The Role of Centralization in the Efficiency of Humanitarian Logistics: A Warehouse Location Model-Based Approach

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The efficiency of humanitarian logistics is crucial for optimizing resource utilization and ensuring timely aid delivery in crisis situations. However, the lack of coordination among humanitarian agencies often leads to redundant efforts and excessive costs. This study investigates the benefits of a centralized coordination approach in humanitarian logistics, particularly in the allocation and management of warehouses during emergency responses. Using a multi-period mixed-integer linear programming model, we compare decentralized and centralized strategies for warehouse location and resource distribution. The Mosul Offensive (Iraq, 2016–2017) serves as a case study to assess the operational and economic impact of centralized coordination. Our findings demonstrate that centralizing logistical operations and fostering inter-agency cooperation lead to significant cost reductions, improved resource allocation, and enhanced service levels. The results highlight a trade-off between economies of scale and service proximity, reinforcing the importance of strategic coordination in humanitarian supply chains. The study contributes to the field by providing quantitative evidence on the advantages of centralization and offering practical insights for policymakers and humanitarian organizations aiming to optimize logistics operations in complex emergency scenarios

Keywords: Humanitarian logistics, centralization, multiperiod, location models, operations research.

1. Introduction

The increasing frequency and severity of disasters, coupled with constrained funding and fragmented relief efforts, demand more efficient and coordinated humanitarian operations. Humanitarian supply chains operate in highly volatile environments, requiring agility and effective resource management to ensure timely aid delivery (Leiras et al. 2014). These operations involve multiple stakeholders-beneficiaries, governments, and organizations-functioning under uncertain conditions that challenge logistics and coordination.

Relief supply chains respond to over 500 disasters annually, impacting mil- lions (Kovacs e Spens 2012). For instance, the Iraq Civil War (2014–2017) led to over 60,000 deaths and displaced more than three million people (ICB 2019; IOM 2019). Funding shortfalls have become increasingly acute, forcing humanitarian agencies to prioritize efficiency and cost-effectiveness (Humanitaires 2024; Parliament 2024).

A major operational challenge lies in logistics, which can account for over 80% of total humanitarian expenditures (34; Kovacs e Spens 2012; Wassenhove 2006).

Yet many operations remain decentralized, with each agency managing its own warehouses, often resulting in inefficiencies and duplication. Research suggests that centralized and cooperative logistics networks could reduce costs and improve coordination (Dohale et al. 2024; Negi 2022; 21), but the lack of quantitative evidence limits broader adoption.

The strategic placement and capacity of warehouses-central and local distribution centers-are central to effective humanitarian logistics. Cen- tralized models can reduce infrastructure redundancy and improve last-mile service levels (25). However, these decisions must adapt to evolving crises, particularly in war zones where needs change unpredictably over time.

This study proposes a multi-period mixed-integer linear programming model that compares decentralized and centralized humanitarian logistics networks. The model captures decisions on warehouse location, capacity, expansion, and allocation of shelters, considering fluctuating demand and long-term uncertainty. We focus on cooperative prepositioning strategies to improve operational performance and cost efficiency.

As a case study, we apply the model to the Mosul Offensive (Iraq, 2016–2017), demonstrating how coordinated logistics planning can optimize resource allo- cation in a protracted emergency. The findings aim to inform evidence-based strategies for humanitarian agencies operating in complex conflict settings.

The remainder of this paper is structured as follows: Section 2 reviews relevant literature. Section 3 details the model and methodology. Section 4 presents the case study. Section 5 offers a sensitivity analysis. Section 6 concludes with insights and implications for future research.

2. Background Literature

2.1 Lack of Coordination among Humanitarian Stakeholders

Effective humanitarian logistics depends on coordination among NGOs, gov- ernments, international agencies, and local responders. However, such coor- dination is often lacking, leading to inefficiencies, delays, and redundant op- erations (Wassenhove 2006; Kovacs e Spens 2012). Organizations frequently make decentralized decisions based on individual mandates and priorities, rather than collective goals, driving up operational costs.

Conflicting agendas and competition for donor funding further hinder collaboration. Agencies may prioritize visibility over efficiency, discouraging

joint efforts that could enhance logistics performance (Tomasini e Wassenhove 2009). Cultural and political differences also reduce information sharing and joint decision-making (Holgu´ın-Veras et al. 2012).

Technical barriers add to the problem. Humanitarian actors often use incompatible logistical systems, lacking the standardized platforms common in commercial supply chains. This fragmentation hampers real-time visibility and synchronization across operations (35; 7), making it difficult to identify critical shortages or redundancies.

The volatile nature of crises worsens the situation. In rapidly evolving contexts, organizations frequently act independently, competing for limited transport, storage, and local resources. For instance, during the 2010 Haiti earthquake, overlapping supply chains from multiple actors caused port and distribution congestion (Apte 2009).

Despite these challenges, initiatives like the UN's Cluster Approach have shown promise in fostering joint planning and information exchange (37). Yet, these frameworks are limited by bureaucratic delays and inconsistent participation. Without strong enforcement, many organizations still priori- tize internal efficiency over coordinated action (Balcik et al. 2010).

2.2 Multiperiod Location Problem in Humanitarian Logistics

Armed conflicts have been a major driver of human suffering over the past decade. According to the United Nations (OCHA 2019), the number of po- litical conflicts increased from 278 in

2006 to 402 in 2016. A survey by (Pettersson e Eck 2018) and (Dupuy e Rustad 2018) identified 285 armed conflicts since 1946, primarily internal but often involving external actors.

These events, defined as organized violence involving state actors and resulting in at least 25 annual battle deaths, have significantly contributed to humanitarian crises.

OCHA reports that 97% of humanitarian responses over the past decade addressed complex emergencies, particularly armed conflict and displace- ment. In 2016, 65.6 million people were forcibly displaced-mostly from Afghanistan, Somalia, South Sudan, and Syria-marking the highest level since World War II (OCHA 2019; UNHCR 2019).

Facility location problems in humanitarian logistics address the siting of key infrastructure such as shelters, distribution centers, and medical facili- ties. These models often integrate additional logistical concerns like stock prepositioning, evacuation, and relief distribution.

A review of 123 articles on facility location in humanitarian contexts revealed that 70 addressed natural disasters, 7 focused on man-made ones (mostly terrorism), and 46 were unspecified. Earthquakes, hurricanes, and floods dominated natural disaster studies, while only one study explicitly dealt with armed conflict.

Regarding disaster onset, 66 articles addressed sudden-onset events, 8 slow-onset, and 49 were unspecified. By lifecycle stage, 41 studies covered both preparation and response, 38 response only, and 31 preparation only.

Most studies used single-period models (93), with only 25 employing multi-period approaches. Additionally, 50 were multi-objective-primarily economic-while 72 were single-objective, with focuses ranging from cost and service level to other criteria.

3. Modeling

3.1. Problem Statement and its Assumptions

Disasters-natural or anthropogenic-often generate mass displacements re- quiring shelters and resources. Effective post-disaster humanitarian response depends on well-structured supply chains. This paper analyzes a two-echelon network: central distribution centers (CDCs), local distribution centers (LDCs), and shelters.

Coordination issues among humanitarian agencies often lead to inefficient logistics. In a decentralized network strategy, agencies manage independent local warehouses (often MSUs), each linked to specific shelters. CDCs, often long-term facilities, are strategically located in disaster-prone areas to hold pre-positioned supplies (25). LDCs, by contrast, are temporary facilities used during emergencies to consolidate and dispatch aid. However, locating cost-effective and secure LDCs remains a challenge for relief agencies (Balcik e Beamon 2008). In the centralized strategy, agencies collaborate by forming shelter clusters. Supply points-MSUs or hard-roof facilities-serve multiple shelters based on proximity or clustering methods.

3.2 Mathematical Formulation

Two models are proposed: one for the decentralized strategy and another for the centralized strategy. Both assume CDCs are fixed. Decisions in- volve assigning CDCs to LDCs, locating LDCs, assigning demand points, and choosing facility types.

The centralized model minimizes total operational costs, including facility setup, transportation, and capacity adjustments, over a multi-period horizon.

Sets

I: Set of Central Distribution Centers (CDC), indexed by i
J: Set of candidate locations for Local Distribution Centers (LDC), indexed by j
K: Set of Demand Locations, indexed by k
T: Set of operation periods, indexed by t
R: Set of capacity levels at period t
S: Set of capacity levels at period t

Model Parameters

a_{sj}: Binary parameter equal to 1 if candidate location j can have capacity level s
q: Average volume of kits
d_{kt}: Families at demand point k in period t
f_{ij}: Freight cost from CDC i to candidate LDC j
f_{jk}: Freight cost from LDC j to demand location k
d_{jk}: Distance between LDC j and demand location k
$d_{\max}$: Maximum allowed distance
c_s^f: Fixed operation cost of capacity level s
c_s^v: Variable operation cost of capacity level s
c_{rs}^a: Opening or expansion cost from level r to s
c_{rs}^d: Decommissioning cost from level r to s
cap_{rs}: Capacity available from level r to s
M: Large number

Decision Variables

X_{ijt}: Flow from CDC i to LDC j in period t
X_{jkt}: Flow from LDC j to demand location k in period t
O_{rsjt}: 1 if LDC j increases capacity from r to s at time t
W_{rsjt}: 1 if LDC j keeps capacity level s at time t
Z_{rsjt}: 1 if LDC j decreases capacity from r to s at time t
Y_{jkt}: 1 if demand location k is assigned to LDC j in period t

Model

$$\begin{aligned} \min \sum_{t\in T}\sum_{j\in J}\sum_{i\in I} f_{ij}X_{ijt} + \sum_{k\in K} f_{jk}X_{jkt} + \\ \sum_{t\in T}\sum_{j\in J}\sum_{r\in R}\sum_{s\in S}\left(c_s^f W_{rsjt} + c_{rs}^a O_{rsjt} + c_{rs}^d Z_{rsjt}\right) + \\ \sum_{k\in K} c_{rs}^v X_{jkt} W_{rsjt} \end{aligned} \tag{1}$$

Constraints

$$\sum_{i\in I} X_{ijt} - \sum_{k\in K} X_{jkt} = 0 \qquad \forall t\in T, j\in J \tag{2}$$

$$\sum_{j\in J} a_{jk}X_{jkt} \geq qd_{kt} \qquad \forall t\in T, k\in K \tag{3}$$

$$\sum_{r\in R}\sum_{s\in S} a_{sj}\mathrm{cap}_{rs}W_{rsjt} \geq \sum_{k\in K} X_{jkt} \qquad \forall t\in T, j\in J \tag{4}$$

$$W_{rsjt} - Z_{rsjt} = 0 \qquad \forall t>0, j\in J, r\in R, s\in S | r>s \tag{5}$$

$$W_{rsjt} - O_{rsjt} = 0 \qquad \forall t>0, j\in J, r\in R, s\in S | r<s \tag{6}$$

$$\sum_{r\in R} W_{raj(t-1)} \geq \sum_{s\in S} W_{asjt} \qquad \forall t>0, j\in J, a\in R \tag{7}$$

$$W_{0aj0} \geq \sum_{s\in S} W_{asj1} \qquad \forall j\in J, a\in R \tag{8}$$

$$\sum_{r\in R}\sum_{s\in S} W_{rsjt} = 1 \qquad \forall t\in T, j\in J \tag{9}$$

$$d_{jk}Y_{jkt} \leq d_{\max} \qquad \forall t\in T, j\in J, k\in K \tag{10}$$

$$X_{jkt} \leq MY_{jkt} \qquad \forall t\in T, j\in J, k\in K \tag{11}$$

$$\sum_{j\in J} Y_{jkt} = 1 \qquad \forall t\in T, k\in K \tag{12}$$

$$X_{ijt}, X_{jkt} \geq 0 \tag{13}$$

$$O_{rsjt}, W_{rsjt}, Z_{rsjt}, Y_{jkt} \in \{0,1\} \tag{14}$$

The constraints 2 represent the flow balance between the income and outcome of each period. The group of constraints 3 guarantee that all the demand of each period needs to be met, and the constraints 4 state that the capacity installed at one period needs to be suitable to the quantity of products distributed to the demand points in that period. Constraints 5, 6, 7, 8 and 9 establish the temporal continuity, enabling the model to change the capacities installed over the periods. Equations 5 and 6 capture the status of the network, whether an increase or decrease of capacity, as equations 7 and 8 create the temporal connection between periods. The coverage constraints 10 are also included, and linking constraints 11 are created. Constraints 12 impose that each demand point is supplied by only one LDC. Finally, the constraints 13, 14, and 15 define the boundary conditions of the model. In the centralized model, the demand has the possibility to be supplied by one MSU cluster (set before the optimization) or by one of the hard roofs. In contrast to the decentralized model in which each demand point had its own LDC and could only be provided by it at each period. The parameter ajk is in charge to delimit these possibilities of assignment, and the type of facility associated to each candidate location is defined by the asj, where each capacity level belongs to one of the two types allowed. The decentralized model, which makes the baseline, is quite similar to the previous model. It differs by removing the costs associated with the transportation between LDCs and demand points from the objective function. Besides that, the coverage constraints (10, 11, 12) are relaxed, due to the distance between demand points and its respective LDCs being considered equal to zero.

4. Numerical Example

This study examines how different configuration strategies affect the ef- ficiency of humanitarian operations, using real data from the Iraq Civil War-specifically the 2016 Battle of Mosul. The context, marked by pro- longed conflict, offers a relevant setting to evaluate the benefits of collabora- tive storage and resource-sharing in humanitarian logistics.

4.1 Input Data

We focus on 27 IDP camps that were actually occupied out of the 65 initially planned. For the centralized case, 33 candidate nodes were selected for Local Distribution Centers (LDCs), while in the decentralized case, demand points themselves serve as potential facility locations. Three Central Distribution Center (CDC) nodes were also considered. Candidate sites were chosen based on proximity to Mosul (230 km) and a minimum population of 40,000.

A p-median model was used to determine MSU (Mobile Storage Unit) locations. Distances between locations were estimated via Google Maps. De- mand data were extracted from 49 ReliefWeb reports (Oct 2016–Jul 2017) and over 2,000 CCC-MIRAQ files. Python was used to process and consolidate the information. Only installations relevant to the Mosul response were retained.

The humanitarian supply chain included food, water, hygiene kits, and other essentials based on Sphere Project standards. An average demand of 109.43 kg per six-member family was assumed. Five sizes of hard roof facilities and six MSU sizes were modeled, with MSUs considered expandable. Cost estimates for installation, operation, and freight were based on real data from aid agencies and developing countries.

4.2 Problem Definition

The study focuses on consolidating relief items in three Iraqi hubs-Dohuk, Erbil, and Baghdad-used as transshipment points before truck delivery to MSUs near IDP camps. MSUs typically measured 10x20m or 10x32m, storing up to 750 metric tons (Catholic Relief Services (CRS) 2019). Generally, each organization maintained its own LDCs.

This led to fragmented and redundant logistics networks, often with du- plicated efforts and excess inventories at camps, raising operational costs. Shared infrastructure could have reduced fixed costs, particularly where camps were geographically close.

The proposed model advocates for centralized, shared logistics to stream- line operations. It eliminates on-site stockpiling by delivering supplies directly from vehicles, aiming to cut costs and improve resource utilization.

4.3 Results

This study focuses on determining the locations of Local Distribution Centers (LDCs) and their monthly assignments. The problem was solved using Gurobi v9.1 on a machine with 64 GB of RAM and an Intel Core i9 processor. Optimal solutions were obtained within 100 seconds for the mesh sizes of the examples.

Logistics cost analysis (Table 1) shows savings of 2.4 million dollars with centralization. Storage savings surpassed transport costs, with the most significant reduction in fixed installation costs (around 3 million dollars). Additionally, the need for resources to adapt the network was minimized, though increased coordination between agencies is necessary for success.

Table 2 presents potential savings from a joint storage strategy. Cost apportionment was tested using three methods: simple, proportional, and mixed. The simple strategy equally divided warehouse costs and transportation, yielding savings for 4 of 6 entities. The proportional method allocated costs based on demand, while the mixed method distributed costs according to volume for operational expenses and equally for fixed warehouse costs.

The new configuration proved beneficial for IOM, UNDP, UNHCR, and the Iraqi government (MoMD and N.Gov).

Table 1: Comparison between the costs of the current optimized network and the costs of the proposed network optimized in the study for the 15 months of demand.

Strategy	Total cost	Transportation (first segment)	Transportation (second segment)	Fixed operation	Variable operation	Opening and expansion	Deactivation
1 Multiperiod decentralized	$9,456,220	$1,333,881	–	$7,234,483	$355,730	$511,126	$21,000
2 Multiperiod centralized	$7,027,430	$132,344,200	$1,148,550	$4,079,597	$231,172	$227,669	$17,000
Static centralized	$9,162,144	$3,397,532	$1,615,701	$3,850,425	$123,779	$174,707	$0
Variation ($) (1-2)	-$10,439	$1,148,550	-$3,154,886	-$124,558	-$283,457	-$4,000	-$2,428,790
Variation (%) (1-2)	-1%	100%	-44%	-35%	-55%	-19%	-26%
% of total costs (Current)	14%	0%	77%	4%	5%	0%	-
% of total cost (Alternative)	19%	16%	58%	3%	3%	0%	-

The results compare the collaborative (centralized) and non-collaborative (decentralized) strategies based on actual demand in the camps. In the decentralized strategy, each camp has its own warehouse, and warehouse openings fluctuate with demand, resulting in up to 21 facilities operating at peak times.

The centralized solution streamlines the supply chain, requiring fewer facilities. The peak operational month is November, with 11 facilities running, as two new camps were occupied. Compared to the decentralized strategy, the centralized approach reduces the number of facilities by 119 over the period, averaging 7.9 fewer installations per month. This leads to a 10,000-ton reduction in the system's capacity.

An experiment was conducted using a 15-month horizon to evaluate the multi-period model's performance, comparing it with a static model, both using the centralized strategy. The static model used average demand over the period, with unchanged decisions, while the multi-period model adjusted based on demand fluctuations.

Table 2: Savings per agency generated by the adoption of the new distribu- tion structure

Agency	Simple Apportionment	Proportional apportionment	Mixed apportionment
MoMD & UNHCR	-$ 226,587	-$ 77,406	-$ 80,897
N. Gov & UNHCR	-$ 113,337	-$ 43,725	-$ 45,999
IOM	$ 83,433	-$ 8,779	-$ 4,882
MODM	-$1,165,169	-$ 999,661	-$ 1,012,781
UNDP	$ 43,367	-$ 35,805	-$ 33,952
UNHCR	-$ 1,050,496	-$ 1,263,415	-$ 1,250,279
Total savings	-$ 2,428,791	-$ 2,428,791	-$ 2,428,791

The locations selected in both models were similar, except for Chamakor- IOM and Laylan. In the static model, Chamakor-IOM was not chosen, so its demand was assigned to Al-Hamadaniya, which also served other camps. In the multi-period model, Chamakor-IOM opened in January 2017 and operated until April 2017, after which its demand was transferred to Al- Hamadaniya. Laylan only operated in the first period of the dynamic model, with its demand assigned to Kirkuk after October 2016.

Efficiency was analyzed by comparing installed capacities and demand fulfillment over the 15 months. Table 3 shows that although the static model's installed capacity theoretically met demand, capacity utilization in the multi- period model was more balanced, ranging from 9% to 68%, compared to 1% to 77% in the static model. Both models had an average utilization rate of 53%, but the static model showed greater variability.

Table 3: Aggregated warehouse occupancy over the 15-month planning hori- zon for the static model and the multi-period model

Model	Oct/16	Nov/16	Dec/16	Jan/17	Feb/17	Mar/17	Apr/17	May/17	Jun/17	Jul/17	Aug/17	Sep/17	Oct/17	Nov/17	Dec/17
Multiperiod	9%	42%	43%	56%	50%	55%	64%	56%	58%	57%	58%	62%	68%	57%	56%
Static	1%	19%	27%	42%	44%	57%	66%	67%	77%	76%	74%	72%	64%	57%	51%

Despite adequate capacity, the static model had inefficiencies due to its assumption that demand must be met within a 40 km radius. Comparing Tables 4 and 5, the static model had significant idle capacity, with three facilities unused per period on average. It also experienced capacity shortages in four warehouses for 13 of the 15 months, with an average of 1.8 facilities undercapacity each month. The static model used 180 operational points over the 15 months, while the dynamic model only needed 137 points, with a maximum of 11 warehouses in operation each month.

Although the static model's total capacity could meet demand, inefficien- cies arose from coverage constraints and demand assignments. The inability to redistribute excess capacity led to unfeasible outcomes, impacting service levels and system security. Therefore, direct cost comparisons between the two models were not possible, as unmet demand or non-compliance was not modeled.

Table 4: Warehouse occupancy over the 15-month horizon for the decisions of the multi-period model

Candidate site	Oct/16	Nov/16	Dec/16	Jan/17	Feb/17	Mar/17	Apr/17	May/17	Jun/17	Jul/17	Aug/17	Sep/17	Oct/17	Nov/17	Dec/17
Al-Hamdaniya	-	-	-	-	-	-	-	8%	52%	56%	56%	90%	69%	66%	66%
Basateen Al Sheuokh UNDP	-	-	-	-	-	-	-	-	-	-	-	-	-	12%	12%
Chamakor IO	-	-	-	34%	31%	35%	34%	-	-	-	-	-	-	-	-
Debaga 2 UNHCR	-	-	-	89%	38%	37%	35%	35%	35%	34%	92%	91%	61%	52%	46%
Haj Ali IOM	-	-	-	10%	41%	36%	64%	64%	67%	61%	61%	54%	54%	50%	56%
Hammam al-Alil MODM	-	-	-	79%	34%	58%	85%	86%	87%	82%	95%	74%	68%	64%	71%
Hasansham M1 MODM	7%	72%	54%	63%	54%	66%	66%	67%	65%	63%	61%	68%	79%	52%	
Kirkuk	-	51%	51%	77%	64%	76%	75%	76%	75%	70%	62%	55%	45%	36%	28%
Laylan UNHCR	7%	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Narziglia MODM	7%	54%	54%	63%	49%	62%	61%	62%	62%	57%	49%	41%	97%	69%	46%
Qayyarah Bridge tbc	25%	27%	49%	76%	98%	71%	96%	98%	66%	68%	63%	63%	100%	97%	92%
Surdesh UNHCR	-	-	-	-	-	-	-	-	-	-	-	-	-	10%	10%

Tikrit	-	0%	5%	9%	28%	26%	26%	17%	16%	16%	17%	26%	21%	19%	16%
Zelikan UNHCR	1%	28%	28%	34%	28%	17%	12%	16%	7%	6%	5%	3%	-	-	-

Table 5: Warehouse occupancy over the 15-month horizon for the decisions of the static model

Candidate site	Oct/16	Nov/16	Dec/16	Jan/17	Feb/17	Mar/17	Apr/17	May/17	Jun/17	Jul/17	Aug/17	Sep/17	Oct/17	Nov/17	Dec/17
Al -Hamdaniya	0%	0%	0%	11%	10%	11%	11%	29%	118%	124%	122%	148%	143%	135%	132%
Basateen Al Sheuokh UNDP	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	12%	12%
Chamakor_IOM	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Debaga 2UNHCR	0%	0%	0%	89%	113%	110%	105%	106%	104%	103%	92%	91%	61%	52%	46%
Haj Ali_IOM	0%	0%	0%	3%	14%	36%	64%	64%	67%	61%	61%	54%	54%	50%	56%
Hammam al -Alil_MODM	0%	0%	0%	26%	34%	58%	85%	86%	87%	82%	95%	74%	68%	64%	71%
Hasansham M1 MODM	2%	72%	107%	125%	109%	132%	131%	120%	116%	114%	112%	101%	74%	49%	0%
Kirkuk	2%	51%	51%	77%	64%	76%	75%	76%	75%	70%	62%	55%	45%	36%	28%
Laylan_UNHCR	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Narziglia_MODM	2%	54%	54%	63%	49%	62%	61%	62%	62%	57%	49%	41%	32%	23%	15%
Qayyarah Bridge_tbc	4%	4%	25%	38%	49%	71%	96%	98%	110%	113%	106%	105%	100%	97%	92%
Surdesh UNHCR	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	10%	10%
Tikrit	0%	0%	5%	9%	28%	26%	26%	17%	16%	16%	17%	26%	21%	19%	16%
Zelikan UNHCR	1%	28%	28%	34%	28%	17%	12%	16%	7%	6%	5%	3%	0%	0%	0%

5. Robustness Tests

This study analyzes the impact of a multi-period approach on the planning of humanitarian facilities and collaboration strategies. The results show significant gains from improved coordination, reducing the number of required facilities and centralizing operations, leading to better resource utilization and economies of scale.

When comparing the static and multi-period models, the latter showed superior performance in facility location and demand allocation, accommodating temporal and spatial variations. The static model lacked robustness, often requiring frequent adjustments and violating constraints. In contrast, the multi-period model effectively optimized resource use, addressing demand variations over time.

Further investigation with additional demand scenarios could enhance the model. Extending it to include stochastic optimization or tactical decisions like inventory management and evaluating potential supply shortages would improve its applicability. Issues such as delays caused by checkpoints or facility breakdowns were also identified, potentially disrupting the supply distribution.

To assess the impact of warehouse coverage radius, experiments varied the distance parameter between 8 and 200 km. Transportation costs were significant, but installation costs had a greater impact on decision-making. Transportation costs showed stability, with a coefficient of variation of 8%, while operating costs had a coefficient of 47%. Installation costs varied by millions, while transportation costs fluctuated by thousands.

The transportation cost ranged from 2.35 million to 3 million dollars, showing an inverse relationship between the first and second segment costs. For example, when comparing an 8 km radius to a 200 km radius, there was an 11,000-kilometer reduction in the first segment and a 21,000-kilometer increase in the second, resulting in a 10,000-kilometer net increase. Despite an 83% increase in distance, total costs increased by 27

Except for variable operating costs, other costs decrease with fewer ware- houses. Fixed operating costs remain stable after a radius of 119 km, and from 148 km, installations stay below four per period. Variable costs decrease with the coverage radius, attributed to better mechanization in hardroof warehouses, though fluctuations occur due to warehouse type decisions.

Opening and closing costs decrease with more hardroof warehouses, which are less flexible for expansion. These costs remain significant but have a lesser impact on total cost composition. Additionally, shorter distances lead to greater variation in installations, while a larger radius stabilizes the number of installations due to the increased use of hardroof warehouses, which are less adaptable.

6. Conclusions

This study explored the impact of a multi-period modeling approach on humanitarian facility planning and inter-agency collaboration during complex emergencies, specifically applied to the Mosul Offensive case. Results showed that greater coordination and centralization improved supply chain efficiency

by reducing the number of required facilities and optimizing resource use, leading to economies of scale.

The multi-period model outperformed the static approach, achieving a 25.7% cost reduction ($2.43 million) compared to the decentralized configuration. These savings resulted from better resource utilization, especially in storage infrastructure, and reduced deactivation and expansion costs. The model's adaptability was key to minimizing idle capacity while maintaining service levels.

The static model was less responsive to demand and supply variations, often leading to suboptimal solutions. In contrast, the multi-period model effectively adjusted facility locations and demand allocation as the crisis evolved, demonstrating superior flexibility.

These findings support centralized, cooperative logistics frameworks, a concept long theorized but rarely tested in complex scenarios. This study expands on previous research by offering a dynamic multi-period framework applied to a real-world crisis, strengthening the case for inter-agency coop- eration in humanitarian logistics.

From a theoretical standpoint, centralization strategies must be respon- sive to demand variability and proportionally structured to meet affected populations' needs. Dynamic models, such as the one used here, align with the necessity for adaptable logistics networks in crises.

Further research should test the model under varying demand scenar- ios and explore stochastic optimization to better capture uncertainty. In- tegrating inventory control, lead time variability, and disruptions, such as checkpoints or warehouse malfunctions, could enhance decision-making. Ad- ditionally, as humanitarian funding becomes scarcer, cost-effective and scal- able strategies like centralization will be crucial.

Technological advancements, such as blockchain and AI, could address co- ordination challenges, enhancing transparency and decision-making. Despite limited adoption, these technologies offer promising solutions for improving humanitarian logistics efficiency.

In conclusion, this study bridges conceptual models and field applications, encouraging the transition to strategic, evidence-based planning in human- itarian logistics. It underscores the need for data-informed collaboration models to improve relief efforts.

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