

Multi-agent multi-objective coordination in humanitarian logistics

by

Ayesha Farooq

B.E., National University of Sciences and Technology, Pakistan, 2016

AN ABSTRACT OF A DISSERTATION

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requirements for the degree

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Department of Industrial and Manufacturing Systems Engineering
Carl R. Ice College of Engineering

KANSAS STATE UNIVERSITY
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Abstract

Humanitarian crises are escalating in both frequency and complexity, placing unprecedented demands on response systems composed of government agencies, non-governmental organizations, and private actors. These entities must coordinate their operations in a decentralized manner under limited resources and often competing objectives. Existing coordination frameworks rely on centralized control or assume alignment of goals, thereby falling short in settings where autonomous decision-makers require assurances of fairness to remain engaged. Addressing this deficiency requires a formal methodology capable of reconciling multiple objectives, preserving incentive compatibility, and quantifying the concessions necessary to sustain coordination.

This research advances the body of knowledge in multi-objective multi-agent humanitarian logistics through a sequence of interlinked contributions. First, it delivers a systematic literature review that maps existing work at the intersection of game theory and optimization for coordination in humanitarian contexts. The review categorizes existing studies by modeling approaches, coordination mechanisms, and decision contexts. It identifies four primary coordination mechanisms: resource sharing, information sharing, contracting, and strategic action. The review also reveals the absence of models that consider fairness in decentralized settings with conflicting objectives.

Building on the review insights, a new mathematical concept *Chebyshev least core* is introduced and formalized, extending classical cooperative game theory, to quantify the smallest uniform concession necessary to achieve near-stable outcomes when perfect equity is unattainable. Moreover, a novel mathematical framework is developed by integrating cooperative game theory with multi-objective optimization to enable equitable and sustainable coordination by computing the Chebyshev least core. Specifically, a Cooperative Goal Optimization (CGO) model is proposed to identify fair allocations by minimizing the maximum

relative shortfall each actor experiences compared to their stand-alone performance. The model also incorporates the preference core and nondominance core concepts into a single model, allowing practitioners to distinguish solutions that satisfy all imposed conditions from those that involve trade-offs. Computational experiments demonstrate that the CGO approach yields more stable, equitable, and scale-invariant outcomes than conventional allocation rules, and that it accommodates objectives expressed in disparate units without the need for commensurability assumptions.

Finally, the framework is validated with a case study using real-world data on hurricane staging-area planning. The case study offers empirical evidence on how coordination mechanisms reshape operational choices in hurricane response. Joint planning alters routing, and pre-positioning decisions to make the disaster response more effective, efficient, and equitable. By applying the developed framework, it is demonstrated that equitable cost and benefit-sharing rules can be constructed so that no organization has an incentive to deviate from coordinated arrangements. Lastly, the study bridges theory and practice by quantifying the exact price of coordination for multi-objective multi-agent relief operations.

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Approved by:

Major Professor
Dr. Jessica L. Heier Stamm

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Dedication

To my son, Huzaifa, who taught me about depths of patience, essence of resilience, and the
true meaning of joy.

To my husband, Farrukh, whose sincerity radiates and warms my heart with
love and light.

Chapter 1

Introduction

Humanitarian crises are growing in frequency and severity. Given their complexity, no single organization can address these challenges alone ([United Nations, 2023](#)). Humanitarian response efforts involve urgent decision-making under pressure, further complicated by the participation of multiple autonomous actors such as governments, non-governmental organizations, United Nations agencies, donors, private companies, and local communities. Supplies may be plentiful in one location yet critically scarce in another, information can be fragmented or rapidly evolving, and delays can cost lives. Organizations must balance efficiency and effectiveness while ensuring efforts are complementary rather than duplicative. Studying the behavior of these complex systems with multiple independent actors where each pursues multiple, sometimes competing objectives, is therefore essential for developing methods that keep activities aligned, and maximize overall humanitarian impact.

In this work, *coordination* is defined as the alignment of actions among autonomous decision makers such that the overall system benefits. Disaster response depends on seamless coordination among participating entities, including government agencies, non-governmental organizations, and private actors. Effective coordination is achieved through networks and partnerships that emphasize resource sharing, open communication, and the establishment of clear objectives. Scholarly work indicates that such coordination yield better outcomes than traditional hierarchical command-and-control systems, especially in decentralized settings

when decision making is not controlled by a central authority ([Waugh Jr and Streib, 2006](#)).

Decentralized disaster relief environments present significant challenges due to the absence of a central authority and the involvement of multiple autonomous decision makers. In such contexts, effective coordination is both critical and difficult to achieve. The complexity is further intensified by the fact that the willingness of actors to engage in coordinated efforts is closely tied to their perception of fairness in how responsibilities are allocated and outcomes are distributed. When coordination mechanisms fail to address disparities in effort, exposure, or advantage, actors may disengage or act unilaterally, undermining system-wide effectiveness. Thus, understanding and designing coordination strategies that account for the presence of diverse and autonomous actors is essential for improving the effectiveness and efficiency of disaster relief operations.

Multi-objective environments arise naturally in disaster relief operations due to the diverse and often competing priorities that organizations must balance. Humanitarian actors operate under mandates that span multiple goals, such as minimizing response time, maximizing coverage, reducing operational costs, ensuring equity in aid distribution, and maintaining long-term sustainability. These objectives are not only distinct but frequently conflict with one another, for example, the fastest deployment strategy may not be the most cost-effective or equitable. Moreover, different organizations may assign varying levels of importance to these objectives based on their institutional values, donor expectations, or operational capacities. As a result, disaster relief efforts unfold in inherently multi-objective settings, where trade-offs are inevitable and optimizing for a single goal is neither realistic nor desirable. Recognizing and explicitly modeling this multi-objective nature is essential for designing decision-making frameworks that reflect real-world complexities and support more effective and accountable humanitarian outcomes.

In high-stakes, resource-constrained environments, perceived inequities in how responsibilities are assigned or outcomes are distributed can quickly lead to dissatisfaction, disengagement, or strategic behavior that undermines collective effectiveness. Fairness ensures that no actor feels disproportionately burdened or insufficiently recognized, fostering a sense of legitimacy and mutual respect among participants. Stability, in turn, reflects the resilience

of coordinated actions—ensuring that no subset of actors has a strong incentive to deviate from the agreed-upon plan. In the absence of fairness and stability, even technically optimal plans can fail in practice due to lack of sustained commitment. Therefore, any approach to improving coordination in disaster relief must account not only for operational efficiency but also for the equitable distribution of efforts and outcomes, ensuring that solutions are both implementable and durable over time.

This research seeks to find innovative solutions for improving coordination in multi-objective, multi-agent humanitarian settings. Existing literature has largely overlooked the challenge of sustaining equitable coordination in decentralized humanitarian settings where multiple actors pursue conflicting objectives. Specifically, there is a critical gap in understanding how fairness-driven coordination can be achieved without centralized authority. The complexity is compounded by the fact that the willingness of autonomous decision makers to coordinate is intrinsically linked to the perceived fairness in the distribution of costs and benefits. This research aims to bridge this gap by developing a framework that is uniquely suited to capture conflicting objectives, diverse agents’ interests, and fairness considerations inherent in disaster relief coordination. Unlike traditional methods, this framework explicitly models the strategic interactions while simultaneously optimizing multiple and competing objectives. By leveraging the strengths of both game theory and multi-objective optimization, this methodology offers a powerful tool for developing innovative, equitable solutions to achieve sustainable coordination for enhancing the efficiency and effectiveness of humanitarian interventions.

1.1 Research Motivation

The primary motivation behind this research is to develop innovative solutions that enhance coordination within complex humanitarian contexts. This work addresses a critical gap in the literature by introducing a formal mathematical framework for identifying equitable allocations in multi-objective, multi-agent settings. Existing approaches neither provide a systematic method for ensuring sustainable and fair coordination in systems characterized by

multiple actors and conflicting objectives nor offer a principled way to quantify the minimum concession required to sustain coordination when perfectly equitable solutions are unattainable. The developed framework delineates how such coordination can be achieved. By quantifying the necessary incentives, the framework aims to improve disaster relief effectiveness through more efficient resource allocation, faster response times, and better outcomes for affected populations.

Furthermore, the research is expected to have substantial societal impact by fostering more effective humanitarian operations and reducing post-disaster suffering. Its focus on real-world applications ensures that the theoretical advancements offer practical benefits for humanitarian practitioners and policymakers. From a scientific standpoint, the integration of cooperative game theory with optimization techniques advances the understanding of complex multi-agent systems and provides novel tools for modeling and analyzing such environments.

Additionally, the developed framework is readily generalizable and can be adapted to other complex multi-stakeholder scenarios, such as public health initiatives, environmental conservation efforts, and urban planning. By promoting fair and efficient collaboration among diverse entities, this work contributes to building more resilient and equitable societies.

1.2 Research Contribution and Organization of the Dissertation

The integration of multi-objective optimization and cooperative game theory particularly in humanitarian contexts is an unexplored area of research. This dissertation seeks to investigate this uncharted research domain. The study emphasizes both theoretical advancement and practical application. Its contributions are expected to enhance operational effectiveness in complex humanitarian scenarios. The research described in this dissertation is designed to achieve three objectives:

1. To investigate the integration of game theory with optimization to model coordination in humanitarian operations in existing academic literature.
2. To develop innovative solutions by integrating cooperative game theory with multi-objective optimization to enable coordination in multi-objective, multi-agent settings.
3. To validate the developed framework to analyze coordination and equitable allocation of costs and benefits in real-world humanitarian logistics scenarios.

1.2.1 State of Current Literature

A comprehensive systematic literature review is presented in Chapter 2. The review reveals significant gaps in the integration of game theory and optimization in humanitarian operations, particularly in decentralized settings with multiple, conflicting objectives. To the best of the author’s knowledge, there exists no comprehensive systematic literature review on the application of game theory and optimization for facilitating coordination in humanitarian operations. The use of cooperative game theory to model multiple and conflicting objectives in decentralized humanitarian settings remains an unexplored area of research. These gaps present significant opportunities for advancing the field. Several key contributions are made to the literature on humanitarian operations:

1. A detailed review protocol is developed and applied using established guidelines. This methodological rigor ensures that the review is evidence-based, reproducible, and transparent.
2. The review addresses three central research questions. First, it assesses the individual potential of game theory and optimization in achieving coordination. Second, it evaluates how the integration of these two modeling approaches can further enhance coordination. Third, it identifies significant gaps in the existing literature.
3. The literature is categorized by modeling approaches, coordination mechanisms, and decision problems. Four coordination mechanisms are identified: resource sharing,

information sharing, contracting, and strategic actions. These mechanisms are mapped to various decision domains.

4. Critical gaps are identified, including limited attention on multiple objectives and cooperative games, a narrow focus on certain disaster phases, and a lack of using real-world data in model validation.
5. A clear definition of coordination is presented to address ambiguity and inconsistent terminology in literature.

1.2.2 Multi-agent Multi-objective Coordination Framework

Chapter 3 builds on the classic core concept from cooperative game theory, which refers to outcomes where no coalition (a subset of actors) would benefit by acting independently. Its extension to the multi-objective domain through the preference core, which requires meeting all targets for every possible coalition, and the nondominance core, which requires satisfying at least one target for each coalition, is then employed to develop a new mathematical concept as well as a novel framework that integrates cooperative game theory with Chebyshev goal programming to address the challenges of multi-agent multi-objective coordination in humanitarian operations. The framework is designed to capture the inherent conflicting objectives, diverse interests, and fairness considerations among participating agents. The research contributions are as follows:

1. The concept of *Chebyshev least core* is introduced and formalized. It extends the classical cooperative game theory least core concept to the multi-objective domain when exact equity cannot be achieved.
2. A novel and rigorous framework, *Cooperative Goal Optimization (CGO)*, to compute the Chebyshev least core is developed. It is a mathematical programming model that features Chebyshev goal programming to balance multiple, differently scaled objectives, while incorporating constraints that model agents' rationality as per cooperative game theory.

3. The CGO framework application is presented as a method for identifying allocations that lie within the preference core, within the nondominance core, or outside both. The approach enables assessment of stability under conflicting objectives, distinguishing between outcomes that are strongly equitable and those that are less comprehensive yet still acceptable.
4. The CGO framework is shown to outperform traditional allocation rules on tested instances.
5. A scenario analysis is conducted to demonstrate the application of the CGO framework, illustrating how varying input parameters influence resulting allocations and player behavior.

1.2.3 Multi-agent Multi-objective Coordination for Hurricane Preparedness and Response

In Chapter 4, the applicability of the developed CGO framework is demonstrated. Specific contributions of this research are as follows:

1. A detailed case study on hurricane preparedness and response is developed, showcasing the application of the CGO framework for multi-agent multi-objective coordination in both operational and strategic dimensions of disaster logistics.
2. How inter-agency coordination results in a broader and more strategically distributed network of facilities, higher levels of demand fulfillment, and significant efficiency gains, is demonstrated.
3. Approaches for distributing costs and benefits are investigated to ensure that coordination remains a stable and mutually beneficial strategy among organizations responding to hurricanes.

1.2.4 Summary

This research addresses the escalating challenges of humanitarian crises by developing an innovative framework for multi-agent multi-objective coordination in humanitarian logistics. Recognizing that no single organization can manage the complexity and urgency of disasters alone, the study integrates cooperative game theory with multi-objective optimization. Specifically, a Cooperative Goal Optimization (CGO) model is developed to capture conflicting objectives, diverse agent interests, and fairness considerations. Through a systematic literature review and the development of a novel coordination framework, the research advances theoretical understanding. It introduces a novel fairness and stability metric, the Chebyshev least core, that identifies minimum adjustment for coordination sustainability. The framework solution also enables identification of allocations that belong to the preference core or nondominance core. A comprehensive case study on hurricane preparedness and response, utilizing a realistic 30-node network, validates the framework by demonstrating that inter-agency coordination leads to a more strategically distributed network of facilities, enhanced demand fulfillment, and significant efficiency gains. Overall, the research makes substantial theoretical and practical contributions, offering tools that can inform policy and improve the effectiveness of humanitarian operations. Future research directions are identified in Chapter 5.

Chapter 2

Game Theory and Optimization for Facilitating Coordination in Humanitarian Operations: A Systematic Review

Chapter 2 is based on the manuscript, “Game Theory and Optimization for Facilitating Coordination in Humanitarian Operations: A Systematic Review,” which is in preparation for submission to a peer-reviewed journal.

2.1 Introduction

Humanitarian operations are challenging. Whether a disaster is sudden-onset or slow-onset, humanitarian actors must consider a holistic approach for delivering aid in which parallel activities are conducted in harmony to meet diverse needs. Operations are complicated by many factors. There are multiple actors involved, from military and governments to donors and beneficiaries, from private sector to non-governmental organizations, to the United Nations and other international agencies. Uncertainties about demand and supply, time and

place, duration and periodicity, information and a priori knowledge are also prevalent. Resources that are limited at the right place may be in overwhelming abundance at the wrong site (Coles and Zhuang, 2011). There is need for urgent action since costs as high as loss of life are associated with delays due to infrastructure damage or bureaucracy. On an international level, humanitarian response can also become a highly politicized action (Tomasini et al., 2009) due to conflict of interest between different organizations.

Under such circumstances, coordination between multiple heterogeneous entities becomes a critical necessity. We define coordination as incentive alignment among multiple entities such that the overall system benefits. The entities maintain their decision-making autonomy, or in other words, they are decentralized. Coordination enables valuable information and asset exchange. It not only helps in aligning incentives for these actors but also paves the way for more predictable behavior of all entities. By limiting effort duplication and facilitating data-driven decision-making, coordination also reduces waste.

Humanitarian operations aim to achieve specific goals in tightly constrained environments. Coordination requires accounting for multiple perspectives. For these reasons, the challenge of advancing coordination in humanitarian operations may benefit from insights gained by applying optimization and/or game theory concepts. This paper presents a systematic literature review to address questions about the extent to which these tools have been used and opportunities to advance such pursuits. Here we note that, although our focus is coordination as defined above, the terms coordination, cooperation, and collaboration are used in literature rather liberally and often interchangeably. When referencing others' work, we will follow the authors' usage.

For readers less familiar with optimization or game theory, we provide a brief description here. Optimization methods seek decision values that maximize or minimize an objective function subject to constraints that define the acceptable decision space (Rardin, 2016). Representing the problems faced by humanitarian actors as optimization models helps quantify factors that drive performance. Game theory uses mathematical models to represent situations of conflict or cooperation between decision-makers, each with actions/decisions and individual preferences. These models assume that individuals behave rationally. Rational

behavior means that “the action chosen by a decision-maker is at least as good, according to her preferences, as every other available action” (Osborne, 2004). There is potential for both competition and cooperation among autonomous humanitarian actors, making game theory a useful lens through which to examine their decisions. Therefore, we wanted to learn if researchers have used optimization as well as game theory while considering coordination among multiple actors in humanitarian settings. The work described in this paper addresses three research questions.

- Research question 1: What is the potential of game theory and optimization individually for facilitating coordination in humanitarian operations?
- Research question 2: How does integration of optimization with game theory support coordination in humanitarian operations?
- Research question 3: What are the gaps that exist in current literature on coordination in humanitarian operations?

We employed a systematic review methodology because it uses a defined process to synthesize the literature in response to specific questions, and the gap identification is evidence-based, transparent, and unbiased (Robinson et al., 2011). Section 2.2 describes the process we followed for conducting this review, and Section 2.3 provides the quantitative results. In Section 2.4 we present a literature analysis and answer the research questions. We offer conclusions in Section 2.5.

2.2 Methodology

We designed the review methodology based on guidelines from Kitchenham (2004) and Tranfield et al. (2003) for conducting evidence-based, thorough, and rigorous systematic reviews in management and engineering. Although systematic reviews are well-established in the medical science community, where this method facilitates evidence-based literature synthesis to inform policy and health interventions (Cochrane Library, 2021), there is a growing

interest in adapting the process in the management and engineering fields. [Tranfield et al. \(2003\)](#) identify challenges and opportunities for producing reliable and context-specific research in management using the systematic review methodology. [Kitchenham \(2004\)](#) offers guidance for conducting a systematic review in engineering. Both present a step-by-step procedure, informed by the Cochrane Reviewers' Handbooks ([Alderson et al., 2003](#); [Clarke and Oxman, 2001](#)) for planning, conducting, and reporting a systematic review in a fair, transparent, and reproducible manner.

2.2.1 Review Protocol

The review protocol specifies steps for conducting the systematic review and reduces the possibility of researcher bias. We followed the widely accepted PRISMA-P checklist for protocol development ([Moher et al., 2015](#)). The protocol components include the rationale for the review, the databases and search strings to consider, inclusion and exclusion criteria for study selection, data management software to use, and data items to include in the data extraction form. This protocol gears the overall process toward answering the research questions specified in Section 2.1. The review protocol is graphically shown in Figure 2.1.

Review Protocol			
Research questions With respect to coordination in humanitarian operations: 1. What is the potential of game theory and optimization individually? 2. How is optimization being integrated with game theory? 3. What gaps exist in current literature?		Eligibility criteria Inclusion criteria 1. Peer reviewed journal articles 2. Subject: Decision sciences, business, engineering, health professions, computer science, multidisciplinary Exclusion criteria 1. Conference papers, book chapters, and reviews 2. 0 citation papers published before 2019	
Search strategy 1. Scoping searches 2. Keyword selection 3. Advanced search		Database 1. Scopus	Data collection 1. Extraction 2. Management

Figure 2.1: The protocol developed for conducting the systematic review.

The significance of coordination in humanitarian operations cannot be overstated. Our rationale for conducting this review is that optimization and game theory have individual strengths and those, when combined, can lead to more informed decision-making. This is important to contest the ever-increasing risks of natural and man-made disasters.

Searches were conducted in the Scopus database. Two search strings were developed, one for game theory and the other for optimization. As there is limited distinction in the literature between the terms ‘coordination’, ‘cooperation’, and ‘collaboration’, we used Boolean operator OR for searching papers using any of these words. The ‘advanced’ search functionality was used. This searches the full article text for terms in the query string and produces results that may be missed using the ‘basic’ search functionality, which includes only title, abstract, and keywords.

Search strings were refined by conducting scoping searches using multiple terms and combinations. Our familiarity with existing literature assisted in developing a search strategy that would capture as many relevant papers as possible. We reviewed abstracts of papers obtained from each scoping search and finalized the following search strings.

1. Optimization: (“Optimization” AND “Humanitarian”) AND (“Cooperation” OR “Coordination” OR “Collaboration”)
2. Game Theory: (“Game Theory” AND “Humanitarian”) AND (“Cooperation” OR “Coordination” OR “Collaboration”)

Several inclusion and exclusion criteria were defined. Only those peer-reviewed journal articles were included in which authors developed mathematical models. Moreover, articles were limited to those where the subject areas were specified as decision sciences, engineering, mathematics, computer science, business, and/or multidisciplinary. Only English language articles were included. We did not specify a publication timeline since we assumed the emphasis on coordination in humanitarian operations is fairly recent. We excluded conference papers, book chapters, and reviews. Papers that were published before 2019 and had no citations were also excluded.

Zotero ¹ and MS Excel were used for data management. The data extraction form evolved as the full-text reviews began. In it, we recorded the following data items for each paper:

1. What are the paper's key objectives from the authors' perspective?
2. Which disaster phases (mitigation, preparedness, response, recovery) are considered?
3. Does the paper use the terms coordination, cooperation, and/or collaboration?
4. Does the paper study inter- and/or intra-organization coordination?
5. Does the paper study vertical and/or horizontal coordination?
6. Does the paper use game theory, optimization, or a combination of both?
7. Has the developed mathematical model been implemented with real data?
8. What limitations have we identified in the paper?
9. What are the authors' key findings?
10. What are the gaps identified by the authors?
11. Does the paper incorporate uncertainty? (for papers that use optimization or both optimization and game theory)
12. Was cooperative or non-cooperative game theory used? (for papers that use game theory or both optimization and game theory)
13. Which coordination mechanism (defined in Section 4) was used?
14. Which decision problems does the paper focus upon?

Several terms in the data extraction form warrant clear definition. Consistent with the literature, our analysis considers four primary disaster phases (Altay and Green, 2006). Mitigation refers to actions taken to prevent a disaster's calamitous effects. Preparedness is

¹<https://www.zotero.org/>

the development of action plans about what should be done, who should do it, and how it will be done when a disaster occurs. Response refers to actions that are taken once a disaster has already occurred. Recovery describes the efforts undertaken to return operations back to normal once the disaster's emergent phase has passed. Vertical coordination pertains to coordination between entities in different hierarchical levels, whereas horizontal coordination refers to coordination among entities operating in parallel hierarchical levels.

2.2.2 Review Process

Review Process		
Initial search		
("Optimization" AND "Humanitarian") AND ("Cooperation" OR "Coordination" OR " Collaboration")		("Game Theory" AND "Humanitarian") AND ("Cooperation" OR "Coordination" OR " Collaboration")
Eligibility criteria		
772 papers		
Abstract screening		
128 papers		
Full text reviews		
Data extraction form pilot testing: randomly selected papers tested by the authors for coherent extraction of targeted information in agreement with each other		Data items extracted: objectives, disaster phases, inter-/intra- organization, vertical/horizontal coordination, solution methodology, uncertainty, coordination mechanisms limitations, findings, gaps
63 papers		
Final in-scope papers analysis		
Statistics	Categorization	Data synthesis
Literature analysis		

Figure 2.2: The process followed for conducting the systematic review in light of the developed protocol.

We implemented the review protocol and conducted the initial document search in March 2020. The review process is shown in Figure 2.2. After applying the search queries in Scopus along with inclusion and exclusion criteria, 772 papers were identified and imported to data

management software Zotero for abstract screening and further review. We used the Scopus database alert function to capture papers that appeared after the initial search date. These Scopus alerts were enabled through Feb 2021 for the search strings used to obtain the initial results, and all resulting papers were saved in Zotero and were subject to the same review process as the initial results.

Abstracts of the 772 papers were screened and tagged as ‘yes’, ‘no’, or ‘maybe’ for being in scope for this systematic review. When a paper’s abstract clearly showed relevance to humanitarian operations and to coordination, cooperation, or collaboration among decentralized entities, it was tagged as ‘yes’. Articles clearly out of scope were tagged as ‘no’. If the abstract was ambiguous with respect to the review’s aims, it was tagged as ‘maybe’. This process resulted in 128 papers (74 yes, 54 maybe).

Full-text reviews began with pilot testing to assess whether the data extraction form enabled coherent collection of targeted information and consistency between reviewers ([Kitchenham, 2004](#)). Three papers were randomly selected. Each co-author completed the data extraction form for these papers. The reviews were found to be consistent.

The pilot process was followed by full-text reviews of all 128 papers led by the first author in regular consultation with the second author. This review identified 63 in-scope papers.

2.3 Results

This section summarizes the characteristics of the 63 in-scope papers based on the dimensions captured in the data extraction form. Of the papers identified, 52% used optimization, 28% considered game theory, and 20% combined game theory and optimization. Inter-organizational coordination was more prevalent, and only one paper studied a combination of coordination and only a handful explored both in combination. These results are shown in Figure [2.3](#).

Coordination in humanitarian operations is a relatively new concept in research. As shown in Figure [2.4](#), the earliest included paper was published in 2010. Annual research publications describing the use of game theory or optimization for coordination in humani-



Figure 2.3: Paper categorization: (a) number of papers using optimization and game theory modeling methods; (b) number of papers modeling inter-organizational and intra-organizational coordination; (c) number of papers in which vertical or horizontal coordination was used.

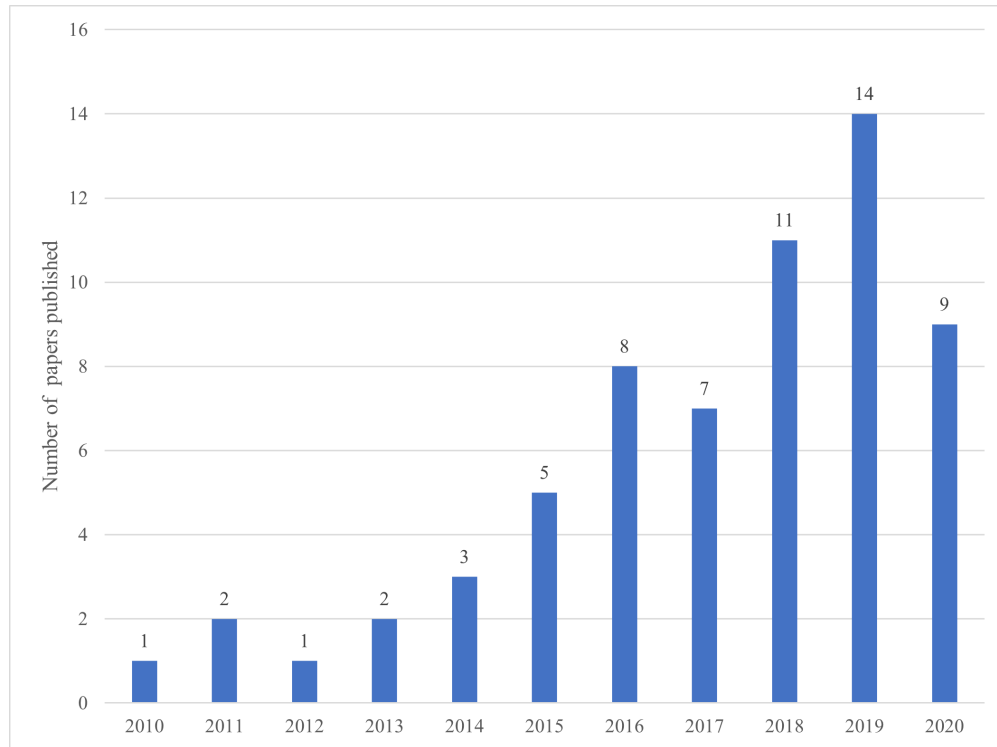


Figure 2.4: In-scope papers by publication year.

tarian operations reached a peak in 2018 and then slowed down a bit.

In-scope papers were published in 33 different journals, many of which published a single relevant paper. Figure 2.5 shows journals that published two or more papers that applied game theory and/or optimization to coordination in humanitarian operations. Many of these released special issues devoted to humanitarian logistics.

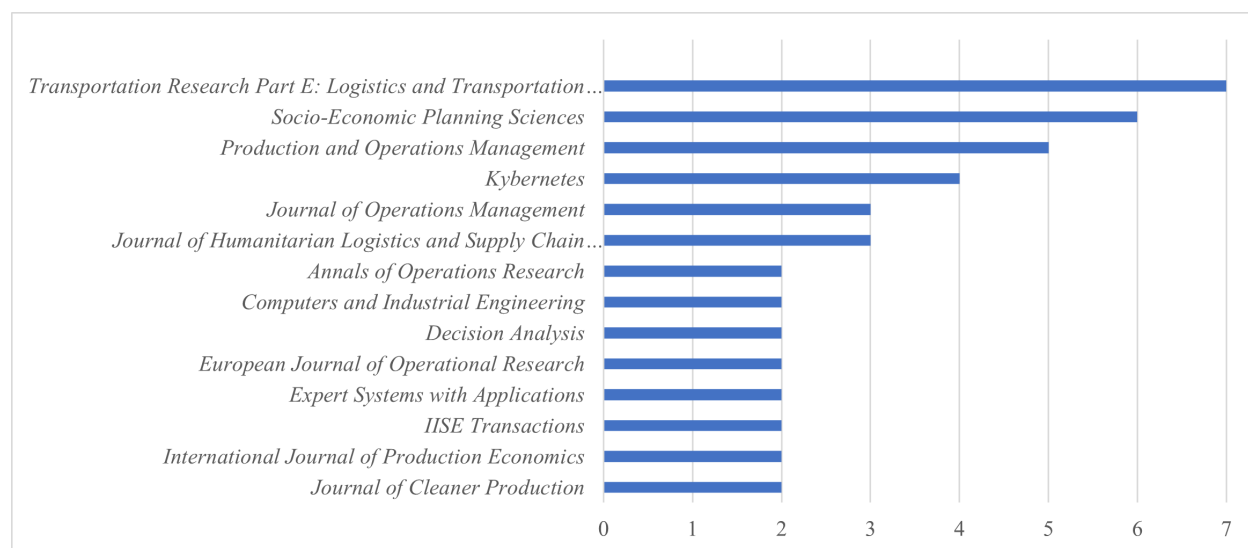


Figure 2.5: Number of in-scope papers published in journals where at least two such papers appear.

The most frequent decision problems modeled in the papers were transportation, supply chain coordination, and inventory management, as illustrated in Fig 2.6. Note that many papers modeled more than one decision problem and therefore the categorization is not mutually exclusive.

Tables 2.1, 2.2, and 2.3 give a more comprehensive overview of the decision problems modeled using game theory, optimization, and a combination of both, respectively.

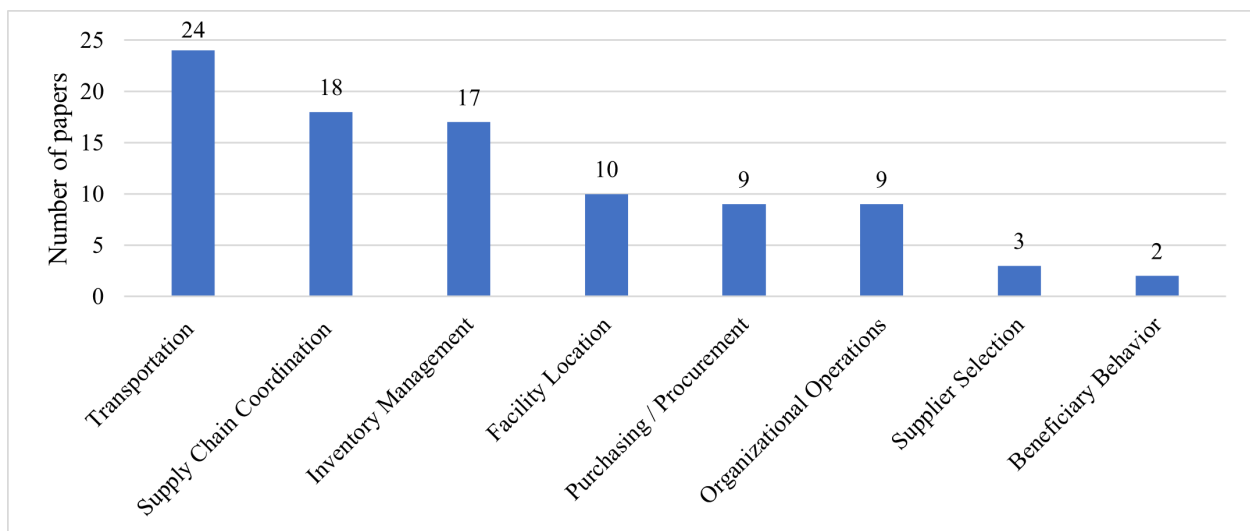


Figure 2.6: Number of in-scope papers that include models for specific decision problems.

Table 2.1: Decision problems modeled for coordination in humanitarian operations using game theory.

Papers	Facility location	Inventory management	Supply chain coordination	Supplier selection	Purchasing / procurement	Transportation	Beneficiary behavior	Organizational operations
Chakravarty 2011			x		x	x		
Toyasaki et al. 2017		x						
Fathalikhani et al. 2020			x					
Ergun et al. 2014			x					
Wakolbinger et al. 2013								x
C. Li et al. 2019								x
Coskun et al. 2019		x						
Fathalikhani et al. 2018								x
Atasu et al. 2017								x
J. Liu and Xie 2016			x					
Gossler et al. 2019			x			x		
Chakravarty 2018								x
Bagchi et al. 2011					x			x
Westerink-Duijzer et al. 2020		x						
Y. Liu et al. 2019			x					
Hu et al. 2019			x					
L. Zhang et al. 2019			x	x	x			
John et al. 2020			x		x			
Total	0	3	9	1	4	2	0	6

Table 2.2: Decision problems modeled for coordination in humanitarian operations using optimization.

Papers	Facility location	Inventory management	Supply chain coordination	Supplier selection	Purchasing / procurement	Transportation	Beneficiary behavior	Organizational operations
Fikar et al. 2016						x		
Maharjan and Hanaoka 2018	x					x		
Regis-Hernández et al. 2017						x		
Aghajani et al. 2020		x	x	x				
Balcik et al. 2019	x	x						
X. Li et al. 2018	x					x		
Higo et al. 2017							x	
Rodríguez-Espíndola et al. 2018a	x	x			x	x		
Rodríguez-Espíndola et al. 2018b						x		
Kochan et al. 2018		x						x
Ali Torabi et al. 2018		x	x	x	x	x		
Adivar and Mert 2010						x		
Davis et al. 2013		x						
Velasquez et al. 2019		x						
J. Chen et al. 2018		x						
Nagurney and Qiang 2020		x			x	x		
Sheu and Pan 2015				x		x		
J.-H. Zhang et al. 2017		x	x					
Y. Chen et al. 2016	x							
Ben Othman et al. 2017						x		
Battini et al. 2014						x		
Akbarpour et al. 2020	x	x	x			x		
Maharjan and Hanaoka 2019	x							
Jahre et al. 2016	x	x						
Rabbani et al. 2015			x					
Acimovic and Goentzel 2016		x						
Diedrichs et al. 2016						x		
Setiawan et al. 2019	x					x		
Kamyabniya et al. 2018	x	x				x		
Zhao et al. 2012								x
Davari 2019	x							x
Total	11	14	5	3	3	16	1	3

Table 2.3: Decision problems modeled for coordination in humanitarian operations using game theory and optimization.

Papers	Facility location	Inventory management	Supply chain coordination	Supplier selection	Purchasing / procurement	Transportation	Beneficiary behavior	Organizational operations
Pedraza-Martinez et al. 2020						x		
Balza-Franco et al. 2017						x		
Nagurney et al. 2016a						x		
Kamyabniya et al. 2019			x					
Nagurney et al. 2019					x	x		
Muggy and Heier Stamm 2020							x	
Bhattacharya et al. 2014			x					
Toyasaki and Wakolbinger 2019								x
Guan et al. 2018								x
Guan and Zhuang 2015								x
Wang et al. 2015			x		x			
Delkhosh 2020						x		
Fereiduni et al. 2016						x		
Camacho-Vallejo et al. 2015					x			
Total	0	0	3	0	3	6	1	3

An important aspect of this review was to identify whether researchers used data to demonstrate the applicability of and generate insight stemming from the use of the models. In 46% of the papers, the mathematical models were implemented using case studies and/or actual data, the latter retrieved from reliable disaster databases or collected through surveys, interviews, and published reports. Some papers developed estimates given the limited availability of information for specific disasters.

With respect to the four disaster phases, we discovered that a major portion of papers focused on the response phase, followed by preparedness, and preparedness and response both. Only one paper studied coordination during the recovery phase of a disaster and one paper focused on mitigation (Fig 2.7).

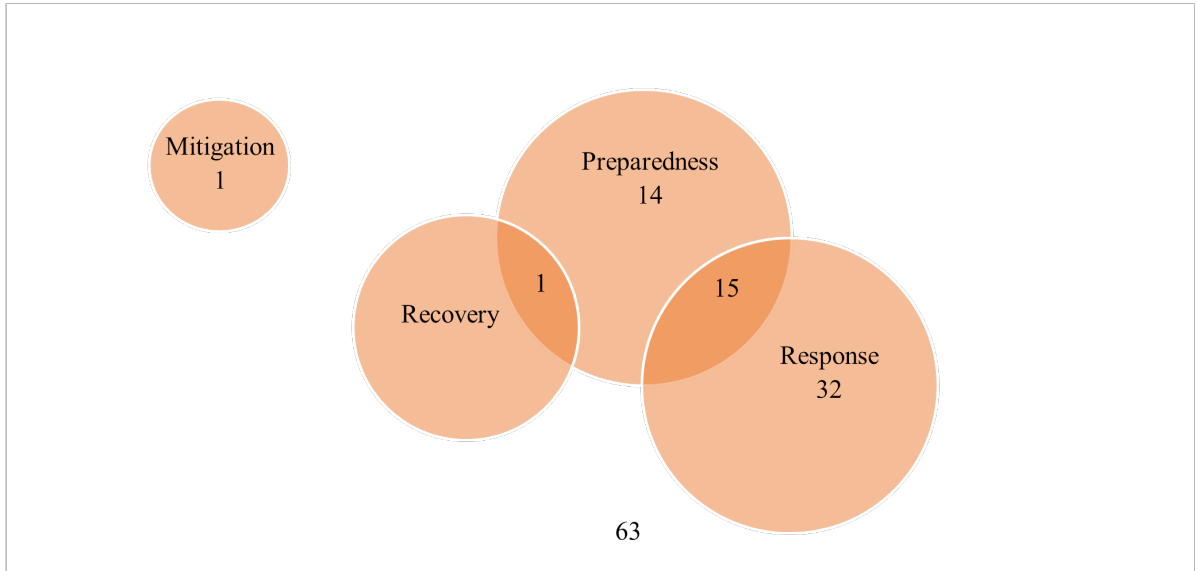


Figure 2.7: Number of papers focusing on each disaster phase and their combinations.

During data extraction, we categorized papers according to the type of game theory and/or optimization models used. In so doing, we found that non-cooperative game models were used much more frequently than cooperative game models. As shown in Fig 2.8, only 2 papers out of 18 in the game theory category and 1 paper out of 13 in the optimization and game theory category modeled a cooperative game.

We found that many models take into account uncertainty, a significant factor that influences decisions in humanitarian operations. Fig 2.9 shows the statistics, namely, that

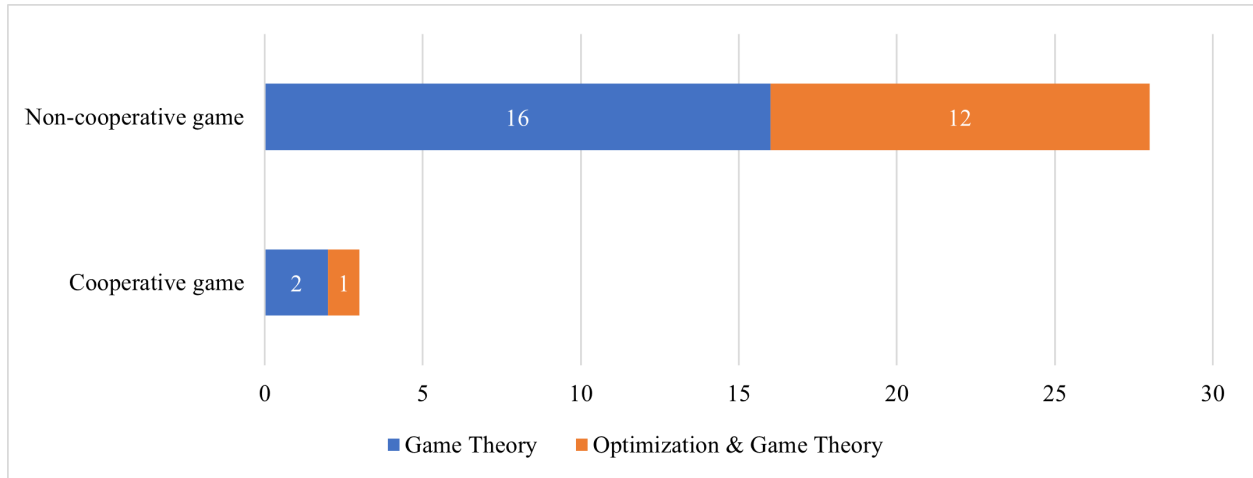


Figure 2.8: Among papers with game theory models or both optimization and game theory models, the number of in-scope papers that use non-cooperative game models vs. cooperative game models.

24 papers that use optimization present stochastic models while 20 present deterministic models.

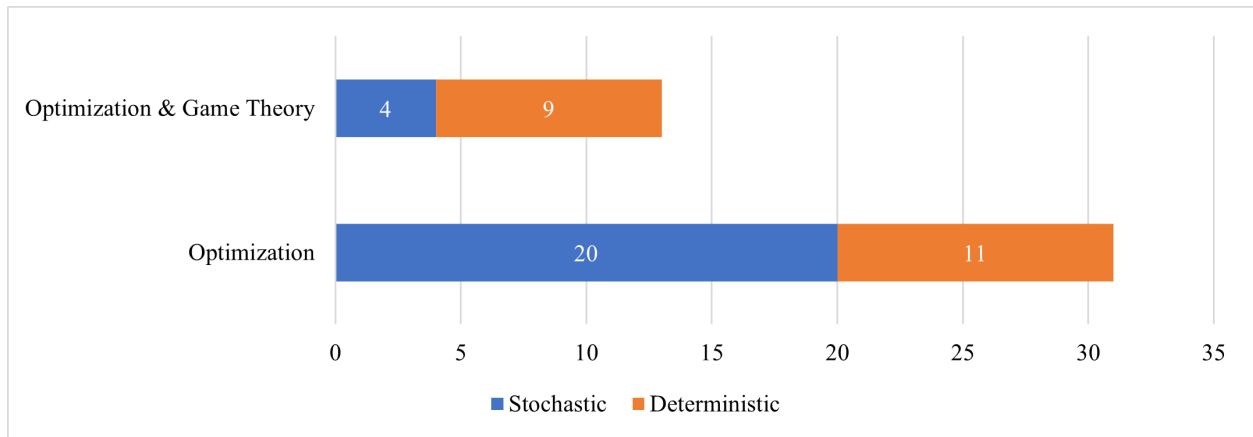


Figure 2.9: Among papers with optimization models or both optimization and game theory models, the number of in-scope papers that use deterministic models vs. stochastic models.

2.4 Literature Analysis

This section synthesizes all the in-scope papers to answer the three research questions we posed. For the first two research questions we present the papers according to whether they use game theory, optimization, or both optimization and game theory. For the third research

question we focus on the identified gaps and present insights for future research.

In summarizing our findings for research questions 1 and 2, we identify coordination mechanisms that have been dominant focus areas in the literature. A coordination mechanism is the set of actions taken to facilitate coordination. In our analysis we identified four patterns that are considered coordination mechanisms. These are resource sharing, information sharing, contracting, and strategic actions. Resource sharing refers to different parties sharing common resources, such as a warehouse to store relief supplies in preparedness for a disaster. Information sharing refers to disseminating information that results in better response from multiple humanitarian actors, such as developing and utilizing a communication network among suppliers and relief workers for real-time demand and supply monitoring. Contracting is the practice of setting up binding agreements among actors, such as a supplier and a non-profit organization arranging for provision of relief items at agreed upon conditions and prices. Strategic actions refer to decisions made about an organization’s practices or policies in accord with its objectives and its understanding about others’ actions and objectives. A strategic action can either be cooperative or competitive. Such actions can lead to a win-win solution that benefits the entire system without a central authority controlling each entity’s actions. Incentive alignment may be achieved even if actors are in competition with each other, such as when total social welfare increases due to relief agencies competing to fulfill demand at a disaster site.

The conceptual map in Fig 2.10 is a visual illustration of answers to the research questions. It shows the relationships between primary modeling approaches, coordination mechanisms, and decision problems identified through this systematic review. The central idea is coordination, from where three arcs originate and enter level 1 circles, representing modeling approaches, respectively, game theory, optimization, and game theory and optimization. From these circles, further arcs and level 2 circles emerge, which represent the coordination mechanisms used in each modeling domain. Finally, the arcs terminate at level 3 circles, which represent the decision problems modeled. Each circle’s size corresponds to the number of papers in that level. Coordination mechanisms are color-coded to easily identify dominant focus areas. Thus, the map helps translate information about how much focus has

been put on each class of decision problems: transportation, inventory management, supply chain coordination, organizational operations, facility location, supplier selection, beneficiary behavior, victim's behavior, purchasing/procurement; using each coordination mechanism: resource sharing, contracting, information sharing, strategic actions, others; and using each modeling approach: game theory, optimization, game theory and optimization.

2.4.1 Research Question 1: What is the potential of game theory and optimization individually for facilitating coordination in humanitarian operations?

2.4.1.1 Game theory

Game theory models have demonstrated potential for facilitating coordination in humanitarian operations in several decision domains, as evidenced by their application in 28% of the surveyed papers. Supply chain coordination was the dominant decision problem followed by organizational operations, transportation, and inventory management. Out of the 18 papers that employ game theory, 16 use non-cooperative game models. All four coordination mechanisms are observed, with contracting the most common and resource sharing the least common in the analyzed literature.

Contracting Contracts act as a bridge connecting multiple stakeholders and provide mutually beneficial solutions to each. Option contracts, which stem from the concept of financial derivatives ([Black and Scholes, 1973](#)), appear frequently as a coordination mechanism in the studied literature given their flexibility and risk-sharing properties. In the humanitarian supply chain coordination context, an option contract allows demand risk sharing by giving the buyer a right, but not obligation, to purchase relief items at a preset price before and after the disaster. At the same time, it also allows the supplier to charge a premium pre-disaster for its commitment to meet the demand post-disaster. [John et al. \(2020\)](#) study how risks associated with inventory understocking or overstocking for a buyer and with overproduction

for a supplier, respectively, can be mitigated using option contracts in a Stackelberg setting between a humanitarian organization and a supplier. [Liu et al. \(2019\)](#) develop a Stackelberg game between government and suppliers to find the optimal relief supply quantities for the government to stock as immediate response inventory and the optimal prepositioning quantity for the suppliers to meet capacity after the disaster. On the other hand, [Hu et al. \(2019\)](#) show the superiority of a put option contract (where the option lies with the seller) over buyback and wholesale price contracts by demonstrating that optimal order quantities with the option contract are higher, thus better meeting need for durable relief items such as tents and sleeping bags.

Negotiations allow entities to come to agreement over action sets and principles, thereby facilitating coordination among them. [Gossler et al. \(2019\)](#) study the impact of transportation rates on distribution decisions as humanitarian organizations negotiate framework agreements with transportation carriers and compete for transportation capacity. [Liu and Xie \(2016\)](#) develop evolutionarily stable equilibria considering suppliers' and the government's decision preferences. They propose an action principle for negotiations that allows the suppliers to maximize their profit while the government is able to acquire high quality relief items with minimized cost. A quantity commitment contract between government and suppliers with a focus on recycling and replenishment of emergency relief items is developed by [Zhang et al. \(2019\)](#), where they find that it is in government's best interest to cooperate with suppliers who have lower operational costs and bigger market shares.

Disasters cause infrastructure destruction that may hamper relief operations. Only one paper used contracting to tackle this significant aspect: [Chakravarty \(2011\)](#) develop contracts between humanitarian organizations and an infrastructure provider to minimize post-disaster social cost by decreasing delay in infrastructure repair and increasing resource provision to disaster sites through a contingent response plan.

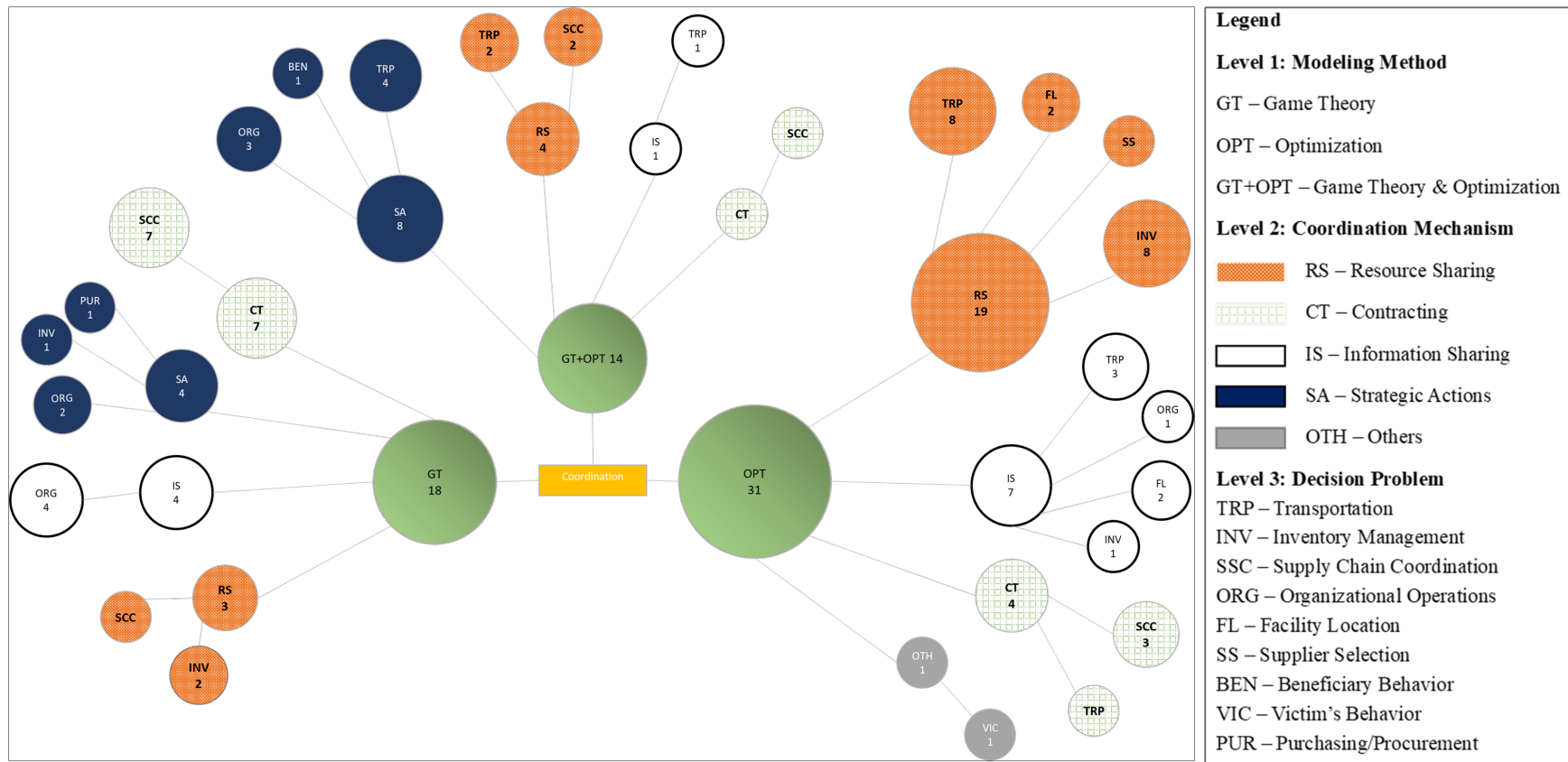


Figure 2.10: Conceptual map of in-scope papers categorized by modeling methods (Level 1), coordination mechanisms (Level 2), and decision problems (Level 3); color (or shade / pattern) identifies coordination mechanism used and circle size corresponds to number of papers.

Information sharing Information sharing is the second dominant coordination mechanism observed in game theory papers. Direct as well as indirect information sharing among cooperative and competitive players has been shown to facilitate alignment of incentives leading to better outcomes for social good.

Coordination is not easy to achieve when organizations are reluctant to share information due to the risk of losing their competitive edge. Keeping this predicament in perspective, a combination of cooperation and competition termed as coopetition has been studied by [Wakolbinger et al. \(2013\)](#), [Fathalikhani et al. \(2018\)](#), and [Fathalikhani et al. \(2020\)](#). Information sharing may directly or indirectly facilitate coordination. The former is explored by [Wakolbinger et al. \(2013\)](#) using a framework to explain aid agencies' behaviors when they cooperate for effectiveness but compete for donations in context of information technology-enabled information sharing. The ad hoc nature of disasters may not allow developing long-term relationships among organizations; thus, information sharing is a critical but expensive choice. Information sharing also benefits the overall system indirectly when non-profits that rely mostly on donations are able to disclose more information to donors about their relief activities. Two studies note that both total donations and social welfare increase when non-governmental organizations (NGOs) enter a coopetition scenario; the Stackelberg models consider the roles of NGOs and donors ([Fathalikhani et al., 2018](#)) and NGOs, donors, and government ([Fathalikhani et al., 2020](#)), respectively.

Strategic actions Strategic actions can align objectives among multiple players and play a pivotal role in achieving coordination that benefits the overall system. Using strategy to facilitate coordination provides the opportunity for players with complementary as well as conflicting objectives to come together.

Relief organizations and governments often have complementary objectives since both aim to reduce overall social cost. Even so, it may not be possible for organizations to coordinate due to incentive misalignment. Such interactions between government and relief organizations in context of flood mitigation are studied by [Chakravarty \(2018\)](#). Pre- and post-disaster actions, such as fundraising and supply procurement by the relief organization

and building levee capacity by the government, are integrated to develop a sequential game that shows how strategic coordination can make efficient disaster preparedness and effective disaster response possible. [Toyasaki et al. \(2017\)](#) find that incentive misalignment between the United Nations Humanitarian Response Depot and the humanitarian organizations operating under the agency’s umbrella causes sub-optimal system performance. They develop a newsvendor model to analyze inventory management practices. Based on their analysis, they provide managerial recommendations that can facilitate system optimality in a horizontal coordination scenario by resolving issues that cause this misalignment.

Achieving coordination among players with conflicting objectives is a challenging task. [Bagchi et al. \(2011\)](#) study the auction-based procurement process used by the US Department of Agriculture to match bids from international food aid suppliers and ocean carriers. The system incentivized gaming and inflated bids. The authors propose a uniform price auction that pairs suppliers and carriers before bidding to help identify operational cost savings available through transshipment and routing. This enabled lower joint bids and increased the amount of food aid that can be transported to beneficiaries. [Atasu et al. \(2017\)](#) find that making operational changes can also facilitate coordination when conflicting objectives are present. They propose a pull-based inventory management process to eliminate recipient competition and improve resource allocation practices used by a medical surplus recovery organization, which deploys unused or donated medical supplies to fulfill needs of underserved healthcare facilities in developing countries. In the presence of conflicting objectives, organizations must also evaluate whether coordination will prove beneficial or not. [Li et al. \(2019\)](#) develop a game theory model to determine whether, in the absence of perfect information, coordination between a humanitarian organization and the private sector is an optimal strategy, and, if so, how to coordinate effectively.

Resource sharing We found that resource sharing is the least studied coordination mechanism in the game theory papers. [Coskun et al. \(2019\)](#) incorporate disaster risk into a newsvendor model to analyze horizontal coordination between two relief aid agencies. A Nash equilibrium is found for the optimal stock quantities to be prepositioned in disaster

prone areas. The resource sharing category is also the only one where we found cooperative game theory models employed. [Ergün et al. \(2014\)](#) develop a cooperative game theory model to study how information technology tools may facilitate collaboration among multiple agencies responding to a disaster. The proposed system has benefits and costs, and the agencies' decisions depend on the cost allocation among them. The authors analyze conditions for which a cost allocation mechanism incentivizes coordination and note that simple proportional mechanisms are not sufficient. [Westerink-Duijzer et al. \(2020\)](#) also use cooperative game theory from a resource sharing perspective to study the effect of sharing vaccine doses among different health agencies to fight an infectious disease outbreak. The model considers both direct and indirect cooperation costs, and the authors analyze conditions under which a stable (core) cost allocation among players exists.

2.4.1.2 Optimization

The potential of optimization for facilitating coordination in humanitarian operations has been demonstrated in the literature, and research in various decision domains is growing. Models focused on transportation decision problems are the most prevalent followed by those considering inventory management. Several papers consider multiple and/or integrated decision problems, yet comparatively few study organizational operations, facility location, supplier selection, or supply chain coordination. In contrast to what we observed in the game theory category, resource sharing was found to be the most dominant coordination mechanism used in the optimization category, followed by information sharing and contracting.

Resource sharing Resource sharing is the most frequently observed coordination mechanism in optimization papers, and this approach has been applied to facilitate coordination in several settings. Organizations can increase demand satisfaction and their overall utility while minimizing effort duplication by sharing transportation assets, temporary medical facilities, and inventory spaces. Better informed decision-making is also enabled when decisions related to facility location and supplier selection are based on coordination among stakehold-

ers. In our review, we find that transportation assets are the most widely studied shared resources. This occurs, for example, when different organizations share vehicles or use the same freight carriers to deliver supplies. Related to this, other researchers have noted that transportation is the most studied decision problem in humanitarian logistics ([Besiou et al., 2018](#)). Last mile distribution is a crucial task in disaster response and a natural application for optimization methods. [Fikar et al. \(2016\)](#) develop a simulation and optimization based decision support system (DSS) considering disaster impacts on transportation infrastructure to analyze last mile distribution decisions. The system facilitates coordination between private and relief organizations for shipments traversing between demand, transfer, and supply points. A mixed integer program is developed to minimize the lead time, and it is found that coordination is particularly useful when lead time increases due to closed roads causing demand surge. Last mile distribution using co-transportation and multiple modes is studied by [Battini et al. \(2014\)](#) using integer programming. Co-transportation means that different suppliers use the same vehicle for shipping, and trucks and helicopters are included. The model is implemented on aid distribution data from Haiti, where two organizations, World Food Program and United Nations Children’s Fund, distributed food and hygiene kits.

Researchers also have studied agencies that share resources in the form of temporary facilities established to speed distribution and delivery processes during disaster response activities. Coordination between these facilities and the main respondents is critical for minimizing waste and duplication as well as maximizing humanitarian actors’ abilities to fulfill their objectives. [Kamyabniya et al. \(2018\)](#) study vertical and horizontal coordination among hospitals, blood centers, and temporary emergency shelters to fulfill platelet demand more efficiently in response to a sudden-onset disaster. The default coordination mechanism is the vertical coordination from blood centers to hospitals and temporary emergency shelters. The study contrasts this with a proposed horizontal resource sharing mechanism where hospitals with excess supply can act as suppliers to provide platelets to hospitals in need. This system reduces the overall cost and increases platelet distribution efficiency by reducing wastage and response time. [Setiawan et al. \(2019\)](#) also consider the significance of temporary facilities and develop three different mathematical models to tackle decisions about locating

temporary medical and relief distribution facilities, allocation of vehicles and disaster sites to these facilities for relief distribution, and evacuating victims from the disaster sites. The authors conclude that resource sharing across geographic boundaries and across different relief activities can improve upon current practices in location, allocation, distribution, and evacuation.

Resource sharing can help avoid effort duplication, which can be counterproductive in disaster response and may result in increased social cost. The problem of minimizing duplicate efforts and service gaps has been studied by [Nagurney and Qiang \(2020\)](#). The authors develop models with and without horizontal cooperation among humanitarian organizations responding to a slow-onset disaster in a multiproduct supply chain context. The synergy associated with cooperation is measured as the percentage difference between total costs with and without cooperation. Using numerical examples, the authors demonstrate greater benefits for both the humanitarian organizations and the impacted populations in the cooperative scenario. [Rodríguez-Espíndola et al. \(2018a\)](#) consider the effectiveness of multiple organizations responding to a disaster at the same time. The authors use geographic information systems analysis to obtain information about flood risk and potential damages and incorporate this into optimization models. The result is a tailored combination of organizations and resources for each scenario that maximizes efficiency and effectiveness, eliminates effort duplication, and helps avoid resource shortage by limiting unnecessary flow of material and human resources. The authors conclude that simply having more organizations involved in disaster relief may not give the best outcome. In a similar work, [Rodríguez-Espíndola et al. \(2018b\)](#) use optimization to investigate how multiple organizations can be coordinated and how the required environment can be created for coordination to occur by optimizing the number of participants to work towards a common goal. They develop a mixed integer program that models multiple commodities, time periods, and transportation modes while multiple organizations respond to a disaster.

Coordination facilitated by resource sharing for prepositioning and inventory management has been studied considerably in the literature. Prepositioning relief items is among the most common disaster preparedness measures. It is cost-effective in comparison to ship-

ping items post-disaster and reduces lead time. In a multi-country context, [Balcik et al. \(2019\)](#) propose that horizontal coordination can be incentivized by using fair cost allocation mechanisms. They develop a two-stage stochastic model for joint prepositioning and use insurance theory to allocate the costs among Caribbean countries for a collective regional response to hurricanes. [Davis et al. \(2013\)](#) also consider a hurricane scenario and develop a two-stage stochastic program. The authors assume there exists a cooperative network willing to share reserve capacity and supplies in response to a disaster, while its members work autonomously in routine operations. The idea is to reposition the local inventory as needed based on the hurricane forecast and preposition items acquired from external suppliers within the critical first 48 hours after a hurricane watch is issued. [Acimovic and Goentzel \(2016\)](#) describe another application involving inventory prepositioning by multiple organizations at multiple locations via a two-stage stochastic program. The model first determines where to stockpile and then allocates supply to demand. By analyzing the model’s output, sector wide metrics are developed. The metrics not only quantify current system performance and highlight how coordinated decision-making is more beneficial than individual decision-making, but also help estimate the value that specific tactical decisions produce.

[Chen et al. \(2018\)](#) study prepositioning of multiple products governed by coordination between the relief agency and the supplier using a newsvendor approach. The model tackles overage and underage risks while considering the uncertainties related to disaster occurrence, demand, and post-disaster donation availability. [Li et al. \(2018\)](#) focus on maximizing appeal coverage (ratio of demand covered to demand needed) by proposing horizontal coordination among multiple NGOs’ distribution centers to better utilize their capacity. Their model demonstrates that allowing NGOs to use each other’s facilities minimizes the need to establish independent temporary distribution centers, increasing funds available for procuring supplies to meet disaster demands. [Adivar and Mert \(2010\)](#) do not explicitly consider prepositioning but model the United Nations’ practice of consolidating relief items at their collection points in the affected country preceding transportation to final delivery points, minimizing total cost and maximizing credibility. Credibility is defined as ‘meeting the needs on time’; it is quantified as a nonlinear fuzzy function and calculated based on each item’s arrival time at

the entry point. The authors consider uncertainty and imprecision in decision-making and use a fuzzy credibility-based model to prioritize and allocate resources for disaster relief.

Government bodies, United Nations entities, and major international NGOs have expansive supply chains focusing on different objectives, and intra-organizational coordination between such systems has been explored in the literature. [Jahre et al. \(2016\)](#) develop a stochastic scenario-based mathematical program to study a warehouse location problem for joint prepositioning by integrating United Nations High Commissioner for Refugees' ongoing operations and emergency response supply chains. The model accounts for the two supply chains' differing objectives. The authors find that network redesign by merging the two supply chains helps capture scale economies, reduce lead time, and reduce need for costly air transport due to improved planning before an emergency occurs. Joint reserves, a prepositioning strategy in which a government and relief suppliers coordinate such that distribution centers set up by government are used by suppliers to store items, has also been studied. The strategy decreases suppliers' inventory costs and increases demand satisfaction for the government. [Velasquez et al. \(2019\)](#) demonstrate this with a robust three-level supply chain model that consists of NGOs and suppliers, distribution centers, and demand points, respectively. [Zhang et al. \(2017\)](#) use a framework agreement to develop a joint reserves model between government and relief suppliers.

We found two papers that employ optimization to examine coordinated facility location decisions in a resource sharing context. [Chen et al. \(2016\)](#) develop a facility location model for an area with several regions. They propose regional cooperation while maintaining a territorial priority principle and demonstrate with a scenario-based model how such cooperation minimizes maximum expected cost of each region. [Davari \(2019\)](#) uses a multi-period facility location model to design a cooperative preventive healthcare network by integrating search heuristics and integer programming. The network is designed using a non-linear mixed integer program in which facilities are added incrementally to the network and all facilities cooperate to provide services to the population centers.

Supplier selection ensures that the right suppliers are chosen based on their capability to meet specific needs, as well as their ability to collaborate with aid agencies. [Sheu and](#)

[Pan \(2015\)](#) develop a supplier selection model that utilizes fuzzy clustering and stochastic dynamic programming to overcome lack of coordination in humanitarian response efforts. The model aims to assist governments in identifying NGOs that are willing to collaborate with each other and have the required collaborative attributes, such as incentive alignment and resource and information sharing, to improve disaster response. The model initially categorizes NGOs based on their collaborative attributes and then determines the necessary quantity of relief resources to allocate.

Information sharing Information sharing is the second most common coordination mechanism observed in optimization papers. The criticality of information sharing among in humanitarian operations cannot be overstated as it can support effective communication, identification of stakeholders’ preferences, and improved supply chain visibility, all contributing to better coordination. Coordination facilitated by communication between relief actors can prevent effort duplication and resource mismanagement. [Diedrichs et al. \(2016\)](#) use system dynamics and superimpose a transportation network with a communication network to quantify the significance of information sharing for logistical coordination. In the absence of effective information flow, a surplus of certain items and a shortage of others occurs, thereby increasing monetary costs and loss of life as measured by time deprivation in demand fulfillment. [Ben Othman et al. \(2017\)](#) and [Zhao et al. \(2012\)](#) also model communication networks among multiple stakeholders responding to a disaster using an agent-based modeling approach. These models are not only examples of successful inter-organizational coordination backed by information sharing, but they can also serve as helpful tools for humanitarian logisticians to automate decision-making tasks in a coordinated manner in the field.

It is often not possible to find a solution that satisfies all stakeholders’ preferences; however, information sharing can help achieve a good solution that satisfies most preferences. [Regis-Hernández et al. \(2017\)](#) use the analytic hierarchy process to translate qualitative preferences obtained from literature into quantitative measures. They develop a framework that allows information exchange among different levels of decision-making. Incorporating preferences into an optimization model facilitates vertical coordination between government,

NGOs, donors, private organizations, and the military. [Maharjan and Hanaoka \(2018, 2019\)](#) propose decision-making frameworks where coordination happens through information exchange between the entities involved, which are then used to make optimal decisions that benefit the overall system. The first paper uses an optimization model to implicitly coordinate the entities to find the optimal location of temporary logistics hubs, while the second paper uses a group decision-making method to explicitly coordinate the stakeholders to find the order in which the hubs should be established.

The supply chain visibility that information sharing provides also greatly improves performance in context of inventory control, order fulfillment, and order placement and production processes. [Kochan et al. \(2018\)](#) use causal loop diagrams and equivalent system dynamics models to analyze hospital supply chains' performance if coordination between the hospital pharmacy, the pharmaceutical distributor, and the manufacturer is facilitated by cloud-based information sharing. A simulation-based comparison between a traditional supply chain and one with cloud-based information sharing shows that inventory, supply, and shortage costs are reduced in the latter.

Information sharing among individuals impacted by disaster may also prove useful. [Higo et al. \(2017\)](#) focus on such coordination. They develop a multi-agent-based simulation model to study flood evacuation. Agents are modeled as autonomous entities that can communicate with each other, share information, and make decisions based on their individual goals and their group's goals. The authors introduce rules that incentivize agents to help each other during the evacuation process. The simulation results show that cooperation can significantly improve the survival rate of individuals and groups during underground flooding scenarios.

Contracting Contracting has also been proposed as a coordination mechanism in relief supply chains in optimization papers. We find that option contracts have been a major focus area for researchers, though other contract structures also may facilitate coordination and have been studied.

Contracting most frequently is used to facilitate vertical coordination. [Akbarpour et al. \(2020\)](#) develop an option contract between the humanitarian organizations (or government)

and suppliers to preposition pharmaceutical items considering demand uncertainty and perishability. The contract allows items to be returned before their expiration if they are not utilized. [Aghajani et al. \(2020\)](#) consider option contracts between a humanitarian organization and multiple suppliers and develop a multi-objective scenario-based mixed possibilistic stochastic programming model. The authors find conditions that increase responsiveness for critical items and improve cost-efficiency for non-critical items. In the model proposed by [Rabbani et al. \(2015\)](#), disaster intensity is a factor in the number of contract options that can be exercised to supply relief items for disaster victims. [Ali Torabi et al. \(2018\)](#) develop a quantity flexibility contract between a supplier and a relief organization to integrate decisions related to prepositioning and early post-disaster (first 72 h) procurement. For a fixed cost, the contract allows for pre-disaster orders to be prepositioned at central and local warehouses and for post-disaster secondary orders to be fulfilled by the supplier directly to local warehouses. Compared with the current practice, this contract increases responsiveness and cost-efficiency by decreasing prepositioned quantities.

2.4.2 Research Question 2: How does integration of optimization with game theory support coordination in humanitarian operations?

Game theory and optimization were integrated in 14 in-scope papers. We observe that integration of game theory and optimization has been done in three different ways: 1) best response functions of different players developed using non-cooperative game theory are incorporated into an optimization model; 2) an optimization model maximizes savings or minimizes costs, which are then allocated using cooperative game theory principles; and 3) multi-level leader-follower models are developed in a sequential game framework and each level is solved as an optimization model. Therefore, we find evidence that integrating optimization with game theory supports coordination in humanitarian operations. Literature analysis shows researchers applied this concept to study decision problems including beneficiary behavior, supply chain coordination, transportation, organizational operations, and

procurement. Strategic actions appeared as the most common coordination mechanisms in these papers, followed by resource sharing and contracting. Information sharing was not observed in any studies. Research shows incentive alignment is possible by integrating game theory and optimization, whether players cooperate or compete with each other.

Strategic actions Coordination among different organizations responding to a disaster can be achieved even if each organization operates independently. This can be achieved by taking strategic actions that benefit the overall system. Conflicting objectives due to imperfect information can cause difficulty in incentive alignment even within an organization. Using the mechanism design concept where the principal can design a game that can influence other players' actions, [Pedraza-Martinez et al. \(2020\)](#) consider a fleet coordination problem in an international humanitarian organization with a decentralized structure comprising two decision-making parties whose misaligned incentives lead to subpar system performance. The authors develop a mechanism for incentive alignment that reduces the overall system cost and helps to achieve a centralized benchmark solution despite a decentralized decision-making structure. [Nagurney et al. \(2016\)](#) also study decentralized decision-making using noncooperative game theory to explore the effect of shared constraints for demand fulfillment on competing NGOs during post-disaster humanitarian relief operations. A contrast of Nash and generalized Nash equilibrium solutions shows that with the Nash equilibrium, NGOs maximize their utility at the expense of those in need due to increased waste, whereas a generalized Nash equilibrium guarantees that there will be no waste.

Strategic orientation of goals can enable coordination between government and other organizations, making efficient disaster response possible. [Fereiduni et al. \(2016\)](#) develop a bi-level model where the government of an earthquake-affected country is the leader and international relief organizations as suppliers are the followers. The government tries to minimize total evacuation and distribution costs, and the international suppliers try to minimize their transportation costs. To deal with demand uncertainties, the authors propose a robust model. Considerable total cost reductions were observed when the model was illustrated using a case study. [Camacho-Vallejo et al. \(2015\)](#) develop a similar bi-level model to highlight

the significance of two coordination modes: (1) between aid agencies sending relief materials to a country, and (2) between the country’s government and foreign aid agencies. [Delkhosh \(2020\)](#) focuses on large magnitude disasters in which a government may have limited ability to respond. The author develops a dynamic multi-level programming model in which local government and international relief suppliers are players and each level is an optimization model. The overall system works as a sequential game where government seeks to minimize unmet demand and operational costs of evacuation and rescue, and relief agencies seek to minimize their transportation costs. A case study shows significant reduction in unsatisfied demand and total costs. [Guan and Zhuang \(2015\)](#) focus on interactions between public and private sector using sequential games with sub-game perfect Nash equilibrium. The public sector moves first by subsidizing private sector investments in damage reduction. The private sector then makes an investment to protect the target. Both parties try to minimize their expected cost. In a similar study, [Guan et al. \(2018\)](#) explore public-private partnerships and account for the private sector actor’s risk preferences. They find that, for any public subsidy level, a risk-averse private sector entity invests most, while a risk-seeking entity invests least. Results from a behavioral experiment with 91 participants’ responses confirm those from the model.

Few papers focus on coordination among organizations and individuals who play a role in disaster response, such as donors or beneficiaries. [Toyasaki and Wakolbinger \(2019\)](#) develop two sequential game theory models to study the behavior of donors and aid agencies. In competitive mode, two humanitarian organizations and donors are players, and donors decide how to allocate their donations among different aid agencies. In joint mode, first an intermediary organization proposes a predetermined allocation rule, followed by aid agencies’ decisions to participate in or decline joint fundraising. After the participating agency sets their fundraising expenses, donors choose their contributions, but they have no discretion over allocation. The authors find that for an agency with high overhead costs, competitive mode is more beneficial as it prevents underinvestment in fundraising, whereas for an agency with low overhead costs, joint fundraising is better. [Muggy and Heier Stamm \(2020\)](#) model beneficiaries’ decentralized choices among service facilities using congestion games and incor-

porate coordination mechanisms to improve outcomes. Beneficiaries choose facilities based on the distance and the congestion they will experience at a facility. An optimization model computes congestion-based incentive values that can transform a centrally optimal solution into an equilibrium solution with minimized cost. They find that incentivizing beneficiaries' decisions enables coordination even in a decentralized decision-making structure.

Resource sharing Resource sharing as a coordination mechanism was observed in several studies integrating game theory and optimization. Transportation, inventory management, and organizational operations were the most common decision problems studied in this context.

There are often multiple organizations performing similar activities in disaster response. While such organizations may share resources, they may also share similar constraints associated with those resources. Generalized Nash equilibrium is the most common technique used in surveyed literature to tackle shared constraints. [Nagurney et al. \(2019\)](#) develop a game theory model with financial and logistical constraints; the former concern purchasing and budgeting and the latter capture the freight service providers' limited capacity that is shared by humanitarian organizations. Since each humanitarian organization's decision affects others', a generalized Nash equilibrium using variational inequalities is developed and Lagrange analysis is used to derive conditions that maximize freight capacity utilization and demand satisfaction. [Bhattacharya et al. \(2014\)](#) also use generalized Nash equilibrium concepts to design an efficient humanitarian supply chain under funding constraints and donor earmarks such that the autonomous decision-making authority rests with local entities. The authors find that resource transfer scenarios are ranked in decreasing order of social welfare: no resource transfer, resource transfer between programs, and resource transfer controlled by a central authority. Thus, the policy recommendation for humanitarian supply chain design is that a central entity should facilitate asset transfer between different aid programs.

Coordination by sharing resources with and among heterogeneous organizations has also been studied. [Balza-Franco et al. \(2017\)](#) study whether cooperation for prepositioning relief items is beneficial among various commercial suppliers who engage in relief efforts. The

authors analyze scenarios where suppliers may compete or cooperate using an optimization model to find cost savings. Shapley value is used to allocate those savings. The model demonstrates that competition favors no one whereas cooperation leads to an increase in overall network efficiency. [Kamyabniya et al. \(2019\)](#) show how heterogeneous relief organizations can coordinate for platelet provision in humanitarian operations in a decentralized network such that response time and corresponding costs are minimized and a win-win solution for all is achieved. They develop a bi-level mathematical optimization model formulated as a Stackelberg game. A relief-rescue organization and a blood transfusion organization share capacity and make their individual decisions regarding platelet provision to a disaster area. An equilibrium point that increases both organizations' utilities is then identified.

Contracting Only one paper used both optimization and game theory and considered contracting as a coordination mechanism. [Wang et al. \(2015\)](#) develop an option contract model where the humanitarian organization is a purchaser and pays a premium price to the supplier in advance to guarantee the option to purchase relief supplies at a certain price after a disaster occurs. The authors derive a Nash bargaining solution for option contract implementation considering the supplier's and purchaser's risk preferences. They find that the option contract is superior to buy-back as well as instant-purchasing with return policy contracts as it enables achievement of Pareto improvement.

2.4.3 Research Question 3: What are the gaps that exist in current literature on coordination in humanitarian operations?

Here we present observations deduced from the systematic review and identify priorities for the research community to address moving forward.

Ambiguity in the use of terms There is a pressing need for consensus on the definition of 'coordination'. It is frequently used interchangeably with collaboration and cooperation, which are also ambiguously used. The humanitarian operations research community needs

a term that uniquely identifies scenarios where multiple autonomous entities align their individual objectives such that the overall system benefits. While conducting this review, we observed that many authors did not define the terms used in their research work. Several papers that seemed in-scope for this review had to be excluded after full text reviews; although they apparently focused on coordination, these papers introduced centralized models where organizations made decisions as per the central authority’s directions. Three out of sixty-three in-scope papers included explicit definitions for cooperation, coordination, or collaboration. However, distinctions are not clear or consistent. For example, one paper defined cooperation as a set of coordinated and complementary activities undertaken by different companies ([Balza-Franco et al., 2017](#)), whereas another defined collaboration as the relationship between organizations whose operations are coordinated ([Ergün et al., 2014](#)). We also observed widespread inconsistency in the use of these terms within a single research paper in multiple instances. Importantly, our review also identified several papers that did not use any of the terms despite developing a coordination-based model. In some, but not all, words such as ‘joint’, ‘partnership’, or ‘negotiation’ indicated their relevance to this review. Yet we only found these papers by searching all fields in the Scopus database; the cited references included cooperation, coordination, or collaboration in their titles, making them visible in our search. Basic searches for title, abstract, and keywords may cause relevant research work to be overlooked, a concerning consequence arising from the lack of a widely adopted term for coordination.

Disparity in focus on disaster phases and types There is opportunity to expand the research focus to encompass all disaster phases and types. We observe that coordination in the response and preparedness phases have been studied extensively, whereas the mitigation and recovery phases have so far been neglected. We found only one paper that considered decisions related to the disaster recovery phase ([Toyasaki and Wakolbinger, 2019](#)) and another related to mitigation ([Chakravarty, 2018](#)). A primary barrier to coordination has been the need for urgent action, which is less critical in mitigation and recovery phases; therefore, researchers should consider how to maximize the utility that can be derived when

there is more time to coordinate. Much research has focused on responding to and preparing for sudden-onset disasters. However, there is a need for focus on coordinated activities to manage slow-onset disasters, salient examples of which include pandemic and famine. Unlike sudden-onset disasters, slow-onset disasters develop gradually, and their effects are not immediately apparent, leading to complex and often interrelated consequences. The COVID-19 pandemic has taught us a hard but valuable lesson that even small inadequacies in planning for a full spectrum of disasters may result in widespread adverse impact ([Office of Inspector General, U.S. Department of Homeland Security, 2021](#)). Similarly, the World Food Programme recognizes coordination as a means for addressing famine’s root causes by tackling factors that contribute to hunger, such as conflict, climate change, and economic instability, by bringing stakeholders together to develop integrated and sustainable solutions ([World Food Programme, 2021](#)).

Lack of data Data is essential for informed decision-making. We observe that a significant number of research papers did not use real-world data to demonstrate their models’ effectiveness. Instead, they presented hypothetical numerical examples, which may not reflect the complexity and variability of actual situations. This may be due to insufficient data availability. It is, therefore, necessary for the humanitarian research community to develop methods that facilitate better data collection and management by relevant organizations. This would enable more nuanced, data-driven modeling efforts, and in turn, more effective decision-making in humanitarian operations.

In practice, data can also play a significant role in humanitarian operations. Real-time data availability can inform decisions about where to allocate resources and how to respond to emergencies. However, there are challenges associated with collecting and managing this data. Organizations must ensure that they have appropriate data collection systems in place and that they are gathering relevant data in a timely and accurate manner. In addition, they must have the capacity to analyze and interpret the data effectively. These challenges can be particularly acute in resource-constrained settings, where technology and infrastructure may be limited. Nevertheless, the use of data in practice can be a powerful tool for improving the

efficiency and effectiveness of humanitarian operations, ultimately leading to better outcomes for those in need.

Gaps specific to modeling While there is remarkable work being done using game theory, optimization, and a combination of both, there are still opportunities for models that better capture these systems. We observed these gaps specific to modeling: to integrate game theory with optimization in more creative ways, to explicitly consider uncertainty, to examine fair resource allocation, and to focus on dynamic disaster attributes.

Given the conceptual overlaps in game theory and optimization, there is opportunity for researchers to explore more ways to integrate the two. For example, game theory may be used to incorporate imperfect knowledge and conflicting objectives in optimization models. Game theory can model the presence of multiple entities, some competitors and other partners; this perspective can then be integrated with optimization to maximize each player’s utility. While optimization may provide optimal solutions to a problem, game theory can help identify whether the optimal solution is also stable when the implied decisions must be executed by autonomous entities.

Uncertainty is an undeniable fact of disasters. We observe that stochasticity has been incorporated comparatively better in optimization papers than in papers that use game theory or a combination of both methods. Furthermore, most of the research considered demand uncertainty, whereas there are many other ways in which it manifests.

We also observe gaps specific to game theory applications. Ironically, there were very few papers that applied cooperative game theory to model coordination among multiple entities. This points to an important opportunity to leverage the capability of cooperative game models, particularly the ways in which they examine the fair allocation of costs or savings among coordinating entities. Cooperative games also highlight the fact that it is not necessary for all entities to coordinate; in game theory terms, a grand coalition may not always be possible or desirable in humanitarian settings ([Ergün et al., 2014](#)). Moreover, we find that games with perfect information are prevalent in literature, which may be unrealistic in the humanitarian operations setting. Opportunities exist for incorporating limited or

imperfect information into game theory models to enrich the decision problems represented.

Coordination among decentralized entities is a challenge. A bigger challenge is achieving coordination while considering dynamic system attributes. Changes over time impact many decisions that arise in humanitarian operations. For example, in a sudden-onset disaster criticality declines after the first 72 hours. This is contrasted with slow-onset disasters such as famine or drought, in which criticality may increase over weeks, months, or years, or with disasters like landslide or disease that have sudden trigger events followed by slowly spreading follow-on impacts. Allocating and reallocating resources, including staff, equipment, and funds, in response to changing circumstances is important and challenging. Game theory and optimization models to support decision-making based on dynamic and potentially real-time information are unexplored avenues for research.

2.5 Conclusion

Humanitarian operations stand to benefit greatly from coordination, the process of aligning incentives among autonomous entities such that their actions improve system-wide outcomes. Researchers recognize the potential for optimization and game theory models to facilitate such coordination, as evidenced by the papers described here. Yet despite the increasing publication trend in this domain, this systematic review identified important opportunities to expand the models' relevance and impact.

Chapter 3

Integrating Cooperative Game Theory and Goal Programming for Multi-agent Multi-objective Coordination in Humanitarian Operations

Chapter 3 is based on the manuscript, “Integrating Cooperative Game Theory and Goal Programming for Multi-agent Multi-objective Coordination in Humanitarian Operations,” which is in preparation for submission to a peer-reviewed journal.

3.1 Introduction

Humanitarian crises are increasing in both frequency and severity, creating a mounting challenge for global response systems. According to the United Nations Office for the Coordination of Humanitarian Affairs (OCHA), 363 million people worldwide required humanitarian assistance in 2023 alone, a record-high figure that underscores the escalating impact of nat-

ural disasters, armed conflicts, and pandemics (OCHA, 2023). Humanitarian organizations' ability to respond effectively in such crises is critical for saving lives and alleviating suffering. However, these efforts are often complicated by urgency, resource scarcity, and the interested parties' diverse, sometimes conflicting, goals. The complexity calls for innovative frameworks that can enhance coordination, optimize resource utilization, and improve collective impact.

Coordination has long been identified as a cornerstone for effective humanitarian response. The Inter-Agency Standing Committee (IASC) emphasizes that improved coordination can reduce redundancies, close critical gaps, and ensure that assistance reaches those who need it most (IASC, 2023). Despite its importance, achieving effective coordination in the humanitarian domain remains elusive. Factors such as decentralized decision-making, overlapping responsibilities among organizations, and varying priorities between governments, non-governmental organizations (NGOs), and private entities contribute to fragmented efforts. These inefficiencies can lead to significant resource wastage, delayed responses, and, ultimately, greater human suffering. Addressing these issues necessitates a paradigm shift in how humanitarian operations are planned, executed, and evaluated.

Game theory offers a unique perspective for decision-making in humanitarian logistics by providing a structured framework to analyze interactions among multiple actors. While non-cooperative game theory has been applied to study competitive behaviors in humanitarian contexts, cooperative game theory has received comparatively little attention. This oversight is significant, as cooperative game theory aligns naturally with the collaborative goals inherent in disaster response. By modeling situations where agents can form coalitions to achieve shared objectives, cooperative game theory has the potential to address key challenges in coordination, such as equitable resource allocation and stability of cooperative arrangements.

This study seeks to advance the state of knowledge by proposing a novel framework that integrates cooperative game theory and Chebyshev goal programming techniques to improve coordination in multi-objective, multi-agent settings. The framework is uniquely suited to capture the conflicting objectives, diverse agent interests, and fairness considerations inherent in disaster relief coordination. Unlike traditional methods, this framework explicitly models

the strategic interactions among interested parties while simultaneously optimizing multiple, often competing, objectives. This work addresses a critical gap in the literature: while existing concepts provide identification of stable allocations in multi-objective, multi-agent settings, they do not offer a principled method for determining the minimum concession necessary to sustain coordination when such allocations do not exist. The demonstrated application of the framework in humanitarian context not only advances theoretical understanding of coordination in complex settings but also has practical implications for improving efficiency and effectiveness in disaster relief preparedness and response.

Section 3.2 reviews the literature on cooperative game theory in humanitarian contexts, laying a foundation for this study. Section 3.3 provides preliminaries on cooperative game theory followed by the proposed framework, which combines cooperative game theory with Chebyshev goal programming to address the complexities of multi-objective, multi-agent coordination. Section 3.4 demonstrates the practical efficacy of the proposed approach through numerical experiments that validate its superior performance relative to traditional allocation methods. This section also describes results from a scenario analysis that yields managerial insights and actionable recommendations for enhancing coordination and operational efficiency in disaster response.

3.2 Literature Review

This paper’s contributions to the cooperative game theory literature are at the intersection of two application areas: (1) enhancing coordination in humanitarian operations, and (2) multi-objective decision-making in logistics.

3.2.1 Cooperative Game Theory for Coordination in Humanitarian Operations

There is now rich literature addressing coordination in humanitarian contexts (see [Wankmüller and Reiner \(2020\)](#), [Adsanver et al. \(2024\)](#), and the references therein). The use of game

theory particularly in non-cooperative settings has also been studied well (see [Muggy and Heier Stamm \(2014\)](#)).

Horizontal coordination (alignment of actions among actors at the same operational level) and coordination mechanisms (structured processes that facilitate collective action or decision-making among actors) have been widely explored in disaster logistics to improve resource allocation and efficiency. [Balza-Franco et al. \(2017\)](#) investigate benefits in horizontal cooperation among commercial suppliers for managing and supplying relief items during disasters. Using an optimization model and the Shapley value, they analyze scenarios where suppliers either compete or cooperate. The study finds that while the grand coalition minimizes logistics costs, it is unstable due to imbalanced incentives among suppliers. [Ergün et al. \(2014\)](#) develop a cooperative game theory model that examines technology-enabled coordination. They demonstrate that while information technology tools can significantly enhance coordination and efficiency, simple proportional cost allocation mechanisms fail to account for the complexities and synergies influencing costs and benefits. [Sabahfar \(2024\)](#) develops a cooperative game theory framework for optimizing multi-agency collaboration in humanitarian supply chains with non-subadditive cost structures. An optimization model is introduced to determine which agencies should collaborate to minimize societal costs, since in this context larger coalitions need not be better. Additionally, a cost allocation method adapted from the ϵ -core in subadditive games is developed to ensure near-stable solutions.

The application of cooperative game theory in multi-stage models is gaining increasing attention in recent logistics research. [Pineda-Martinez et al. \(2021\)](#) present a two-stage model for optimizing emergency logistics. The first stage uses a mixed-integer programming model to minimize logistics costs and deprivation costs, and the second stage applies cooperative game theory, using the Shapley value to evaluate cost savings and allocate contributions among players. [Ghasemi et al. \(2022\)](#) present a two-stage stochastic mathematical model for humanitarian relief chain management in earthquake scenarios. It integrates location-routing-inventory decisions with cooperative game theory, addressing pre-disaster planning and post-disaster response. The model incorporates demand uncertainty through simulation-based estimation and applies multi-objective stochastic fractal search and ϵ -constraint solu-

tion approaches.

Cooperative game theory has also been applied to specific challenges in disaster logistics, such as vaccine dose sharing, resource flow problems, and risk reduction. [Westerink-Duijzer et al. \(2020\)](#) apply cooperative game theory to analyze vaccine dose sharing among health agencies during disease outbreaks. They examine conditions under which dose sharing is beneficial and stable, focusing on scenarios with S-shaped return functions that capture non-linear health benefits from vaccination. The research highlights stable (core) allocations as crucial for ensuring cooperation among parties, considering direct and indirect costs. The study provides insights into conditions for a non-empty core, indicating when cooperation is plausible and advantageous. [Ergün et al. \(2023\)](#) develop a cooperative flow game to address logistical challenges in disaster relief after a possible earthquake in Istanbul, Turkey. The flow problem is modeled using cooperative game theory as an approach to solve the logistic network problem, ensuring efficient resource allocation and transportation. Solution concepts like the Shapley value, τ value, nucleolus, and core are applied to fairly distribute gains among the players. [Jeong et al. \(2018\)](#) propose a cooperative framework for funding disaster mitigation infrastructure, focusing on fair cost allocation using the Shapley value. Unlike other studies on post-disaster response, this study emphasizes proactive disaster risk reduction by integrating economic efficiencies and flood damage prevention benefits into cost-sharing mechanisms.

3.2.2 Cooperative Game Theory in Multi-Objective Decision-making in Logistics

An emerging body of research is exploring the integration of multi-objective optimization and cooperative game theory in collaborative logistics. [Wang et al. \(2018\)](#) model integrating distribution and pickup centers, customers, semitrailer trucks, and shared vehicles to optimize resource utilization. They design a bi-objective model that minimizes operating costs and the number of vehicles, evaluating the impact collaboration has on the logistics network. Using a hybrid heuristic for routing optimization and the cost gap allocation method

for profit distribution, they validate their approach through an empirical study, demonstrating its real-world effectiveness. [Mrabti et al. \(2022\)](#) develop a multi-objective framework for optimizing hub location, transportation planning, and cost-sharing in collaborative logistics while incorporating economic, environmental, and social sustainability. Cooperative game theory is applied to ensure fair cost-sharing through egalitarian, volume-based, and Shapley value approaches. Application on a real-world distribution network is also demonstrated. Authors find cooperative game approaches for cost allocation to be most appropriate. [Amiri and Farvaresh \(2023\)](#) also study a vehicle routing problem and develop a bi-objective model. They consider both transferable (profit) and non-transferable (customer coverage) utilities, and introduce concepts of generalized core and generalized Shapley set for fair coalition formation embedding the classical concepts with transferable and non-transferable utilities simultaneously. A heuristic algorithm and full enumeration method identify Pareto-optimal solutions, showing that collaboration enhances profitability while maintaining service coverage. [Sampath et al. \(2020\)](#) design a decentralized collaborative shipping marketplace using blockchain, cooperative game theory, and multi-objective optimization. They apply the Shapley value for fair cost-sharing among shippers and use Pareto-efficient solutions to balance cost efficiency, truck utilization, and shipment fulfillment. [Abou Mjahed et al. \(2022\)](#) present a bi-objective coalition model for selecting the right partners for coalition formation and equitably distributing the benefits generated among them. Using cooperative game theory, ϵ -constraint optimization, and dynamic programming, they show that smaller coalitions often outperform the grand coalition due to capacity limits and coordination costs.

3.2.3 Research Gaps

Cooperative game theory applications in modeling coordination for humanitarian operations show promise, but current research reveals significant limitations. First, existing studies predominantly focus on single-objective scenarios, highlighting a critical gap in addressing the complexities inherent in multi-objective settings that pertain to humanitarian logistics. While [Ghasemi et al. \(2022\)](#) incorporate a multi-objective perspective, their approach dif-

fers fundamentally from the proposed work. They rely on metaheuristic simulation without explicit resolution of trade-offs using structured optimization. They also overlook equity considerations in parallel for the beneficiaries and humanitarian actors, a focus that distinguishes this study. Secondly, the literature offers no framework in multi-objective multi-agent contexts for quantifying how much concession is required to align actions of diverse decision-makers and transform uncoordinated outcomes into a coordinated, near-stable arrangement.

This research addresses the identified gaps by introducing the *Chebyshev least core*, a new concept that formalizes the minimum uniform concession required to stabilize coordination when perfect equity cannot be achieved in multi-objective multi-agent settings. Moreover, a mathematical model *Cooperative Goal Optimization (CGO)* is developed by integrating cooperative game theory with goal programming, that enables principled decision-making that is both equitable and sustainable across diverse actors. The proposed model resolves multi-objective trade-offs by minimizing the maximum deviation from agent-defined goals, thereby ensuring fairness in allocation decisions, coalitions' stability, and collective rationality in decision-making. This novel approach offers a comprehensive method for balancing conflicting objectives among multiple actors while highlighting nuances of fairness, effectively modeling the complex dynamics of coordination in decentralized humanitarian operations.

3.3 Multi-objective Cooperative Game Model

In this section, a mathematical model that integrates cooperative game theory and optimization techniques to address the challenge of equitably allocating costs and benefits among multiple objectives in multi-agent settings, is developed. An equitable allocation refers to a fair distribution among multiple players. The model employs goal programming, a multi-objective optimization technique that minimizes deviations from target values for each objective. Specifically, the proposed approach utilizes Chebyshev goal programming, which focuses on minimizing the maximal deviation from predefined goals to achieve balanced and fair solutions. The goals selected for this work are derived from rationality principles in cooperative game theory, ensuring fairness in the allocations. These principles guarantee

that all interested parties receive outcomes that satisfy individual rationality (outcomes are reasonable and justifiable when considered independently for each participant) and collective rationality (outcomes are equitable and consistent when viewed in the group context). This ensures that the distribution is both fair and stable across all participants.

This section begins with an overview of cooperative game theory concepts before detailing the proposed integrated model.

3.3.1 Preliminaries on Cooperative Game Theory

Cooperative game theory provides a framework to model situations where players (agents) may form coalitions to achieve better outcomes than they could individually (Peleg and Sudhölter, 2007). Consider a set of players $N = \{1, 2, \dots, n\}$ that can form coalitions. A group of players formed by the subset $S \subseteq N$ is called a coalition and the set N itself is called the grand coalition.

3.3.1.1 Single-objective Cooperative Game Theory

Definition 3.3.1 (Characteristic Function). A *characteristic function* (Barichard et al., 2009) is a real-valued function $v : 2^N \rightarrow \mathbb{R}$, where $v(S)$ is the worth of coalition $S \subseteq N$, and $v(\emptyset) = 0$.

Definition 3.3.2 (Superadditivity). A game (N, v) is *superadditive* (Peleg and Sudhölter, 2007) if

$$(S, T \subseteq N \text{ and } S \cap T = \emptyset) \implies v(S \cup T) \geq v(S) + v(T). \quad (3.1)$$

Definition 3.3.3 (Subadditivity). A game (N, v) is *subadditive* (Peleg and Sudhölter, 2007) if

$$(S, T \subseteq N \text{ and } S \cap T = \emptyset) \implies v(S \cup T) \leq v(S) + v(T). \quad (3.2)$$

Superadditivity implies that players have incentives to form larger coalitions, as they can achieve at least as much utility together as they can separately, and possibly more. Similarly, a game exhibits subadditive costs if the cost of a coalition performing a task is less than or equal to the sum of the costs of smaller coalitions performing the same task separately. In games with superadditive benefits (subadditive costs), the grand coalition achieves the greatest total benefit (least total cost).

Definition 3.3.4 (Single-Objective Game Core). Consider a single-objective game where x_i is the allocation to player i . The *core* (Peleg and Sudhölter, 2007) is defined by expressions (3.3) and (3.5) if the game is superadditive and by expressions (3.4) and (3.5) if the game is subadditive.

$$\sum_{i \in S} x_i \geq v(S), \forall S \subseteq N \quad (3.3)$$

$$\sum_{i \in S} x_i \leq v(S), \forall S \subseteq N \quad (3.4)$$

$$\sum_{i \in N} x_i = v(N) \quad (3.5)$$

The core of a game comprises all allocations such that no subset of players can improve their collective outcome by forming a separate coalition.

Definition 3.3.5 (Excess). For a coalition $S \subseteq N$, and allocation $x \in \mathbb{R}^N$, with respect to a game (N, v) , the excess $e(S, x, v)$ is the difference between the characteristic function value and the allocation (Peleg and Sudhölter, 2007).

Definition 3.3.6 (Least Core). For $\epsilon \geq 0$, the least core (Peleg and Sudhölter, 2007), for a game (N, v) is defined as

$$\epsilon^* = \min \{ \epsilon \geq 0 : \exists \mathbf{x} \in \mathbb{R}^N | e(S, x, v) \leq \epsilon \}.$$

The least core is the minimal relaxation that keeps all coalitions' potential grievances within the bound ϵ^* ; when $\epsilon^* = 0$, the ordinary core is non-empty, and when $\epsilon^* > 0$ the allocation

lies in the least core.

3.3.1.2 Multi-Objective Cooperative Game Theory

The concepts above are extended to multi-objective cooperative games as follows. In a multi-objective cooperative game, a coalition's worth is measured by multiple (k) criteria and is specified by a vector in $\mathbb{R}^k$.

Definition 3.3.7 (Multi-Objective Vector-Valued Game). A multi-objective vector-valued game is a tuple (N, V) where $N = \{1, \dots, n\}$ is a set of players and V is a set-valued mapping from 2^N to $\mathbb{R}^k$ that gives each coalition's worth by k different criteria $V(S) = (v_1(S), v_2(S), \dots, v_k(S))$, $V(S) \subseteq \mathbb{R}^k, \forall S \subseteq N$ (Barichard et al., 2009).

In multi-objective games, the allocation concept is extended by using an allocation matrix with k rows (objectives) and n columns (players).

Definition 3.3.8 (Allocation Matrix). Allocation X in a multi-objective cooperative game is a matrix where element x_j^i represents the allocation to player i for objective j . The i th column X^i represents the allocation to player i for each criteria: $X^i = (x_1^i, x_2^i, \dots, x_k^i)$. The j th row X_j contains allocations corresponding to criterion j for each player: $X_j = (x_j^1, x_j^2, \dots, x_j^n)$. The sum $X^S = \sum_{i \in S} X^i$ is a column vector whose rows represent the allocations to coalition S for each objective j (Fernández et al., 2002).

In multi-objective games, the core concept is expanded into two distinct forms: the nondominance core and the preference core. An allocation belongs to the nondominance core if it guarantees that each player or coalition achieves an outcome in at least one objective that is equal to or better than what they could attain on their own. This concept reflects a readiness to accept compromise solutions. In contrast, an allocation belongs to the preference core if it ensures that each player or coalition receives outcomes across all objectives that are at least as favorable as, if not superior to, what they could independently secure (Fernández et al., 2002; Hinojosa et al., 2005).

Definition 3.3.9 (Excess Function). The excess function (Nan et al., 2024) measures the excess of the coalition S about the allocation matrix X for each objective j . It is a vector function $e(S, X)$, whose components are

$$e_j(S, X) = v_j(S) - \sum_{i \in S} x_j^i. \quad (3.6)$$

Now the cores of a multi-objective cooperative game using the above concepts are defined. Let $\mathcal{C}$ denote the set of subadditive objectives, and $\mathcal{D}$ denote the set of superadditive objectives, with $\mathcal{C} \cap \mathcal{D} = \emptyset$ and $\mathcal{C} \cup \mathcal{D} = \{1, \dots, k\}$. The nondominance core and preference core are defined as follows:

Definition 3.3.10 (Nondominance Core). The *nondominance core*, denoted by $\text{nDC}(N, V; \not\geq)$, is defined as:

$$\text{nDC}(N, V; \not\geq) = \left\{ X \mid \forall S \subseteq N, \exists j \in \{1, \dots, k\} \text{ such that } e_j(S, X) \begin{cases} \geq 0, & \text{if } j \in \mathcal{C} \\ \leq 0, & \text{if } j \in \mathcal{D} \end{cases} \right\}. \quad (3.7)$$

This means that for every subcoalition S , there exists at least one objective for which the worth obtained by the subcoalition S is not less than its individual worth.

Definition 3.3.11 (Preference Core). The *preference core*, denoted by $\text{PC}(N, V; \geq)$, is defined as:

$$\text{PC}(N, V; \geq) = \left\{ X \mid \forall S \subseteq N, \forall j \in \{1, \dots, k\} \text{ such that } e_j(S, X) \begin{cases} \geq 0, & \text{if } j \in \mathcal{C} \\ \leq 0, & \text{if } j \in \mathcal{D} \end{cases} \right\}. \quad (3.8)$$

3.3.2 Framework for Finding Equitable Allocations Across Multiple Objectives

In decentralized decision-making systems, multiple independent actors must coordinate their actions while preserving individual autonomy. Achieving fair coordination is difficult when objectives conflict, because enhancing one goal can undermine another. Without a central authority directing decisions, each participant must see enough benefit from joint action to be at least as well off as they would by acting on their own. Therefore, this work introduces and formalizes the notion of a *Chebyshev least core*; the smallest uniform relaxation required to prevent any coalition from being disproportionately dissatisfied on every objective as part of the grand coalition. It is argued that this is the pivotal concept for guaranteeing stable and equitable coordination in such settings. By bringing the Chebyshev least core to the forefront, the author provides the first optimization-based framework that advances the body of knowledge in cooperative games by extending classical least core reasoning to the multi-objective domain while ensuring that the solution concept is independent of the units in which individual objectives are expressed.

Finding equitable allocations across multiple objectives in a multi-agent setting is challenging. To address this, a multi-stage framework that integrates optimization, goal programming, and cooperative game theory to address this is presented. This work makes the following main contributions: (1) A new mathematical concept, the Chebyshev least core is introduced and formalized, (2) A novel rigorous framework for computing the Chebyshev least core is developed, (3) A unified approach generalizable to multiple settings, for finding equitable allocations across multiple and differently scaled objectives is developed, and (4) The use of developed framework to capture stability under conflicting objectives while preserving different scales of objectives is introduced by extending the concepts of the preference core and nondominance core.

The proposed framework has two stages, and is applicable to any system involving interactions among multiple agents with diverse objectives and is generalizable enough to accommodate any number of objectives and players.

1. **Characteristic Function Value Generation:** Characteristic function values are needed for each subcoalition for each objective. These may, for instance, be computed using an optimization model tailored to the application domain.
2. **Cooperative Goal Optimization (CGO):** Characteristic function values constitute input parameters for a Chebyshev goal programming model that integrates rationality constraints from cooperative game theory. The model minimizes the maximum deviation from the target values (goals) across all objectives and coalitions. The CGO model formulation is such that the decision variable values in any feasible solution may be used to determine whether the solution belongs to the preference or nondominance cores.

The mathematical representation of the framework is presented below.

Parameters

N : Set of players, $N = \{1, 2, \dots, n\}$.

S : Coalition, a subset of N .

$\mathcal{J}$: Set of objectives.

$v_j(S)$: Characteristic function value of objective j achievable by coalition $S \subseteq N$.

Decision Variables

x_j^i : Allocation to player i for objective $j \in \mathcal{J}$.

p_j^S : Positive deviation from goal for subcoalition $S \subset N$ with respect to objective $j \in \mathcal{J}$.

n_j^S : Negative deviation from goal for subcoalition $S \subset N$ with respect to objective $j \in \mathcal{J}$.

λ : Maximal deviation.

3.3.2.1 Stage 1: Characteristic Function Value Generation

The characteristic function values $v_j(S)$ quantify the performance or worth of a coalition S for each objective j , and they are determined using methods tailored to the specific context of the problem. This determination may involve solving single-objective or multi-objective optimization models that encapsulate the relevant constraints, costs, and benefits specific to the application domain. Alternatively, these values can be estimated using historical data or expert knowledge, providing a practical way to capture real-world nuances. Ultimately, these values serve as the foundational inputs to the second stage in the framework, to analyze and ensure fair allocations and stable coalition formations.

3.3.2.2 Stage 2: Cooperative Goal Optimization (CGO)

The Cooperative Goal Optimization (CGO) model is now presented. The model leverages pre-determined, context-specific characteristic function values to identify equitable and stable allocations. The characteristic function values for each subcoalition and each objective, calculated in stage 1, are provided as input to the CGO model and serve as target values for the optimization process.

Minimize λ

subject to:

$$\sum_{i \in S} x_j^i + p_j^S - n_j^S = v_j(S) \quad \forall S \subset N, \forall j \in \mathcal{J}, \quad (3.9)$$

$$\sum_{i \in S} x_j^i = v_j(N) \quad \forall j \in \mathcal{J}, \quad (3.10)$$

$$\frac{p_j^S}{v_j(S)} \leq \lambda \quad \forall S \subset N, \forall j \in \mathcal{J}, \quad (3.11)$$

$$\frac{n_j^S}{v_j(S)} \leq \lambda \quad \forall S \subset N, \forall j \in \mathcal{J}, \quad (3.12)$$

$$p_j^S, n_j^S \geq 0 \quad \forall S \subset N, \forall j \in \mathcal{J}, \quad (3.13)$$

$$\lambda \geq 0 \tag{3.14}$$

The objective function minimizes the maximum allowable deviation λ across all objectives and coalitions. Constraint (3.9) and constraint (3.10) are the rationality constraints. Constraint (3.9) ensures that for each coalition S and each objective j , the total allocated amount $\sum_{i \in S} x_j^i$ must match the stand-alone characteristic function value $v_j(S)$, up to positive or negative deviations p_j^S and n_j^S . Constraint (3.10) specifies that the sum of individual players' allocations must equal the best-achievable value $v_j(N)$ on each objective j for the grand coalition. Constraints (3.11) and (3.12) employ percentage normalization measure to accommodate varying objective units, ensuring that the relative deviations from the target values $\frac{p_j^S}{v_j(S)}$ and $\frac{n_j^S}{v_j(S)}$ do not exceed the maximum allowable fraction λ for each coalition. Constraints (3.13) and constraint (3.14) enforce nonnegativity on the deviation variables and λ .

3.3.2.3 Chebyshev least Core

The CGO model described in Section 3.3.2.2 computes a *Chebyshev least core* using the Chebyshev distance metric, the maximum deviation across all objectives. In single-objective cooperative games, the least core is obtained by determining the minimal relaxation (ϵ) of coalitional payoff constraints required to ensure stability, thereby minimizing the maximum incentive for any subcoalition to deviate from the grand coalition. In comparison, in a multi-objective setting, each subcoalition may experience dissatisfaction across multiple objectives, with dissatisfaction measured separately for each. Subcoalitions are not only concerned with the extent of shortfall on individual objectives but also seek to understand the trade-offs required to collectively meet all their objectives, making stability more complex to evaluate and achieve. By minimizing the worst-case deviation λ across *all* subcoalitions for *all* objectives, the CGO model identifies the smallest percentage adjustment across all objectives such that no subcoalition would have an incentive to deviate from the grand coalition.

Definition 3.3.12 (Chebyshev least Core). An allocation $x = \{x_j^i\}_{i \in N, j \in \mathcal{J}}$ is in the *Chebyshev least core* if it minimizes the worst-case relative deviation across all subcoalitions and objectives. Formally, let

$$\lambda^* = \min_x \max_{S \subseteq N, j \in \mathcal{J}} \frac{|\sum_{i \in S} x_j^i - v_j(S)|}{v_j(S)}, \quad (3.15)$$

where the minimization is taken over all feasible x . Then the *Chebyshev least core* is the set

$$\left\{ x \mid \max_{S \subseteq N, j \in \mathcal{J}} \frac{|\sum_{i \in S} x_j^i - v_j(S)|}{v_j(S)} \leq \lambda^* \right\}. \quad (3.16)$$

If $\lambda^* = 0$, then all subcoalitions simultaneously meet or exceed their goals for every objective, and the resulting solution is in the *preference core*.

If $\lambda^* > 0$, then the solution is in the *Chebyshev least core*; it is the smallest uniform adjustment required so that no subcoalition's dissatisfaction exceeds λ^* when measured relative to its stand-alone outcome $v_j(S)$ for each objective.

Analyzing this Chebyshev least core reveals whether the grand coalition is sustainable or further resources or policy modifications (e.g., financial incentives or revised cost-sharing rules) are needed to maintain stability.

The CGO-based solution when $\lambda > 0$ is referred to as the *Chebyshev least core* because it uses a single, unified optimization to control the worst-case deviation across all objectives simultaneously. In comparison, existing work in the literature on this topic differs from this work. [Hinojosa et al. \(2005\)](#) finds a multi-objective least core by solving a separate linear program for each objective and combining the outcomes without explicitly linking them through intercriteria utility comparisons. [Nan et al. \(2024\)](#) builds on the concept by developing a preemptive goal programming model to determine a multi-objective least core, which they refer to as a *preference p-core*. In their model, priority factors are assigned so

that higher-priority objectives dominate lower-priority ones. By contrast, the CGO model treats all objectives in a unified manner, minimizing the worst relative deviation λ across all subcoalitions and objectives simultaneously. This approach prevents any single objective from dominating due to a higher user-assigned weight and ensures no subcoalition suffers disproportionately. The CGO model is thus particularly suited to cases where precise priority rankings are not specified or where finding a balanced solution among all objectives is desired.

3.3.2.4 Preference Core and Nondominance Core

The CGO model presented in Section 3.3.2.2, will identify a preference core allocation if one exists. To determine whether the solution belongs to the preference core or the nondominance core, the deviational variable values can be inspected. Note that when $\lambda = 0$, then from constraint (3.11) $p_j^S = 0$, and from constraint (3.12) $n_j^S = 0$. This indicates that all goals are met or exceeded by the identified allocation; therefore any allocation for which $\lambda = 0$ is in the preference core. An allocation that is in the preference core is also in the nondominance core, but the converse is not true.

Lemma 1 shows how to determine whether any feasible solution, including an optimal solution, belongs to the preference core PC or the nondominance core nDC. The result is presented for a problem with two objectives and readily generalizes by extending the corresponding variables and constraints for each additional objective.

Lemma 1. Let the decision variable values in a feasible solution to the CGO model be n_d^S, p_d^S, p_c^S , and n_c^S , where d corresponds to a superadditive objective to be maximized and c to a subadditive objective to be minimized. Then the following conditions hold for allocation X :

$$X \in \text{PC}(N, V; \geq) \iff \forall S \subset N \left((n_d^S > 0 \vee (p_d^S = 0 \wedge n_d^S = 0)) \wedge (p_c^S > 0 \vee (p_c^S = 0 \wedge n_c^S = 0)) \right), \text{ and}$$

$$X \in \text{nDC}(N, V; \not\geq) \iff \forall S \subset N \left((n_d^S > 0 \vee (p_d^S = 0 \wedge n_d^S = 0)) \vee (p_c^S > 0 \vee (p_c^S = 0 \wedge n_c^S = 0)) \right).$$

Proof. The result follows from the definitions of the preference and nondominance cores. $\square$

3.4 Computational Experiments

In this section, the framework developed in 3.3.2 is demonstrated with illustrative examples and computational results are presented. The focus is on a three-player relief distribution system that incorporates two widely recognized objectives, maximizing demand fulfillment and minimizing overall costs. The setting involves three distinct organizations responding to a disaster, each with different capabilities and operational priorities. These organizations face the challenge of balancing costs and service levels. For effective response, organizations must coordinate their efforts across three locations, each representing an area where disaster relief is needed. The coordinating organizations must determine how much aid to send to each location and how to share costs fairly among coalition members.

First, the framework is demonstrated using a base case. Then, multiple scenarios are generated by varying key parameters. Finally, synthesis of results and managerial insights are presented. The optimization model and the CGO model are solved using Gurobi 10.0.2 on a system equipped with an Intel® Core™ i7 processor (quad-core, base frequency 1.80 GHz), 16 GB RAM, and the Windows 11 operating system.

3.4.1 Base Case

Consider a scenario involving three organizations: a large organization, a small organization, and a medium-sized organization, responding to a disaster affecting three distinct locations. Initially, each organization operates independently, leading to varying effectiveness levels and resource utilization. The large organization controls the greatest warehouse capacity and budget but is the only actor that must absorb a fixed facility charge; its transport costs are lowest for the nearby location, moderate for the remote site, and highest for the central site. The small organization escapes any fixed facility cost and operates with the smallest budget and capacity, and its transport costs are consistently higher than those of the large organization across all locations. The medium organization lies between the other two in budget and capacity but faces the highest holding, purchasing, and transportation

costs. Demand requirements at the three locations are the same for every organization. Coalition inputs incorporate economies of scale: Pairing any two organizations lowers the unit purchasing cost while pooling capacity and budget. Any coalition that includes the large organization can distribute its fixed facility cost among partners, whereas the coalition of the small and medium organizations incurs no fixed cost at all. The grand coalition further reduces the purchasing cost, aggregates the largest combined capacity and budget, and retains only a single shared facility charge. These input parameters are shown in Table 3.1.

Table 3.1: Coalition-wise input data for base case scenario. Organizations in coalitions are represented as 1: large organization, 2: small organization, 3: medium-sized organization.

Coalition	Holding Cost	Purchasing Cost	Fixed Cost	Capacity (units)	Budget (\$)	Cost Loc 1	Cost Loc 2	Cost Loc 3	Demand Loc 1	Demand Loc 2	Demand Loc 3
{1}	0.2	5	1500	70	2000	2	9	6	85	95	105
{2}	0.2	5	0	50	500	5	10	7	85	95	105
{3}	0.5	6	0	60	1500	45	35	15	85	95	105
{1,2}	0.2	3	1500	120	2500	2	9	6	85	95	105
{2,3}	0.2	3	0	110	2000	5	10	7	85	95	105
{1,3}	0.2	3	1500	130	3500	2	9	6	85	95	105
{1,2,3}	0.2	2	1500	180	4000	2	9	6	85	95	105

The mathematical model underlying this scenario is based on the following assumptions: (1) costs are subadditive; (2) demands are superadditive; (3) the total demand at each location is known and fixed; and (4) all parameters required to compute the characteristic functions are known for every possible subcoalition.

3.4.1.1 Stage 1: Characteristic Function Value Generation

Characteristic function values for each coalition are generated using optimization since this methodology prescribes the best possible outcomes. In a multi-agent, multi-objective setting, each coalition makes strategic decisions to optimize their own objectives such as minimizing costs or unmet demands, or maximizing efficiency or profits. By formulating an optimization model, the highest attainable performance levels are systematically determined for different coalitions, providing a benchmark for assessing stability in later stages.

The following optimization model is used to generate characteristic function values for

total cost and total demand fulfillment that every possible subcoalition ($2^n - 1$ combinations, where n represents the number of players) can achieve on its own. Service level is defined as each coalition's demand fulfillment capacity, represented in this model by the amount of quantity shipped to each location q_l . It is a critical effectiveness measure in humanitarian logistics. Based on findings by [Gralla et al. \(2014\)](#), the amount of cargo delivered is the most valued objective among humanitarian logistics experts. To determine the highest achievable service level for each subcoalition across all demand locations, the optimization model is iteratively solved for varying δ levels, the parameter that specifies the percentage of demand that must be fulfilled, for each possible subcoalition. The largest δ for which the model produces a feasible solution is chosen. Differences arise due to the subcoalitions' budget and cost characteristics. The following are the parameters and decision variables used in the optimization model.

Parameters

L : Set of demand locations, $l \in L$

Ω : Procurement cost

f : Fixed cost of opening the warehouse

c_l : Per-unit shipment cost to location l

d_l : Demand at location l

δ : Percentage of demand to be fulfilled

B : Budget

C : Capacity of the warehouse

Decision variables

y : Amount stored in the warehouse

q_l : Amount shipped to location l

Maximize $\sum_{l \in L} q_l$

subject to:

$$f + \Omega y + \sum_{l \in L} c_l q_l \leq B, \quad (3.17)$$

$$\sum_{l \in L} q_l \leq y, \quad (3.18)$$

$$y \leq C, \quad (3.19)$$

$$q_l \geq \delta d_l, \quad \forall l \in L \quad (3.20)$$

$$q_l \leq d_l, \quad \forall l \in L \quad (3.21)$$

$$q_l \in \mathbb{Z}^+, \quad \forall l \in L \quad (3.22)$$

$$y \in \mathbb{Z}^+ \quad (3.23)$$

The objective function maximizes total service level across all demand locations. Constraint (3.17) ensures the subcoalition's characteristic function value for cost does not exceed the available budget. Constraint (3.18) limits total shipment to available inventory, while Constraint (3.19) restricts warehouse storage to its capacity. Constraint (3.20) requires that, for every location, the demand fulfillment must meet at least a minimum fraction of the total demand. Constraint (3.21) ensures quantity shipped to each location does not exceed demand. Constraints (3.22) and (3.23) are non-negativity constraints for shipment and inventory.

3.4.1.2 Stage 2: Cooperative Goal Optimization Model

The outputs of the optimization model are utilized as inputs to build the CGO model as follows.

The service level $\sum_{l \in L} q_l$ from the optimization model are chosen as the demand characteristic function value $v_d(S)$ for each coalition. Similarly, the cost characteristic function values $v_c(S)$ come from the total cost output $(f + \Omega y + \sum_{l \in L} c_l q_l)$.

Parameters:

N : Set of players, $N = \{1, 2, \dots, n\}$

S : Coalition, a subset of N

$v_d(S)$: Characteristic function value of demand for coalition S

$v_c(S)$: Characteristic function value of cost for coalition S

Decision variables:

x_j^i : Allocation to player i for objective j , $\forall i \in N$ and objective j , $j \in \{c:\text{cost}, d:\text{demand}\}$

p_j^S : Positive deviation from goal for subcoalition S and objective j , $j \in \{c:\text{cost}, d:\text{demand}\}$

n_j^S : Negative deviation from goal for subcoalition S and objective j , $j \in \{c:\text{cost}, d:\text{demand}\}$

λ Maximal deviation

Minimize λ

subject to:

$$\sum_{i \in S} x_d^i + p_d^S - n_d^S = v_d(S), \quad \forall S \subset N \quad (3.24)$$

$$\sum_{i \in S} x_c^i + p_c^S - n_c^S = v_c(S), \quad \forall S \subset N \quad (3.25)$$

$$\sum_{i \in S} x_d^i = v_d(N), \quad (3.26)$$

$$\sum_{i \in S} x_c^i = v_c(N), \quad (3.27)$$

$$\frac{p_d^S}{v_d(S)} \leq \lambda, \quad \forall S \subset N \quad (3.28)$$

$$\frac{n_c^S}{v_c(S)} \leq \lambda, \quad \forall S \subset N \quad (3.29)$$

$$p_c^S, n_c^S \geq 0, \quad \forall S \subset N \quad (3.30)$$

$$p_d^S, n_d^S \in \mathbb{Z}^+, \quad \forall S \subset N \quad (3.31)$$

$$x_d^i \in \mathbb{Z}^+, x_c^i \in \mathbb{R}^+, \forall i \in S \subset N \quad (3.32)$$

$$\lambda \geq 0 \quad (3.33)$$

The objective function minimizes the maximal deviation λ from cost and demand goals. Constraint (3.24) is the demand fulfillment constraint, incorporating the individual rationality principle. For each coalition S , the sum of demand allocations x_d^i for all players $i \in S$, plus the positive (p_d^S) and negative (n_d^S) deviations, must exactly meet the superadditive demand value $v_d(S)$. Conversely, constraint (3.25) is the cost allocation constraint. For each coalition S , the sum of cost allocations x_c^i for all players $i \in S$, plus the positive (p_c^S) and negative (n_c^S) deviations, must exactly meet the subadditive cost $v_c(S)$. Constraints (3.26) and (3.27) are the collective rationality constraints for each objective, ensuring that the sum of allocations equals the grand coalition value for total demand fulfillment and total cost incurred, respectively. Notice when $p_d^S > 0$, $\sum_{i \in S} x_d^i < v_d(S)$, and when $n_c^S > 0$, $\sum_{i \in S} x_c^i > v_c(S)$. Therefore, the deviations we are interested in minimizing are p_d^S and n_c^S . Using percentage normalization, constraints (3.28) and (3.29) scale the deviation variables p_d^S and n_c^S for each objective, facilitating comparison across objectives within the CGO model, and define λ as the maximum deviation from any goal. Constraints (3.30), (3.31), (3.32), and (3.33) enforce non-negativity and integrality conditions.

3.4.2 Results

The optimization model results from stage 1 are summarized in Table 3.2. Note that larger coalitions consistently meet a higher percentage of total demand at a lower per unit cost, indicating subadditive costs and superadditive demands. Table 3.3 shows the CGO model results.

Fig. 3.1 illustrates characteristic functions for cost and demand for all coalitions alongside the CGO model allocations for cost and demand. The vertical axis shows costs (Fig.3.1a) and demands (Fig.3.1b); coalitions are identified on the horizontal axis in each plot. In Fig.3.1a, the bars on the right, representing allocated costs, either match or fall below the

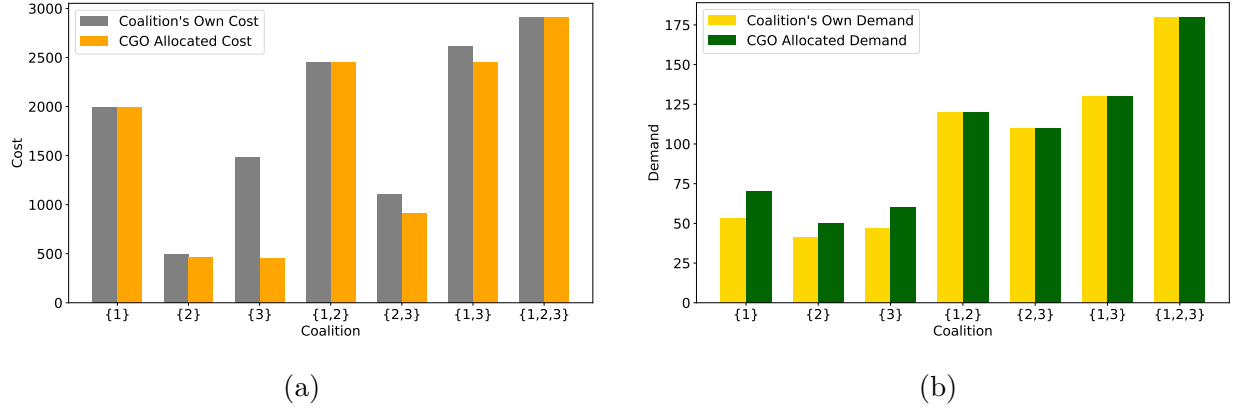


Figure 3.1: Characteristic function values vs allocations from CGO model: (a) cost; (b) demand fulfillment. Organizations in coalitions are represented as 1: large organization, 2: small organization, 3: medium-sized organization.

Table 3.2: Results of the optimization model run for every subcoalition. Organizations in coalitions are represented as 1: large organization, 2: small organization, 3: medium-sized organization.

Coalition	δ (% of total demand)	Total demand met	Total cost
{1}	0.1	53	1995
{2}	0.1	41	490
{3}	0.1	47	1480
{1,2}	0.3	120	2455
{2,3}	0.3	110	1111
{1,3}	0.4	130	2610
{1,2,3}	0.6	180	2907

bars on the left, which depict the coalition's own costs. This demonstrates the CGO model's effectiveness in minimizing costs while meeting coalition objectives, particularly notable in coalitions {3}, {2,3}, and {1,3}. Similarly, the right bars in Fig.3.1b, representing allocated demand, closely match or surpass the left bars, which indicate the coalition's own demand, indicating that the CGO model efficiently meets demand requirements. This is critical in humanitarian logistics, where it is essential to reduce costs without compromising service quality and demand fulfillment.

In this instance, note in Table 3.3 that the deviation variables of interest for demand and cost, p_d^S and n_c^S , respectively, have value 0 for all coalitions. Therefore, the allocation identified by the CGO model belongs to both the preference and nondominance cores, ensuring that the solutions are not only optimal but also fair and acceptable to all parties involved.

Table 3.3: Results of the CGO model. Organizations in coalitions are represented as 1: large organization, 2: small organization, 3: medium-sized organization.

Coalition	Cost allocation	Demand allocation	Cost-positive deviation (p_c^S)	Cost-negative deviation (n_c^S)	Demand-positive deviation (p_d^S)	Demand-negative deviation (n_d^S)
{1}	1995	70	0	0	0	17
{2}	459	50	30	0	0	9
{3}	452	60	1028	0	0	13
{1,2}	2455	120	0	0	0	0
{2,3}	911	110	199	0	0	0
{1,3}	2447	130	162	0	0	0
{1,2,3}	2907	180	0	0	0	0

3.4.3 Comparison with Other Allocation Rules

The CGO model determines allocations based on rationality constraints; when $\lambda = 0$, stable allocations are identified where no player has an incentive to deviate. The allocations determined by the CGO model for each coalition are compared to two widely-adopted allocation rules from the literature, namely, Shapley value and proportional allocations. The fairness and stability of these allocations are assessed to determine whether each allocation belongs to the preference or nondominance cores. This evaluation identifies which allocations are both stable and acceptable to all the interested parties.

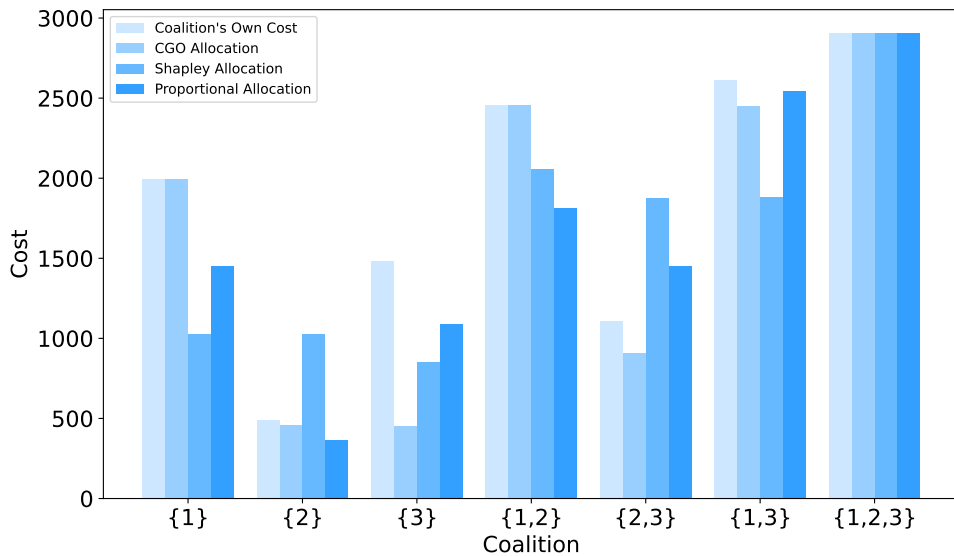


Figure 3.2: Comparison of allocation rules in terms of cost

Shapley value ([Shapley, 1953](#)) allocations assign a value to each player based on their

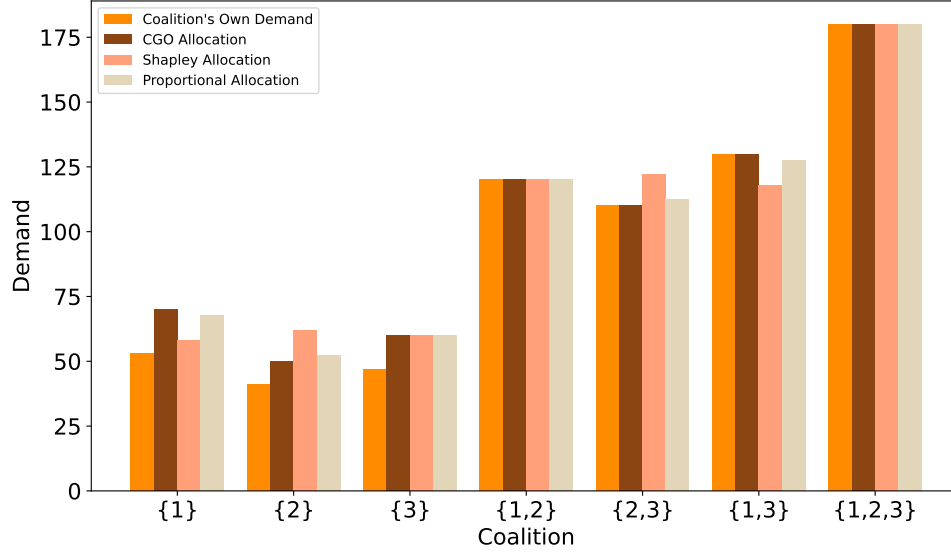


Figure 3.3: Comparison of allocation rules in terms of demand

marginal contribution to different subcoalitions. The Shapley allocations are calculated using equation (3.34).

$$\phi_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} \times (v(S \cup \{i\}) - v(S)) \quad (3.34)$$

The proportional allocation rule distributes resources such that each player's share is directly proportional to their contribution compared to the collective contributions of all players. These concepts are typically applied within a single-objective framework. In this study, they are utilized individually for each objective. For every player $i \in S$ the proportional allocations are calculated using equation (3.35) for cost and (3.36) for demand. For every coalition, this allocation is the sum of its individual members' allocations.

$$\text{Proportional Cost Allocation}_i = \frac{\text{Budget}_i \times \text{Grand Coalition Cost}}{\text{Grand Coalition Budget}} \quad (3.35)$$

$$\text{Proportional Demand Allocation}_i = \frac{\text{Demand}_i \times \text{Grand Coalition Demand}}{\text{Sum of All Players' Individual Demands}} \quad (3.36)$$

Figure 3.2 and Figure 3.3 show the cost and demand allocations, respectively, for each coalition under different allocation rules, with the coalition's characteristic function value

serving as a baseline. The analysis shows that Shapley and proportional allocations fail to meet the criteria for the preference or nondominance core, as some subcoalitions consistently receive higher cost or lower demand allocations than their own characteristic function values. In contrast, the allocation identified by the CGO model satisfies the requirements for both the preference and nondominance cores.

3.4.4 Scenario Analysis

In this section, a scenario analysis is presented to examine how varying model parameters, particularly budget and capacity for each player, affects allocation decisions and player behavior. Building on the base case, multiple scenarios are generated by varying the budget and capacity levels of the three organizations. The results are shown in Fig. 3.4. Scenarios L1–L6 capture changes in parameters for large organization, S1–S6 for small organization, and M1–M6 for medium-sized organization. The complete details of the scenarios are shown in Tables 3.4, 3.5, and 3.6 whereas the input parameters for the base case model are shown in Table 3.1. The analysis examines how changes in budget and capacity influence cost and demand allocations and explores the implications for inter-organizational coordination. Note that we only consider scenarios where costs are subadditive and demands are superadditive.

3.4.4.1 Impact of Budget and Capacity Increases

The impact of changes in organizations' budgets and capacities on allocations and player behaviors is analyzed and an overview is visualized in Fig. 3.4. The horizontal axis in each plot represents the tested scenarios. The vertical axis in the top three plots (a, b, c) indicates cost allocations in dollars, and in the bottom three plots (d, e, f), it represents demand allocations measured in units of relief items. The bars in each plot illustrate the allocation distribution, where large organization, small organization, and medium organization are distinguished by different shading patterns. The numerical values displayed above the bars in the top plots correspond to the grand coalition's total budget, while those in the bottom plots represent the grand coalition's total demand fulfillment.

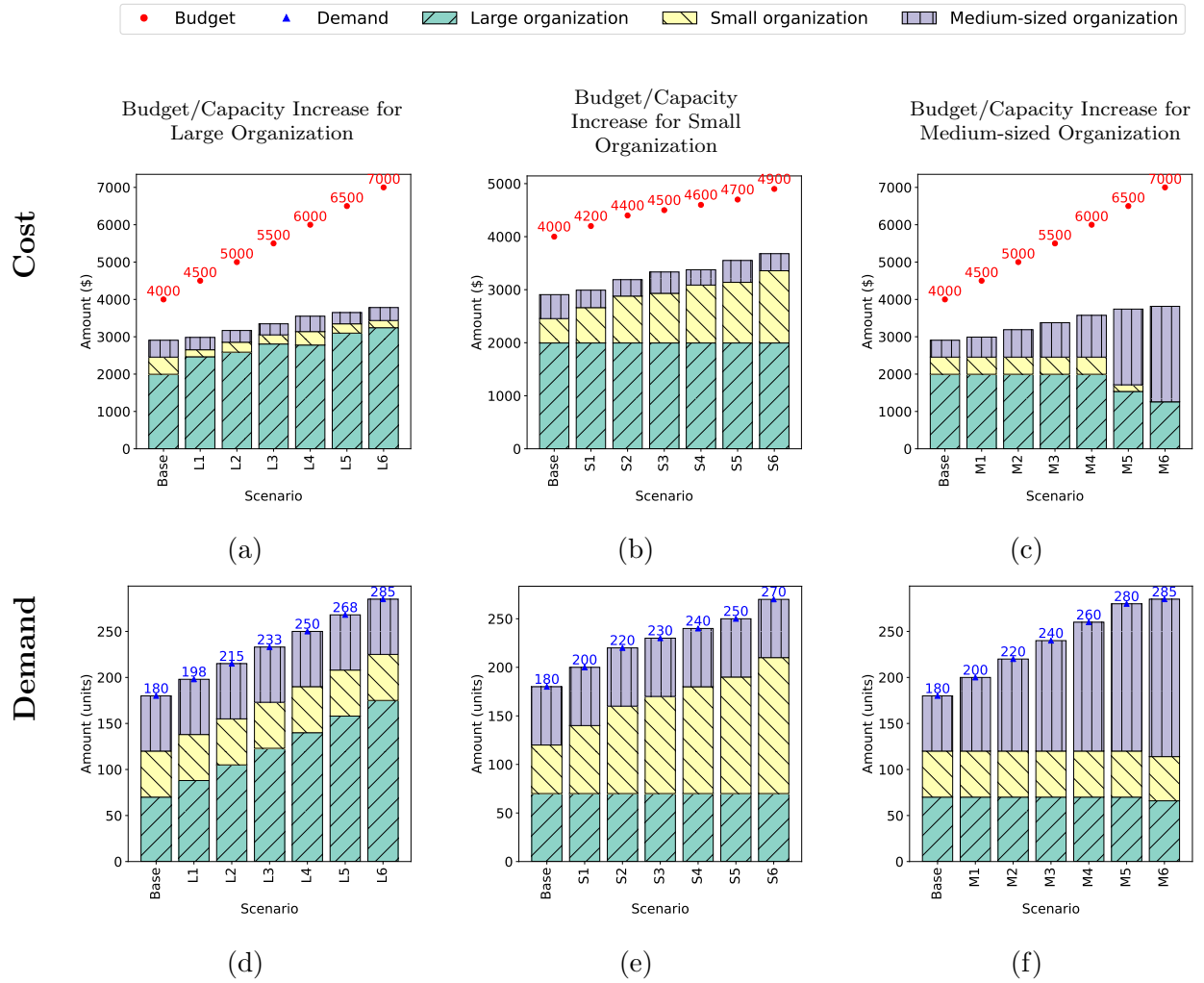


Figure 3.4: Impact of changes in budget and capacity for the large, small, and medium-sized organizations, respectively, on allocated costs ((a)-(c)) and allocated demands ((d)-(f)). Scenarios L1–L6 capture changes in parameters for the large organization, S1–S6 for the small organization, and M1–M6 for the medium-sized organization.

Scenario 1: Large Organization’s Budget and Capacity Increase

Increasing the budget and capacity of the large organization takes a significant share of costs away from the small and medium-sized organizations. Note the almost linear relationship of increased demand fulfillment with increased budget and higher cost allocation (Figs. 3.4a, 3.4d). As the budget is increased, the large organization can absorb more costs, providing financial relief to other organizations. However, despite the decrease in their cost allocations, the demand assigned to the small and medium-sized organizations remains constant, indicating that the increased budget and capacity for the large organization does not alter their roles in demand fulfillment. Also, while it can absorb higher costs, diminishing returns exist as the cost increase for scenario L5 is much higher for the same level of demand increase relevant to other scenarios. These patterns highlight the importance of coordinated efforts to ensure that any additional resources are deployed effectively to enhance system-wide efficiency, rather than leading to potential redundancies or oversupply in non-critical areas.

Scenario 2: Small Organization’s Budget and Capacity Increase

Budget and capacity increases for the small organization (Figs. 3.4b, 3.4e) lead to notable changes in both cost and demand allocation. As its budget increases, we notice a significant decrease in cost allocation for the medium-sized organization, while the cost allocation for the large organization remains largely unaffected. The small organization’s increased budget also allows it to take on a larger share of demand whereas the demand allocations for others remain unchanged, demonstrating that its increased budget and capacity primarily enhances its own role without disrupting the broader system. This dynamic highlights the critical role that smaller organizations can play in improving overall system efficiency when adequately resourced. By increasing its budget, the small organization expands its impact, addressing previously unmet or underserved needs.

Scenario 3: Medium-Sized Organization’s Budget and Capacity Increase

When the medium-sized organization’s budget and capacity are increased, (Figs. 3.4c, 3.4f), it can be noted that with greater resources, the medium-sized organization can absorb logistical and transport burdens, thereby driving down costs for both the large and small organizations and freeing them to focus on their respective strengths. The small organization sees a marked drop in its own allocated costs; see, for example, scenario M6, where the allocated cost approaches zero. Meanwhile, the large organization’s direct cost allocation remains unchanged until the medium one’s capacity surpasses it, at which point the large organization sees tangible cost savings. The ability of the medium-sized organization to absorb costs and provide stability to the system underscores its strategic importance. With sufficient funding, it can act as a bridge between the larger and smaller organizations, ensuring smoother coordination and greater cost savings. This scenario highlights how strategically resourcing a medium-sized actor can harmonize the entire system, yielding mutual benefits in both cost savings and demand fulfillment.

The analysis highlights the critical importance of strategic coordination and resource sharing in humanitarian operations. Larger organizations play a foundational role in absorbing costs and stabilizing the system. However, their efficiency diminishes without collaborative efforts, as excessive budget increases yield limited additional benefits. Medium-sized organizations emerge as pivotal actors, balancing cost responsibilities and providing critical support to smaller organizations. Meanwhile, smaller organizations thrive when adequately resourced, using increased budgets to expand their role in demand fulfillment and reduce their dependency on other actors. Thus, each expansion strategy raises total demand coverage and can reduce average costs for the system. Expanding the largest organization’s capacity generates faster gains in cost-effectiveness on a per-unit basis, as it rapidly scales up coverage. Empowering the smaller or medium-sized organization, however, can more dramatically lift the total number of beneficiaries reached, because these initially constrained actors move to higher activity levels.

In conclusion, while budget increases improve cost-efficiency and relieve financial pressures on smaller organizations, the most significant gains are achieved through strategic coordination among organizations of different sizes. Synergy among all three organizations emerges as the key to leveraging their complementary strengths, ensuring expanded coverage while constraining both individual and collective costs. By pooling resources, aligning capacities, and coordinating operational advantages, each organization can pursue its own objectives, controlling costs and maximizing demand coverage while ensuring that the overall humanitarian response is both efficient and equitable.

3.4.4.2 Impact of Budget Increase on Demand Fulfillment

The impact of budget increase on overall demand fulfillment is also analyzed. Starting from the base case, each scenario is created by increasing each organization's budget to different levels independently and consequently added to the grand coalition's budget. After solving the model, the resulting increase in grand coalition's demand fulfillment is reported. Table 3.7 shows this information. Fig. 3.5 present the results of analyzing the impact of budget increases relative to demand fulfillment for each organization's investment. Each pair of bars represents a comparison: the left bar indicates the percentage increase in budget for the grand coalition, while the right bar shows the corresponding grand coalition's percentage of satisfied demand increase.

The comparison of the large, small, and medium-sized organizations highlights differences in budget efficiency and demand fulfillment capacity. The large organization experiences diminishing returns, where budget increases outpace demand fulfillment, indicating inefficiencies or constraints in resource utilization. The small organization demonstrates high budget efficiency, with highest return for investment. However, despite this efficiency, the small organization's maximum fulfilled demand remains lower than that of the large and medium-sized organizations, suggesting an inherent capacity limitation. The medium-sized organization follows a proportional growth pattern, where demand fulfillment scales steadily with budget increases, but signs of saturation emerge at higher levels. While the small

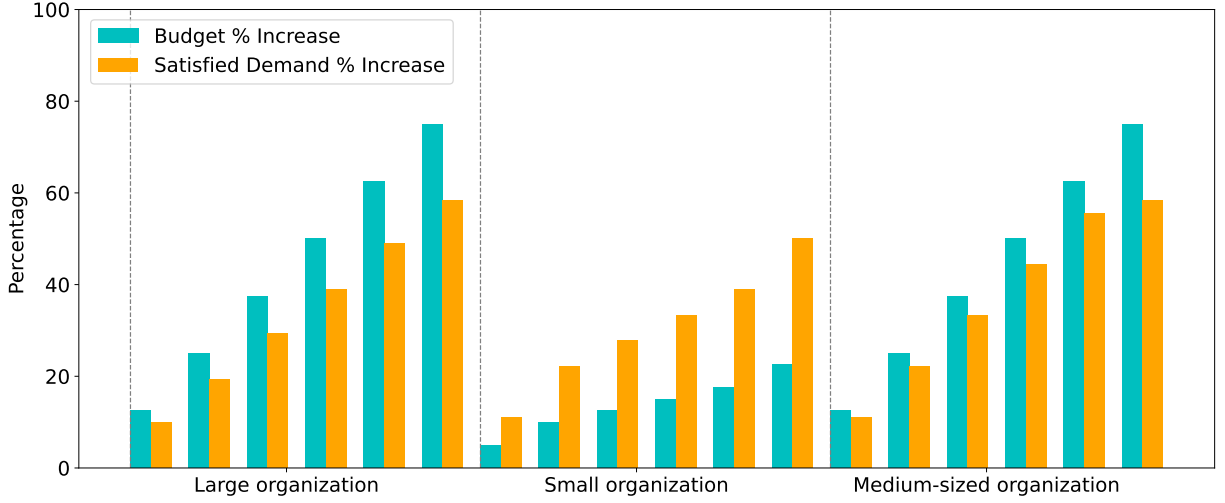


Figure 3.5: Impact of budget increase on demand fulfillment

organization is the most efficient in utilizing its budget, the large and medium-sized organizations ultimately fulfill a greater total demand, indicating that budget alone is not the sole determinant of impact.

3.5 Conclusion

This study presents a novel integration of cooperative game theory and goal programming to address the complex challenges of multi-objective, multi-agent coordination in humanitarian operations. A new mathematical concept, Chebyshev least core, to quantify the minimum concession necessary to make coordination a stable strategy is introduced and defined. Moreover, a framework is developed that explicitly models the strategic interactions among multiple agents while balancing conflicting objectives such as cost minimization and demand fulfillment. By leveraging the Chebyshev goal programming approach, the CGO model ensures fairness and stability. The model is designed such that the optimal variable values indicate whether a solution belongs to the preference core, the nondominance core, or neither. When no preference core allocation exists, the model calculates the value of the Chebyshev least core that would restore stability. This provides a rigorous, quantitative basis for assessing fairness and stability in coordinated relief operations.

The results of the numerical example and scenario analysis demonstrate the framework’s ability to improve coordination, enhance resource allocation, and promote equity among multiple agents. The CGO model outperforms traditional allocation rules such as the Shapley value and proportional allocation for the examined instance, ensuring that no subcoalition has an incentive to deviate. This is particularly crucial in humanitarian contexts where effective coordination directly impacts lives and resources.

The scenario analysis highlights the importance of strategic allocation decisions and coordination among organizations of varying sizes. Larger organizations provide foundational stability, but their efficiency diminishes without collective efforts. Medium-sized organizations act as critical intermediaries, balancing cost responsibilities and supporting smaller organizations, while adequately resourced smaller organizations can significantly improve overall system efficiency and reduce dependency on others.

Overall, this research advances the theoretical understanding of cooperative game theory in multi-objective domains and provides practical insights for enhancing coordination in humanitarian logistics. The findings emphasize the need for tailored strategies that leverage the unique strengths of each interested party to maximize system-wide efficiency, equity, and impact. Future work could explore the application of this framework in other domains, such as healthcare or public policy, and extend it to account for dynamic and uncertain environments.

Table 3.4: Increase in large organization’s budget and capacity. Organizations in coalitions are represented as 1: large organization, 2: small organization, 3: medium-sized organization.

Scenario	Coalition	Budget	Total Cost	Total Demand	CGO Allocated Cost	CGO Allocated Demand	Shapley Cost	Shapley Demand	Proportional Cost	Proportional Demand
L1	{1}	2500	2464.6	88	2464.6	88	1175.2	73	1657.0	99
	{2}	500	490.2	41	187	50	1041.3	68	331.4	46
	{3}	1500	1480.5	47	331	60	766.1	57	994.2	53
	{1,2}	3000	2651.6	138	2651.6	138	2216.5	141	1988.4	145
	{2,3}	2000	1111	110	518	110	1807.4	125	1325.6	99
	{1,3}	4000	2817.6	148	2795.6	148	1941.3	130	2651.2	152
	{1,2,3}	4500	2982.6	198	2982.6	198	2982.6	198	2982.6	198
L2	{1}	3000	2587	105	2587	105	1282	81	1900.8	117
	{2}	500	490.2	41	267	50	1131.2	77	316.8	46
	{3}	1500	1480.5	47	314	60	754.8	57	950.4	52
	{1,2}	3500	2854	155	2854	155	2413.2	158	2217.6	163
	{2,3}	2000	1111	110	581	110	1886	134	1267.2	98
	{1,3}	4500	2906	165	2901	165	2036.8	138	2851.2	169
	{1,2,3}	5000	3168	215	3168	215	3168	215	3168.0	215
L3	{1}	3500	2819.6	123	2806.6	123	1386.4	90	2129.7	136
	{2}	500	490.2	41	244	50	1217.4	86	304.2	45
	{3}	1500	1480.5	47	296	60	742.8	57	912.7	52
	{1,2}	4000	3050.6	173	3050.6	173	2603.8	176	2433.9	181
	{2,3}	2000	1111	110	540	110	1960.2	143	1216.9	97
	{1,3}	5000	3102.6	183	3102.6	183	2129.2	147	3042.4	188
	{1,2,3}	5500	3346.6	233	3346.6	233	3346.6	233	3346.6	233
L4	{1}	4000	2942	140	2779	140	1480.6	99	2367.3	154
	{2}	500	490.2	41	360	50	1294.7	94	295.9	45
	{3}	1500	1480.5	47	412	60	775.8	57	887.8	52
	{1,2}	4500	3139	190	3139	190	2775.2	193	2663.3	198
	{2,3}	2000	1111	110	772	110	2070.5	151	1183.7	96
	{1,3}	5500	3191	200	3191	200	2256.4	156	3255.1	205
	{1,2,3}	6000	3551	250	3551	250	3551	250	3551.0	250
L5	{1}	4500	3185.6	158	3097.6	158	1559.4	108	2525.3	172
	{2}	500	490.2	41	249	50	1355.4	103	280.6	45
	{3}	1500	1480.5	47	301	60	732.8	57	841.8	51
	{1,2}	5000	3346.6	208	3346.6	208	2914.8	211	2805.8	217
	{2,3}	2000	1111	110	550	110	2088.3	160	1122.3	96
	{1,3}	6000	3398.6	218	3398.6	218	2292.2	165	3367.0	223
	{1,2,3}	6500	3647.6	268	3647.6	268	3647.6	268	3647.6	268
L6	{1}	5000	3411	175	3243	175	1630.2	116	2701.4	190
	{2}	500	490.2	41	192	50	1409.3	112	270.1	44
	{3}	1500	1480.5	47	347	60	742.5	57	810.4	51
	{1,2}	5500	3435	225	3435	225	3039.5	228	2971.6	234
	{2,3}	2000	1111	110	539	110	2151.8	169	1080.6	95
	{1,3}	6500	3590	235	3590	235	2372.7	173	3511.9	241
	{1,2,3}	7000	3782	285	3782	285	3782	285	3782.0	285

Table 3.5: Increase in small organization’s budget and capacity. Organizations in coalitions are represented as 1: large organization, 2: small organization, 3: medium-sized organization.

Scenario	Coalition	Budget	Total Cost	Total Demand	CGO Allocated Cost	CGO Allocated Demand	Shapley Cost	Shapley Demand	Proportional Cost	Proportional Demand
S1	{1}	2000	1995.6	53	1995.6	70	1096.8	68	1424.3	66
	{2}	700	694.2	61	666.4	70	1081.1	72	498.5	76
	{3}	1500	1480.5	47	329.0	60	813.2	60	1068.2	58
	{1,2}	2700	2662.0	140	2662.0	140	2177.8	140	1922.8	142
	{2,3}	2200	1340.0	130	995.4	130	1894.3	132	1566.7	134
	{1,3}	3500	2610.0	130	2324.6	130	1910.0	128	2492.5	124
	{1,2,3}	4200	2991.0	200	2991.0	200	2991.0	200	2991.0	200
S2	{1}	2000	1995.6	53	1995.6	70	1205.5	79	1449.5	67
	{2}	900	891.8	74	884.4	90	1170.6	80	652.3	94
	{3}	1500	1480.5	47	309.0	60	812.9	61	1087.2	59
	{1,2}	2900	2880.0	160	2880.0	160	2376.1	159	2101.8	161
	{2,3}	2400	1576.0	150	1193.4	150	1983.5	141	1739.5	153
	{1,3}	3500	2610.0	130	2304.6	130	2018.4	140	2536.7	126
	{1,2,3}	4400	3189.0	220	3189.0	220	3189.0	220	3189.0	220
S3	{1}	2000	1995.6	53	1995.6	70	1259.2	84	1481.8	66
	{2}	1000	993.8	84	936.4	100	1234.3	85	740.9	105
	{3}	1500	1480.5	47	402.0	60	840.6	61	1111.3	59
	{1,2}	3000	2932.0	170	2932.0	170	2493.4	169	2222.7	171
	{2,3}	2500	1658.0	160	1338.4	160	2074.9	146	1852.2	164
	{1,3}	3500	2610.0	130	2397.6	130	2099.8	145	2593.1	125
	{1,2,3}	4500	3334.0	230	3334.0	230	3334.0	230	3334.0	230
S4	{1}	2000	1995.6	53	1995.6	70	1295.6	90	1467.8	68
	{2}	1100	1096.4	87	1091.4	110	1281.0	87	807.3	112
	{3}	1500	1480.5	47	289.0	60	799.5	62	1100.9	60
	{1,2}	3100	3087.0	180	3087.0	180	2576.5	178	2275.1	180
	{2,3}	2600	1740.0	170	1380.4	170	2080.5	150	1908.2	172
	{1,3}	3500	2610.0	130	2284.6	130	2095.1	153	2568.7	128
	{1,2,3}	4600	3376.0	240	3376.0	240	3376.0	240	3376.0	240
S5	{1}	2000	1995.6	53	1995.6	70	1370.1	95	1511.1	67
	{2}	1200	1198.4	97	1143.4	120	1333.0	92	906.6	123
	{3}	1500	1480.5	47	412.0	60	848.0	62	1133.3	60
	{1,2}	3200	3139.0	190	3139.0	190	2703.0	188	2417.7	190
	{2,3}	2700	1887.0	180	1555.4	180	2181.0	155	2039.9	183
	{1,3}	3500	2610.0	130	2407.6	130	2218.1	158	2644.4	127
	{1,2,3}	4700	3551.0	250	3551.0	250	3551.0	250	3551.0	250
S6	{1}	2000	1995.6	53	1995.6	70	1444.1	106	1501.6	66
	{2}	1400	1392.2	116	1361.4	140	1421.9	102	1051.1	145
	{3}	1500	1480.5	47	322.0	60	813.0	63	1126.2	59
	{1,2}	3400	3357.0	210	3357.0	210	2866.0	208	2552.8	211
	{2,3}	2900	2051.0	200	1683.4	200	2234.9	165	2177.4	204
	{1,3}	3500	2610.0	130	2317.6	130	2257.1	168	2627.9	125
	{1,2,3}	4900	3679.0	270	3679.0	270	3679.0	270	3679.0	270

Table 3.6: Increase in medium-sized organization's budget and capacity. Organizations in coalitions are represented as 1: large organization, 2: small organization, 3: medium-sized organization.

Scenario	Coalition	Budget	Total Cost	Total Demand	CGO Allocated Cost	CGO Allocated Demand	Shapley Cost	Shapley Demand	Proportional Cost	Proportional Demand
M1	{1}	2000	1995.6	53	1995.6	70	937.6	57	1329.3	64
	{2}	500	490.2	41	459.4	50	928.9	61	332.3	50
	{3}	2000	1996.5	71	536.0	80	1124.5	81	1329.3	86
	{1,2}	2500	2455.0	120	2455.0	120	1866.5	119	1661.7	114
	{2,3}	2500	1340.0	130	995.4	130	2053.4	143	1661.7	136
	{1,3}	4000	2828.0	150	2531.6	150	2062.1	139	2658.7	150
	{1,2,3}	4500	2991.0	200	2991.0	200	2991.0	200	2991.0	200
M2	{1}	2000	1995.6	53	1995.6	70	927.5	60	1275.6	69
	{2}	500	490.2	41	459.4	50	852.8	64	318.9	54
	{3}	2500	2481.0	74	734.0	100	1408.7	96	1594.5	97
	{1,2}	2500	2455.0	120	2455.0	120	1780.3	124	1594.5	123
	{2,3}	3000	1576.0	150	1193.4	150	2261.5	160	1913.4	151
	{1,3}	4500	2932.0	170	2729.6	170	2336.2	156	2870.1	166
	{1,2,3}	5000	3189.0	220	3189.0	220	3189.0	220	3189.0	220
M3	{1}	2000	1995.6	53	1995.6	70	862.2	60	1227.6	66
	{2}	500	490.2	41	459.4	50	809.0	64	306.9	51
	{3}	3000	2997.0	98	921.0	120	1704.9	117	1841.5	123
	{1,2}	2500	2455.0	120	2455.0	120	1671.1	123	1534.5	118
	{2,3}	3500	1740.0	170	1380.4	170	2513.8	181	2148.4	174
	{1,3}	5000	3139.0	190	2916.6	190	2567.0	177	3069.1	189
	{1,2,3}	5500	3376.0	240	3376.0	240	3376.0	240	3376.0	240
M4	{1}	2000	1995.6	53	1995.6	70	811.8	63	1191.3	71
	{2}	500	490.2	41	459.4	50	753.1	67	297.8	55
	{3}	3500	3488.5	99	1119.0	140	2009.2	131	2084.8	133
	{1,2}	2500	2455.0	120	2455.0	120	1564.8	129	1489.2	127
	{2,3}	4000	1969.0	190	1578.4	190	2762.3	197	2382.7	189
	{1,3}	5500	3357.0	210	3114.6	210	2821.0	193	3276.2	205
	{1,2,3}	6000	3574.0	260	3574.0	260	3574.0	260	3574.0	260
M5	{1}	2000	1995.6	53	1536.0	70	755.3	62	1151.1	69
	{2}	500	490.2	41	177.0	50	682.1	66	287.8	53
	{3}	4000	3983.0	122	2028.0	160	2303.5	152	2302.2	158
	{1,2}	2500	2455.0	120	1713.0	120	1437.5	128	1438.8	122
	{2,3}	4500	2205.0	210	2205.0	210	2985.7	218	2589.9	211
	{1,3}	6000	3564.0	230	3564.0	230	3058.9	214	3453.2	227
	{1,2,3}	6500	3741.0	280	3741.0	280	3741.0	280	3741.0	280
M6	{1}	2000	1995.6	53	1259.3	66	654.8	60	1090.0	69
	{2}	500	490.2	41	0.0	48	585.6	64	272.5	53
	{3}	4500	4489.0	126	2555.7	171	2574.5	161	2452.5	163
	{1,2}	2500	2455.0	120	1259.3	114	1240.5	124	1362.5	122
	{2,3}	5000	2434.0	230	2555.7	219	3160.2	225	2725.0	216
	{1,3}	6500	3801.0	250	3815.0	237	3229.4	221	3542.5	232
	{1,2,3}	7000	3815.0	285	3815.0	285	3815.0	285	3815.0	285

Table 3.7: Increase in satisfied demand resulting from budget increase by organization. The grand coalition base budget is \$4000.0 and base demand is 180 units in each case.

Organizations	Budget Increase (\$)	Grand Coalition Budget (\$)	Budget % Increase	Grand Coalition Demand Satisfied (units)	Satisfied Demand % Increase
Large organization	500.0	4500.0	12.5	198.0	10.0
	1000.0	5000.0	25.0	215.0	19.4
	1500.0	5500.0	37.5	233.0	29.4
	2000.0	6000.0	50.0	250.0	38.9
	2500.0	6500.0	62.5	268.0	48.9
	3000.0	7000.0	75.0	285.0	58.3
Small organization	200.0	4200.0	5.0	200.0	11.1
	400.0	4400.0	10.0	220.0	22.2
	500.0	4500.0	12.5	230.0	27.8
	600.0	4600.0	15.0	240.0	33.3
	700.0	4700.0	17.5	250.0	38.9
	900.0	4900.0	22.5	270.0	50.0
Medium-sized organization	500.0	4500.0	12.5	200.0	11.1
	1000.0	5000.0	25.0	220.0	22.2
	1500.0	5500.0	37.5	240.0	33.3
	2000.0	6000.0	50.0	260.0	44.4
	2500.0	6500.0	62.5	280.0	55.6
	3000.0	7000.0	75.0	285.0	58.3

Chapter 4

Multi-agent Multi-objective Coordination for Hurricane Preparedness and Response: A Case Study

4.1 Introduction

Natural disasters such as hurricanes pose significant logistical challenges to emergency response systems. Effective coordination is the cornerstone of hurricane disaster response, where multiple independent organizations must work together under urgent, resource-constrained, and infrastructure-disrupted conditions. Beyond the physical challenges of deploying relief resources and positioning staging facilities, the real difficulty lies in aligning decisions across diverse actors to ensure timely and equitable outcomes. A central aspect of hurricane response involves the strategic placement of staging facilities and the efficient distribution of essential supplies to affected regions. Given the challenging factors such as limited resources, urgency, and infrastructure damage associated with hurricane scenarios and the presence of multiple actors involved in disaster response, a coordination framework is essential for guid-

ing informed decision-making.

In this chapter, a case study approach is employed to illustrate and validate the framework presented in Chapter 3. It is designed to answer the following questions:

1. Impact on response: How does coordination affect the decisions made by organizations in the response?
2. Stability: Do there exist ways to share costs and benefits such that coordination is a stable strategy among multiple organizations responding to hurricanes?

The analysis focuses on a ten-state region in the southeast United States, an area frequently highlighted in hurricane risk assessments. A significant increase in tropical cyclone activity is projected in this region by the 2030s, especially along Florida’s Gulf Coast, with the most pronounced increases occurring in high-intensity storms (Hall et al., 2021).

In this chapter, the costs and benefits of coordination in time-sensitive disaster response for multiple organizations with multiple objectives are captured. The application of the developed CGO framework to serve as a decision-support tool for these organizations is shown, enabling more informed decision-making in complex disaster response situations.

4.2 Case Study Parameters

Three hurricane scenarios are developed based on historical data about three major storms, Bertha, Hugo, and Katrina. Each scenario assumes a forecasted hurricane with a 48-hour lead time, during which responding organizations must mobilize and establish staging areas. Three relief agencies that differ in size and budget are considered. Both independent and coordinated response strategies are captured. For each scenario and each subcoalition, the characteristic function vector is generated by solving two optimization models. These capture the decisions made by each coalition about staging area location, storage, and equitable relief distribution with respect to its own financial capacity. Then the CGO framework is applied to each scenario to identify allocation decisions. These allocations represent a fair way

to share the total costs and relief workloads among the agencies, i.e., how expenses and responsibilities would be divided in a coordinated response.

4.2.1 Network

The network utilized in this study is derived from the 30-node system originally proposed by [Rawls and Turnquist \(2010\)](#), as shown in Fig. 4.1 and Table 4.1. An undirected, fully connected graph of 435 arcs is constructed using the Google Maps API ([Google, 2025](#)) to obtain realistic travel distances across the network on major highways. The following subsections describe the input parameters associated with each hurricane scenario.

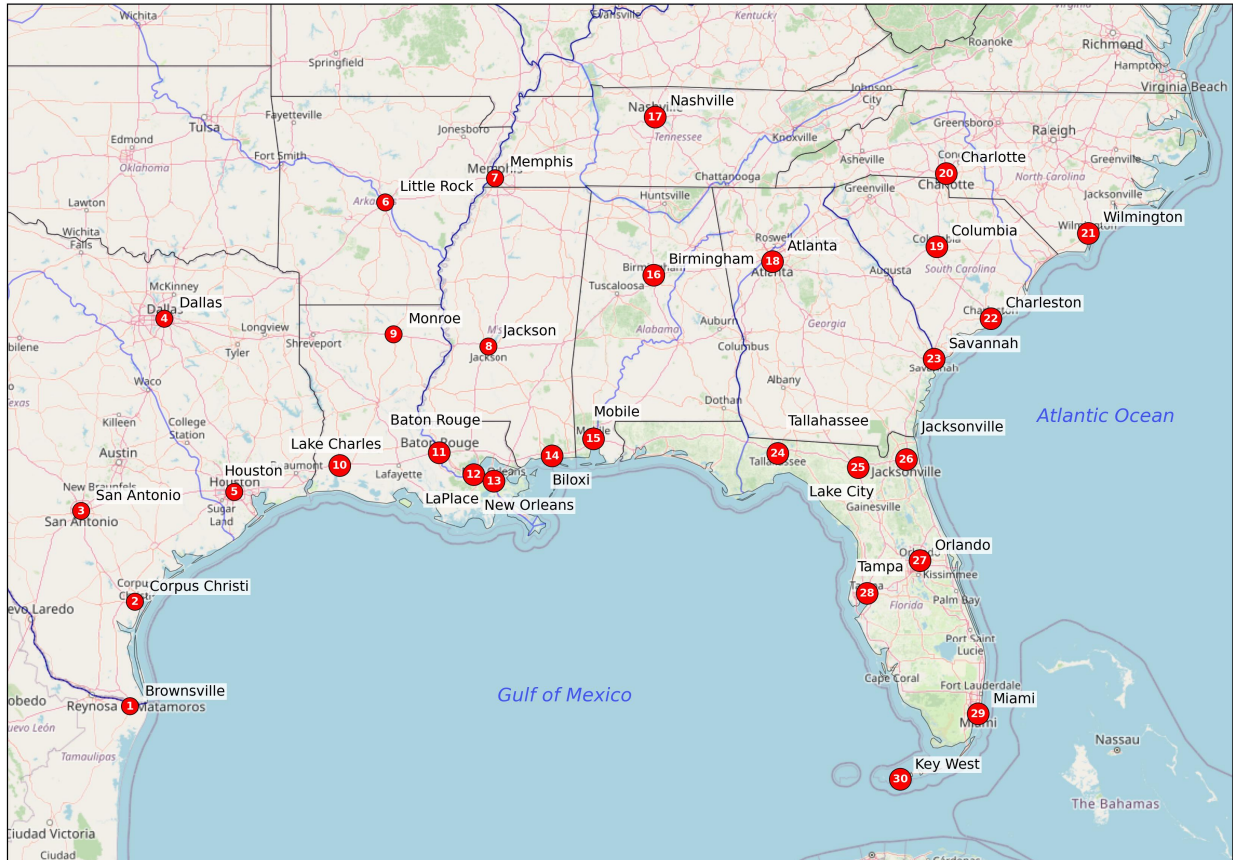


Figure 4.1: The 30-node system utilized in this case study

Table 4.1: Node-city mapping for case study network

Node	City	Node	City	Node	City
1	Brownsville, TX	11	Baton Rouge, LA	21	Wilmington, NC
2	Corpus Christi, TX	12	Laplace, LA	22	Charleston, SC
3	San Antonio, TX	13	New Orleans, LA	23	Savannah, GA
4	Dallas, TX	14	Biloxi, MS	24	Tallahassee, FL
5	Houston, TX	15	Mobile, AL	25	Lake City, FL
6	Little Rock, AR	16	Birmingham, AL	26	Jacksonville, FL
7	Memphis, TN	17	Nashville, TN	27	Orlando, FL
8	Jackson, MS	18	Atlanta, GA	28	Tampa, FL
9	Monroe, LA	19	Columbia, SC	29	Miami, FL
10	Lake Charles, LA	20	Charlotte, NC	30	Key West, FL

4.2.2 Organizations' Budgets and Coalitions

Three distinct organizations engaged in disaster preparedness and response are considered, each with a different operational scale, denoted small, medium, and large. These classifications are based on differences in resource capacity, with organizational budgets serving as proxies for relative size. Given the participation of three organizations, a total of seven non-empty coalitions are possible, encompassing singleton coalitions, pairwise coalitions, and the grand coalition involving all three. For every non-singleton coalition, the total budget is the sum of its individual members' budgets.

Budget levels for each singleton coalition are selected based on data from past hurricane response efforts and documented expenditures by both governmental and non-governmental agencies to represent realistic financial capabilities and constraints. For each hurricane scenario, it is assumed that up to 90% of the total demand can be met with the combined budget of all organizations. This threshold is adopted to reflect the realistic constraints of disaster response, recognizing that even the coordinated efforts of major organizations are unlikely to fully satisfy demand due to logistical, financial, and operational constraints inherent to large-scale emergencies. The budget values for each coalition in each hurricane scenario are shown in Table 4.2.

Coalition	Bertha	Hugo	Katrina
{1}	29,605	44,222	1,500,000
{2}	8,882	13,266	450,000
{3}	19,836	29,628	1,005,000
{1,2}	38,487	57,488	1,950,000
{2,3}	28,718	42,894	1,455,000
{1,3}	49,441	73,850	2,505,000
{1,2,3}	58,323	87,116	2,955,000

Table 4.2: Budget (\$) for each coalition and hurricane scenario

4.2.3 Commodity Costs

The emergency commodity analyzed in this case study is the medical kit, as illustrated in Fig. 4.2 (Uline, 2025). The procurement cost includes purchasing and storage. Each kit has a unit purchase price of \$38. To reflect cost efficiencies gained through coordination, economies of scale are modeled as reductions in unit cost, set at \$24 for pairwise coalitions and \$17 for the grand coalition. The storage cost is assumed to be 25% of the purchase price.

4.2.4 Transportation Costs

Transportation costs are estimated based on item dimensions and truck capacity. Each kit (10in $\times$ 7in $\times$ 3in; 1.57 lbs) is shipped in a 27in $\times$ 15in $\times$ 16in box holding 18 kits. A 28-foot box truck can carry 140 boxes (2,520 kits) without pallets. Based on a \$2,400 quote for 662.5 miles FreightRun.com (2025) (\$3.62/mile), the transport cost is approximately \$0.00143 per kit per mile. Total cost is calculated by multiplying the number of kits, distance, and the unit-mile rate.

4.2.5 Facility Capacities and Costs

Facility capacities are defined relative to the total demand in each hurricane scenario. A large staging area can accommodate up to 100% of the total demand, a medium facility



Figure 4.2: Medical kits, the commodity considered for this case study. Source: [Uline \(2025\)](#)

holds up to 50%, and a small facility is limited to 10%. This sizing approach reflects the typical distribution of needs during hurricanes, where a few locations near landfall experience very high demand, while the majority of locations further inland have less need. Considering multiple facility sizes allows coalitions to make flexible and cost-effective decisions that account for this variability in demand across affected areas.

The facility opening cost structure exhibits economies of scale. As facility size increases, the fixed cost per unit of capacity decreases. This is consistent with common assumptions in logistics facility planning. These parameters are shown in Table 4.3.

Hurricane	Facility Size	Facility Capacity(Kits)	Fixed Cost (\$)
Bertha	Small	300	43.9
	Medium	1,500	219.6
	Large	3,000	402.6
Hugo	Small	448	71.4
	Medium	2,240	300.6
	Large	4,481	601.4
Katrina	Small	15,200	1,854.4
	Medium	76,000	8,344.8
	Large	152,000	14,835.2

Table 4.3: Facility sizes, capacities, and costs for different hurricanes

4.2.6 Demands

Demand estimates are extracted from [Rawls \(2008\)](#) and adjusted to reflect the number of individuals that each medical kit can serve (25 people). Table [4.4](#) contains the demand information for each hurricane scenario.

4.2.7 Hurricane Damage Assumptions

It is assumed that organizations make decisions regarding the establishment of staging facilities and distribution plans approximately 48 hours prior to the projected landfall of a hurricane. As a result, cities expected to be directly impacted by the storm are excluded from the set of candidate locations for facility placement. This exclusion is based on data from [Rawls and Turnquist \(2010\)](#), with a slight modification: rather than differentiating between damaged and destroyed sites, all such locations are removed from consideration, as the focus here is on temporary staging areas and not permanent warehouses. Excluded nodes for each hurricane are identified in Table [4.4](#).

4.3 Framework Application to Case Study

The application of the framework presented in section [3.3.2](#) for multi-agent, multi-objective coordination is presented in this section. A two-phase capacitated facility location and distribution model is first built to determine optimal facility location, inventory management, and distribution strategies for each coalition, ensuring equitable demand fulfillment by each coalition for each location. These optimization models generate characteristic function values that quantify both the incurred costs and the demand fulfilled. Building on these outputs, the subsequent CGO model allocates costs and demand responsibilities among the agencies by minimizing the maximum relative deviation from their ideal targets. This two-pronged approach not only ensures operational efficiency by strategically positioning facilities to reduce response times and transportation costs, it also promotes fairness and stability in resource-sharing arrangements. The models described below embody the trade-offs between broad

service level and cost efficiency, forming a valuable decision-support tool for coordinated disaster management.

4.3.1 Two-Phase Capacitated Facility Location and Distribution Model

This section describes a two-phase capacitated facility location and distribution model designed to support coordinated decision-making among multiple organizations in the context of hurricane preparation and response. The model incorporates both the fixed and variable costs associated with opening facilities of various sizes, storing inventory, and distributing supplies to demand points. It is solved for every possible coalition of organizations, enabling the generation of characteristic function values in terms of cost incurred and demand fulfilled.

The model is solved independently for each coalition $S \subseteq N$. In Phase 1, the objective is to maximize δ_S , the proportion of total demand fulfilled, while respecting capacity, budgetary, and logistical constraints. Phase 2 then minimizes the total cost required to achieve the optimal service level δ_S^* obtained in Phase 1. The model captures key operational features relevant to disaster logistics, such as facility sizing, inventory allocation, equitable demand fulfillment, and hurricane-related disruptions.

Sets

I : Set of potential facility locations for a hurricane scenario

J : Set of demand locations

K : Set of facility sizes, where $K = \{\text{small, medium, large}\}$

Parameters

f_k : Fixed cost of opening a facility of size $k \in K$

C_k : Capacity of a facility of size $k \in K$

Ω : Procurement cost

c_{ij} : Transportation cost per unit from facility $i \in I$ to demand point $j \in J$

d_j : Demand at location $j \in J$

B_S : Total available budget for subcoalition S

Decision Variables

$x_{ik} \in \{0, 1\}$: 1 if a facility of size k is opened at location i , 0 otherwise

y_i : Inventory stored at location i

q_{ij} : Quantity shipped from facility i to demand point j

δ_S : Minimum fraction of demand satisfied at each location by subcoalition S

Phase 1: Maximize Service Level

Maximize δ_S

subject to:

$$y_i \leq \sum_{k \in K} C_k x_{ik} \quad \forall i \in I \quad (4.1)$$

$$\sum_{k \in K} x_{ik} \leq 1 \quad \forall i \in I \quad (4.2)$$

$$\sum_{i \in I} \sum_{k \in K} f_k x_{ik} + \sum_{i \in I} \Omega y_i + \sum_{i \in I} \sum_{j \in J} c_{ij} q_{ij} \leq B_S \quad \forall S \subseteq N \quad (4.3)$$

$$\sum_{j \in J} q_{ij} \leq y_i \quad \forall i \in I \quad (4.4)$$

$$\sum_{i \in I} q_{ij} \geq \delta_S d_j \quad \forall j \in J, \forall S \subseteq N \quad (4.5)$$

$$x_{ik} \in \{0, 1\} \quad \forall i \in I, \forall k \in K \quad (4.6)$$

$$y_i \in \mathbb{Z}^+ \quad \forall i \in I \quad (4.7)$$

$$q_{ij} \in \mathbb{Z}^+ \quad \forall i \in I, \forall j \in J \quad (4.8)$$

$$0 \leq \delta_S \leq 1 \quad (4.9)$$

Let δ_S^* be the optimal value of δ_S obtained in Phase 1.

Phase 2: Minimize Cost Given Optimal Service Level

Minimize $\sum_{i \in I} \sum_{k \in K} f_k x_{ik} + \sum_{i \in I} \Omega y_i + \sum_{i \in I} \sum_{j \in J} c_{ij} q_{ij}$
subject to:

Constraints [4.1](#), [4.2](#), [4.3](#), [4.4](#), [4.6](#), [4.7](#), [4.8](#),

$$\sum_{i \in I} q_{ij} \geq \delta_S^* d_j \quad \forall j \in J \quad (4.10)$$

Constraint [\(4.1\)](#) ensures that the inventory stored at a facility does not exceed the total installed capacity at that location. The capacity is determined by the facility size selected from the available set K , and only contributes if the corresponding facility is opened. Constraint [\(4.2\)](#) restricts each location to at most one facility, regardless of size. This reflects realistic limitations on space or infrastructure that prevent multiple facilities from being installed at the same site. Constraint [\(4.3\)](#) imposes a budget constraint. The total cost of opening facilities, storing inventory, and transporting goods from facilities to demand points must not exceed the available budget B_S . Constraint [\(4.4\)](#) ensures that the quantity shipped from any facility does not exceed the inventory available at that location. This condition maintains the conservation of flow and guarantees that outgoing shipments reflect actual on-hand supply. Constraint [\(4.5\)](#) enforces a proportional fulfillment requirement at each demand location. Specifically, it requires that each demand point receives at least a fraction δ_S of its total demand d_j , where δ_S is a variable representing the minimum service level achieved by each coalition S across all demand points. This formulation promotes equity in distribution, particularly important in disaster response scenarios imposing that locations that are farther away may not be disadvantaged due to distance. Constraints [\(4.6\)](#), [\(4.7\)](#) and [\(4.8\)](#) impose standard non-negativity and domain restrictions on the decision variables. Constraint [\(4.9\)](#) restricts the demand satisfaction variable δ_S to the range $[0, 1]$, with 0 indicating no fulfillment and 1 indicating 100% demand fulfillment.

In Phase 2, the model minimizes the total operational cost while satisfying the optimal service level δ_S^* identified in Phase 1. All constraints from the first phase are retained, except

for Constraint (4.5), which is replaced by (4.10) where δ_S is fixed at δ_S^* . This modification ensures that the cost minimization step adheres to the previously determined level of demand fulfillment.

The characteristic function values that result from the optimization models provide a foundation for further game-theoretic analysis, including cost-sharing and incentive allocation among coordinating agents. This framework supports equitable and efficient coordination in multi-agency disaster logistics planning, promoting both strategic coordination and operational resilience in the face of natural hazards.

4.3.2 Cooperative Goal Optimization

Coordination among multiple organizations is essential to efficiently deploy resources and achieve equitable service delivery. Following the solution of the two-phase capacitated facility location and distribution model, each possible coalition of organizations $S \subseteq N$ is associated with a pair of characteristic function values: $v_c(S)$, representing the total cost of staging area setup and distribution operations, and $v_d(S)$, representing the total demand fulfilled for that coalition under a given hurricane scenario. These values serve as the foundation for a subsequent analysis.

To support fair and balanced allocations across participating organizations, the Cooperative Goal Optimization (CGO) model from Chapter 3 is adapted to the case study. The CGO model seeks an allocation of cost and demand responsibilities to individual organizations such that the aggregate outcomes for all coalitions remain as close as possible to their respective cost and demand targets. Specifically, the model minimizes the maximum relative deviation from the ideal cost and demand contributions across all coalitions, thereby promoting fairness in multi-agency coordination.

Parameters

N : Set of organizations, $N = \{1, 2, \dots, n\}$

S : Coalition, a subset of N

$v_d(S)$: Characteristic function value of demand for coalition S

$v_c(S)$: Characteristic function value of cost for coalition S

Decision Variables

x_c^i : Cost allocation to organization i

x_d^i : Demand allocation to organization i

p_d^S : Deviation from demand goal for subcoalition S

n_j^S : Deviation from cost goal for subcoalition S

λ : Maximal deviation

Minimize λ

subject to:

$$\sum_{i \in S} x_d^i + p_d^S \geq v_d(S), \quad \forall S \subset N \quad (4.11)$$

$$\sum_{i \in S} x_c^i - n_c^S \leq v_c(S), \quad \forall S \subset N \quad (4.12)$$

$$\sum_{i \in N} x_d^i = v_d(N), \quad (4.13)$$

$$\sum_{i \in N} x_c^i = v_c(N), \quad (4.14)$$

$$\frac{p_d^S}{v_d(S)} \leq \lambda, \quad \forall S \subset N \quad (4.15)$$

$$\frac{n_c^S}{v_c(S)} \leq \lambda, \quad \forall S \subset N \quad (4.16)$$

$$n_c^S \geq 0, \quad \forall S \subset N \quad (4.17)$$

$$p_d^S \in \mathbb{Z}^+, \quad \forall S \subset N \quad (4.18)$$

$$x_d^i \in \mathbb{Z}^+, x_c^i \in \mathbb{R}^+, \forall i \in S \subset N \quad (4.19)$$

$$\lambda \geq 0 \quad (4.20)$$

Constraint (4.11) ensures that the total demand allocated to members of any coalition S , adjusted by a non-negative deviation p_d^S , meets or exceeds the coalition's own demand value $v_d(S)$. Constraint (4.12) similarly ensures that the sum of cost allocations to a coalition's members does not exceed the coalition's total cost value $v_c(S)$, adjusted downward by a non-negative deviation term n_c^S . These constraints enforce the *rationality* property from cooperative game theory, ensuring that each player receives at least as much as they could achieve individually. Constraint (4.13) enforces demand balance across the entire system by requiring that the total allocated demand across all organizations equals the grand coalition's demand $v_d(N)$. Likewise, Constraint (4.14) ensures that the total allocated cost matches the overall system cost $v_c(N)$. These two constraints together enforce the *efficiency* property from cooperative game theory, ensuring that the total value of the grand coalition is fully distributed among the players without surplus or deficit. Constraints (4.15) and (4.16) normalize the deviation terms p_d^S and n_c^S , respectively, by their corresponding coalition values. The resulting ratios must be less than or equal to the maximum allowable deviation λ , which is minimized in the objective function. This formulation ensures that fairness is measured across all objectives and across all coalitions. Constraint (4.17) guarantees that the negative cost deviation variables n_c^S are non-negative. Constraint (4.18) similarly enforces that the positive demand deviation variables p_d^S are non-negative integers, suitable for representing shortfalls in demand fulfillment. Constraint (4.19) defines the domains of the decision variables: demand allocations x_d^i are non-negative integers, while cost allocations x_c^i are non-negative continuous variables, consistent with their real-world interpretations. Finally, Constraint (4.20) requires the maximum deviation λ to be non-negative.

4.4 Results

The models presented in section 4.3 are implemented on three hurricane scenarios using the data presented in 4.2, and the results are described in this section. Decisions related to facility location, distribution, and satisfied demand percentages are the outcomes of the two-phase facility location and distribution model presented in 4.3.1. The adapted CGO

model from 4.3.2 outputs specify the cost and demand allocations for each coalition. The two-phase model and the CGO model were solved using Gurobi 10.0.2 on a system equipped with an Intel Core™ i7 processor (quad-core, base frequency 1.80 GHz), 16 GB RAM, and the Windows 11 operating system. The Gurobi MIPGap parameter is set to 0.2% for the Bertha scenario and 0.0% for the Katrina and Hugo scenarios.

4.4.1 Coordinated and Non-coordinated Location Decisions

Table 4.4 compares facility siting choices when the three organizations deploy resources independently and in coordination to satisfy each hurricane’s demand. Singleton columns, $\{1\}$, $\{2\}$, and $\{3\}$, report the locations selected when each organization optimizes with its own budget. Pairwise columns, $\{1,2\}$, $\{2,3\}$, and $\{1,3\}$, show the joint decisions of two-member coalitions, whose spending limits equal the sum of their individual budgets. The right-most column, $\{1,2,3\}$, presents the grand coalition outcome achieved when all three organizations pool budgets. For each hurricane scenario, the table lists each city where a facility is opened and the facility’s size.

4.4.2 Distribution Decisions

Table 4.5 lists, for every demand point in the Bertha, Hugo, and Katrina scenarios, the staging area(s) from which it receives supplies under each coalition configuration. Each row identifies a hurricane, a demand location, and its estimated demand; the subsequent columns are coalitions labeled $\{1\}$, $\{2\}$, $\{3\}$, $\{1,2\}$, $\{2,3\}$, $\{1,3\}$, and $\{1,2,3\}$, and show the origin cities selected when the corresponding coalition optimizes its own network. Cells contain one or more city names, indicating whether a location is served from a single hub or from multiple origins. Demand nodes marked with an asterisk are themselves ineligible to host a facility but receive supplies from other sites.

4.4.3 Demand Fulfillment

Table 4.6 shows the minimum fraction of demand (δ_S^*) each coalition can guarantee at every demand location for each hurricane scenario. The rows depict coalitions, while columns list specific hurricanes. Higher δ values point to higher demand fulfillment across all demand points. Each δ value refers to the minimum percentage of demand met across all locations in each hurricane; thus, for any location, the demand met may be higher than the corresponding δ but never lower.

4.4.4 Allocations and Coalitions' Goals

For each hurricane, two key metrics are evaluated for each coalition based on the output of the underlying two-phase facility location and distribution model: (i) the total cost incurred and (ii) the total demand fulfilled. These are compared against the values obtained from the CGO model, which allocates cost and demand across organizations to ensure fairness while minimizing maximum relative deviation from the ideal cost and demand goal values.

Table 4.7 presents this comparison of own coalition values versus CGO allocated outcomes for both cost and demand. Each row corresponds to a specific hurricane scenario, with values computed for all individual organizations and their possible coalitions. The columns correspond to coalitions, with coalitions ($\{1\}$, $\{2\}$, $\{3\}$) representing organizations acting independently, pairwise coalitions ($\{1,2\}$, $\{2,3\}$, $\{1,3\}$), and the grand coalition $\{1,2,3\}$ representing organizations working in coordination.

Table 4.4: Location decisions for different coalition structures across hurricanes. Organizations in coalitions are denoted as 1: large, 2: small, 3: medium.

Hurricane	City (Node)*	Demand	Coalition						
			{1}	{2}	{3}	{1,2}	{2,3}	{1,3}	{1,2,3}
Bertha	Columbia (19)	898				Columbia (19)(s)			
	Charlotte (20)	773	Columbia (19)(s)	Savannah (23)(s)	Columbia (19)(s) Charlotte (20)(s)	Charlotte (20)(s)	Columbia (19)(s)	Columbia (19)(m)	Columbia (19)(m)
	Wilmington (21)	148	Charlotte (20)(s)			Wilmington (21)(s)	Charlotte (20)(s)	Charlotte (20)(s)	Charlotte (20)(s)
	Charleston (22)	1180	Charleston (22)(s)			Charleston (22)(s) Savannah (23)(s)	Charleston (22)(s) Savannah (23)(s)	Charleston (22)(s)	Wilmington (21)(s) Charleston (22)(m)
Hugo	Columbia (19)	1512							
	Charlotte (20)	868	Columbia (19)(s)	Columbia (19)(s)	Columbia (19)(s) Charlotte (20)(s)	Columbia (19)(m)	Columbia (19)(s)	Columbia (19)(m) Charlotte (20)(s)	Columbia (19)(m) Savannah (23)(m)
	Wilmington (21)	111	Charlotte (20)(s)				Charlotte (20)(s)		
	Charleston (22)*	1764	Savannah (23)(s)				Wilmington (21)(s)		
	Savannah (23)	226					Savannah (23)(s)		
Katrina	Jackson (8)	47							
	Monroe (9)	46							
	Lake Charles (10)	1859							
	Baton Rouge (11)	7816							
	New Orleans (13)*	55954							
	Biloxi (14)	221	Laplace (12)(s)	Laplace (12)(s) Orlando (27)(s)	Laplace (12)(s) Orlando (27)(s)	Baton Rouge (11)(s) Laplace (12)(s) Orlando (27)(s) Tampa (28)(s) Key West (30)(s)	Baton Rouge (11)(s) Laplace (12)(s) Tampa (28)(s) Key West (30)(s)	Baton Rouge (11)(s) Laplace (12)(s) Biloxi (14)(s) Orlando (27)(s) Tampa (28)(s) Key West (30)(s)	Laplace (12)(m) Orlando (27)(s) Tampa (28)(s) Key West (30)(m)
	Mobile (15)	6646	Tampa (28)(s)						
	Key West (30)(s)		Key West (30)(s)						
	Orlando (27)	13773							
	Tampa (28)	22382							
	Miami (29)*	43041							
	Key West (30)	215							

*City sustained extensive damage and was not a candidate facility location. (s): small facility, (m): medium facility, (l): large facility.

Table 4.5: Staging locations chosen by each coalition to serve each demand node. Organizations in coalitions are denoted as 1: large, 2: small, 3: medium.

Hurricane	Demand location	Demand	Coalition supplying city(-ies)						
			{1}	{2}	{3}	{1,2}	{2,3}	{1,3}	{1,2,3}
Bertha	Columbia (19)	898	Columbia	Savannah	Columbia	Columbia, Wilmington	Columbia	Columbia	Columbia
	Charlotte (20)	773	Charlotte	Savannah	Charlotte	Charlotte, Wilmington	Charlotte	Columbia, Charlotte	Columbia, Charlotte
	Wilmington (21)	148	Columbia	Savannah	Charlotte	Wilmington	Charlotte	Charleston	Wilmington
	Charleston (22)	1180	Charlotte, Charleston	Savannah	Columbia	Charleston, Savannah	Charleston, Savannah	Columbia, Charleston	Charleston
Hugo	Columbia (19)	1512	Columbia	Columbia	Columbia, Charlotte	Columbia	Columbia, Charlotte	Columbia	Columbia
	Charlotte (20)	868	Charlotte	Columbia	Charlotte	Columbia	Charlotte	Charlotte	Columbia
	Wilmington (21)	111	Charlotte	Columbia	Charlotte	Columbia	Wilmington	Columbia	Columbia, Savannah
	Charleston (22)*	1764	Savannah	Columbia	Columbia	Columbia	Wilmington, Savannah	Columbia	Savannah
	Savannah (23)	226	Savannah	Columbia	Columbia	Columbia	Savannah	Columbia	Savannah
Katrina	Jackson (8)	47	Laplace	Laplace	Laplace	Baton Rouge	Baton Rouge	Baton Rouge, Biloxi	Laplace
	Monroe (9)	46	Laplace	Laplace	Laplace	Baton Rouge	Baton Rouge	Baton Rouge	Laplace
	Lake Charles (10)	1859	Laplace	Laplace	Laplace	Baton Rouge	Baton Rouge	Baton Rouge	Laplace
	Baton Rouge (11)	7816	Laplace	Laplace	Laplace	Baton Rouge	Baton Rouge	Baton Rouge	Laplace
	New Orleans (13)*	55954	Laplace	Laplace	Laplace	Laplace	Laplace	Laplace, Biloxi, Baton Rouge	Laplace
	Biloxi (14)	221	Laplace	Laplace	Laplace	Baton Rouge	Baton Rouge	Biloxi	Laplace
	Mobile (15)	6646	Laplace	Laplace	Laplace	Baton Rouge, Orlando	Baton Rouge	Biloxi	Laplace
	Orlando (27)	13773	Tampa	Orlando	Orlando	Orlando	Tampa	Orlando	Orlando
	Tampa (28)	22382	Tampa	Orlando	Orlando	Tampa	Tampa	Tampa	Orlando, Tampa, Key West
	Miami (29)*	43041	Key West	Orlando	Orlando	Orlando, Key West	Key West	Orlando, Tampa, Key West	Key West
	Key West (30)	215	Key West	Orlando	Orlando	Key West	Key West	Key West	Key West

*City sustained extensive damage and was not a candidate facility location.

Table 4.6: Minimum percentage of demand (δ) values for coalition configurations for three hurricanes. Organizations in coalitions are represented as 1: large organization, 2: small organization, 3: medium-sized organization.

Coalition	Bertha	Hugo	Katrina
{1}	20.60	20.62	20.59
{2}	6.10	6.15	6.15
{3}	13.81	13.76	13.78
{1,2}	42.43	42.34	42.24
{2,3}	31.63	31.55	31.57
{1,3}	54.45	54.43	54.17
{1,2,3}	90.54	90.41	90.24

Table 4.7: Comparison of allocations and goals for each coalition and hurricane scenario. Organizations in coalitions are denoted as 1: large, 2: small, 3: medium.

Hurricane	Cost(\$), Demand(units)	Coalitions						
		{1}	{2}	{3}	{1,2}	{2,3}	{1,3}	{1,2,3}
Bertha	Own Cost	29,604.73	8,876.53	19,833.27	38,472.49	28,700.38	49,433.89	58,316.42
	CGO Allocated Cost	29,609.62	8,871.48	19,835.32	38,481.10	28,706.80	49,444.94	58,316.42
	Own Demand	620	185	415	1273	950	1634	2717
	CGO Allocated Demand	817	950	950	1767	1900	1767	2717
Hugo	Own Cost	44,213.88	13,259.39	29,602.06	57,478.98	42,872.37	73,840.75	87,107.29
	CGO Allocated Cost	44,230.10	13,264.25	29,612.93	57,494.36	42,877.18	73,843.03	87,107.29
	Own Demand	925	277	619	1899	1416	2442	4053
	CGO Allocated Demand	1221	1416	1416	2637	2832	2637	4053
Katrina	Own Cost	1,495,878.93	449,115.78	1,001,728.69	1,942,779.58	1,452,439.10	2,490,656.93	2,950,555.42
	CGO Allocated Cost	1,499,142.37	450,763.08	1,000,649.97	1,949,905.45	1,451,413.05	2,499,792.34	2,950,555.42
	Own Demand	31,302	9,348	20,946	64,208	47,989	82,341	137,165
	CGO Allocated Demand	41,187	47,989	47,989	89,176	95,978	89,176	137,165

4.4.5 Existence of Core Allocations

Table 4.8 summarizes the CGO model output for each hurricane scenario. In this table, the worst-case deviation, denoted by λ , quantifies the maximum shortfall across all subcoalitions and objectives. A value of $\lambda = 0$ indicates that the CGO model identified a preference core allocation that meets or exceeds each coalition's demand and cost goals, whereas $\lambda > 0$

indicates that the preference core is empty. In such cases, the model identifies a Chebyshev least core allocation where λ represents the minimum adjustment required to stabilize the overall coordination. A nondominance core allocation exists for all hurricane scenarios, as there exists at least one objective for each coalition where the target goal is met or exceeded. In each scenario studied, the demand fulfillment goal is met for each coalition, while for some coalitions, there does not exist a cost allocation that meets the corresponding goals.

Table 4.8: Existence of preference, nondominance, or Chebyshev least core allocations in each hurricane scenario

Hurricane	λ	Preference Core Allocation	Nondominance Core Allocation	Chebyshev Least Core Allocation
Bertha	0.0002		✓	✓
Hugo	0.0003		✓	✓
Katrina	0.0037		✓	✓

4.4.6 Return on Investment

Figure 4.3 compares the percentage change in total cost with the percentage change in demand satisfied when the three organizations act together as a grand coalition rather than individually. The percentage differences are calculated by contrasting the grand coalition outcomes with the summed results of the individual organizations. For each hurricane, the left bar represents the relative increase in cost, while the right bar represents the relative increase in demand fulfilled. The figure points to a consistent trend across hurricanes: while the total cost tends to increase modestly under the grand coalition, the percentage of demand fulfillment improves substantially.

4.4.7 Discussion

This section analyzes the case study results with respect to the original research questions. Specifically, results are examined to understand how coordination changes the response and

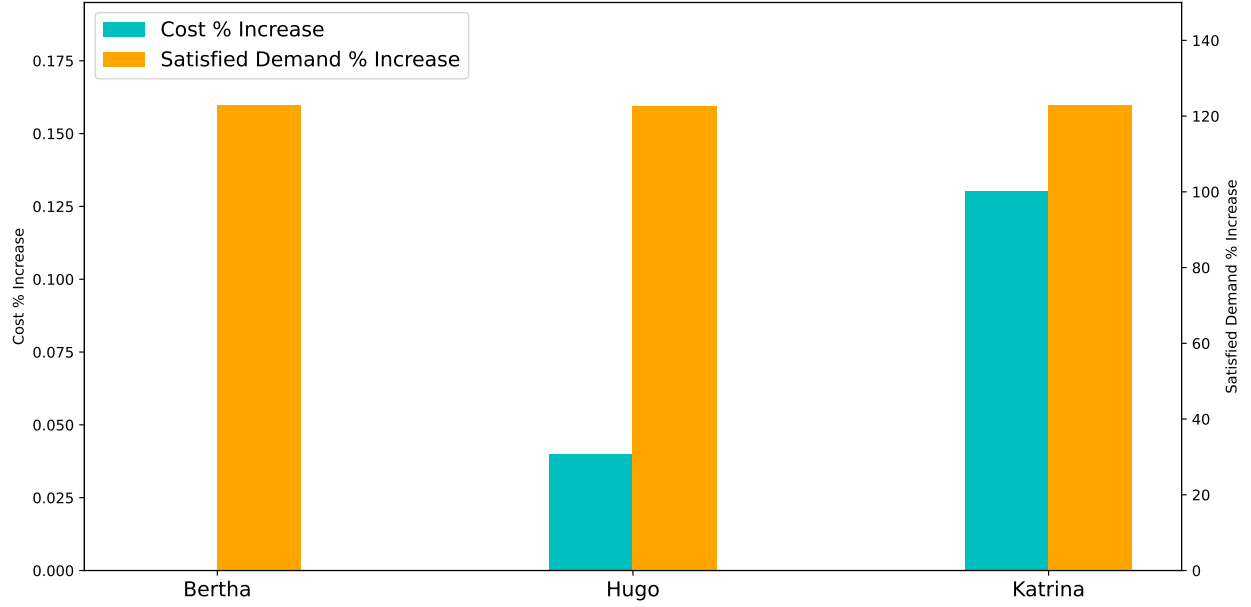


Figure 4.3: Comparison of cost and demand fulfillment percentage increase in the grand coalition relative to individual coalition totals

whether coordination is a stable strategy.

4.4.7.1 Impact of Coordination on Response

Coordination yields immediate operational synergies. As Table 4.4 shows, a single organisation can afford only small staging areas and often has to scatter them across several cities to cover demand. Once two agencies pool their budgets, and even more so in the three-agency grand coalition, coalitions either open additional sites or consolidate several small staging areas into a single, bigger one that serves more demand. In Hurricane Hugo, for example, organizations {1} and {2} individually establish small facilities in Columbia, Charlotte, and Savannah; together, coalition {1,2} concentrates resources on one medium facility in Columbia and meets higher demand with simpler logistics. Similar shifts from multiple small to fewer medium-sized sites occur for coalition {1,3} and for the grand coalition, as well as in the Bertha and Katrina scenarios, where joint action consistently upgrades small facilities to medium ones while satisfying a much larger share of overall demand.

Because the grand coalition budget equals the sum of the three individual budgets, performance gains stem from more strategic spending. The results in Table 4.7 in combination

with Tables 4.4 and 4.5 show that pooling resources enables larger or more advantageously sited staging areas to be opened, thereby increasing demand fulfillment at the same total cost. Figure 4.3 reinforces this point: the grand coalition incurs only a fractional increase in expenditure yet more than doubles the demand served.

Demand fulfillment at each location also improves. As reported in Table 4.6, the grand coalition guarantees at least 90 % fulfillment at every location, whereas no singleton agency can assure more than 21 %. Because the metric δ is computed on a location-by-location basis, it prevents remote or hard-to-reach communities from being neglected. In sum, combining budgets translates the same total financial outlay into far higher service levels. Policymakers or relief agencies can observe which coalitions produce the greatest improvements. This knowledge can inform negotiations on resource sharing, helping identify the best partner organizations for more effective disaster response.

The results highlight two strategic approaches enabled by coordination. First, larger coalitions can position multiple facilities closer to different demand points, reducing transport distances, cutting variable costs, and enabling faster response times. Alternatively, coalitions can open fewer but larger facilities, simplifying logistics at the cost of some flexibility. Both patterns are evident in Table 4.5 and reinforce the importance of coordinated planning. For example, pairwise coalitions in the Hurricane Katrina scenario are able to open more facilities than the singleton counterparts and serve more demand. On the other hand, the grand coalition opens two medium and two small facilities only and serves 90% of demand across all locations. In sum, as coalition size increases, the overall configuration shifts beyond simply combining smaller coalition plans. In the Bertha, Hugo, and Katrina scenarios, the grand coalition is not merely a union of smaller coalitions, but a distinct configuration that achieves higher demand satisfaction than any standalone or pairwise coalition strategy. By comparing each organization’s standalone strategy to the grand coalition strategy, it is evident that coordination yields better response capability for the same total budget.

4.4.7.2 Stability of a Coordinated Response

A coordinated response is stable only if no organization can improve its overall utility by leaving the grand coalition. In a multi-objective context, this requirement can be formalized in two ways: (i) preference core allocation, where each coalition receives at least as much or more utility in every objective as it could secure on its own; or (ii) nondominance core allocation, where each coalition does better in at least one objective.

The results in Table 4.8 indicate that the maximal relative deviation, λ , is positive for all three hurricanes, ruling out a preference core solution. However, observe from Table 4.7 that deviations to be minimized only exist in terms of cost as coalitions' own costs are slightly smaller than allocated costs. However, demand allocations across all coalitions in all scenarios are larger. Thus, there exist a nondominance core allocation and a stable grand coalition is achievable even though a strict preference core allocation does not exist.

In Table 4.8, the worst-case deviation, denoted by λ , quantifies the maximum shortfall across all subcoalitions and objectives. It represents the minimum adjustment, whether in the form of policy change, financial incentive, or additional investment, required to stabilize the overall coordination. Notably, the Katrina scenario exhibits the highest deviation ($\lambda = 0.0037$), indicating a more pronounced challenge in aligning the cost and demand objectives for all coalitions. In contrast, the Bertha and Hugo scenarios, with λ values of 0.0002 and 0.0003, respectively, demonstrate that quite small adjustments are needed to achieve stable, near-equitable allocations. The λ values indicate that stabilizing the coalition requires an adjustment of approximately 0.37% of the total budget in the Katrina scenario, and less than 0.03% in the Bertha and Hugo scenarios. In practice, organizations may consider addressing this shortfall by reallocating contingency or overhead funds, subsidizing the most burdened partners, or securing grants or donations that match the identified shortfall to ensure that no coalition is worse off than it would be under independent operations.

The findings demonstrate that stable coordination among autonomous agencies can be achieved with only modest changes to their individual decisions. While a perfectly equi-

table outcome for all participants across every objective may not always be possible, the concessions required to ensure collective stability are small. This makes the proposed framework especially relevant for multi-agent humanitarian settings, where decision-makers retain control over their actions but benefit from aligning actions.

Beyond stability, coordination leads to meaningful operational gains. Joint action of organizations, without relinquishing autonomy, enables collectively meeting significantly more demand than they would in isolation, often with only a slight increase in cost. These results highlight that effective, decentralized coordination mechanisms can deliver both fairness and efficiency, reinforcing the value of structured collaboration in disaster response.

4.5 Conclusion

This chapter presented a comprehensive case study on facility location and distribution for hurricane response, demonstrating the effectiveness of a multi-agent, multi-objective coordination framework. The approach integrated a two-phase capacitated facility location and distribution model with a Cooperative Goal Optimization (CGO) model, enabling the evaluation of both operational and strategic aspects of disaster logistics. The analysis revealed that coordinated strategies, achieved through resource pooling among multiple organizations, lead to a broader and more strategically distributed network of facilities compared to independent actions. In addition, the framework successfully ensured a high level of equitable demand fulfillment across all affected areas while maintaining near-optimal cost efficiency. Moreover, the allocation studies highlighted that with minor adjustments, fair distribution of costs and demands is attainable, emphasizing the stability and sustainability of inter-agency coordination. Overall, the findings imply that integrated resource management not only enhances operational responsiveness and service level in hurricane scenarios but also delivers superior returns per dollar invested, offering valuable insights for policymakers and disaster response planners.

Chapter 5

Conclusion and Future Work

Humanitarian logistics systems often face operational challenges stemming from decentralized decision-making, uncertain environments, and urgent demands. This dissertation contributes to the understanding and improvement of such systems through three distinct but related studies, leveraging optimization and game theory to analyze and enhance coordination among decision makers. This chapter summarizes the major findings of the dissertation, discusses the broader implications of the research, and outlines directions for future work.

5.1 Summary of Contributions

Chapter 2 provides a systematic review of the literature at the intersection of humanitarian operations, game theory, and optimization. It identifies coordination as a recurring challenge across various domains within humanitarian logistics and classifies prior work based on modeling approach, coordination mechanisms, and decision context. The review highlights the scarcity of studies that integrate cooperative game-theoretic constructs with optimization models to address the coordination problem, especially in settings where agencies retain decision autonomy and have multiple objectives. By framing coordination as a problem of alignment of actions, this chapter lays a conceptual foundation for the models developed in subsequent chapters.

Chapter 3 introduces a novel framework that integrates cooperative game theory with Chebyshev goal programming to address the challenge of coordinating multiple agents with conflicting objectives in humanitarian operations. It first defines the Chebyshev least core, a new concept for evaluating the minimal relaxation needed to achieve fairness. Building on this, the Cooperative Goal Optimization (CGO) framework, featuring a mathematical programming model that computes the Chebyshev least core, is developed. The model’s solution indicates whether the outcome lies within the preference core, the nondominance core, or neither. Computational experiments and scenario analyses show that CGO consistently outperforms traditional methods such as the Shapley value and proportional rules, yielding more stable, equitable, and sustainable results. Overall, the chapter provides both a theoretical advancement and practical insights for improving coordination in multi-objective decentralized humanitarian response systems.

Chapter 4 presents a comprehensive case study on facility location and relief distribution for hurricane response, demonstrating the effectiveness of a multi-agent multi-objective coordination framework. The proposed approach uses a two-phase capacitated facility location and distribution model to generate characteristic function values and then applies the CGO model, enabling simultaneous evaluation of operational and strategic aspects of disaster logistics. The analysis reveals that coordinated strategies, facilitated by resource pooling among multiple organizations, more than double the relief distribution capacity compared to individual actions. Furthermore, the framework ensures equitable demand fulfillment across affected areas while maintaining efficiency. Allocation studies indicate that fair distributions of cost and demand can be achieved with relatively minor adjustments, reinforcing the stability and sustainability of inter-agency coordination. These findings highlight that integrated resource management not only improves service level and operational responsiveness in hurricane contexts, but also offers greater returns on investment, providing actionable insights for policymakers and humanitarian logistics planners.

This research contributes to both theoretical understanding and practical application of coordination mechanisms in humanitarian contexts. The integrated framework developed herein transcends traditional single-objective approaches by explicitly modeling the multi-

objective nature of humanitarian operations. By capturing both the strategic interactions among interested parties and the multiple competing objectives they face, the model provides a comprehensive approach to coordination challenges that have historically hampered effectiveness in humanitarian response.

The theoretical contributions of this work extend beyond humanitarian logistics to the broader fields of cooperative game theory and multi-objective optimization. The Chebyshev least core concept advances the state of knowledge by providing mechanisms to identify allocations that satisfy both individual and collective rationality principles and can lead to sustainable coordination.

5.2 Practical Implications

Beyond its theoretical contributions, this research offers several practical implications for humanitarian organizations and policymakers. The framework developed provides a systematic approach for aligning diverse goals among humanitarian actors, potentially elevating the collective effectiveness of humanitarian response efforts.

For practitioners, the model offers a decision support tool that can guide resource allocation decisions and coordination strategies. By explicitly accounting for multiple objectives and fairness considerations, the framework can help humanitarian organizations balance competing priorities such as cost efficiency, coverage, and speed of response. Moreover, the model can identify potential synergies from coordination that might otherwise remain unexplored.

The scenario analysis results have direct implications for capacity planning and resource allocation in humanitarian operations. The finding that strategic increases in capacity across different sizes of organizations can substantially improve collective outcomes suggests that funding agencies and policymakers should consider coordination potential when making investment decisions.

Additionally, the framework can support negotiations among humanitarian actors by providing a structured approach to identify stable and equitable allocations. This could

potentially reduce conflicts over resource distribution and encourage greater coordination among organizations with diverse missions and constraints.

5.3 Directions for Future Research

This dissertation opens several promising directions for future research. A natural extension involves adapting the framework to settings where forming the grand coalition is not socially optimal, thereby broadening its relevance to alternative coordinating structures. Exploring innovative integrations of other multi-objective optimization techniques with cooperative game theory constitutes a further natural avenue for extension. Another important direction is the development of alternative methods for generating characteristic function values beyond optimization-based approaches, such as data-driven estimation or expert elicitation, which may be better suited to contexts with limited modeling capabilities.

Incorporating uncertainty into the model would further enhance its applicability, particularly in humanitarian operations where volatility in demand, supply, and logistics is pervasive. Integrating stochastic programming techniques with the current framework could enable more robust decision-making under uncertain conditions.

Future work could also enhance the behavioral realism captured by the model. Drawing on insights from behavioral economics and organizational theory, researchers could incorporate factors such as trust, reputation, and organizational culture that influence coordination decisions in practice but are often overlooked in standard optimization models.

Applying the framework to other domains involving complex multi-agent coordination with conflicting objectives such as sustainable supply chains, public health planning, or environmental governance could provide further empirical validation and theoretical insights.

Finally, real-world implementation and evaluation of the framework in humanitarian contexts would offer critical feedback for its refinement. Coordination with humanitarian organizations to pilot the approach could generate actionable insights and support the translation of theoretical contributions into operational impact.

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