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DISASTER RELIEF INVENTORY SIMULATION: MANAGING RESOURCES IN HUMANITARIAN CAMPS

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ABSTRACT

Natural disasters and conflicts often result in humanitarian crises, necessitating effective inventory management to meet the needs of displaced populations. This paper introduces a sophisticated simulation model tailored for disaster relief scenarios. By integrating real-world dynamics and constraints, such as perishability of goods, budget constraints, and uncertain demand, the model offers a robust framework for decision-makers in humanitarian organizations addressing post-disaster inventory management challenges. The simulation tool is open source, promoting widespread adoption and adaptation, thereby enriching the humanitarian logistics toolbox. Computational experiments are conducted to validate the simulation engine and provide valuable insights.

1 INTRODUCTION

Natural and human-made disasters, such as earthquakes and conflicts, possess the devastating power to displace millions of people, leaving them without homes and essential resources. A striking example of this occurred in February 2023, when a powerful earthquake struck both Türkiye and Syria, impacting millions of lives and rendering large populations homeless (Zilio and Ampuero 2023). However, the effects of such disasters extend beyond immediate displacement. In the case of Syria, the protracted conflict that began in 2011 led to millions of Syrians becoming refugees worldwide (UNHCR 2024). According to the UNHCR Global Trends Report 2022, there were a total of 35.3 million refugees. When considering internally displaced individuals, the global count of displaced persons climbed to a staggering 108.4 million worldwide due to various reasons (UNHCR 2023). The Russian invasion of Ukraine alone caused one of the largest displacement crises since the Second World War. By the end of 2022, an estimated 5.9 million people were internally displaced within Ukraine, and around 5.7 million refugees and asylum-seekers had spread across Europe (UNHCR 2022).

The challenges and complexities arising in the aftermath of natural and human-made disasters are collectively categorized as *post-disaster* scenarios within the realm of humanitarian supply chain literature (Balcik et al. 2016). Post-disaster inventory management addresses the issues that arise after a disaster occurs. In post-disaster settings, the affected population is typically situated in humanitarian camps for extended periods. In response to this effect, this study aims to construct a comprehensive simulation model that focuses on the unique and dynamic environment of post-disaster humanitarian inventory management problems. In these critical moments, efficient inventory and resource management become vital, as they directly affect the well-being and survival of those affected by the crises. The intention is to provide insights and solutions that will empower humanitarian organizations and policy-makers to benchmark and optimize their inventory management strategies, ultimately enhancing the effectiveness of their response efforts in these challenging settings. While conceptual research plays a crucial role in the foundational stages of disaster relief management, there is an increasing imperative for quantitative and qualitative empirical research to rigorously test and validate theoretical frameworks and assumptions (Seifert et al. 2018). Recognizing this, we introduce the first comprehensive, non-problem-specific, open source simulation tool for post-disaster inventory management – a topic that has been overlooked, particularly in the context of humanitarian inventory management (Yale et al. 2020). This tool not only fills a critical gap in the literature, but also provides a robust platform for empirical testing and refinement of inventory strategies in real-world disaster scenarios.

In post-disaster scenarios, organizations are generally managed by central policy-makers due to the complexity of the system. The aim is to distribute aid to the population and understand, how inventory policies are realized under different settings. This study investigates the problem from the perspective of a central decision-maker. There are several types of problems related to post-disaster inventory management. While the literature lacks a clear distinction, the problems are presented based on their aspects. Different aspects present unique challenges and considerations. The simulation engine strives to encompass all these aspects to the best of its ability. Rather than providing a comprehensive literature survey, the unique settings of these problems are investigated, and how they are addressed in the engine is explored.

2 RELATED LITERATURE

Existing research often focuses on isolated aspects of inventory management, such as stochastic demand, perishability, and funding uncertainty. However, this paper integrates these components into a comprehensive, open source simulation model that accommodates diverse real-world scenarios. This approach is novel for two reasons: (i) it integrates various aspects into a single problem, a feat not previously achieved in such a comprehensive manner, and (ii) it is the first open source simulation engine that enables the simulation of all or some aspects of the problem using a single input file.

Among the most fundamental identifiers for an inventory study are the goals and objectives. Each model seeks to optimize various metrics to efficiently manage inventory. Typically, the following cost metrics are considered in the literature: ordering, holding, transportation, backorder, deprivation, and shortage (Balcik et al. 2016). While most of these metrics are used in classical inventory management problems, some are restructured exclusively for the humanitarian domain. An example is *deprivation*, which is the costs of shortage on the welfare of the population. The idea is to penalize unmet demand exponentially with respect to time, because the suffering of a depriving person increases in that manner (Holguín-Veras et al. 2013). Shao et al. (2020) provide an excellent review of the concept of deprivation on humanitarian setting.

One or more items might be distributed to the system in the post-disaster inventory management problems. There are two main issues associated with items: demand characteristics and perishability. Some settings assume that demand is deterministic (Shen et al. 2011), while others assume it is stochastic (Beamon and Kotleba 2006). The proposed simulation engine supports both approaches and can simulate hybrid settings as well. For each region and item, there might be distinct demand distributions. Moreover, certain items, particularly food and medicine, can be perishable. Despite limited literature addressing perishability in post-disaster inventory management, perishability patterns are accommodated in the simulation. Ferreira et al. (2018) explain the perishability concept in humanitarian inventory management and solve it using Markov Decision Processes.

In camp-based systems, particularly refugee camps, demographics are subject to change due to migration (Prasad et al. 2023). Therefore, it is essential to consider this phenomenon. There are three types of migration to consider: migration into the system, migration between camps within the system, and migration from the system. In addition to those definitions, another dimension is the demand source, which includes internal and external population from the surrounding region. This not only doubles the types of migration, but also brings additional challenges to inventory control. Aid inventory control requires a mechanism to respond differently to internal and external demand. Maintaining internal and external population information, simulating migration, and controlling inventory for two types of demand become crucial. However, there is limited work on inventory control approaches with multiple types of demand. One threshold-based approach for refugee camps is provided by Azizi et al. (2021).

In humanitarian inventory management, one of the most critical concepts is funding. Typically, funds are sourced from multiple agencies and can be classified as in-kind (product-based) or cash-based. Funding can also be classified as earmarked to a camp or product or not (Burkart et al. 2016). Natarajan and Swaminathan

(2014) consider a finite-horizon periodic-review inventory model for a single product for showing the effect of funding uncertainty and later extend the study for multiple demand classes (Natarajan and Swaminathan 2017). The authors emphasize the crucial role of funding timing, noting that receiving a smaller amount of funding promptly can be more beneficial than receiving a larger amount of funding delayed. Kotsi et al. (2022) compare in-kind and cash funds, highlighting the importance of such comparisons.

Another concept is to model shortages or supply disruptions. Unlike commercial supply chains, in a humanitarian setting shortages occur due to demand shocks, and demand is often not well known (Balcik et al. 2016). Atan and Rousseau (2016) model random disruptions using a Markov chain for an infinite-horizon, single-echelon system with a single perishable product, employing periodic review and dynamic programming to determine the base stock level, considering perishability and supply disruptions. For a comprehensive discussion on inventory management in humanitarian settings, Ye et al. (2020) and Balcik et al. (2016) offer insightful reviews.

This study aims to create a simulation environment for a wide range of inventory management problems. To achieve this, the commonly studied settings of post-disaster inventory problems are investigated. While no existing study captures all the features comprehensively, some address specific aspects as discussed. The proposed engine aims to integrate these features into a cohesive and comprehensive simulation tool. By simulating the complex interplay of demand, funding, migration, and supply disruptions, the model provides a robust framework for decision-makers in humanitarian organizations. This allows for the testing and refinement of inventory strategies under varying conditions, ultimately enhancing the effectiveness of disaster relief efforts. The open source nature of the simulation tool promotes widespread adoption and adaptation, encouraging further research and development in this vital area of humanitarian logistics. Although there are some open-source frameworks such as Stockpyl (L.V. Snyder 2023), there is no simulation engine specifically designed for post-disaster inventory management.

3 SIMULATION APPROACH

In this study, a simulation engine is proposed, implemented in Java using object-oriented programming principles. The goal is to build a fast, flexible, modular, and comprehensive simulation engine for post-disaster inventory management problems. This section outlines the problem, solution strategy, and design of the simulation engine for allocating humanitarian inventory in post-disaster camps, as well as the mechanics of the simulation. The problem is discussed, followed by an explanation of the engine, and the implemented inventory policy is provided with numerical results.

3.1 Problem Description

This study focuses on optimizing the inventory management of a central warehouse that supplies items to various demand points, referred to as camps. The supply chain operates under a multi-echelon structure, with items sourced from suppliers who have stochastic lead times and then stored in a central warehouse before being distributed to the camps. The complexity of this problem is enlarged by the presence of multiple perishable items, and the necessity of balancing inventory allocation under budget constraints.

The demand at each camp is stochastic, varying over time and influenced by factors such as migration, which makes it non-stationary. Each camp has specific demand patterns for each product, influenced by diverse distributions and parameters that reflect the internal and external populations. On the supply side, lead times from suppliers are also uncertain and may be affected by disruptions or shortages. This adds to the complexity of managing the supply chain.

The supply chain consists of several levels, where items are first sourced from suppliers and then stored in a central warehouse before being distributed to the camps. Key decisions include determining the quantity to order from suppliers, the timing and amount of replenishment to the camps, and the transshipment of inventory between camps to balance supply and demand effectively. Additionally, the system operates under budget constraints, where both the timing and the amount of the budget are stochastic, affecting the decision-making process for inventory management. Furthermore, funding can be monetary or product-based and might be earmarked.

The problem is analyzed over a finite time horizon, with a specific number of days allocated to optimize operations. Inventory decisions are made periodically, necessitating regular reviews and adjustments to strategies. Demand at camps is divided into two groups: (i) internal demand, which, when unmet, results in backlogged orders and deprivation costs; and (ii) external demand, which, when unmet, results in lost sales and referral costs. Backlogged orders need to be satisfied on the upcoming periods. This distinction influences how inventory management is prioritized. Another critical aspect of the decision-making process involves determining whether to share inventory with external demand. Since this is not a continuous inventory control system, establishing a threshold or amount for sharing inventory is essential to contributing to the overall objective of minimizing costs.

The primary objective is to optimize various aspects of inventory management, including ordering items from suppliers, holding inventory at the central warehouse, backordering to manage delayed fulfillment, and managing lost sales. By considering all these factors, the goal is to balance supply and demand effectively, minimize costs, and meet the stochastic budget constraints. This requires a strategic approach to manage the perishability of certain items and to handle the multiple demand classes while adhering to budget constraints. The problem with only two camps is illustrated in Figure 1.

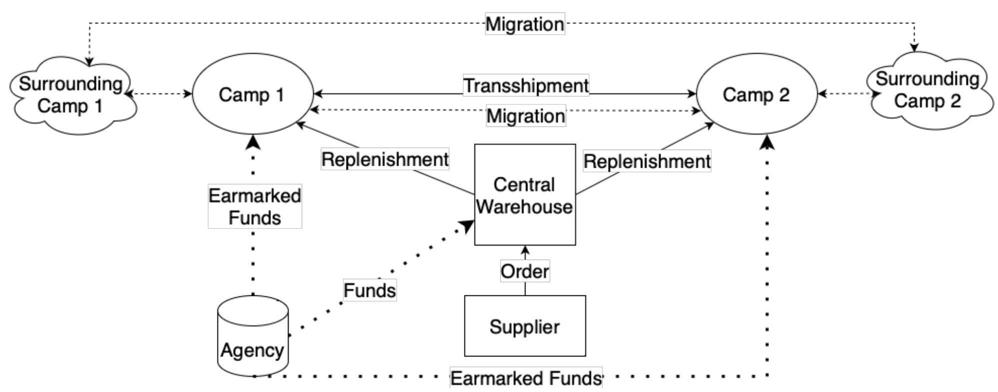

Figure 1: Overview of the problem for a case with two camps.

3.2 Events and Objects

This research delineates two primary categories of events within the simulation framework: decision-dependent and system-related events. Decision-dependent events pertain to the integration of inventory management strategies into the simulation model, which are further explored in subsequent sections. On the other hand, system-related events cover categories such as demand, funding, migration, and supply status changes, which are essential for event generation in simulation. A UML diagram for the events can be found in Kundakcioglu (2024). Each event category utilizes pertinent data to instantiate events, with all event classes incorporating two probability objects – one for the timing of the event occurrence and the other one for the magnitude or quantity involved. The distributions and parameters are tailored to each specific event type, as detailed in the associated discussion.

The *demand* aspect, closely associated with an *item*, is a fundamental component in the simulation framework. Tailored to individual camps, each *demand* operates independently, requiring no additional camp-specific data. To define each *demand*, the engine uses the following attributes: *Demand timing* helps determine when demand occurs, offering three commonly studied options: single instance (once), random occurrences (sporadic), or regular intervals (periodic). Similarly, *quantity type* distinguishes between two types of demands: multiple quantities (batch) and individual units (single). For batch demands, ratios representing internal and external sources are maintained, considering camp population dynamics. Arrival times and demand quantities are determined based on relevant data categories and other pertinent factors. The engine can generate demand not only with the widely-used memoryless property, e.g., exponential interarrival times, but also with any general distribution.

Three distinct migration scenarios are identified: migration into the system from an external camp (into system), migration from the system to an external camp (from system), and migration within the system from one camp to another (within system). The *migration* aspect, encapsulates these scenarios along with the originating and destination camps, defined within the *camp* aspect. Arrival times and the number of individuals migrating are determined by analyzing relevant data categories and other pertinent factors.

To define the *funding* concept, essential information regarding both the product and the camp is required. This necessity arises from the classification of funds in humanitarian aid literature, where funds are categorized as either product-based or monetary, and allocated to a camp or product or not (Burkart et al. 2016). In cases, where funding is earmarked, the camp information is stored to ascertain the recipient camp. Similarly, product information is retained to identify the products associated with the funding.

The *supply status change (switch)* events signify interruptions spanning the entire system. These interruptions are defined in terms of products, with each product having its own interruption event. While camp-based supply interruptions are conceivable, this approach is deemed unrealistic from a centralized decision-making standpoint, so interruptions are defined exclusively on a product basis.

At the heart of the simulation model lie three fundamental entities: items, camps, and agencies. The *item* object serves as a blueprint for defining products, encapsulating vital attributes such as name, perishability, and price. In contrast, *camp* boasts a more intricate structure compared to the *item*. It encompasses attributes such as an array of *demands* representing internal and external population counts, and camp-external demand satisfaction type. This governs the management of external population demand satisfaction, offering options such as full satisfaction, no satisfaction, or threshold-based satisfaction, where specific thresholds determine satisfaction levels. Additionally, the *camp* includes data associated with the population type, categorized as regular, prioritized, or disadvantaged, aimed at enabling the simulation of diverse population characteristics.

Agencies are devised to differentiate between relevant institutions involved in *funding* events. It maintains a record of agencies and associated *funding* events. The *environment* class serves as a central repository for all simulation-related data. Consuming data efficiently and storing it in appropriate data structures are critical steps in the development of a successful simulation engine. Simulating complex systems requires a well-structured approach to data input. To achieve this, it is essential to express data in interpretable objects. This approach not only enhances the readability of the project, but also increases its usability. For this purpose, the engine employs input files to create corresponding objects, storing them within the *environment* class for seamless access and management. These input files are formatted using the human-readable data serialization language industry standard "Yet Another Markup Language" (YAML). YAML is widely used for configuration files due to its minimal and easy-to-read syntax.

3.3 Simulation

Up to this point, the discussion focuses on how to store data within objects. Next, the production mechanism and simulation details are examined. The *state* class serves as a repository for system state information, encompassing detailed current inventory levels, internal and external populations of camps, and the presence of supply interruptions. Its fundamental task is to maintain and monitor system data. An additional feature of *state* is its ability to facilitate direct interaction with decision modules, holding the necessary information for them and serving as an authorization layer. This flexibility allows for the seamless use of both continuous and periodic inventory control systems. The state can be considered a subclass of the *environment* class, carrying system characteristics that decision modules should not access.

While running the simulation, the relevant events need to be created, namely demand, funding, migration, supply disruption, and recovery. In addition to these events, there are the transfer, replenishment, and inventory control events for decision processes. Each of these events implements an interface with properties such as time, an interarrival generator, and a method to process the event. After discussing the *simulate* class, the event processing mechanism is revisited.

In the *simulate* class, there are several components including the *environment*, *state*, generators for interarrival times and quantities, a *KPI manager*, and a priority queue for holding events. These generators are tasked with creating the timing of events, i.e., InterarrivalGenerator, and determining the quantities or amounts associated with these events, i.e., QuantityGenerator.

The simulation engine utilizes a priority-based queue structure to organize events in a sequential order. This arrangement proves efficient for comparing events and managing their processing. The *KPI manager* serves as a central component responsible for computing costs and evaluating performance metrics by monitoring changes in the system state. It encompasses various indicators, including deprivation costs derived from humanitarian aid literature. Moreover, the KPI manager allows for the seamless integration of additional performance metrics. As events are processed sequentially, they are forwarded to the KPI manager for updating cost-related metrics and other performance indicators.

All events are created at the beginning from each event source (event data). Then, the events are processed one by one. When an event is dequeued from the priority queue, the engine processes it. Depending on the realization of the event, the engine updates the system state. In this setting, it is important to note that if the population changes, all corresponding demand events must be deleted and regenerated, since the demand parameters are changed. To effectively manage this, the engine maintains the demand events in a separate demand queue. This approach allows the engine to maintain the sequence between events and keep up with system changes for the creation of subsequent events without losing their order.

3.4 Decision and Policy

For this problem, the periodic (s,S) inventory control policy is implemented to manage inventory levels effectively. The policy is implemented as follows: When the level of on-hand inventory reaches a level of s, the difference between S and the current inventory position units is placed (Nahmias and Olsen 2015). Reorder points and order-up-to levels are calculated for both camp-specific and central inventory levels, ensuring adequate inventory to meet the demand while minimizing stockouts (i.e., deprivation and referral costs) and excess inventory.

For camp-specific inventory levels of item i at camp j, the reorder point (s_{ij}) and order-up-to level (S_{ij}) are calculated based on the mean occurence rate of internal individuals (D_{ij}) and external individuals (D'_{ij}), expected lead time (L_{ij}), buffer ratio (B_j), and the internal (P_{ij}) and external populations (P'_{ij}). The respective equations for reorder point and order-up-to level are

$$s_{ij} = (D'_{ij}P'_{ij} + D_{ij}P_{ij}) \times L_{ij} \times (1 + B_j) \tag{1}$$
$$S_{ij} = (D'_{ij}P'_{ij} + D_{ij}P_{ij}) \times (C_j + L_{ij}) \times (1 + B_j) \tag{2}$$

where C_j is the replenishment cycle length (i.e., period count) for camp j. The buffer ratio B_j is defined to adjust the inventory decisions. For the central warehouse inventory, the cumulative demand across all camps is considered, i.e., summation over all j in equations (1-2), incorporating adjustments for internal and external population and excluding camps that do not satisfy external demands. For the central inventory levels of item i at the central depot, the model computes reorder points and order-up-to levels across all camps. It calculates the total demand across all camps for item i, considering lead times, population distributions, and central buffer ratios. The reorder points and order-up-to levels are determined similarly to the camp-specific levels, ensuring that the central inventory adequately supports the overall demand for each item across all camps.

Depending on the set replenishment cycle length, the model generates inventory control events periodically. These events act as triggers for the decision module. Within this module, the system evaluates the reorder points alongside the available funding, generating replenishment requests to procure items from suppliers for replenishing the central depot's inventory. In cases where the available funding falls short, the model decides on a proportionate ordering ratio for replenishment. Similarly, camps follow suit. When faced with insufficient inventory to fulfill all replenishment requests (i.e., demand from the camp), they procure items based on their respective needs in a proportional manner. The engine orchestrates both types of requests considering the inventory positions to optimize the replenishment process.

This section introduces the foundational data structures and objects that form the basis of event data within the simulation framework. These structures allow flexible modeling of various events. In the next section, scenarios for the simulation model will be created by combining these data structures with other objects. The simulation engine can be referred to in the Github repository (Kundakcioglu 2024).

4 NUMERICAL ANALYSIS

This section performs computational studies to demonstrate the simulation engine's capabilities and provide insights into the setting. Realistic data from Azizi et al. (2021) are used to obtain meaningful results. Essential data information is presented here; for a detailed discussion, refer to the original paper.

4.1 Baseline Scenario

This case study aims to investigate refugee camps in Türkiye, encompassing a total of seven camps. Information regarding these camps is provided in Figure 2. All settings will be simulated for three years, totaling 1,080 days. Two types of products are considered: perishable (e.g., medicine) and non-perishable (e.g., hygiene kits). For medicine, the time from their arrival at the central depot's inventory until expiration is assumed to follow a uniform distribution, ranging from 30 to 60 days. Additionally, a triangular distribution is utilized for supply lead times. All supply times, whether from the supplier to the central depot or from the central depot to the camps, will be generated using a triangular distribution with parameters (1, 2, 4).

Area	Population		
	Total	Internal	External
Hatay-1	146,247	2,142	144,105
Hatay-2	146,247	3,213	143,034
Hatay-3	146,247	5,355	140,892
Adana	246,462	21,414	225,048
Osmaniye	49,544	12418	37,126
Kilis	112,192	8,492	103,700
Kahramanmaraş	92,293	10,872	81,421

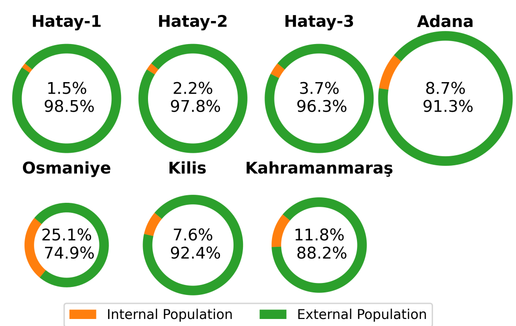

Figure 2: Refugee population in camps for the case study with internal and external population percentages.

Throughout the simulation, four fundamental cost components are incorporated: ordering, holding, deprivation, and referral costs. The ordering costs represent a fixed expense associated with each product replenishment to the central depot. For hygiene kits, the costs are assumed to be 1,200 units per replenishment, while for medicine, the costs are set to 2,400 units.

In humanitarian inventory management, the main aim is to use resources effectively while ensuring that inventory levels are adequate but not excessive. This helps to avoid unnecessary costs, as resources are limited and could be used elsewhere. To achieve this balance, it is necessary to consider the holding costs of inventory. These costs are calculated based on the time inventory spent in storage before being used or expiring. For simplicity, holding costs of one unit per day is assumed for each product.

Any unmet demand raises deprivation costs, which varies depending on the elapsed time (Holguín-Veras et al. 2013). While modeling the actual costs of deprivation can be complex, it is approximated by balancing it with holding inventory costs. It is assumed that a shortage of 24 days for medicine and 48 days for hygiene kits corresponds to an annual holding cost equivalent to that of holding the product for one year. This can be represented analytically as $f(t) = e^{tc} - 1$, where t is the elapsed time and c is a coefficient.

With this information, solving the analytical model yields a shortage coefficient of 0.245 for medicine from the equation $e^{24c} - 1 = 360$, and 0.12 for hygiene kits from the equation $e^{48c} - 1 = 360$.

While meeting the demand of camp residents is essential for the inventory system, residents outside the camps do not have the same requirements. However, rejecting their demand leads to their inability to fulfill their needs, warranting a penalty. This penalty is assumed to be equivalent to holding the product for four days for medicine and two days for hygiene kits. It is assumed that each month there is a 20% probability that a camp resident will demand medicine and a 25% probability that a camp resident will demand hygiene kits. Similarly, the probability of arrival for a resident from outside the camp each month is 2% for medicine and 2.5% for hygiene kits. Demand arrivals follow exponential interarrival times.

In the decision-making process, periodic (s, S) inventory control policy is explored. This strategy involves ordering additional stock up to the level S when inventory levels fall to a certain threshold s. A buffer acts as a multiplying factor for the order-up-to levels and reorder points to enhance the inventory control. A positive buffer value increases these levels, while a negative buffer value decreases them by some percent. The buffer serves as an adjustment parameter, allowing the policy to be fine-tuned for specific scenarios. This fine-tuning enables the policy to better fit demand variability and supply chain uncertainties, thereby enhancing the efficiency of the inventory management system.

4.2 Sensitivity to Replenishment Cycle Length

In this section, the sensitivity of the system to changes in the replenishment cycle length within the framework of the baseline scenario is analyzed. The primary aim is to find the most effective cycle length for the periodic inventory control method. Figure 3 presents the trajectory of costs across different cycle lengths.

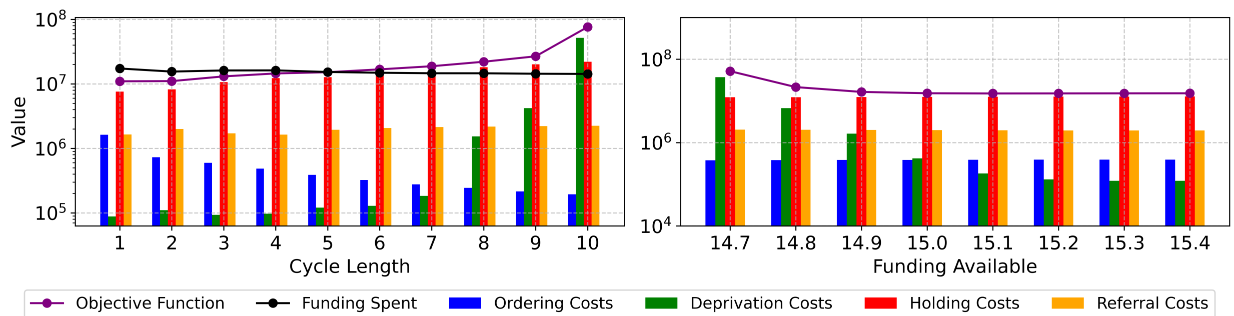

Figure 3: Impact of replenishment cycle length and available funding on costs.

The observed trend indicates a direct relationship between the objective function and the length of the replenishment cycle. Specifically, with the extended replenishment cycles, there is a notable increase in the objective function. Although shorter replenishment cycles yield lower objective function values, they may be impractical for managing large-scale camps due to the high frequency of inventory control required. Therefore, a replenishment cycle of five days is chosen to make the simulation more closely resemble real-life conditions in humanitarian camps.

Lengthening the cycle reduces ordering costs, because fewer orders are needed. However, this also increases the order frequency, contributing to a further reduction in ordering costs. Beyond the sixth period, deprivation costs start to grow exponentially. In contrast, referral costs initially decrease with shorter cycle lengths, then gradually increase, though not rapidly, due to their inherent setup.

Holding costs are dominant, particularly in the initial cycle lengths. While the three-year simulation justifies substantial holding costs, it is important to recognize that these costs could bias the interpretation of results. Therefore, despite the apparent advantages of longer replenishment cycles in reducing ordering costs, the implications of increased holding costs must be carefully considered in decision-making processes. Finally, as the cycle length increases, the inventory policy's total expenditure decreases from 17.4 million to 14.3 million, failing to adequately meet both external and internal demands.

4.3 Sensitivity to Funding

A limitation on available funding is introduced, contrary to the previous assumption of infinite funds. This adjustment allows exploration of the impact of varying levels of funding on the system. Initially, the relationship between costs and available funding is examined. Specifically, a periodic inventory control policy is employed with a replenishment cycle of five days. Even under conditions of unlimited cash, the model spends nearly 15.4 million. Thus, an analysis is conducted to observe the effects of each 100k decrement starting with a budget of 15.4 million.

Figure 3 provides crucial insights on the relationship between funding and associated costs. Notably, the first 100k increment from 14.7 million to 14.8 million sharply reduces deprivation costs, while subsequent increments exhibit diminishing contributions. The imposition of budget constraint results in significant deprivation, particularly in the early stages of the simulation.

Next, the effects of the funding arrival pattern are explored. To observe trade-offs more clearly, the total budget is limited to 14.9 million. It is assumed that funding arrives at fixed intervals, with the same amount being delivered at each arrival.

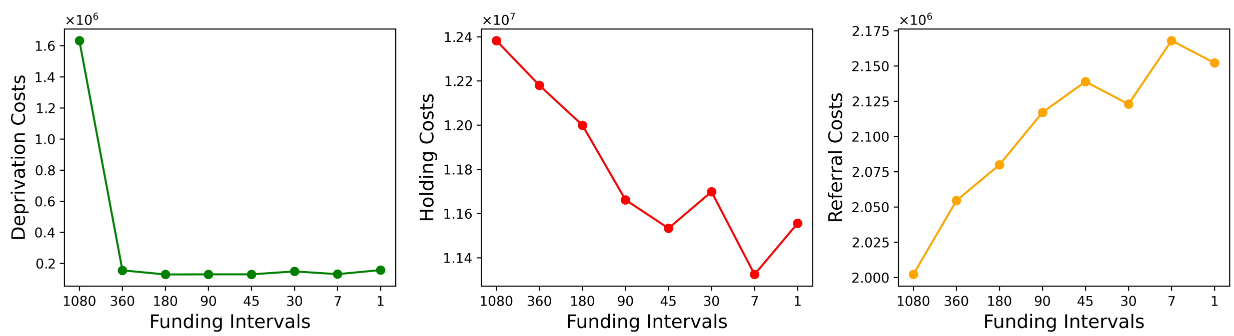

Figure 4: Effect of fixed intervals of funding on cost components.

Figure 4 shows that when dividing the funds into fixed intervals and sending them more frequently rather than giving them in advance, deprivation costs decrease dramatically. Since periodic policy fully shares inventory with external demand, which is quite high compared to the internal demand, the inventory policy tends to satisfy external demand rather than fulfilling prior demands. Additionally, the inventory on hand diminishes as orders are placed less frequently. In contrast, the referral costs increase significantly. This picture reveals two important insights which are investigated in the following sections: (i) The development of an effective sharing policy is necessary to balance between external and internal demand, and (ii) adjusting safety stock and reorder points can decrease inefficiencies in inventory management.

The impact of having perfect information about funding arrivals is explored. Instead of fixed intervals, it is assumed that the funds arrive according to a Bernoulli process, arriving quarterly with a certain probability. Additionally, it is assumed that funding always arrives during the initial period. Processes are generated for probabilities ranging from 0.2 to 1.0. As the probability increases, the number of arrivals generally increases, and the average time between arrivals decreases. However, due to the stochastic nature of the process, this is not always the case, as seen in the sample case in Figure 5 from 0.2 to 0.4.

This analysis supports the previous insights. Figure 6 illustrates that as funding frequency increases, even with the same total amount, the policy tends to prioritize external demand, leading to a decrease in referral costs. When the intervals between fund disbursements are inconsistent – such as when the central

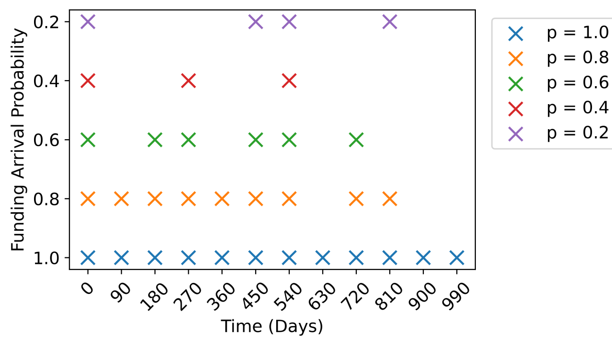

Figure 5: Sample distribution for funding arrivals with different probabilities.

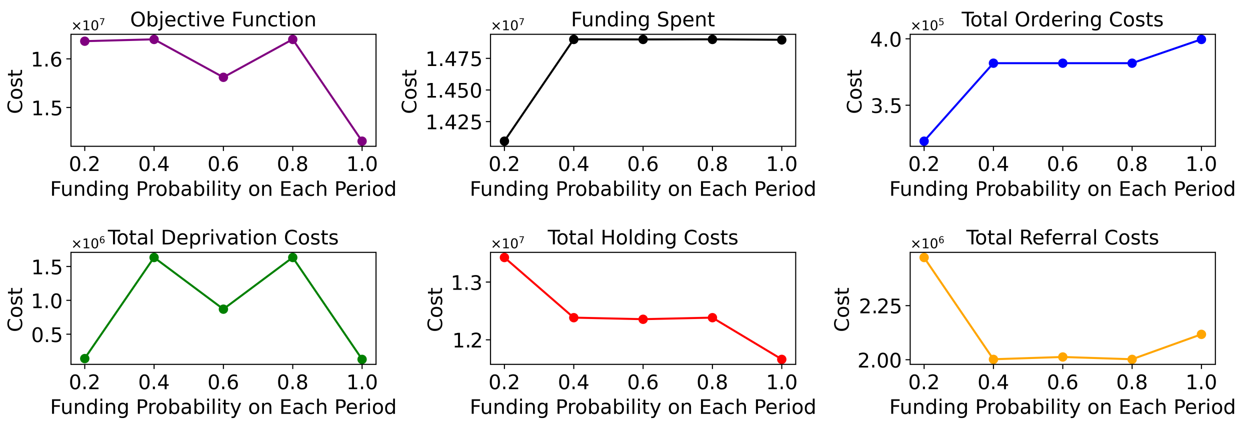

Figure 6: Costs breakdown for different funding availability scenarios.

decision maker receives funds earlier – there is a tendency for faster expenditure. Notably, there is an abundance of funds at lower p-values, suggesting that an ideal funding pattern involves equally spaced and frequent intervals. An unexpected observation is the similarity in deprivation costs between the 0.2 and 1.0 scenarios. The reasoning behind this is distinct in each case. In scenarios with low funding frequency, funds are often front-loaded, providing an early influx of resources. As the p-value increases, deprivation costs generally rise. However, the ideal scenario involves equally spaced and frequent fund arrivals, which allows the decision maker to benefit from consistency, resulting in lower deprivation costs.

4.4 Sensitivity to Buffer Ratios

The baseline scenario is a periodic inventory control policy with a replenishment cycle length of five and 14.9 million $ initial budget at hand. While investigating the funding intervals, it is observed that adjustment on reorder points and safety stock are necessary. Next, the aim is to investigate the effect of different buffer ratios from the perspective of both central warehouse (replenishment) and camps (transfers).

Figure 7 shows that changing the buffer ratio or tuning the replenishment decisions predominantly affects the deprivation costs. For instance, adjusting the buffer ratio from -0.2 to 0.2 results in an increase in holding costs of approximately 29% for the central warehouse and 27% for the camps. However, due to the dominance of the deprivation costs, this change appears negligible. Decreasing the buffer levels for both the central warehouse and the camps slightly improved all metrics except for the referral costs. On the other hand, even a 5% increase in the buffer significantly raised the objective function. As the order quantity increases, i.e., buffer level increases, more resources (budget) are shared with external demand.

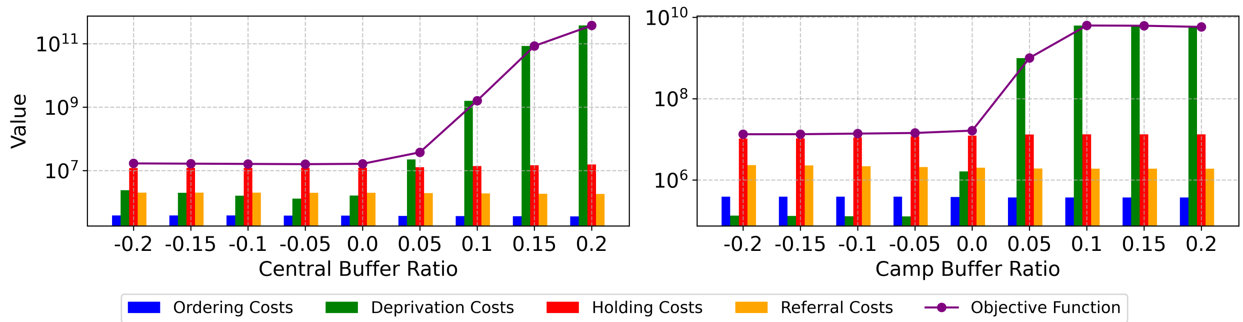

Figure 7: Impact of buffers for central depot and camps.

Again, because the deprivation costs are so dominant, the change in referral costs cannot be seen clearly, but there is a 10% decrease in referral costs in both cases. Therefore, funding becomes insufficient for internal needs, leading to a higher objective function due to exponential growth on deprivation costs.

5 CONCLUDING REMARKS

This paper presents a comprehensive, open source simulation model implemented in Java for post-disaster inventory management in humanitarian camps, addressing a critical gap in the current research landscape. This model demonstrates the capability to simulate complex and dynamic scenarios involving multiple camps, diverse product needs, and the uncertain conditions typical of disaster-stricken areas. The simulation's key features include modeling stochastic demand distributions, accommodating various types of funding and migration scenarios, and managing both perishable and non-perishable goods. These elements are crucial in significantly enhancing the efficiency of humanitarian aid distribution.

The development and validation of the simulation model underscore the pressing need for empirical research to test and refine theoretical frameworks in disaster relief operations. Providing a tool that allows for detailed analysis and strategy testing, this work supports disaster response coordinators and policy makers in making informed decisions that can lead to more-effective allocation of resources and better outcomes for affected populations.

In conclusion, the simulation model developed in this study not only enriches the academic discourse on disaster management, but also offers a practical tool for improving the lives of those impacted by disasters through more effective and timely humanitarian responses. The proposed engine is expected to enable researchers to test their claims and benchmark their performance.

For future work, several enhancements are planned. First, a web application will be developed to simplify the creation of input YAML files. Additionally, extending the current order-up-to policy and its continuous version to include a wider range of policies is necessary. Moreover, the engine has potential applications for inventory routing problems, a highly relevant and popular topic in the field.

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