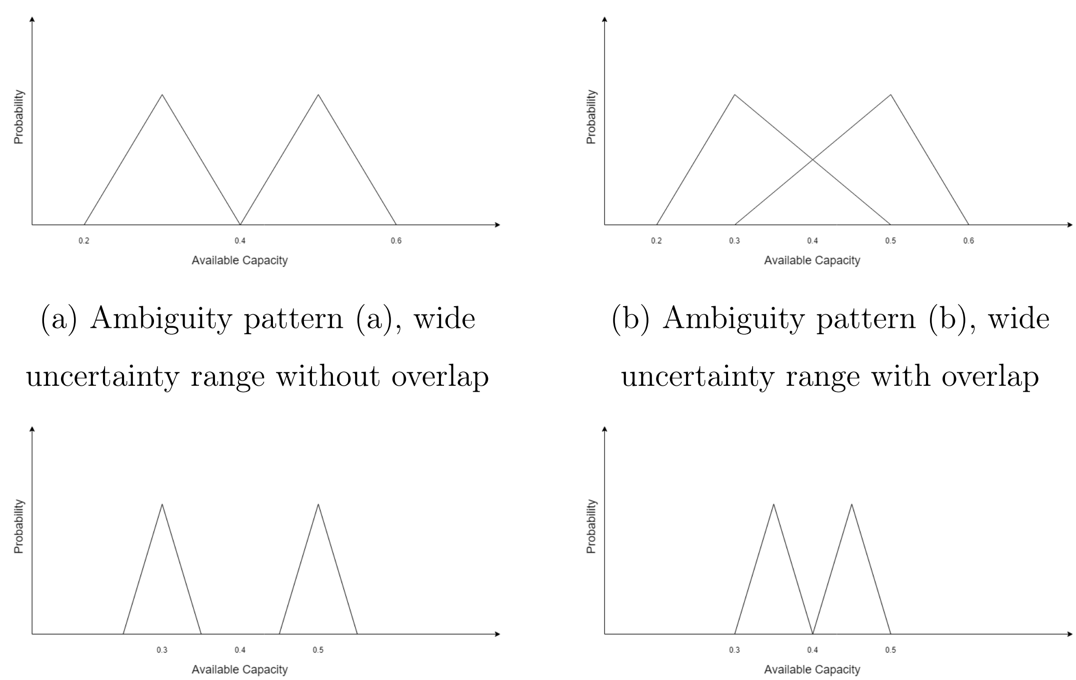
Since the locations of the DCs are not provided in the IFRC reports, we use the DBSCAN algorithm (Ester et al., 1996) to generate DCs using the beneficiary groups as the candidate locations. The DBSCAN algorithm uses two parameters: the epsilon parameter that denotes the neighborhood radius of the DCs in the same cluster, and the minimum number of neighbors to cluster the beneficiary groups based on distance and density. The value of these parameters is set by a domain expert, leading to the most appropriate cluster for the study problem (Mendes & Cardoso, 2006).

The transportation costs are calculated based on the driving distance between hubs. The walking distances between beneficiary groups for the DBSCAN algorithm are obtained from an online routing engine (Luxen & Vetter, 2011), which operates on the OpenStreetMap.

In addition to the data associated with the deterministic parameters, the demand and damage assessments provide the necessary information to estimate the uncertain parameters, including demand, transportation, and inventory capacities. Since the assessments are time-consuming processes, the affected region is divided into smaller sub-regions (e.g., 81 sub-regions in this case study) to speed up the process, and the damage and demand assessments are performed on a set of locations sampled from each sub-region (Balcik & Yanıkoğlu, 2020; Balcik, 2017). In the following experiments, we assume two data sources are available, providing estimations on the value of uncertain parameters. The estimations derived from these two data sources are inconsistent, with the first data source always yielding more pessimistic estimates than the second data source.

3.5.1.1 Ambiguity Patterns

We here focus on four different ambiguity patterns, illustrated in Figure 3.2, which characterize the different relationships that two different distributions can have to each other. Ambiguity pattern (a) represents the estimations provided by two data sources, each with a high level of uncertainty and no overlap, causing a high level of ambiguity. Ambiguity pattern (b) contains the same level of uncertainty as ambiguity pattern (a), as they both have the same range of estimation for uncertain parameters. However, as the estimations provided by the two data sources overlap, the level of ambiguity in (b) is lower than (a). The mode of the distributions in the ambiguity pattern (c) is the same as in the ambiguity pattern (a). However, the range of the distributions in (c) is less than (a), reducing both uncertainty and ambiguity levels. Finally, the probability distributions presented in ambiguity pattern (d) have the same range as ambiguity pattern (c), but there is no gap between the two distributions, reducing the ambiguity in (d) compared to (c). We can consider each of these four distinct ambiguity patterns for each problem instance.



(a) Ambiguity pattern (a), wide uncertainty range without overlap

(b) Ambiguity pattern (b), wide uncertainty range with overlap

(c) Ambiguity pattern (c), tight uncertainty range with gap

(d) Ambiguity pattern (d), tight uncertainty range without gap

Figure 3.2: The four considered ambiguity patterns for two data sources.

3.5.1.2 Scenario Sampling

As we do not have access to the raw assessment data of the earthquake on Lombok Island, we simulated triangular distributions (Hakimifar et al., 2021; Benini et al., 2017). The minimum and maximum values of the triangular distributions are set within the range of the data gathered from humanitarian organizations' websites IFRC (2021a). To approximate the proposed models, as well as to evaluate the performance of the obtained solutions, a set of scenarios is required that effectively captures the different variations of the uncertain parameters. Assuming the same confidence level for all data sources used to obtain the probability distributions, an equal number of scenarios are generated from each probability distribution. Furthermore, we consider equal probability for all scenarios generated from each triangular distribution. A total of 3000 scenarios are generated from each data source (6000 per problem instance), which we here assume to represent the ground truth (i.e., an accurate estimation of the possible realization of the uncertain parameters). However, since solving such a problem would be computationally intractable, using the Sample Average Approximation method (Kleywegt et al., 2002), we generate smaller scenario sets (i.e., sample scenario sets) with 300 scenarios per data source and solve the models for such smaller scenario sets. Each instance is then composed of two ground truths (one per data source) and two sample scenario sets.

3.5.1.3 Instance Generation

We generate multiple problem instances, each including one ground truth and one sample scenario set. Each instance is generated using the data from the 2018 earthquake in Indonesia. First, a subset of the beneficiary groups containing at least 80 percent of the 349 beneficiary groups is randomly selected for each instance to enhance the variability among instances. The DBSCAN algorithm then generates the candidate DCs. Two or three candidate warehouses and points of entry are selected at random, and a set of candidate services is added between hubs in different layers. Finally, the available budget depends on a budget ratio parameter relative to the *population* size. Equation (3.37) defines how the budget ratio is formulated.

$$budget\ \ ratio = \frac{z^0 + \sum_{t \in T} z^t}{population}. \tag{3.37}$$

The first ten instances are generated with a budget ratio of 640, as used in (Daneshvar et al., 2023). Ten additional instances are generated with a budget ratio of 512, computed by considering only 80 percent of the former budget ratio. This amounts to a total number of 20 instances.

3.5.2 Computational Results

This section presents the experimental results to determine the most suitable model for decision-makers to adopt under each ambiguity pattern, and based on their preference for either optimism or conservatism. To this end, we first analyze the Pareto frontier to evaluate the dominance of the obtained solutions in Section 3.5.2.1. Then, a ranking analysis is carried out in Section 3.5.2.2 to identify the best performing models under different ambiguity patterns. Finally, a comparative performance analysis complements the previous studies in Section 3.5.2.3, identifying average performance of the models and their relative performance to the competing models. Managerial insights are then summarized in Section 3.5.2.4.

The data for the above-mentioned analyses is prepared as follows. For each instance-ambiguity pattern, the sample scenario sets are used to obtain two solutions, each using one of the data sources. The solutions are then evaluated using the corresponding instance's ground-truth scenario set. In some instances, resources and budgets are sufficiently high, causing all models' solutions to have negligible differences in performance and to satisfy almost all the demand. In the following experiments, we exclude instances with a percentage difference of 2% (i.e., the best and worst solution evaluation gap is less than two percent of the best solution). The reason is that such a small percentage gap provides limited insights into the relative efficacy of the alternative models. With equal confidence levels attributed to both data sources in each instance, the following analysis presents findings outlined according to the evaluation results of the studied instances. The implementation employs the Pyomo software package (Hart et al., 2011, 2017), executed on the Calcul Québec servers with a computational infrastructure featuring 6 CPU cores and 256 GB of memory.

3.5.2.1 Pareto Frontier Analysis

The Pareto frontier represents the set of optimal solutions where enhancing one criterion comes at the expense of another, highlighting the inherent trade-offs in multi-objective decision-making problems. In the here-studied problem, we have two ground-truth scenario sets, with the expected penalty of each solution for each ground-truth serving as one criterion. To better understand the models' relative performance in different ambiguity patterns, we calculated the number of instances each model locates on the Pareto frontier. The Pareto frontier consists of all feasible solutions that are not dominated by any other feasible solution. A solution is dominated if another solution is better for at least one objective and no worse for the others. Figure 3.3 outlines the proportion of instances within each model wherein a solution is attained on the Pareto frontier.

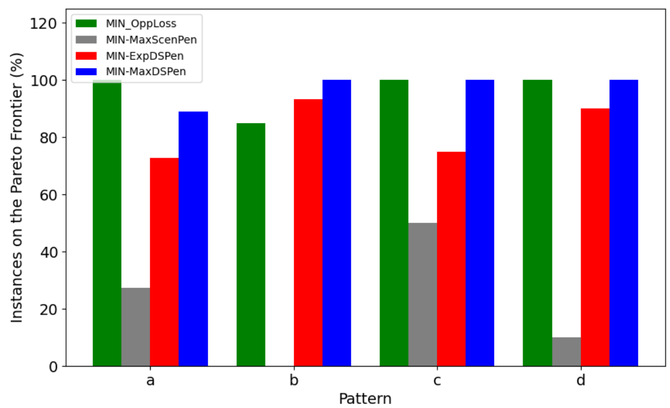


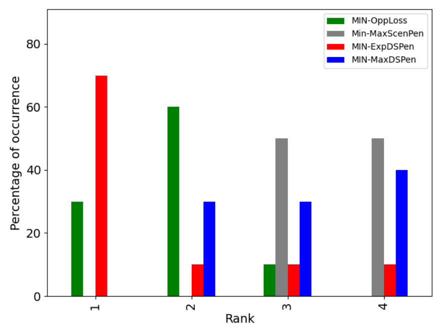
Figure 3.3: The percentage of instances each model's solution was on the Pareto frontier.

None of the models consistently attains Pareto optimality. Considering the ambiguity patterns (c) and (d), it is noteworthy that the MIN-OppLoss and MIN-MaxDSPen models consistently reside on the Pareto frontier (i.e., the solution is not dominated by any other solution for any criteria). However, for ambiguity pattern (a), only the MIN-OppLoss model consistently lies on the Pareto frontier, while MIN-MaxDSPen lies on the frontier most of the time. Meanwhile, for ambiguity pattern (b), the MIN-MaxDSPen model consistently lies on the Pareto frontier.

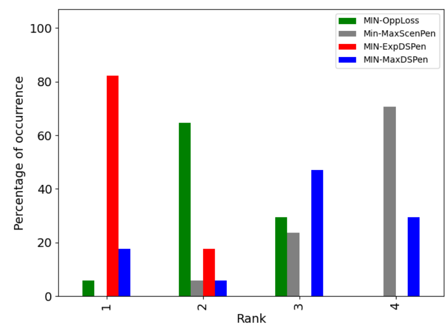
While no model obtains nondominated solutions for all ambiguity patterns, MIN-OppLoss and MIN-MaxDSPen solutions are always nondominated when only considering ambiguity patterns (c) and (d). While such an attribute indicates the value of MIN-OppLoss and MIN-MaxDSPen models, in many real-world HSCN problems, indicating the ambiguity pattern is a complex task. We hence perform additional experiments to gain more insights into the proposed models that are valid for all ambiguity patterns.

3.5.2.2 Ranking Analysis

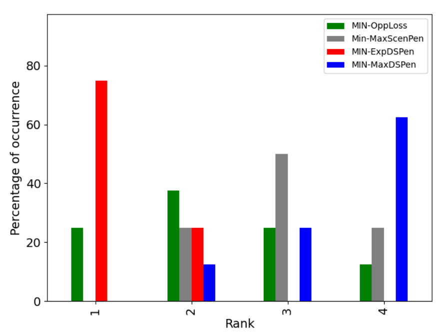
Our interest lies in tracing the individual performance of models concerning each data source. To this end, we now analyze the ranking of solutions obtained by the models across various instances. This approach affords an understanding of how effectively the models address each element of the multi-objective optimization problem.



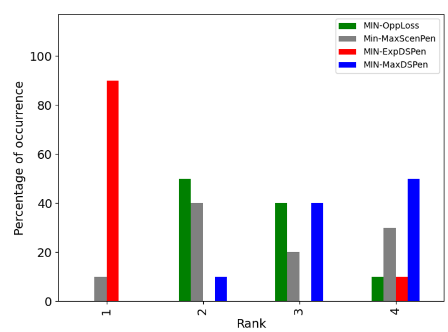
(a) ambiguity pattern (a)



(b) ambiguity pattern (b)

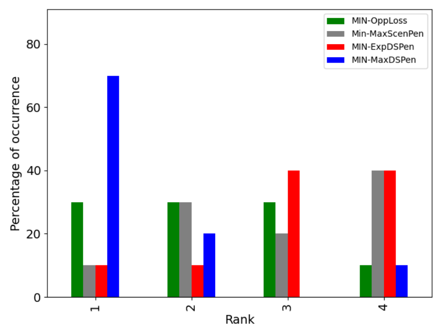


(c) ambiguity pattern (c)

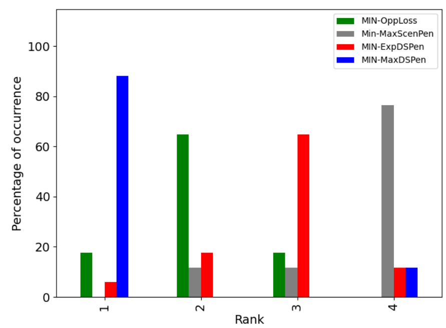


(d) ambiguity pattern (d)

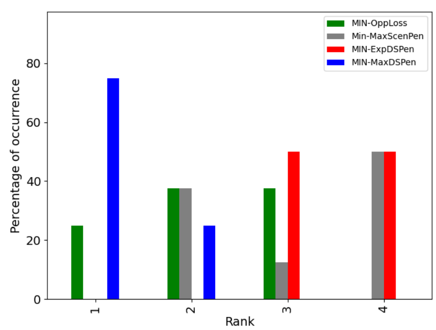
Figure 3.4: The ranking distribution of modes over the 20 instances on the first data source.



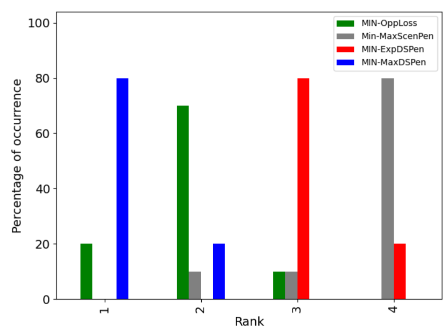
(a) ambiguity pattern (a)



(b) ambiguity pattern (b)



(c) ambiguity pattern (c)



(d) ambiguity pattern (d)

Figure 3.5: The ranking distribution of modes over the 20 instances on the second data source.

We evaluate the proposed models' solutions by ranking them according to their performance on the GTs, and then computing the frequency with which each model's solution obtains each rank. This procedure is carried out independently for each data source. Figure 3.4 and Figure 3.5 represent the ranking distributions of models for the first and second data sources, respectively. According to Figure 3.4, considering the first data source, MIN-ExpDSPen has the highest probability of providing the best-performing solution. Furthermore, Figure 3.5 indicates that MIN-MaxDSPen has the highest probability of providing the best solution when considering the second data source. Therefore, in a problem setting where the decision-makers are biased toward one of the data sources, regardless of the ambiguity pattern, the best choise is MIN-ExpDSPen when biased towards the first data source, and MIN-MaxDSPen when biased toward the second data source.

3.5.2.3 Comparative Performance Analysis

Within the context of the ranked-based analysis, it is noteworthy that none of the models consistently attain the highest ranking. For instance, when considering the first data source in the ranked-based analysis of ambiguity pattern (a), for 30% of instances, the MIN-ExpDSPen model fails to secure the first rank. To provide a clearer picture of which optimization models yield the most efficient results overall, we conduct a series of comparative analyses that directly assess the results obtained using each proposed model relative to the top-ranked model in each case. The motivation for these analyses is to offer decision-makers insights into the potential risks associated with selecting a particular optimization approach based on the observed trends of the ranking results. Moreover, in instances with equal confidence levels associated with the available data sources, the utility of the ranking analysis diminishes. We, therefore, use the performance gap (p-gap) and absolute performance gap (abs-p-gap) to evaluate the performance of the introduced models in all instances and across the considered ambiguity patterns. The evaluation of each solution represents the expected penalty of the solution over the ground truth. Therefore, the evaluations are converted to the p-gap, enabling comparisons to be conducted across the instances. For each instance, we identify the Best Evaluation Value (BEV) as the lowest penalty evaluated on the ground-truth among all four models. Then, equation (3.38) calculates the p-gap of each model.

$$\text{p-gap} = [(\text{model's evaluation} - \text{BEV})/\text{BEV}] * 100 \tag{3.38}$$

Furthermore, the absolute gap between solutions obtained from different models, abs-p-gap is calculated as the gap between the model's evaluation and BEV, see equation (3.39).

$$\text{abs-p-gap} = [(\text{model's evaluation} - \text{BEV})] \tag{3.39}$$

Table 3.3 presents the results of this experiment, including the average abs-p-gap and penalty over considered instances. The table is structured to show results for each data source separately, followed by the total mean across both data sources.

For each model and metric, results are presented separately for the first and second data sources. Each row represents the average absolute performance gap (abs-p-gap) and expected penalty for the specified model and ambiguity pattern. The "mean" columns provide the average values obtained for all ambiguity patterns for each data source.

The "Total mean" section shows the overall average values for both data sources combined, providing a comprehensive view of the models' performance across all data sources.

To increase the readability of the table, the total *penalty* values in Table 3.3 have been scaled down by a factor of one million.

When considering the first data source, the MIN-ExpDSPen model has the lowest *abs-p-gap* mean values, outperforming other models when using the uncertainty estimations provided by the first data source in the evaluation. MIN-ExpDSPen

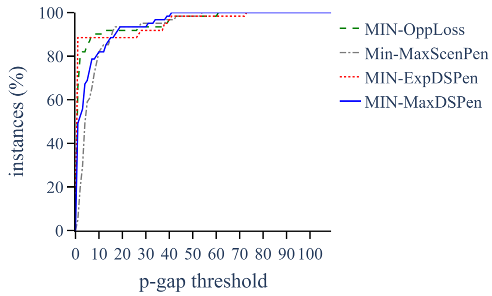
Table 3.3: The average abs-p-gap and expected penalty values (in millions) over the studied problem instances

Model	Metric	pattern (a)	pattern (b)	pattern (c)	pattern (d)	mean
FIRST DATA SOURCE						
MIN-OppLoss	abs-p-gap	5.38	44.4	0.01	47.9	**24.42**
	penalty	248.38	158.40	301.47	136.80	**211.26**
MIN-MaxScenPen	abs-p-gap	9.29	52.6	0.00	29.1	**22.74**
	penalty	257.84	174.22	306.48	141.22	**219.94**
MIN-ExpDSPen	abs-p-gap	8.54	10.20	1.50	36.7	**14.23**
	penalty	247.18	156.64	300.22	134.74	**209.69**
MIN-MaxDSPen	abs-p-gap	4.67	26.7	0.00	46.5	**19.46**
	penalty	257.06	166.76	318.20	146.44	**222.11**
SECOND DATA SOURCE						
MIN-OppLoss	abs-p-gap	75.9	59.9	87.4	42.5	**66.42**
	penalty	174.84	31.17	34.15	45.44	**71.4**
MIN-MaxScenPen	abs-p-gap	14.7	1.80	37.4	49.5	**25.85**
	penalty	167.41	42.11	39.93	53.17	**75.65**
MIN-ExpDSPen	abs-p-gap	26.3	1.55	57.9	58.8	**36.13**
	penalty	177.40	36.96	39.77	50.48	**76.15**
MIN-MaxDSPen	abs-p-gap	8.51	0.0	23.8	37.4	**17.42**
	penalty	171.28	27.96	29.73	42.56	**67.88**
BOTH DATA SOURCES						
MIN-OppLoss	abs-p-gap	40.64	52.15	43.71	45.2	**45.42**
	penalty	211.61	94.78	167.81	91.12	**141.33**
MIN-MaxScenPen	abs-p-gap	11.99	27.2	18.70	39.3	**24.29**
	penalty	212.63	108.17	173.21	97.20	**147.79**
MIN-ExpDSPen	abs-p-gap	17.42	5.88	29.7	47.75	**25.18**
	penalty	212.29	96.8	170.00	92.61	**142.92**
MIN-MaxDSPen	abs-p-gap	6.59	13.35	11.90	41.95	**18.44**
	penalty	214.17	97.36	173.97	94.5	**144.99**

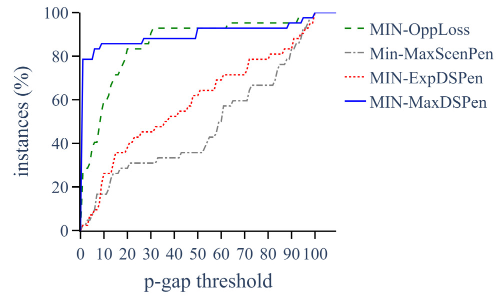
seeks to find a solution that minimizes the expected penalty of the data source with the highest expected penalty, hence outperforming other models when evaluated on the first (pessimistic) data source. Similarly, considering the second data source, the MIN-MaxDSPen outperforms other models. In particular, for the second data source, the conservative models, including MIN-ExpDSPen and MIN-MaxScenPen, have relatively high mean values. Furthermore, the MIN-OppLoss model does not explicitly consider data-source ambiguity. Therefore, MIN-MaxDSPen outperforms other models when the evaluation is performed on the optimistic data source.

Finally, the “Total mean" section presents the overall mean across both data sources. In other words, the values in the "Total mean" section indicate the opportunity loss over the instances considered. MIN-MaxDSPen has the least *abs-p-gap* value, making it an attractive option under data-source ambiguity.

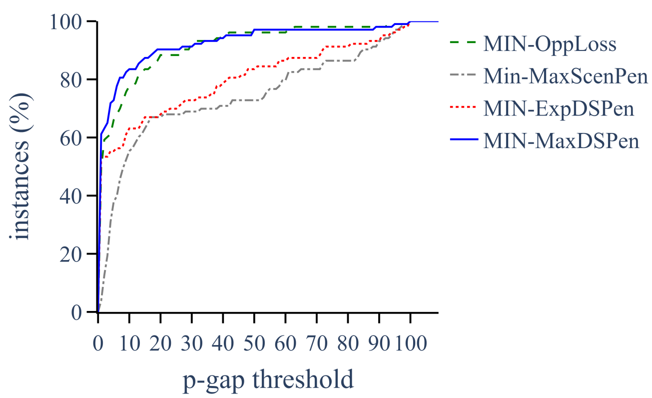
Figure 3.6 presents the performance profile of the here studied models. The top figures represent the performance profile over one data source, and the figure at the bottom shows the performance profile when considering both data sources. In these figures, the x-axis represents the threshold of the *p-gap*, and the y-axis indicates the percentage of instances with a lower *p-gap* than the value indicated on the x-axis. The performance profile of the first data source indicates that the MIN-ExpDSPen model has the best *p-gap* for about 90 percent of the instances. For the remaining instances, its *p-gap* becomes rather high when compared to the other models. The second data source performance profile indicates that the MIN-MaxDSPen model outperforms other models by a considerable margin for almost 90% of the instances. Finally, the performance profile over both data sources suggests that MIN-MaxDSPen is superior to all other models, followed by MIN-OppLoss. Both the MIN-ExpDSPen and the MIN-MaxScenPen models underperform the other models. Overall, MIN-MaxDSPen shows clear benefits under data source ambiguity, being the best performing model for most instances. For problem instances where it is not the best-performing model, it underperforms other models less than its competitors do.



(a) first data source



(b) second data source



(c) both data sources

Figure 3.6: Performance profile of the studied models considering either one or both data sources.

3.5.2.4 Managerial Insights

The following managerial insights can be summarized from the conducted experiments, providing a valuable understanding of the presented models accounting for the here-studied ambiguity in the HSCN design problem.

1. Regardless of the level of risk aversion, under data source ambiguity, explicitly accounting for such ambiguity in the HSCN design problem has economic advantages on average and mitigates risk, alleviating the worst-case outcome (see, e.g., Table 3.3 and Figure 3.6).

2. In problem settings with a low level of uncertainty and ambiguity (i.e., ambiguity patterns (c) and (d)), which translate into a planning context where there is a higher level of confidence regarding the estimations obtained, MIN-OppLoss (the most popular approach in the literature) and MIN-MaxDSPen solutions are always on the Pareto frontier, representing the best trade-offs between the estimations obtained from the data sources (see Figure 3.3).

3. The MIN-ExpDSPen model, regardless of the ambiguity pattern, has the highest probability of obtaining the best solution when assessed based on the information obtained from the pessimistic (first) data source (see Figure 3.4, Table 3.3 and Figure 3.6). As such, if a decision-maker is interested in hedging the risk based on the most pessimistic assessments, this is the approach of choice.

4. The MIN-MaxDSPen, regardless of the ambiguity pattern, has the highest probability of obtaining the best solution when assessed based on the information obtained from the optimistic (second) data source (see Figure 3.5, Table 3.3 and Figure 3.6). This conclusion aligns with the fact that MIN-OppLoss does not explicitly consider ambiguity, whereas MIN-ExpDSPen and MIN-MaxScenPen are conservative models prioritizing the pessimistic data source.

5. According to the data presented in Table 3.3 and Figure 3.6, in situations where no bias towards a specific data source is evident and the ambiguity

pattern remains indistinct, the MIN-MaxDSPen model emerges as the most favourable choice.

3.6 Conclusion

In this paper, we have proposed four optimization methods, including Minimization of expected opportunity loss (MIN-OppLoss), Minimization of Maximum Data-Source Penalty (MIN-MaxDSPen), Minimization of Expected Data-Source Penalty (MIN-ExpDSPen), and Minimization of Maximum Scenario Penalty, that explicitly account for ambiguity caused by inconsistent estimates of uncertain parameters obtained from multiple data sources involved in the demand and damage assessments in the context of solving the HSCN design problem. We then compare the performance of the proposed models over four different ambiguity patterns with two data sources on 20 instances extracted from a real-world data set on the 2018 Indonesia earthquake.

The results obtained and analysis performed led us to the following conclusion. In an HSCN design problem with narrow uncertainty and ambiguity (e.g. ambiguity patterns (c) and (d)), then MIN-MaxDSPen and MIN-OppLoss models could be used as their solutions always fit on the Pareto frontier, indicating a solution that is not dominated by solutions obtained from other models. Furthermore, if the ambiguity pattern is unknown and the decision-makers are slightly biased toward one of the two data sources, then the following applies: if they are biased toward the pessimistic data source, they should use MIN-ExpDSPen, and if biased toward the optimistic data source, they should use MIN-MaxDSPen. Finally, if no information is available regarding the ambiguity pattern with the same confidence level toward the data sources, then the decision-makers should use the MIN-MaxDSPen model.

This paper opens several research directions on the impact of ambiguity in HSCN design problems. Of particular interest is the question of how to design and adjust the HSCN in response to evolving patterns of ambiguity as new information becomes available throughout the planning horizon. Another research line would involve considering a varying level of confidence in the data sources while also considering a higher number of data sources directly leading to higher levels of complexity in the ambiguity patterns.

CHAPTER IV

THE BENEFITS OF CONSIDERING INFORMATION DYNAMIC AND DEMAND SPREAD IN HUMANITARIAN SUPPLY CHAIN NETWORKS

Abstract

This study considers the Humanitarian Supply Chain Network (HSCN) planning problem following natural disasters, focusing on the uncertainties in demand and capacity. The goal is to study the value of increasing stages (i.e., decision-making points over the time horizon) when modeling the post-disaster HSCN design problem. This study proposes a three-stage stochastic model that allows for dynamic adjustments to transportation resources based on evolving information obtained over time. The primary objective is to assess the value gain using a three-stage model incorporating flexibility to adjust the designed HSCN during the relief operation compared to its two-stage counterpart commonly applied in the literature. Experiments conducted using real-world data from the 2018 Indonesia earthquake demonstrate the advantages of our model over its two-stage counterpart. Specifically, the evaluation results indicate the solution obtained from the proposed three-stage model transfers resources only in 33% of the scenarios. In comparison, the two-stage counterpart transfers resources in 79% of scenarios, a time-intensive process requiring complicated management operations. The findings highlight that incorporating an additional stage enables better resource utilization, reduces unmet demand, and enhances adaptability to uncertainty. Our model also considers the cumulative and spreading effects of unmet demand across time and critical supplies, providing a more realistic representation of real-world settings. While the three-stage model incurs higher computational costs, the resulting decision quality and operational efficiency improvements justify its application in practice.

Keywords: Humanitarian Supply Chain, Stochastic Programming, Humanitarian Relief Distribution, Post-disaster

4.1 Introduction

Relief distribution for vulnerable people after the onset of a natural disaster is a pivotal operation conducted by humanitarian organizations. Its importance increases with the frequency of natural disasters over the years, impacting more people worldwide (Mani et al., 2003). Meanwhile, humanitarian organizations encounter intensified budgetary restrictions due to a lack of proportional donation growth relative to their escalating financial needs (UNOCHA, 2021b). For instance, the global appeals (i.e., the amount of budget humanitarian organizations require for one year) amounted to 37.6 billion US$ in 2021, whereas only 20.1 US$ was provided to humanitarian organizations, covering only 54% of the annual appeal (UNOCHA, 2021b). More than 75 percent of humanitarian organizations' budget is used to design and operate relief supply chains (Besiou & Van Wassenhove, 2020; Van Wassenhove, 2006; Stegemann & Stumpf, 2018); hence, a shortage of budget results in a lack of access to critical supplies by people affected by natural disasters, negatively impacting their health. The insufficiency of financial resources reduces humanitarian organizations' ability to deliver critical supplies (e.g. shelter, food, and hygiene), deepening the harm to people. Therefore, optimizing the distribution of critical supplies using the available budget and resources is crucial to limit such harm.

Humanitarian organizations design and operate Humanitarian Supply Chain Networks (HSCN) (Tavana et al., 2018; Hong & Jeong, 2019) to distribute critical supplies among vulnerable populations affected by natural disasters. The design and operation of an HSCN are particularly challenging and complex because of the limited available resources and budget in the affected region, and the demand being at its peak (i.e., many people need access to survival essentials) (Holguín-Veras et al., 2013) and coordination with other humanitarian operations is required to minimize the harm. In addition, the decision-making process is conducted in a setting with a high level of uncertainty regarding the situation in the region. Damage and demand assessments are therefore conducted in the affected region to obtain information on the level of damage, available resources and the level of demand (Balcik, 2017; Balcik & Yanıkoğlu, 2020). Various data sources (e.g., media, governmental documents, satellite imagery) are used in the assessments to estimate the probability distribution of the problem's uncertain components, which decision-makers then use to design and operate the HSCN.

The complexity of coordinating humanitarian operations necessitates the immediate establishment of the HSCN following a natural disaster. However, more information about the region's state becomes available later in time, and some HSCN design characteristics (e.g., transportation resources) could be adjusted over the planning horizon accordingly. On the other hand, the cost of purchasing resources for the HSCN increases over time due to a significant demand for such resources. This results in a trade-off between purchasing lower-priced transportation resources and delaying decision-making for information with lower uncertainty.

In the literature, stochastic programming is the predominant approach for modeling and solving the HSCN design problem (Anaya-Arenas et al., 2014). Existing literature has modeled HSCN problems as two-stage stochastic planning frameworks, which involve making facility location and capacity allocation decisions in the first stage and operational decisions, such as transportation and distribution, in the second stage. A stage denotes a distinct point within the time horizon at which decisions are made, considering the informational context at that moment. This includes both the known parameters and those that remain uncertain, representing the stochastic elements of the decision-making process. However, in real-world settings, uncertainty is often revealed incrementally over time, making three-stage models or even more detailed multi-stage frameworks more accurate in capturing the problem's dynamics. Stochastic programming in its two-stage form provides an approximation by using the second stage to adapt decisions based on realized uncertainties, but it may fall short of fully addressing the progressive nature of uncertainty revelation and decision-making in practice. The proposed models typically involve making design decisions in the first stage, followed by a set of scenarios in the second stage, representing possible realizations of uncertain parameters. These scenarios enable the model to account for fluctuations in uncertain parameters when providing a solution. In this paper, we propose a three-stage stochastic model to solve the HSCN design problem, which incorporates an additional decision-making stage, allowing for updates to the transportation resources as more information becomes available. This additional stage ensures that decisions evolve with the progression of the disaster, thereby enhancing the operational efficiency of the HSCN. Moreover, our model incorporates the spread factor, which accounts for how unmet demands for critical supplies at one stage affect future demand at subsequent stages, providing a more dynamic and flexible approach. While increasing the number of stages brings the model closer to real-world decision-making processes, it also introduces greater complexity, demanding more computational resources and time to solve. This paper investigates the benefits of increasing the number of stages when modeling the HSCN design problems by proposing a three-stage model and comparing its performance to its two-stage counterpart.

The rest of this paper is organized as follows. We present a survey of the related literature in Section 4.2. We describe the problem setting in Section 4.3. The three-stage post-disaster HSCN design model is introduced in Section 4.4. Section 4.5 presents the numerical experiments and analyses. Finally, the conclusion in Section 4.6 completes the paper.

4.2 Literature Review

In this section, we review the literature on the HSCN design problem. Within the broader domain of humanitarian logistics, the study of relief network design is divided into pre-disaster and post-disaster phases, representing two critical phases in humanitarian operations, each posing distinct challenges and requiring tailored solutions. In the pre-disaster phase, emphasis is placed on preparedness and proactive measures to enhance the efficiency of response efforts in the event of a catastrophic event. Studies in this phase often focus on strategic decisions such as warehouse location selection, stockpiling strategies, and resource allocation to optimize readiness and response capabilities. Conversely, the post-disaster phase is characterized by urgency, uncertainty, and resource constraints. Relief networks must rapidly deploy aid to affected areas while navigating disrupted infrastructure and elevated demand. Research in this phase typically addresses decisions such as temporary facility location, transportation resources allocation, beneficiary groups assignment, and supply chain management under uncertainty to expedite relief distribution and alleviate human suffering effectively.

The design of humanitarian relief networks post-disaster poses significant challenges due to the urgent need to distribute aid efficiently amidst uncertainty and limited resources. The rest of this section explores the uncertain parameters, objective functions, and solutions considered in addressing the post-disaster humanitarian relief network design problem.

Designing an HSCN involves uncertain parameters estimated post-disaster through assessments (Balcik, 2017; Balcik & Yanıkoğlu, 2020). Multiple data sources (e.g., surveys and satellite imagery) are used to obtain probabilistic models for the uncertain parameters. However, discrepancies in estimations obtained from various data sources can cause ambiguity (Langewisch & Choobineh, 1996). For instance, Grass et al. (2023) noted demand estimates in Syria from different data sources that barely overlap. Daneshvar et al. (2024) proposed four optimization models to consider such ambiguity in the HSCN design problem. In this paper, the authors consider the possibility of adapting the HSCN design to the evolving information received over the planning horizon.

Various uncertain parameters impact the design of post-disaster humanitarian relief networks, including the lack of information on affected populations, the urban or rural structure of affected regions, and the intensity of the natural disaster and its secondary impacts (Anaya-Arenas et al., 2014; Tofighi et al., 2016). Travel time, supply availability, network reliability, shipping cost, and shipping capacity also contribute to uncertainty in relief operations (Anaya-Arenas et al., 2014; Tofighi et al., 2016; Daneshvar et al., 2023). However, the most common and impactful uncertainty lies in demand estimation, where accurate predictions are crucial for effective resource allocation (Balcik & Beamon, 2008; Dönmez et al., 2021; Anaya-Arenas et al., 2014).

The effects of unmet demand for critical supplies on the demands in subsequent periods have been modeled in various ways in the literature. Shokr et al. (2022) modeled the unmet demand as a penalty in the objective function but did not transferred the unmet demand to the next period. However, (Silva et al., 2024) considered both a penalty for unmet demand and the cumulative nature of unmet demand by adding the unmet demand to the demand of the next period. Daneshvar et al. (2023) not only considered the penalty of unmet demand but also modeled the effect unmet demand for one critical supply has on the level of demand for other critical supplies.

The literature reveals a diversity of objective functions aimed at improving the performance of humanitarian relief networks. These objectives often differ from those in commercial supply chains, emphasizing outcomes such as minimizing unmet demand, optimizing distribution coverage, and enhancing budget utilization (Diabat et al., 2019; Hasani & Mokhtari, 2019, 2018). Some studies integrate multiple objectives, including cost minimization, travel time reduction, and satisfaction maximization (Tzeng et al., 2007). Additionally, fairness and equity considerations have gained attention, aiming to distribute critical supplies equitably among vulnerable populations (Anaya-Arenas et al., 2018; Ismail, 2021).

Various optimization methods have been employed to address the complexities of post-disaster humanitarian relief network design. These methods encompass stochastic programming and robust optimization to account for uncertainty (Grass et al., 2023; Benini et al., 2017). Studies have proposed multi-layer network structures, dynamic supply chain designs, and collaborative relief chain models to optimize resource allocation and distribution efficiency (Afshar & Haghani, 2012; Dufour et al., 2018; Shokr et al., 2022).

The literature on post-disaster humanitarian relief network design reflects a concerted effort to address the unique challenges posed by uncertainty, limited resources, and urgent time constraints. By considering uncertain parameters, diverse objective functions, and innovative solutions, researchers aim to enhance the effectiveness and efficiency of relief operations, ultimately mitigating the impact of disasters on affected populations.

4.3 Problem Definition

We now formally define the here considered HSCN design problem. The key aspects of the problem, including the structure of the network, uncertain parameters and decision variables, are introduced in Subsection 4.3.1. Then, Subsection 4.3.2 outlines the budgetary settings and the subsequent limitations on the HSCN design problem. Finally, the notion of demand and the correlated effect of unmet demand on critical supplies are presented in Subsection 4.3.3.

4.3.1 HSCN Structure

We study a tactical multi-period HSCN design problem faced by humanitarian organizations after a natural disaster. An HSCN is a physical network of hubs that receive, store, and distribute critical supplies to beneficiary groups over a defined planning horizon. The critical supplies required for the beneficiary groups vary based on the type of natural disaster, the geographical characteristics of the affected region, and the season. The International Federation of Red Cross and Red Crescent Societies (IFRC) has published a catalog indicating the demand of vulnerable people for each critical supply.

We adopt a three-layer structure for HSCN, representing a common configuration in practice (Séguin, 2019). Figure 4.1 illustrates an example HSCN structure, with the top diagram presenting all available hubs, services, and assignments, while the bottom diagram shows the HSCN with the selected hubs, services, and assignments. A layer is a set of hubs with specific characteristics designed to carry out part of the relief distribution operation. The hubs in the first layer are ports of entry (e.g. airport, seaport, train station), where the critical supplies are received and sent to the second layer of the HSCN. Each port of entry has a capacity for receiving the critical supplies determined based on its infrastructure. For instance, a small port has a lower capacity to receive critical supplies than an international airport. The second layer of the HSCN consists of warehouses. A warehouse receives the critical supplies from the ports of entry, stores them, and sends them to the third layer. Each warehouse has inventory resources (e.g., classrooms, containers), and the quantity of these resources is decided upon at the design time. Finally, Distribution Centers (DC) belong to the third layer of the HSCN structure. Each DC can provide critical supplies for multiple beneficiary groups, but each beneficiary group is assigned to one DC. The reason being the complexity of the coordination required with other humanitarian operations (e.g., debris removal) and the lack of access to the beneficiary groups for communication because of the infrastructural damages.

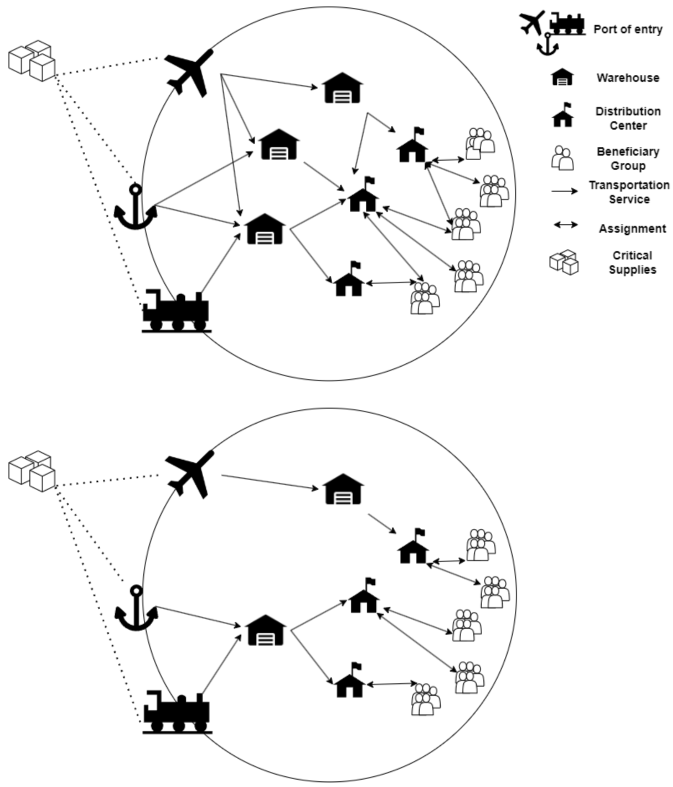


Figure 4.1: Top: all available hubs, services, and assignments. bottom: selected hubs, services, and assignments in an example HSCN

The complexity of the coordination among the humanitarian operations (e.g., debris removal), the urgency of the relief distribution, and the competition among humanitarian organizations to acquire resources force some decisions to be made right after the natural disaster occured. These decisions include selecting the hubs, transportation services, number of transportation and inventory resources and assigning the beneficiary groups to the DCs. A transportation resource is a vehicle with a capacity used by a transportation service that moves critical supplies from an origin into a destination hub and then returns to the origin hub to repeat the process. The remaining decisions are primarily operational and made over the planning horizon. These decisions include the quantity of critical supplies received at ports of entry, stored at warehouses, assigned to beneficiary groups at DCs, and the quantity of critical supplies transferred by transportation resources.

In this study, we consider the possibility of relocating the transportation resources between services over periods in response to the new information available to improve the performance of the HSCN. We also consider the possibility of adding new transportation resources in response to the demand over the planning horizon. Regardless, the cost of adding new transportation resources after the design time will considerably increase. The reason being the lack of access to available resources, as there is a high demand for such resources in the aftermath of a natural disaster. The transportation resources update decisions are made over the first period, and the new structure will be in effect in the second period. The reason for considering only one update to the network structure is that the majority of the demand happens in the first few days after the natural disaster (e.g. shelter, blanket), and hence, updating the network in the first period would have the most effect on the performance of the HSCN designed. We also limit the updates to the selected transportation services at the design time (i.e., no new transportation service is added to the network).

The HSCN must be designed quickly after a natural disaster to start the relief distribution operation, reducing the damage and harm to people's health. However, multiple sources of uncertainty exist in the aftermath of a natural disaster, including a lack of access to accurate information necessary for relief operations (e.g., demographical distribution data), damaged infrastructure, and secondary impacts (e.g., aftershocks, landslides), which causes uncertainty regarding the value of some parameters involved in the HSCN design problem, including the demand and the capacity of both storage and transportation resources. Over time, more information is available regarding the region's state, and the estimation of the uncertain parameters improves.

4.3.2 Budget

The design and operation of the HSCN incur some costs associated with the decisions made, limited by the available financial resources referred to as budget. Humanitarian organizations have some financial resources available to respond to natural disasters, and they also receive financial aid, which will be available over time. We refer to the budget available at the design time as the initial budget and the financial resources that become available during the planning horizon as donations.

Since in the here studied HSCN design problem, the structure of the HSCN can be updated over time, the design expenses include the fixed cost of selecting hubs and services at the design time, as well as the fixed cost of relocating the transportation resources or adding extra transportation resources during the planning horizon. The initial budget limits the costs related to design decisions at the design time. The operating expenses are the flow cost and are proportional to each critical supply for each service, calculated per unit of distance (e.g. km). The expenses incurred by design decisions during the planning and the costs related to the operational decisions are limited by the available budget (i.e., donations received plus the remaining budget of previous periods) at each period.

4.3.3 Demand

In the HSCN design problem, demand is considered an uncertain parameter due to the variability in the population sizes of each beneficiary group. This uncertainty necessitates that demand be computed proportionately to the respective group populations. Moreover, the demand is characterized by its cumulative and spreading nature. Specifically, any unmet demand for a critical supply not only escalates the demand for the same supply in the subsequent time period but also heightens the demand for other critical supplies. The spread factor (Daneshvar et al., 2023), presented as $s^{k'k}$, quantifies the degree to which unmet demand for a specific critical supply k' influences the demand for another critical supply k. Using the spread factor provides the possibility to understand better how shortages in one period amplify challenges in the next. Equation (4.1) defines the total demand $\hat{d}^{kt}l$ of beneficiary group l for critical supply k in period t.

$$\hat{d}_l^{kt} = \tilde{d}_l^{kt} + \sum_{k' \in K} s^{k'k}(\hat{d}_l^{k't-1} - \sum_{i \in V_{DC}} \bar{a}_{il}^{k't-1}) \tag{4.1}$$

In this formulation, $\tilde{d}^{kt}l$ symbolizes the base demand of beneficiary group l for critical supply k at period t, $s^{k'k}$ captures the spread factor reflecting the influence of critical supply k' on supply k, and $\bar{a}_{il}^{k't-1}$ represents the allocation of critical supply k' from distribution center i to beneficiary group l during period $t-1$. In the next Section, we propose a mathematical model for the HSCN design problem.

4.4 Mathematical Model

In the HSCN design problem, the value of uncertain parameters is revealed over time by the availability of more information from the field. However, humanitarian organizations must make design decisions early after a natural disaster due to the competition to acquire limited available resources in the field by different organizations. Furthermore, the cost of booking resources increases as fewer resources will be available over time. However, postponing the operational decisions results in better decision-making as more information is available during the decision-making process. In the here-studied HSCN design problem, it is possible to adjust the design of the HSCN to leverage the information obtained over time.

All in all, we propose a three-stage model where, in the first stage, the design decisions are made. In the second stage, the decisions regarding updating the HSCN design, as well as the operational decisions of the first period, are made, and the third stage contains the operational decisions of the remaining periods. In the following, we introduce the sets, presented in Table 4.1, parameters, presented in Table 4.2, and decision variables, presented in Table 4.3, used in the proposed optimization models.

Table 4.1 presents the sets involved in the mathematical model. In this table, V presents the set of all candidate hubs, including the ports of entry,V_I, the warehouses, V_W, and the DCs, V_{DC}. Furthermore, A is the set of services, L is the set of beneficiary groups, K is the set of critical supplies, Ψ is the set of all scenarios, and T is the set of periods.

In this model, the decisions related to the structural design of the HSCN are made in the first stage right after the occurrence of the natural disaster. Furthermore, the second-stage decisions are made at the end of the first period, including the structure update decisions and the operational decisions of the first period. The reason for locating the second stage at the end of the first period is that the first two periods contain the highest level of demand, and the structure update could improve the efficiency of the relief operation of the remaining periods using the available information at the end of the first period. Finally, the third stage contains the operational decisions of the remaining periods which are made at the end of the last period. In the first stage of the model, there is a high level of uncertainty and only the value of deterministic parameters are available. However, in the second stage, the first period's uncertain parameters are also known, reducing the level of uncertainty. Finally, in the third stage, the values of all parameters are known. In the following, we introduce the sets, presented in Table 4.1, parameters, presented in Table 4.2, and decision variables, presented in Table

4.3, used in the proposed optimization 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 $\psi \in \Psi$.
Ψ_o	A subset of scenarios $\psi \in \Psi_o$ that cross node o on the second stage of scenario tree, where $\Psi = \bigcup_{o=1}^{e} \Psi_i$.
T_1	Set of periods in the first stage $\{0\} \in T_1$.
T_2	Set of periods in the second stage $t \in T_2$, where $T_2 \subseteq T$.
T_3	Set of periods in the third stage $t \in T_3$, where $T_3 \subseteq T$.
T	Set of periods $t \in T$, where $T = T_2 \bigcup T_3$.

Table 4.1: Sets used in the optimization models.

Table 4.1 presents the sets involved in the mathematical model. In this table, V presents the set of all candidate hubs, including the ports of entry,V_I, the warehouses, V_W, and the DCs, V_{DC}. Furthermore, A is the set of services, L is the set of beneficiary groups, and K is the set of critical supplies. The set of scenarios generated from the data sources is represented by Ψ. Furthermore, Ψ_o present the set of scenarios that pass through node $o \in \{1, 2, ..., e\}$ in the second stage of the scenario tree. Finally, T is the set of time periods, involved in the second stage, presented by T_2, and periods in the third stage, presented by T_3. T_1 is a set define to unify the formulation notaion and does not include any operational periods.

Deterministic Parameters	
Parameter	Definition
$\hat{f}_{ij}^t$	Cost of selecting one unit of transportation resource of service $(i,j) \in A$ at the design time, $t \in T_1$.
$\hat{f}_{ij}^t$	Cost of selecting one unit of transportation resource of service $(i,j) \in A$ at the first period, $t \in T_2$.
$\hat{f}_i$	Cost of selecting one unit of inventory resource for warehouse $i \in V_W$.
f_i	Cost of selecting a hub $i \in V$.
c_{ij}^k	Cost of transporting one unit of critical supply $k \in K$, 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}^t	Maximum number of transportation resources available at the design time for service $(i,j) \in A$, $t \in T_1$.
m_{ij}^t	Maximum number of transportation resources available at the first period for service $(i,j) \in A$, $t \in T_2$.
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 $k' \in K$.
e	number of nodes in the second stage of the scenario tree.
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 4.2: The parameters of the HSCN design problem.

The parameters of the models are introduced in Table 4.2. For each transportation resource $(i,j) \in A$, there are two selection costs, including the selection at the design time, represented by $\hat{f}_{ij}^0$, and at the first period, represented by $\hat{f}_{ij}^1$. The other fixed cost is associated with selecting one unit of inventory resource for warehouse $i \in V_W$, indicated by $\hat{f}_i$. The other fixed cost is the selection cost of the hub $i \in V$ indicated in the model by f_i. The flow cost of transporting one unit of critical supply $k \in K$, using the service $(i,j) \in A$ is represented by c_{ij}^k. The capacity of one unit of transportation resource of service $(i,j) \in A$ is indicated by u_{ij}, and u_i presents the capacity of one unit of inventory resource of warehouse $i \in V_W$. The maximum number of inventory resources of warehouse $i \in V_W$ are presented by m_i, and m_{ij}^0 and m_{ij}^1 show the maximum number of transportation resources available for service $(i,j) \in A$ at the design time and first period respectively. The maximum quantity of critical supplies $k \in K$ that can be delivered to the port of entry $i \in V_I$ at period $t \in T$ is indicated by n_i^{kt}. The penalty associated with one unit of critical supply $k \in K$ is presented by b^k. The initial budget and the received donations at each period are presented by z^0 and z^t, respectively, where $t \in T$. The last deterministic parameter is presented by $s^{kk'}$ indicating the spread factor of one unit of unmet demand of the critical supply $k \in K$ on the critical supply $k' \in K$.

In the following models, p_ψ indicates the probability of scenario $\psi \in \Psi$. The available inventory resources of hub $i \in V$, at period $t \in T$, in scenario $\psi \in \Psi$ is presented in percentage by $g_{i\psi}^t$. Furthermore, the percentage of available transport resources of service $(i,j) \in A$, at period $t \in T$, in scenario $\psi \in \Psi$ is shown by $g_{ij\psi}^t$. Finally, $d_{l\psi}^{kt}$ and $\hat{d}_{l\psi}^{kt}$ present the base demand and the total demand of beneficiary group $l \in L$, for critical supplies $k \in K$, at period $t \in T$, in scenario $\psi \in \Psi$ respectively.

In this study, a scenario tree is employed to represent the structure of the problem under consideration. Figure 4.2 illustrates the scenario tree of a three-stage model with four time periods and six scenarios. This model's first stage corresponds to the $t = 0$, indicating that, at this point, the operational periods have not started yet. The second stage encompasses the first time period, while the third stage spans the remaining time periods, namely t=2, 3, and 4. In the scenario tree, all scenarios converge at a single node in the first stage, indicating that decisions made at this stage are uniform across all scenarios. In the second stage, the tree branches such that scenarios 1, 2, and 3 share a common node, as do scenarios 4, 5, and 6, necessitating identical decision variables within each respective group of scenarios. By contrast, in the third stage, the scenario tree fully branches out, allowing each scenario to have independent decision variables.

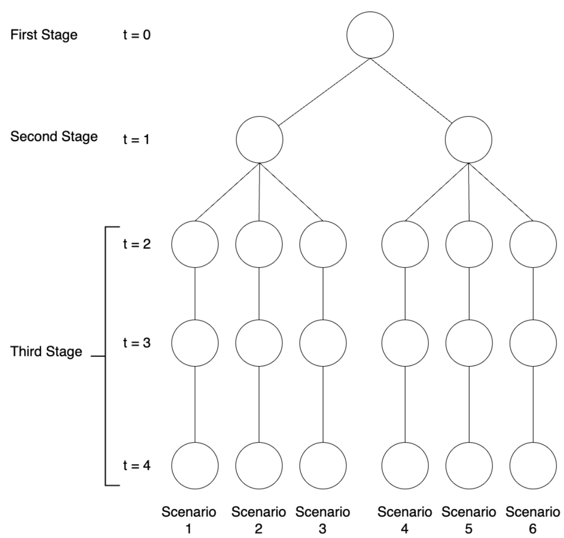


Figure 4.2: A sample scenario three with three stages and four time periods.

First Stage	
Variable	Definition
$x^t_{ij\psi} \in \{0,1\}$	1 if service $(i,j) \in A$ is selected to be part of the HSCN; 0 otherwise, where $t \in T_1$, in scenario $\psi \in \Psi$.
$y^t_{i\psi} \in \{0,1\}$	1 if hub $i \in V$ is selected to be part of the HSCN; 0 otherwise, where $t \in T_1$, in scenario $\psi \in \Psi$.
$\hat{x}^t_{ij\psi} \in \mathbb{N}^0$	Number of units of transport resources selected at the design time for service $(i,j) \in A$, where $t \in T_1$, in scenario $\psi \in \Psi$.
$\hat{y}^t_{i\psi} \in \mathbb{N}^0$	Number of units of inventory resources selected for hub $i \in V_W$, where $t \in T_1$, in scenario $\psi \in \Psi$.
$a^t_{il\psi} \in \{0,1\}$	1 if beneficiary group $l \in L$ is assigned to DC $i \in V_{DC}$; 0 otherwise, where $t \in T_1$, in scenario $\psi \in \Psi$.
Second Stage	
Variable	Definition
$\hat{x}^t_{ij\psi} \in \mathbb{N}^0$	Number of units of transport resources added for service $(i,j) \in A$, where $t \in T_2$, in scenario $\psi \in \Psi$.
$v^t_{i'j'ij\psi} \in \mathbb{N}^0$	Number of units of transport resources transferred from service $(i',j') \in A$ to service $(i,j) \in A$, where $t \in T_2$, in scenario $\psi \in \Psi$.
$\bar{x}^{kt}_{ij_\psi} \geq 0$	Quantity of critical supply $k \in K$ transferred through service $(i,j) \in A$ at period $t \in T_2$, in scenario $\psi \in \Psi$.
$\bar{a}^{kt}_{il_\psi} \geq 0$	Quantity of critical supply $k \in K$ at period $t \in T_2$ 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 $t \in T_2$, 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 $t \in T_2$, in scenario $\psi \in \Psi$.
Third 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 $t \in T_3$, in scenario $\psi \in \Psi$.
$\bar{a}^{kt}_{il_\psi} \geq 0$	Quantity of critical supply $k \in K$ at period $t \in T_3$ 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 $t \in T_3$, 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 $t \in T_3$, in scenario $\psi \in \Psi$.

Table 4.3: Decision variables of the proposed three-stage stochastic model.

Table 4.3 provides the list of decision variables of the HSCN design problem. This table includes three parts describing the decision variables in each stage of the proposed three-stage model. In the proposed model, the operations decisions are divided between the second and third stages. Hence, some decision variables are repeated in both the second and third sections of the table.

$$\min \sum_{\psi\in\Psi} p_\psi \sum_{t\in T}\sum_{k\in K} b^k \sum_{l\in L}(\hat{d}^{kt}_{l\psi} - \sum_{i\in V_{DC}} \bar{a}^{kt}_{il_\psi}) \tag{4.2}$$

s.t.

$$2x^t_{ij\psi} \leq y^t_{i\psi} + y^t_{j\psi} \quad \forall(i,j)\in A,\ \forall t\in T_1,\ \forall\psi\in\Psi, \tag{4.3}$$

$$\hat{y}^t_{i\psi} \leq m_i y^t_{i\psi} \quad \forall i\in V_W,\ t\in T_1,\ \forall\psi\in\Psi, \tag{4.4}$$

$$\hat{x}^t_{ij\psi} \leq m^t_{ij} x^t_{ij\psi} \quad \forall(i,j)\in A,\ \forall t\in T_1,\ \forall\psi\in\Psi, \tag{4.5}$$

$$\sum_{i\in V} f_i y^t_{i\psi} + \sum_{i\in W} \hat{f}_i \hat{y}^t_{i\psi} + \sum_{(i,j)\in A} \hat{f}^t_{ij} \hat{x}^t_{ij\psi} \leq z^0 \quad t\in T_1, \forall\psi\in\Psi, \tag{4.6}$$

$$\sum_{i\in V_{DC}} a^t_{il\psi} = 1 \quad \forall l\in L,\ t\in T_1,\ \forall\psi\in\Psi, \tag{4.7}$$

$$a^t_{il\psi} \leq y^t_{i\psi} \ \ \forall i\in V_{DC},\ \forall l\in L,\ t\in T_1,\ \forall\psi\in\Psi, \tag{4.8}$$

$$\begin{aligned} &\sum_{k\in K} \bar{x}^{kt}_{ij_\psi} \leq u_{ij} g^t_{ij_\psi}(\sum_{t'\in T_1 \bigcup T_2} \hat{x}^{t'}_{ij\psi} + \sum_{i'j'\in A} v^{t"}_{i'j'ij\psi} - v^{t"}_{iji'j'\psi}), \\ &\forall(i,j)\in A,\ \forall t" \in T_2,\ \forall t\in T,\ \forall\psi\in\Psi, \end{aligned} \tag{4.9}$$

$$\sum_{t'\in T_1 \bigcup T_2} \hat{x}^{t'}_{ij\psi} + \sum_{i'j'\in A} v^t_{i'j'ij\psi} - v^t_{iji'j'\psi} \geq 0, \quad \forall(i,j)\in A,\ \forall t\in T_2,\ \forall\psi\in\Psi, \tag{4.10}$$

$$\hat{x}^t_{ij\psi} \leq m^t_{ij} x^t_{ij\psi} \quad \forall(i,j)\in A,\ \forall t\in T_2,\ \forall\psi\in\Psi, \tag{4.11}$$

$$\bar{a}^{kt}_{il_\psi} \leq \sum_{(j,i)\in A} \sum_{t'\in T_1 \bigcup T_2} m^{t'}_{ji} u_{ji} g^{t}_{ji_\psi} a^{t"}_{il\psi}, \quad \forall i \in V_{DC},\ \forall l \in L,$$
$$\forall k \in K,\ \forall t \in T,\ t" \in T_1,\ \forall \psi \in \Psi, \tag{4.12}$$

$$\bar{a}^{kt}_{il_\psi} \leq \hat{d}^{kt}_{l\psi}, \quad \forall i \in V_{DC},\ \forall l \in L,\ \forall k \in K,\ \forall t \in T,\ \forall \psi \in \Psi, \tag{4.13}$$

$$\sum_{l\in L} \bar{a}^{kt}_{il_\psi} \leq \sum_{j\in W} \bar{x}^{kt}_{ji_\psi}, \quad \forall i \in V_{DC}, \forall k \in K,\ \forall t \in T,\ \forall \psi \in \Psi, \tag{4.14}$$

$$\hat{d}^{kt}_{l\psi} = d^{kt}_{l\psi} + \sum_{k'\in K} s^{k'k} (\hat{d}^{k't-1}_{l\psi} - \sum_{i\in V_{DC}} \bar{a}^{k't-1}_{il_\psi}), \quad \forall l \in L,\ \forall k \in K,$$
$$\forall t \in T,\ \forall \psi \in \Psi, \tag{4.15}$$

$$\sum_{i\in V} f_i y^{t"}_{i\psi} + \sum_{i\in V_W} \hat{f}_i \hat{y}^{t"}_{i\psi} + \sum_{t'\in T_1 \bigcup T_2} \sum_{(i,j)\in A} \hat{f}^{t'}_{ij} \hat{x}^{t'}_{ij\psi} + \sum_{t'=1}^{t} \sum_{(i,j)\in A} \sum_{k\in K} c^{k}_{ij} \bar{x}^{kt'}_{ij_\psi} \leq$$
$$z^0 + \sum_{t'=1}^{t} z^{t'}, \quad \forall t \in T,\ t" \in T_1,\ \forall \psi \in \Psi, \tag{4.16}$$

$$\hat{r}^{kt}_{j_\psi} \leq r^{kt-1}_{j_\psi} \quad \forall j \in V_W,\ \forall k \in K,\ \forall t \in T,\ \forall \psi \in \Psi, \tag{4.17}$$

$$\sum_{k\in K} \hat{r}^{kt}_{j_\psi} \leq u_j g^{t}_{j_\psi} \hat{y}_{j\psi} \quad \forall j \in V_W,\ \forall t \in T,\ \forall \psi \in \Psi, \tag{4.18}$$

$$\sum_{k\in K} r^{kt}_{j_\psi} \leq u_j g^{t}_{j_\psi} \hat{y}_{j\psi} \quad \forall j \in V_W,\ \forall t \in T,\ \forall \psi \in \Psi, \tag{4.19}$$

$$r^{kt}_{j_\psi} = \hat{r}^{kt}_{j_\psi} + \sum_{(i,j)\in A} \bar{x}^{kt}_{ij_\psi} - \sum_{(j,i)\in A} \bar{x}^{kt}_{ji_\psi} \quad \forall j \in V_W,\ \forall k \in K,$$
$$\forall t \in T,\ \forall \psi \in \Psi, \tag{4.20}$$

$$\sum_{(i,j)\in A} \bar{x}^{kt}_{ij_\psi} \leq n^{kt}_i \quad \forall i \in V_I,\ \ \forall k \in K,\ \forall t \in T,\ \forall \psi \in \Psi, \tag{4.21}$$

$$x^t_{ij\psi} = x^t_{ij\chi} \quad \forall (i,\, j) \in A,\; t \in T_1,\; \forall \psi,\, \chi \in \Psi, \tag{4.22}$$

$$y^t_{i\psi} = y^t_{i\chi} \quad \forall i \in V,\; t \in T_1,\; \forall \psi,\, \chi \in \Psi, \tag{4.23}$$

$$\hat{x}^t_{ij\psi} = \hat{x}^t_{ij\chi} \quad \forall (i,\, j) \in A,\; t \in T_1,\; \forall \psi,\, \chi \in \Psi, \tag{4.24}$$

$$\hat{y}^t_{i\psi} = \hat{y}^t_{i\chi} \quad \forall i \in V,\; \forall \psi,\, \chi \in \Psi, \tag{4.25}$$

$$a^t_{il\psi} = a^t_{il\chi} \quad \forall i \in V,\; \forall l \in L,\; t \in T_1,\; \forall \psi,\, \chi \in \Psi, \tag{4.26}$$

$$\hat{x}^t_{ij\psi} = \hat{x}^t_{ij\chi} \quad \forall \psi,\, \chi \in \Psi_o,\; o \in \{1, ..., e\}, \forall (i,\, j) \in A,\; t \in T_2 \tag{4.27}$$

$$v_{i'j'ij\psi} = v_{i'j'ij\chi} \quad \forall \psi,\, \chi \in \Psi_o,\; o \in \{1, ..., e\}, \forall (i,\, j) \in A, \forall (i',\, j') \in A, \tag{4.28}$$

$$\bar{x}^{kt}_{ij_\psi} = \bar{x}^{kt}_{ij_\chi} \quad \forall \psi,\, \chi \in \Psi_o,\; o \in \{1, ..., e\}, \forall (i,\, j) \in A,\, k \in K, t \in T_2, \tag{4.29}$$

$$\bar{a}^{kt}_{il_\psi} = \bar{a}^{kt}_{il_\chi} \quad \forall \psi,\, \chi \in \Psi_o,\, o \in \{1, ..., e\}, \forall i \in V_{DC}, \forall l \in L, \forall k \in K, t \in T_2, \tag{4.30}$$

$$r^{kt}_{i_\psi} = r^{kt}_{i_\chi} \quad \forall \psi,\, \chi \in \Psi_o,\; o \in \{1, ..., e\}, \forall i \in V_W, \forall k \in K, t \in T_2, \tag{4.31}$$

$$\hat{r}^{kt}_{i_\psi} = \hat{r}^{kt}_{i_\chi} \quad \forall \psi,\, \chi \in \Psi_o,\; o \in \{1, ..., e\}, \forall i \in V_W, \forall k \in K, t \in T_2, \tag{4.32}$$

$$\begin{aligned} &\hat{x}^{t"}_{ij\psi} \in \mathbb{N}^0,\; \hat{y}^{t"}_{i\psi} \in \mathbb{N}^0,\; x^{t"}_{ij\psi} \in \{0,1\},\; y^{t"}_{i\psi} \in \{0,1\},\; a^{t"}_{il\psi} \in \{0,1\}, \\ &\hat{x}^{t'}_{ij\psi} \in \mathbb{N}^0,\; v^{t'}_{i'j'ij\psi} \in \mathbb{N}^0, \\ &\bar{x}^{kt}_{ij_\psi} \geq 0,\; \bar{a}^{kt}_{il_\psi} \geq 0,\; r^{kt}_{i_\psi} \geq 0,\; \hat{r}^{kt}_{i_\psi} \geq 0,\; \forall (i,j) \in A, \\ &\forall (i', j') \in A,\; \forall i \in V,\; \forall k \in K,\; \forall t \in T,\; \forall t' \in T_2,\; \forall x" \in T_1,\; \forall l \in L,\; \forall \psi \in \Psi. \end{aligned} \tag{4.33}$$

The objective function (4.2) minimizes the expected penalty over all scenarios $\psi \in \Psi$. Constraints (4.3) make the selection of services conditional to selecting both their origin and destination hubs. The limits on the number of inventory resources at each warehouse are enforced by constraints (4.4). Furthermore, the number of selected transportation resources at the first stage is limited by constraints (4.5). Constraint (4.6) assures the initial budget constraint is respected. Constraints (4.7) guarantee each beneficiary group is assigned to one DC, and constraints (4.8) guarantee such DC is part of the HSCN. Constraints (4.9) limit the services transported critical supplies' quantity to the capacity of the service at each period. Constraints (4.10) limit the number of transportation resources leaving a service by its available transportation resources. The number of added transportation resources to each service at the second stage is limited by constraints (4.11). Constraints (4.12) limit allocating the critical supplies to beneficiary groups at DCs. Constraints (4.13) ensure non-anticipativity, limiting the allocated critical supplies to each beneficiary group up to their demand at each period. The flow constraints (4.14) guarantee that the allocated critical supplies to beneficiary groups at each DC are limited by the received critical supplies by the DC. The level of demand for each period of T is calculated in constraints (4.15). Constraints (4.16) limit the expenses to the available budget at each period. Constraints (4.17) limit the inventory level of the warehouses at the beginning of each period by its inventory level at the end of the previous period. Constraints (4.18) and (4.19) confine the inventory level of warehouses by their inventory capacity. The inventory level of warehouses at the end of each period is calculated by constraints (4.20). Constraints (4.21) bound the received critical supply at each port of entry by the maximum capacity of the port of entry. Constraints (4.22)-(4.26) enforce the non-anticipativity constraint of first stage decision variables and constraints (4.27)-(4.32) enforce non-anticipativity constraint for second stage decision variables, ensuring the value of decision variables in each node of the scenario tree are equal across scenarios. Finally, constraints (4.33) present the bounds of the decision variables.

4.5 Experiments

In this section, we present the dataset and experiments designed and applied to answer the research questions considered in this paper. Subsection 4.5.1 introduces the dataset, including the characteristics of the natural disaster, sources used in the dataset compilation, and generating scenarios. Furthermore, we present the performed experiments in Subsection 4.5.2, evaluating the value of allowing update decisions during the operational phases compared to making update decisions at the design (first) stage. In this subsection, we also compare the solution obtained from the proposed three-stage model with its two-stage counterpart, assessing their performance based on the two defined metrics. Finally, Subsection 4.5.3 provides the managerial insights obtained from the experiments conducted in this section.

4.5.1 Dataset

We generate a dataset using collected data from the earthquake that occurred in Lombok Island, Indonesia, in 2018. The region experienced over 1500 aftershocks, among which four were the most intense shocks, including the main earthquake on July/29 with 6.4 M_L (i.e., Richter magnitude scale), the first strong aftershock with 7 M_L on Aug/05, the second strong aftershock with 5.9 M_L on Aug/09, and the third strong aftershock with 6.4 M_L on Aug/26. As a result of the earthquake, 445,343 individuals relocated to 2700 camps located on Lombok island and the neighboring islands. Responding to the critical situation after the earthquake, the Indonesian government declared a state of emergency from July 29th to August

26th, which we define as the planning horizon. We set the length of each period to one week resulting in four periods in the planning horizon. The International Organization for Migration (IOM) has published a comprehensive list of all camps, including their locations and the number of individuals in each camp (IOM, 2019).

For this study, we selected 96 beneficiary groups on the island. There were 20,950 households (74,246 individuals) residing in these beneficiary groups during the planning horizon. The critical supplies involved in the dataset are shelter, food, and hygiene packs. Since the clean water had a separate distribution network (IFRC, 2021a), we exclude it from critical supplies considered within this dataset. To calculate the base demand for the critical supplies, we use the standard required quantity of each critical supply per individual or household, as determined and published by the International Federation of Red Cross and Red Crescent Societies (IFRC, 2021b).

We gathered the location of six warehouses and four points of entry from the reports published by Palang Merah Indonesia (PMI), the local partner of the IFRC in Indonesia, during their operation on Lombok Island (IFRC, 2021a). According to the published reports, the PMI outsourced the transportation of critical supplies to third-party companies. Thus, we consulted the local transportation companies' sources to obtain the cost and capacity of the provided services.

To generate candidate locations for the DCs, we used the DBSCAN algorithm (Ester et al., 1996) to cluster the beneficiary groups. The DBSCAN has two parameters, the epsilon and the minimum number of neighbors. Variating the parameters leads to various clustering solutions, so a domain expert would choose the best clustering for the study problem (Mendes & Cardoso, 2006). The former indicates the radius of the obtained clusters, and the latter denotes the clusters' density. After indicating the location of the hubs and beneficiary groups, we calculate the driving distances between hubs and the walking distance between the beneficiary groups (as input parameters of the DBSCAN algorithm). We derived the necessary distances utilizing an online routing engine (Luxen & Vetter, 2011) that computes both walking and driving distances between points using OpenStreetMap.

Generating scenarios using a scenario tree involves several steps to capture uncertainties in decision-making. First, relevant data is collected, and probability distributions for uncertain parameters are determined. These distributions generate multiple realizations of parameter values, each forming a node in the second stage of the scenario tree. For each second-stage node, further realizations for the third stage are generated using conditional probability distributions, expanding the tree. This results in a comprehensive set of scenarios that capture a range of possible outcomes and their associated probabilities.

4.5.2 Experimental Results

This section includes the experiments designed and conducted in the context of the considered case study. First, Subsection 4.5.2.1 investigates the appropriate number of scenarios for the following experiments using in-sample and out-of-sample stability analysis. Then, Subsection 4.5.2.2 examines the benefit obtained by adjusting the HSCN design over the planning horizon compared to the fixed-design models in the literature (Daneshvar et al., 2023). Then, Subsection 4.5.2.3 evaluates the performance of the three-stage model and its two-stage counterpart over various spread-factor values. Finally, Subsection 4.5.2.4 compares the cost-benefit of the three-stage model proposed here and its two-stage counterpart.

4.5.2.1 Stability Analysis

This section includes the in-sample and out-of-sample stability analyses (Kaut & Wallace, 2003) of the proposed model. Different solutions may result from solving a problem with distinct scenario sets of equal size. Yet, increasing scenario numbers via appropriate sampling reduces such differences (enhances uncertain parameter approximation) and increases the generated instance's computational cost, including required hardware and time. Thus, we are interested in the number of scenarios that balance estimation quality and computational cost. Assessing both in-sample and out-of-sample stability examines sample size effects on final solution quality. In-sample stability examines solution consistency across varied scenario sizes based on reported objective function values, while out-of-sample stability tests for consistency on the ground truth.

We first choose three different number of scenarios (125, 250, and 500) to perform the in-sample stability test. In the scenario tree used to generate the scenarios, every five scenarios share a node in the second stage. Then, for each number of scenarios, we solve the proposed three-stage model 15 times, each time with different randomly generated scenarios. The average and standard deviation of the objective function value is reported in Table 4.4. To perform the out-of-sample stability test, we calculate the expected penalty of using solutions obtained in the in-sample stability test over the ground-truth scenarios. The ground truth comprises 3,000 scenarios, with 600 nodes in the second stage of the scenario tree and five nodes in the third stage for each node in the second stage. Similar to the in-sample-stability test, we calculate the average and standard deviation of the expected penalty of the solution, presented in Table 4.5.

Number of scenarios	mean	std
125	62,828	5,452
250	65,662	4,221
500	64,128	2,962

Table 4.4: The results obtained from the in-sample stability test of the three-stage model (over 15 runs).

Number of scenarios	mean	std
125	65,701	1,577
250	64,595	582
500	64,500	611

Table 4.5: The results obtained from the out-of-sample stability test of the three-stage model (over 15 runs).

Contrary to the out-of-sample stability test, the objective function values in the in-sample stability test are calculated on different scenario sets; therefore, we cannot use the mean value as a comparison point between different scenario sizes. However, the standard deviation could be used to compare the fluctuation in the objective function value caused by the number of scenarios used when solving the problem. The in-sample stability test results in Table 4.4 indicate that the standard deviation of objective function values reduces from 5,452 for 125 scenarios to 2,962 for 500 scenarios. Furthermore, the average objective function value in the out-of-sample stability test reduces from 65,701 for 125 scenarios to 64,500 for 500 scenarios, showing a 1.83% improvement in the objective function value of the solutions obtained when tested on the ground truth scenario set. Also, the standard deviation of the objective function values has reduced from 1,577 for 125 scenarios to 611 for 500 scenarios, indicating a 61.26% improvement. Based on the observed results of this experiment, we use 500 scenarios to perform the following experiments.

4.5.2.2 Value of Adjusting Transportation Resources

The update decisions involve adjusting the design of the HSCN to accommodate demand by adding new transportation resources and relocating existing ones. Furthermore, over time, the availability of transportation resources declines while their associated costs rise within the region. Consequently, update decisions are considered only in the first period.

This experiment employs two two-stage models to explore the potential advantages of postponing the update decisions from the design phase to the second stage. The first model, referred to as SSUD (i.e., second-stage update decision), is a relaxed version of the three-stage model introduced in Section 4.4, with constraints (4.27) to (4.32) (the non-anticipativity constraints) relaxed. The second model, referred to as FSUP (i.e., first-stage update decision), incorporates the update decisions in the first stage by adding the following constraints to the original two-stage model, enforcing the update decisions to be made in the first stage.

$$\hat{x}^1_{ij\psi} = \hat{x}^1_{ij\chi} \quad \forall \psi,\, \chi \in \Psi,\, \forall (i,\, j) \in A, \tag{4.34}$$

$$v_{i'j'ij\psi} = v_{i'j'ij\chi} \quad \forall \psi,\, \chi \in \Psi,\, \forall (i,\, j) \in A,\, \forall (i',\, j') \in A, \tag{4.35}$$

Five hundred scenarios are generated and used to solve all three models, obtaining one solution per model to compare the SSUD, FSUD, and three-stage models. The solutions are then applied to the ground-truth scenario set. To evaluate the solutions, we use the three-stage model presented in Section 4.4 while fixing the decision variables of the first stage using the solutions' values. Table 4.6 presents the expected penalty obtained by applying the solutions on the ground-truth scenarios. The result indicates that the SSUD outperforms the FSUD model, suggesting that humanitarian decision-makers could improve the performance of their HSCN with a slight increase in computational time when choosing SSUD over the FSUD model. However, when comparing the SSUD and the three-stage models, the latter demonstrates superior performance, with a 4.81% improvement in the expected penalty. While this improvement comes at a computational cost of 14.89%, it provides a more robust and detailed framework for decision-making by incorporating additional flexibility in the timing of update decisions. This suggests that adopting the three-stage model could significantly improve outcomes for humanitarian decision-makers in terms of unmet demand and network resilience. It would also make it a more effective approach in contexts where computational resources are not a limiting factor and decision precision is paramount.

Model	Solution Calculation Time (sec)	Expected Penalty on the Ground-Truth
FSUD	1,101	70,295
SSUD	1,867	67,504
Three-Stage	2,145	64,258

Table 4.6: The computation time to obtain a solution and the expected penalty when the solution is applied on the ground truth for FSUD, SSUD, and three-stage models.

In the following subsection, we study the possible advantages of using a three-stage over the two-stage SSUD model.

4.5.2.3 The impact of the spread factor

The spread factor models the impact of each critical supply's unmet demand on all critical supplies' demands in the next period (Daneshvar et al., 2023).

This section evaluates the spread factor's impact on the model's computational time. Following, we evaluate the impact of increasing spread factor value on the performance gap between the SSUD and three-stage models. The performance gap is the percentage increase in the expected penalty value when transitioning from the three-stage to the SSUD model. This metric quantifies the relative performance loss associated with simplifying from the three-stage to the SSUD model, highlighting the benefits of additional stages in reducing the expected penalty. Changes in the spread factor variations generate new instances, making direct comparisons of expected penalties between instances unattainable. Using the performance gap, we obtain a normalized measure to assess the significance of additional stages across different spread factor values.

To conduct a structured analysis, we define two series of values for the spread factor: one set of diagonal variations to capture the impact of unmet demand for each critical supply on itself (cumulative effect) in the next period and another set of non-diagonal variations to reflect the impact of unmet demand of each critical supply on other critical supplies (spreading effect) in the next period.

We use the following formulation to generate variations of spread factor values.

$$spread\ factor = \Pi_1 I + \Pi_2 (J - I) \tag{4.36}$$

In this context, I represents the identity matrix, with ones on the diagonal and zeros elsewhere, and J is a matrix with all entries equal to one. Also, Π_1 is the parameter indicating the intensity of the cumulative effect, and Π_2 represents the spreading effect's intensity. The spread factor I indicates that the unmet demand of each critical supply transfers to the next period without increase. We define the spread variation factor, where the cumulative variations are represented by Π_1 taking 1, 1.25, 1.5, 1.75, and 2 with Π_2 equal to zero, resulting in spread factor values of I, $1.25I$, $1.5I$, $1.75I$, and $2I$, respectively. For the spreading effect variations, we set Π_1 equal to one with Π_2 taking 0, 0.25, 0.5, 0.75 and 1, resulting in spread factor values of I, $I+0.25(J-I)$, $I+0.5(J-I)$, $I+0.75(J-I)$, J, respectively. This structure enables us to systematically examine how unmet demand impacts propagate both within and across critical supplies in subsequent time periods.

Cumulative Effect			**Spreading Effect**		
Value of Π_1	Value of Π_2	Time (hours)	Value of Π_1	Value of Π_2	Time (hours)
1.00	0.00	0.58	1.00	0.00	0.58
1.25	0.00	1.25	1.00	0.25	2.00
1.50	0.00	3.00	1.00	0.50	5.50
1.75	0.00	7.00	1.00	0.75	20.00
2.00	0.00	10.00	1.00	1.00	20.00

Table 4.7: Cumulative and Spreading Effects on Spread Factors and Computational Time

Table 4.8 presents the performance improvement in the expected penalty over the ground truth made when using the three-stage over the SSUD model. The results are reported for variations of spread factor values considering the cumulative and spreading effects separately. The results show that the percentage of improvement decreases for higher values of the spread factor for both cumulative and spreading effects variations. The results indicate that when demand increases without corresponding adjustments in budget and resources, the performance of the SSUD and three-stage models converges, underscoring the critical importance for decision-makers to ensure the availability of adequate budget and resources to maintain effective humanitarian relief operations.

Cumulative Effect			Spreading Effect		
Value of Π_1	Value of Π_2	three-stage improvement (percent)	Value of Π_1	Value of Π_2	three-stage improvement (percent)
1.00	0.00	4.80	1.00	0.00	4.80
1.25	0.00	4.67	1.00	0.25	4.67
1.50	0.00	1.56	1.00	0.50	1.57
1.75	0.00	0.21	1.00	0.75	1.74
2.00	0.00	0.79	1.00	1.00	1.80

Table 4.8: Performance gap obtained on various variations of spread factor, comparing the three-stage and SSUD models.

4.5.2.4 Solution analysis

This section evaluates the proposed models by examining the solutions obtained on a problem instance with 500 scenarios. First, this analysis compares the distinct design decisions made in each solution, presenting the critical differences between the two networks. Then, the solutions are evaluated based on the updates required in each HSCN designed over the planning periods when assessed against the ground-truth scenario set. By examining the number of scenarios in ground truth that have updated the designed HSCN to align with the observed demand, we better understand each solution's robustness and flexibility.

Table (4.9) compares the number of transportation resources each model selects in HSCN designed by the FSUD, SSUD, and three-stage models. When comparing the total transportation resources units selected in each designed HSCN, all three networks are close to each other. However, the distribution of these resources is different among HSCNs. Specifically, FSUD is overinvested compared to SSUD and Three-Stage in Lombok Airport to Kayanagan transportation and underinvested in ObelObel #2 to DC #104 and from Lombok Airport to ObelObel #2. Comparing SSUD and Three-Stage HSCNs, the HSCN designed by SSUD has more transportation resources on the road from Lombok Airport to ObelObel #1 and ObelObel #1 to DC #104, but the three-stage designed HSCN has more transportation resources on the roads from Lombok Airport to ObelObel #2 and from ObelObel #2 to DC #104. The three-stage model demonstrates a more efficient resource allocation than the other two models. It selects fewer transportation and inventory resources, resulting in a more optimized budget allocation and greater flexibility in operational expenses. Notably, the three-stage model does not allocate any inventory resources, emphasizing the influence of its structural design. This approach reduces the expected penalty when evaluated against the ground-truth scenarios, highlighting the model's effectiveness in minimizing design costs while maintaining flexibility in resource deployment. An important insight for decision-makers is that spending less on design while leveraging the more complex three-stage structure to better estimate the real-world information flow has enabled the three-stage model to achieve the best results.

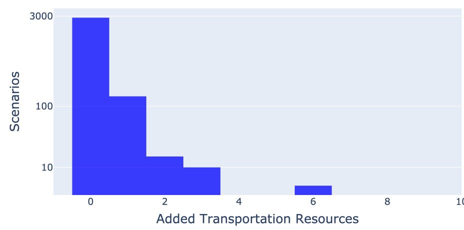
In the previous section, we compared the solutions provided by the FSUD, SSUD, and three-stage models, noting the distinct outcomes associated with each approach. In this section, we further evaluate the performance of the SSUD and three-stage models by introducing two key performance indicators (KPIs), a quantitative basis for comparing their relative strengths and weaknesses. The first KPI focuses on the number of ground truth scenarios in which new transportation resources are added to the HSCN during the first period. Adding new resources in the first period is more costly than the first stage, and there is an increased risk of resource shortages. Consequently, a solution that minimizes the number of scenarios requiring new resources in the first period is considered superior.

Figure 4.3 illustrates the distribution of scenarios in which new transportation resources are added in the first period. The SSUD solution has 175 scenarios that

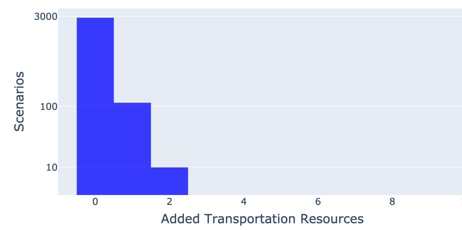
Parameter	From	To	FSUD	SSUD	Three-Stage
Transportation Resources	Kayangan	DC #104	61	51	50
	ObelObel #1	DC #104	68	62	51
	ObelObel #2	DC #104	0	18	28
	Mataram Port	Kayangan	64	62	61
	Mataram Port	ObelObel #1	6	1	1
	Mataram Port	ObelObel #2	0	6	5
	Lombok Airport	Kayangan	21	8	7
	Lombok Airport	ObelObel #1	76	72	60
	Lombok Airport	ObelObel #2	0	15	28
	Total Transportation Resources		**296**	**295**	**291**
Inventory Resources	Kayangan		2	0	0
	ObelObel #1		0	0	0
	ObelObel #2		0	1	0
	Total Inventory Resources		**2**	**1**	**0**

Table 4.9: The transportation and inventory resources acquired by the studied models.

add new transportation resources, whereas the three-stage solution has 130 scenarios with added transportation resources. Furthermore, the SSUD solution adds more resources in scenarios with added resources than the third-stage solution. Therefore, based on this KPI, the three-stage model exceeds the SSUD solution.



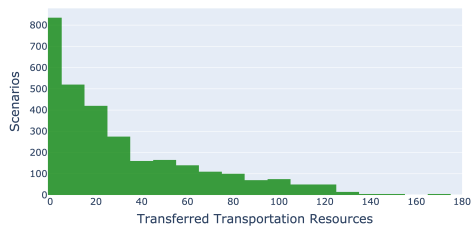
(a) Evaluating SSUD solution on the ground truth.



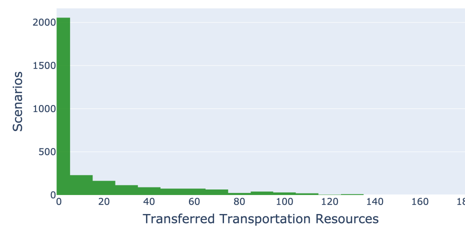
(b) Evaluating three-stage solution on the ground truth.

Figure 4.3: Comparison of the distribution of scenarios across the number of added transportation resources in the first period when evaluating the SSUD (a) and three-stage solution (b) on the ground truth.

The second KPI discussed in this section is the number of scenarios in which transportation resources are relocated between selected services in the designed HSCN. While no direct cost is associated with relocating transportation resources, this task requires complex logistical management. Given the limited telecommunication access in the affected region, solutions involving fewer scenarios of such relocation are preferred. Figure 4.4 illustrate the number of ground truth scenarios where transportation resources are transferred in the first period for the SSUD and three-stage solutions, respectively. When evaluating the SSUD solution, the number of scenarios with transferred resources is 2.63 times greater than in the three-stage solution (2345 and 890 scenarios for the SSUD and three-stage models, respectively). Furthermore, in scenarios where resource transfer occurs, the number of relocated resources is significantly higher when evaluating the SSUD solution compared to the three-stage solution. Overall, the solution obtained by the three-stage model performs better in terms of both the expected penalty and the defined KPIs.



(a) Evaluating SSUD on the ground truth.



(b) Evaluating three-stage solution on the ground truth.

Figure 4.4: The distribution of scenarios across number of transferred transportation resources between selected services in the first period when evaluating the SSUD (a) and three-stage solution (b) on the ground truth.

4.5.3 Managerial Insights

The following insights highlight how humanitarian decision-makers can leverage the proposed model in this paper to enhance planning and optimize relief operations in a region affected by a natural disaster.

Flexibility in Decision Timing During Crises

In fast-moving humanitarian emergencies, resource requirements can change rapidly. The experiments show that deferring design update decisions until the operational phase (i.e., the first period) can lead to better outcomes (see Table 4.6 in Section 4.5.2.4). Specifically, both SSUD and three-stage solution evaluations show that postponing decisions until the disaster's early response phase allows for more effective adaptation to evolving needs, reducing costs and improving response efficiency.

Enhanced Decision-Making with a Three-Stage Model

Adaptive planning is a valuable approach for humanitarian logistics teams. Our results indicate that the three-stage model, though more computationally intensive, provides a superior solution by adjusting the design based on updated information over time (see Figure 4.3 and 4.4 in Section 4.5.2.4). This flexibility enables decision-makers to better respond to unforeseen changes in the disaster's progression and resource availability, ensuring that resources are allocated optimally throughout the relief operation.

Considering Spread Factor in Post-Disaster Situations

The spread factor, reflecting the effects of unmet demand across different time periods, directly impacts the complexity of logistics planning. In uncertain disaster settings, where unmet needs could have both cumulative and spreading effects, the three-stage model performance provides an advantage over its two-stage counterpart, the SSUD model (see Table 4.7 and 4.8 in Section 4.5.2.4). However, humanitarian decision-makers should be mindful of the exponential increase in computational time when considering higher spread factor values with spreading effect, balancing the need for precision with practical time constraints.

Efficient Resource Allocation and Logistics in Crisis Zones

The three-stage model's superior distribution of transportation resources demonstrates its value for resource-limited disaster response efforts (see Figure 4.3 and 4.4 in Section 4.5.2.4). This can guide decision-makers to design more balanced, effective HSCNs that reduce costs while ensuring that affected populations are serviced promptly, a key factor in maintaining the flow of aid.

Minimizing Costs by Postponing Transportation Resource Additions

The three-stage model's ability to reduce the number of new transportation resources needed during the first period is particularly valuable (see Figure 4.3 in

Section 4.5.2.4). In humanitarian logistics, where resources are often scarce and costs are high, minimizing the need for additional transportation units can lead to significant savings and more efficient resource use during the relief operations.

Reducing the Need for Transportation Resource Transfer

The proposed three-stage model also highlights the advantage of minimizing the transferring the transportation resources during the relief operation (see Figure 4.4 in Section 4.5.2.4). Relocating resources can be time-consuming in regions with limited infrastructure. The three-stage model's ability to minimize this logistical challenge provides an operational benefit, ensuring that resources remain in place where they are most needed and streamlining the logistics effort.

In summary, the proposed three-stage model provides clear advantages in terms of adaptability, resource optimization, and cost management for humanitarian logistics decision-makers looking to improve the efficiency and effectiveness of their operations. By using the proposed three-stage model, decision-makers can better handle the uncertain nature of disaster response, ensuring that resources are deployed where they are most needed and at the right time. The insights from this study can directly support more informed, tactical decision-making in real-world humanitarian operations.

4.6 Conclusion

In this paper, we proposed a three-stage model for designing an HSCN to manage the distribution of critical supplies after a natural disaster. The model is built to accommodate the inherent uncertainty of post-disaster environments, enabling dynamic adjustments to transportation resources as more information becomes available. We compared the three-stage model with traditional two-stage approaches and explored its effectiveness in improving HSCN design by reducing unmet demand and minimizing the associated expected penalty. Our results show that the three-stage model significantly outperforms the two-stage counterparts, particularly in managing demand and resource allocation uncertainties.

The experimental results highlighted the substantial benefits of making design decisions dynamically during the operation phase. The three-stage model demonstrated improved flexibility and decision-making by delaying update decisions until more data became available during relief operations. This approach reduced the need for unnecessary investment in transportation resources and minimized logistical inefficiencies. Additionally, the model was able to better adapt to the evolving situation, making the best use of available resources throughout the planning horizon. Specifically, when evaluating on the ground truth, the three-stage model transferred the transportation resources on in 33% of scenarios whereas its two-stage counterpart transferred transportation resources in 79%. Considering the managerial complexity and time-intensive nature of transferring transportation resources during the relief operation, the three-stage model demonstrates a clear advantage over its two-stage counterpart. This advantage is further evident in the expected penalty, which reflects the third-stage model's more efficient distribution of critical supplies.

For future research, exploring heuristic approaches, such as progressive hedging (Rockafellar & Wets, 1991; Crainic et al., 2011; Sarayloo et al., 2023), would be beneficial to make the three-stage model more computationally tractable for real-world instances with larger datasets and more complex scenarios. Furthermore, an extension of this model could include a multi-objective optimization framework that balances cost reduction, resource allocation efficiency, and humanitarian fairness in the distribution of critical supplies. Refining these aspects could improve the model for practical use in disaster response planning and execution.

CHAPTER V

CONCLUSION

Section 5.1 summarizes the research conducted on the design and operation of HSCNs in the context of post-disaster relief and consolidates the key findings and contributions of the three studies presented throughout the thesis, highlighting the importance of addressing uncertainty and ambiguity. Furthermore, Section 5.2 outlines several directions for future research, emphasizing the need for continued advancements in modeling techniques, computational methods, and the practical application of these models in real-world disaster response scenarios.

5.1 Summary

The design and operation of HSCNs following a sudden natural disaster is critical to ensuring that essential critical supplies are delivered to vulnerable populations in a timely manner. The consequences of delivery delays or insufficient access to critical supplies can significantly impact the health and well-being of affected individuals. However, designing an efficient HSCN is challenging due to the high level of uncertainty inherent in both demand and available resources. These uncertainties, compounded by the ambiguity stemming from assessments performed using multiple data sources, necessitate advanced modeling approaches that can accurately capture the complexities of post-disaster logistics.

This thesis includes three studies aimed at improving the design and operation of HSCNs in disaster response contexts. Each study addresses a different aspect of HSCN design under uncertainty and ambiguity, providing a comprehensive framework for optimizing humanitarian logistics in post-disaster settings.

The first study proposes a two-stage mathematical model for the HSCN design problem, which captures both demand and resource uncertainties in a natural disaster context. A novel formulation is introduced to model demand in a way that accounts for the cumulative effect of unmet demand across multiple critical supplies. This approach addresses the dynamic and interdependent nature of demand during disaster relief operations, where shortages in one critical supply can exacerbate demands for others. The study demonstrates the importance of directly incorporating these effects into the optimization process to achieve more accurate and responsive supply chain designs.

The second study expands on the first by exploring the role of ambiguity in humanitarian supply chain models. The study develops models that account for different ambiguity patterns in demand and capacity assessments. Through a series of experiments, the study compares the performance of these models and highlights the impact of different ambiguity patterns on the optimal design of the HSCN. The findings underscore the need for robust optimization techniques that can handle both uncertainty and ambiguity, ensuring that HSCNs are resilient to fluctuations in resource availability and the accuracy of demand and resource estimations.

The third study further advances the HSCN design problem by incorporating the ability to update the HSCN's structure over time. A three-stage model is proposed that allows for the dynamic adjustment of transportation resources in response to evolving conditions during the disaster response phase. This flexibility includes adding new transportation resources and reallocating existing ones to optimize HSCN performance as new information becomes available. The study compares the performance of this three-stage model with the traditional two-stage approach, showing that allowing for updates to the HSCN structure significantly improves the network's responsiveness and overall effectiveness in meeting the fluctuating demand and resources. Through extensive experimentation, the study demonstrates that the three-stage model outperforms the two-stage model, especially in contexts where timely adjustments to resource allocation are crucial.

Together, these three studies provide valuable insights into the design and operation of HSCNs in post-disaster scenarios. By addressing the challenges of uncertainty, ambiguity, and the dynamic nature of disaster response, the research contributes to developing more effective and flexible humanitarian logistics models. The findings emphasize the importance of incorporating cumulative demand effects, considering the role of ambiguity in data, and allowing for real-time updates to the network structure to optimize relief operations.

In conclusion, the research presented in this thesis offers a comprehensive framework for designing and managing HSCNs under complex and uncertain conditions. The proposed models provide humanitarian organizations with the tools needed to make informed decisions during disasters, ensuring that critical supplies are delivered to those in need in the most efficient and effective manner possible.

5.2 Future Work

This thesis addressed the critical issue of optimizing HSCNs under parameter uncertainty and distributional ambiguity, particularly in post-disaster relief operations. The aim was to develop and evaluate mathematical models to assist humanitarian organizations in designing efficient and adaptable HSCNs, reducing harm to the affected populations using available budgets and resources. While significant progress was made in developing two-stage and three-stage models, there remains potential for further research and improvements in several areas, including research on more realistic modeling of the planning problems, research on efficient solution methods, and research on technology transfer into humanitarian organizations.

More realistic planning models. From a modeling perspective, Section 3 proposed four mathematical models to mitigate the ambiguity caused by inconsistent estimates of uncertain parameters obtained from multiple data sources by developing four mathematical models with varying degrees of conservatism. One area for future research considers a varying level of confidence in the data sources while also considering a higher number of data sources. While this is easily incorporated into stochastic programming models, integrating such varying confidence in the data-sources is still rather unexplored in robust optimization.

While the models presented in this thesis incorporate uncertainty in post-disaster humanitarian planning, they still do not fully integrate the dynamic and evolving nature of information revelation in real-world use cases. Specifically, for the two-stage models, the assumption that uncertain parameter values become available in the second stage estimates the continuous progression of information revelation over time. As humanitarian organizations refine their assessments, future research could focus on developing adaptive frameworks that allow organizations to update their HSCN designs in multiple stages as new information becomes available over time. Future work could explore multi-stage models that better align with the evolving data and incorporate adaptive mechanisms, reflecting the multi-stage refinement of assessments as more information becomes available.

Finally, Section 2 experiments on the spread factor, which captures the cumulative effect of unmet demand on future critical supply needs, indicate the overestimation of the spread factor is preferable over underestimating it. Future research exploring whether this assumption holds in broader contexts or across different types of natural disasters would be an important contribution to the literature.

Efficient solution methods. Another potential avenue is applying more advanced solution methodologies to handle more complex instances of the HSCN design problem. As disaster scenarios scale up, both in terms of affected populations and demands, the computational complexity of solving multi-stage models increases. Further, considering multi-stage variants of the here considered planning problems, going beyong three-stage models as proposed in Section 4, will further degrade the tractability of the corresponding optimization models. Here, general-purpose MIP solvers are unlikely to solve those models in reasonable computing times, requiring the development of specialized solution methods. Exploring heuristic or metaheuristic approaches are promising avenues. For example, progressive hedging (Rockafellar & Wets, 1991; Crainic et al., 2011; Sarayloo et al., 2023) and Benders decomposition (Harjunkoski & Grossmann, 2001; Rahmaniani et al., 2017) have been shown to be appropriate for multi-stage mixed-integer programming formulations even for large problem instances. Such methods could equip humanitarian organizations with the tools to handle large-scale operations where traditional exact methods struggle due to computational limitations.

Technology transfer into humanitarian organizations. This thesis has introduced a series of models for HSCN design under uncertainty and ambiguity. Integrating these models into humanitarian organizations' planning and operating frameworks is an essential direction for future work. Moving from theoretical models to practical applications requires robust mathematical formulations and a deep understanding of the operational realities faced by organizations in the field. While the models presented in this research provide valuable insights, translating them into actionable strategies for humanitarian organizations will require extensive testing, validation, and adaptation to real-world conditions. A crucial next step will be to conduct assessments within actual humanitarian operations to evaluate the applicability and effectiveness of these models in diverse disaster scenarios. This involves working closely with field practitioners to ensure the models align with operational constraints, resource availability, and logistical realities. Furthermore, integrating these models into humanitarian organizations' decision-making pipelines will be a significant challenge, as it often involves multiple stakeholders and decision points across different operations levels. Understanding how to inject these models into the pipeline, transforming them from conceptual tools to operational assets, represents an important avenue for future research.

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