Inventory Management for Medical Supplies

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Article Outline

Keywords

Inventory management · Healthcare supply chain · Humanitarian operations · Stochastic programming

MSC Codes

90B05, 90B06, 90B50

Introduction

Managing medical supplies and equipment is crucial in healthcare operations, encompassing everything from procurement to distribution. Efficient inventory management guarantees timely access to the right items in the correct quantities, minimizing waste and costs. However, medical inventory management, distinct from commercial supply chains, prioritizes timely availability over costs due to the critical nature of human lives. Pharmaceutical companies, aligning with recent cost-cutting approaches [11], can benefit from optimized inventory management to avoid over or understocking.

The scope of effective inventory management transcends healthcare facilities, extending its significance to disaster management and humanitarian relief efforts. During crises, inventory management becomes indispensable for swift mobilization and accurate reporting of medical supplies, acknowledged by various organizations (see, e.g., [31, 37, 48]). This recognition underscores the role of well-managed supplies in mitigating the impact of disasters and enhancing outcomes for affected populations.

Automated inventory systems and analytics stand as indispensable tools, playing a pivotal role in tracking and managing supplies throughout the entire lifecycle. These technologies contribute to heightened efficiency and cost reduction in healthcare facility operations and disaster relief efforts. Analytics, leveraging mathematical models and algorithms, is vital in determining optimal

P. M. Pardalos, O. A. Prokopyev (eds.), *Encyclopedia of Optimization*,
https://doi.org/10.1007/978-3-030-54621-2_877-1

inventory levels to minimize costs while ensuring sufficient supplies. These techniques enable informed decisions on procurement, storage, and distribution, considering factors such as demand, lead time, shelf life, and expiration dates.

This chapter explores deterministic and stochastic optimization models, dynamic programming, simulation, and heuristics, providing insights into their advantages and limitations. Applications in healthcare facilities (section "Management of Inventory in Healthcare Facilities") and humanitarian operations (section "Management of Medical Inventory in Humanitarian Operations") offer a comprehensive understanding of these techniques. Armed with this knowledge, healthcare providers and relief organizations can develop effective inventory management strategies, ensuring the availability of medical supplies when and where needed most.

Management of Inventory in Healthcare Facilities

Healthcare operations include a wide range of connected activities aimed at optimizing the delivery of healthcare services. These activities include capacity planning, resource allocation, demand forecasting, scheduling, and inventory management, alongside overall management of operations. This section specifically focuses on inventory management for medical supplies in healthcare facilities. Efficient inventory management is crucial in healthcare systems in order to ensure that the right medications, supplies, and equipment are available at the right time to support patient care, and also efficient inventory management helps to reduce inventory-related costs. Kelle et al. [25] indicate a major part of the costs in the healthcare sector mainly emerge from healthcare inventory products. De Vries [14] demonstrates an increased emphasis on inventory management in hospitals as aiming to improve internal service performance and reduce costs. Advancing inventory decisions can reduce the costs of healthcare operations, improve patient outcomes, and ensure the competent delivery of healthcare services. However, managing inventory in healthcare can be complex and challenging due to unpredictable demand for various items, short lead times, and limited storage space (see e.g., [9]). Inventory management challenges faced by healthcare operations involve managing inventory levels in case of unpredictable changes in demand, concerning inventory expiration dates, finding the right balance for the amount of medical supply while avoiding excessive holding costs, and deciding to place an emergency order in response to stockouts.

In addition to these challenges, several other factors influence inventory control systems in healthcare operations. The choice of replenishment policy has a significant impact on inventory control, and many authors study inventory policy parameter optimization. Depending on the unique requirements of the healthcare organization, various policies, such as periodic review, continuous review, or order-up-to policies, can have a variety of outcomes. Priyan and Uthayakumar [38] propose a continuous review process (s, Q) by considering the trade-offs between the costs of overstocking and understocking when the inventory level drops below a reorder point (s) and a fixed quantity (Q) is ordered to replenish the inventory. Inventory control choices may also be influenced by the targeted service level or amount of product availability that a healthcare organization seeks to achieve. A higher service level may require higher inventory levels and more frequent ordering, which can increase costs. Rosales et al. [41] propose a hybrid policy strategy that combines periodic and out-of-cycle replenishment for a single item, and extend the strategy for multi-item setting in [42]. In order to provide high-quality medical treatment and avoid stockouts, the service level is utilized in mathematical models. Uthayakumar and Priyan [46] describe service level as fill rate, that is, the proportion of all demand that is met directly from the available stock. Emergency purchases are widely used to satisfy the customer demand, albeit with a higher total cost (see e.g., [18]). Therefore, the fill rate is a reliable indicator of acceptable service at reasonable costs.

Demand for medical supplies is uncertain due to variations in patient conditions, changes in treatment protocols, or unexpected emergencies. Moreover, medical conditions of patients might call for different inventory control strategies. For instance, patients with complicated medical disorders or chronic illnesses could need more specialized medications or supplies, which can be more expensive and harder to procure. Due to delivery delays or supply chain disruptions, supply mechanisms may also be uncertain, which make it even more challenging to avoid stockouts or overstocking. Karamshetty et al. [24] address reasons for stockouts in resource-limited settings. Maintaining undisrupted patient care amid absence of medical supplies is usually attempted by categorizing medical supplies based on the type and cost (see [20]). The type of medical supply affects managing low-value/high-use items, e.g., swabs and syringes, and high-value items, e.g., surgical kits and implants. VED (vital, essential, desirable) analysis and ABC (always better control) analysis are two important methods that can help healthcare organizations to manage their inventory effectively. Categorizing items based on their criticality, VED analysis classifies items based on their criticality to the business as vital, essential, or desirable. Similarly, ABC analysis aims to identify high-value (category A) items that require closer monitoring and control. It is essential to take into account the balance between inventory costs and the importance of items when making inventory control decisions in healthcare. For instance, maintaining higher inventory levels of critical items can ensure patient safety but may increase inventory costs. Similarly, the consumption of high-value items may require more frequent monitoring and control to prevent stockouts. Striking the right balance between inventory costs and risks of stockouts or overstocking is crucial for effective inventory management in healthcare. Healthcare organizations can make well-informed decisions about inventory management by taking these factors into account. This allows them to effectively balance costs and prioritize critical items.

Stock level of a medical supply might also be influenced by storage conditions and perishability factors. For certain items, it may be crucial to keep track of humidity, temperature, or remaining shelf life of drugs, and manage stock levels accordingly. Likewise, certain items go through post-use disinfection procedures that take time between uses (e.g., surgical tools). Thus, these cleaning cycles or other procedures should be considered to determine the available quantity of surgical instruments [15].

Complexity of healthcare supply chain has an impact on inventory control decisions. Healthcare supply chains may involve multiple vendors, distributors, and manufacturers, even *gray market* during shortage periods [7], which makes it difficult to manage. Healthcare organizations have a limited budget, which can affect the choice of inventory strategies. In most cases, the objective of inventory management is to ensure that a certain level of service is achieved with minimum cost amidst all the uncertainty and limitations.

Modeling Approaches

The certainty of the contributing elements in healthcare inventory management impacts modeling techniques. Deterministic techniques are employed when investigating known parameters that remain constant over time, while regarding unpredictable factors, stochastic models are frequently used. In most of the studies, authors characterize demand as stochastic and aim to minimize the impact of medical supply shortages in the presence of uncertain disruptions as those that occur in real-life scenarios.

Deterministic Approaches

Deterministic approaches usually offer insights for the problem under several assumptions. Duncan and Norwich [16] and Xu et al. [49] propose deterministic inventory-oriented economic order quantity (EOQ) models where the aim is cost minimization by assuming constant demand over the periods. Lapierre and Ruiz [26] study a general framework for a supply chain-oriented model with a scheduling approach where they add workload balancing objective along with the supply chain model, and formulate the problem with tabu search-based heuristics. The proposed model assumes constant demand, multi-product, multi-period, and multi-echelon and defines service level as the frequency of visits to point-of-use locations. Stecca et al. [44] present a Mixed Integer Linear Programming (MILP) model for drug delivery problems and solve with commercial solvers. Antic et al. [4] propose a dynamic discrete multi-echelon, multi-product inventory control model for pharmaceutical products. Antic et al. [4] present demand as a sales forecast per period for each product.

In the field of inventory management, various models propose cost minimization while maintaining high service levels. The objective function occasionally includes purchasing cost of inventory items, fixed ordering, and holding cost. Other costs that are considered include disposal cost of perishable items, backordering cost, service cost, etc.. Below is a general setting for multiple periods (without loss of generality, assume $T = \{1, 2, \ldots, |T|\}$), where c_k is the unit cost of item $k \in K$, X_{kt} is the inventory level of item $k \in K$ in period $t \in T$, Q_{kt} is the quantity of item $k \in K$ purchased in period $t \in T$, and h_k is the cost of holding one unit of item $k \in K$ in inventory for one period.

$$\min \quad \sum_{k \in K} \sum_{t \in T} c_k Q_{kt} + \sum_{k \in K} \sum_{t \in T} h_k X_{kt} \tag{1}$$

V_{max} is the maximum available storage capacity and v_k is the unit volume of item $k \in K$; thus, space capacity constraint is as follows:

$$\sum_{k \in K} v_k X_{kt} \leq V_{max}, \quad \forall t \in T \tag{2}$$

Typically, the inventory balance constraints follow for deterministic problems, where d_{kt} is the demand for medicine $k \in K$ in period $t \in T$.

$$X_{k,t} = X_{k,t-1} + Q_{kt} - d_{kt}, \quad \forall\, k \in K, t \in T \tag{3}$$

It should be noted that all decision variables are nonnegative and initial conditions (e.g., X_{k0}) are required for completeness.

Stochastic Approaches

In real-life scenarios, demand for medical supplies, the arrival of events, and other influencing factors are uncertain due to variations in patient conditions, changes in treatment protocols, or unexpected emergencies. Moreover, stockouts or overstocking of critical medical supplies can significantly impact patient care and safety, which highlights the need for timely and accurate inventory information. Thereby, healthcare systems are often characterized by environmental unpredictability, which is why models frequently incorporate uncertainty into their formulations. This can involve addressing uncertain demand, cost, lead time, and transportation time, among other factors. Diamant et al. [15] propose a Markov chain model for reusable surgical equipment where equipment enters a disinfection cycle after each use. Rosales et al. [42], Hovav and Tsadikovich [23], Uthayakumar and Priyan [46], and Gorria et al. [19] present stochastic approaches for inventory control decisions. Ahmadi et al. [2] propose robust stochastic MIP formulation for healthcare products that can be stored in multiple locations. Each location incurs holding costs associated with the stocked quantity. Additionally, the authors introduce an emergency cost at the point of use location in case the product is unavailable, which results in supplementary labor expenses and postponement of patient treatment.

Little and Coughlan [28] evaluate the effect of different inventory policies and delivery frequencies under space constraints to maximize the minimum service level for the multi-product, single-period setting. Along with the capacity model as [28] present, [9] propose a service model where the objective is minimizing required capacity for inventory items while ensuring a service level. They present service level as a fraction of satisfied demand where β_k is the desired service level for item k, $s_{kt}(I_{k,t})$ is the probability of satisfying demand for item k at time t given inventory level $I_{k,t}$, and B_k is the fraction of satisfied demand for item k over the planning horizon:

$$\frac{1}{T} \sum_{t \in T} \mathbb{E}[s_{kt}(I_{k,t})] \geq \beta_k, \quad \forall\, k \in \mathcal{K} \tag{4}$$

Here, the left-hand side represents the expected service level of item k over the planning horizon, averaged across all time periods. The goal is to ensure that the fraction of satisfied demand B_k for item k is at least equal to the desired service level β_k.

Saha and Ray [43] develop Markov decision process model to investigate patient-related influencing factors for drug demand, including changing patient condition, ambiguous patient reaction to treatment, and uncertain patient stay. Vila-Parrish et al. [47] develop a two-stage stochastic model for perishable pharmaceutical inventory, where the shelf life of products changes drastically as they move from raw materials to finished goods. They modeled patient demand using a stochastically changing variable that captures the link between patient condition and medication demand. The authors formulated the problem as a Markov decision process, considering two demand fulfillment strategies for responding to shortages. Their findings suggest that the perishability of pharmaceutical products has a significant impact on patient demand, and production activities affect the remaining shelf life of the product. Li et al. [27] also introduce perishability of drugs into a stochastic lead time inventory model with constant demand.

In addition to analytical methods, there are simulation-based modeling approaches where [10] apply a dynamic system approach to determine the optimal replenishment time and reduce total inventory-related cost without stockout occurrence. Based on the simulation-optimization approach, [18] formulate an MIP model for pharmaceutical items and introduce perishability, the shelf life of products, and emergency purchases into the model along with cost function. Neve and Schmidt [34] present inventory models that aim to improve inspection and replenishment policies for addressing inaccurate inventory in healthcare settings, which can lead to overstocking and stockouts.

Modern approaches include machine learning algorithms; [3] employ reinforcement learning methods, Q-learning and Deep Q-Network, to suggest inventory policies for perishable pharmaceutical products. The algorithm furnishes hospitals with near-optimal order quantities and provides distributions outlining the remaining life of the products they are ordering.

Management of Medical Inventory in Humanitarian Operations

Humanitarian operations literature typically includes studies that explore a variety of decision-making areas, such as inventory management, resource allocation, facility location, and routing. These studies aim to optimize the allocation of scarce resources and streamline logistics, to more efficiently deliver assistance to those most in need. However, this chapter focuses specifically on inventory management for medical supplies, rather than a broad range of decision-making areas. Therefore, the focus is on studies that either only examine inventory decisions or primarily focus on inventory decisions. This enables a more in-depth exploration of specific challenges and considerations related to managing medical supplies in humanitarian operations, and to identify best practices for ensuring that these supplies are available when and where they are needed.

While both healthcare facility inventory management and medical inventory management in humanitarian operations involve the efficient handling of medical supplies and equipment, they differ in terms of challenges, objectives, and planning. Healthcare facilities operate in stable environments and focus on ensuring the availability of necessary supplies for quality patient care, using historical data and trends for planning. In contrast, humanitarian operations occur in disaster-stricken or conflict-affected areas, facing more uncertainties in demand, limited resources, logistical constraints, and the need for rapid response. The primary goal in humanitarian operations is to deliver lifesaving medical aid as quickly as possible while addressing the unique complexities of disaster relief and emergency situations. In disaster inventory management problems, *service level* and *response time* are critical factors. Service level refers to the percentage of demand for goods that are met from inventory, while response time is the time taken to respond to a request for goods. High service levels and fast response times are crucial in disaster inventory management, as availability of critical goods, such as food, water, and medical supplies, is often limited. Effective management ensures goods are available when needed most. A failure to manage inventory effectively can result in shortages and delays, with serious consequences.

Humanitarian logistics focuses on distributing scarce critical supplies in a way that maximizes social benefits. Several studies have examined inventory decisions pertaining to disaster preparedness. Balcik et al. [6] categorize research on inventory management in humanitarian settings into pre- and post-disaster phases based on disaster management stages. Disaster preparedness studies typically focus on long-term, pre-disaster decisions around the locations and amounts of pre-positioned goods. On the other hand, disaster response efforts tend to focus on managing relief inventory in the chaotic and tough post-disaster setting, so as to ensure that needed demand is satisfied in the most efficient way. Acar and Kaya [1] propose a novel integrated relief procurement approach that combines pre-disaster stocking decisions with post-disaster relief procurement.

A critical element in humanitarian inventory management optimization models is the planning time period, which significantly influences the effectiveness of relief efforts. Single-period models focus on optimizing inventory decisions for a fixed, one-time horizon, considering factors such as demand, supply, transportation costs, and available resources [1, 12, 17, 45]. These models are particularly useful for short-term planning, focusing on immediate response efforts where rapid action is required, especially when the time frame for relief operations is relatively short. On the other hand, multi-period models capture the evolving nature of humanitarian crises by considering a series of time periods, allowing for better planning and allocation of resources over the entire relief operation [13, 22, 29, 32, 33]. Multi-period models take into account factors such as changing demand patterns, replenishment of resources, and varying operational costs over time. By incorporating the temporal aspect of relief efforts, multi-period models facilitate more effective long-term planning and resource allocation, enhancing the overall efficiency and sustainability of humanitarian inventory management.

Humanitarian inventory management studies typically aim to minimize the overall cost, which may comprise various expenses such as the unit purchase cost of products pre- and post-disaster, holding costs, unmet demand costs, waiting costs for injured individuals, and deprivation costs. Incorporating nonfinancial considerations into the objective function is a defining characteristic of modeling inventory-related operations in humanitarian logistics, which may include maximizing the amount of demand fulfilled or minimizing lead time. This is particularly important because the consequences of inadequate inventory management can lead to human suffering. To ensure demand coverage is maximized, some studies associate a penalty cost with unmet demand and seek its minimization, such as [39]. Another stream of research not only focuses on modeling responsiveness and timely demand satisfaction but also includes a penalty for unmet demand in terms of deprivation cost, thereby representing economic value of the human suffering from unmet need [22]. Deprivation cost is a critical concept in post-disaster humanitarian inventory management, referring to the cost of inadequate essential supplies like food, water, or medicine, resulting in deprivation of basic needs, and has recently been studied extensively [5, 21, 29, 29, 35].

The concept of deprivation cost has been introduced to improve the efficiency of humanitarian operations, enabling organizations to make better decisions when managing inventory in emergency situations. Deprivation cost is influenced by deprivation time and an individual's socioeconomic characteristics, and it is crucial to account for the social, economic, and cultural factors of the impacted population. Despite their importance, these factors may not be considered in emergency post-disaster situations due to the absence of readily available data. The formulation of deprivation cost may also vary depending on the specific context of the problem. Holguín-Veras et al. [22] explore various mathematical frameworks for measuring human suffering, encompassing: (1) *social cost formulations* that are determined by aggregating individual deprivation costs; (2) penalty-based approaches, featuring variable penalty models, constant penalty models, or hard constraints; and (3) strategies aimed at minimizing unmet demands to reduce overall deprivation costs.

All formulations consider a node $i \in \mathcal{N}$, where $\mathcal{N}$ is a set of demand nodes and π_{it} observationally identical individuals undergo the same deprivation cost, and assume individual socioeconomic characteristics are not a factor. The deprivation cost function is $\gamma(\theta, \delta_{it})$, where θ is a parameter vector and δ_{it} is deprivation time. The model assumes non-hysteretic costs, implying that fulfilling needs partially or completely lowers deprivation costs. In the *social cost formulation*, the total deprivation cost at node i and time t, $D_i(t)$, is determined by aggregating individual costs:

$$D_i(t) = \gamma(\theta, \delta_{it})\pi_{it}, \quad \forall\, i \in \mathcal{N} \tag{5}$$

The family of penalty-based formulations originates from commercial logistic models, which are adapted by incorporating penalty mechanisms. It is crucial for these models to precisely represent deprivation cost functions and effectively capture the opportunity costs linked to the delivery strategy. The variable penalty models utilize penalties that are a function of the tardiness of a delivery. Therefore, late deliveries are permitted but incur penalties for not meeting a predefined threshold. In most cases, variable penalties are expressed as piecewise linear functions that depend on the discrepancy between the deprivation time at the moment of delivery and the predefined threshold.

Incorporating deprivation cost into the objective function of humanitarian inventory management can help organizations prioritize their actions and allocate their resources effectively, ultimately leading to a more efficient and effective response.

Modeling Approaches

Stocking decisions hold significant importance in disaster situations, as they directly impact the ability to meet the demand for essential aid materials within budget constraints. The unpredictability of disasters and the inherent difficulty in accurately forecasting demand can lead to situations where relief materials are either insufficient or excessive. While the bulk of studies in humanitarian logistics consider stochastic demands [1, 5, 33], a smaller subset has treated demand as deterministic [17].

Deterministic Approaches

Deterministic methodologies are crucial in strategically positioning storage and distribution centers for critical supplies and inventory levels of these facilities, thereby laying the groundwork for all post-disaster operations. Battarra et al. [8] introduce a linear programming model for inventory allocation to pre-position emergency supplies in preparation for earthquakes, employing a commercial optimization solver for solving the model. Loree and Aros-Vera [29] construct a mixed-integer nonlinear optimization model to determine the location of points of distribution and manage inventory in post-disaster humanitarian logistics, aiming to minimize placement, logistics, and deprivation costs, while enabling service to demand nodes from multiple distribution points. Erbeyoğlu and Bilge [17] construct a mixed-integer linear model for relief network design and response, proposing a logic-based Benders decomposition approach to solve this problem to optimality across all disaster scenarios.

In the context of a single-period setting with multiple distribution centers, denote the inventory quantity of product $i \in \mathcal{I}$ at location $j \in \mathcal{J}$ as X_{ij}, and the overall supply for product i as s_i. Constraint set (6) ensures that the inventory of product $i \in \mathcal{I}$ allocated to all distribution centers does not exceed the total available supply of product i. It is important to note that in humanitarian operations, the total demand often surpasses the available supply.

$$\sum_{j \in \mathcal{J}} X_{ij} \leq s_i, \quad \forall\, i \in \mathcal{I} \tag{6}$$

Denote the capacity of distribution center $j \in \mathcal{J}$ as c_j. Constraint set (7) guarantees adherence to the individual capacity of each distribution center $j \in \mathcal{J}$.

$$\sum_{i \in \mathcal{I}} X_{ij} \leq c_j, \quad \forall\, j \in \mathcal{J} \tag{7}$$

It should also be noted that all decision variables are nonnegative.

Stochastic Approaches

Predominantly, research focusing on stochastic demands leverages a two-stage stochastic programming model, offering a systematic approach to decision-making in the face of uncertainty [1, 30, 36, 40]. Some research has employed the stochastic dynamic programming model [33].

Mete and Zabinsky [30] develop a two-stage stochastic model for disaster management that determines the storage locations and required inventory levels for each type of medical supply, accommodating a wide variety of potential disaster types and magnitudes. They employ a commercial solver to solve their model. Rawls and Turnquist [39] introduce a two-stage stochastic mixed-integer program to determine the location and quantities of pre-positioned emergency supplies, considering uncertainty around the occurrence and location of natural disasters, and develop a heuristic algorithm to solve large-scale problem instances. Rawls and Turnquist [40] propose a stochastic mixed-integer programming model, enhanced with service quality constraints, to ensure a minimum probability of fully meeting the demand while also guaranteeing that the average shipment distance of supplies is no greater than a specific limit. Noyan [36] formulate a risk-averse two-stage stochastic programming model aimed at determining the response facility locations and the inventory levels of relief supplies at each facility, given the uncertainty in demand and the damage level of the disaster network. Noyan [36] also constructs two decomposition algorithms based on the generic Benders-decomposition approach to solve such problems. Acar and Kaya [1] introduce a newsvendor model tailored for a single product setting and a two-stage stochastic model for two-product cases. These models aim to determine the procurement quantities for each type of material pre- and post-disaster, considering budgetary constraints.

Conclusion

In conclusion, the effective management of medical supplies and equipment emerges as a critical imperative in healthcare operations, with a focus on mitigating deprivation rather than solely prioritizing cost considerations. This article underscores the paramount importance of optimized inventory management not only in healthcare facilities but also in disaster management and humanitarian relief efforts. As pharmaceutical companies align with cost-cutting approaches, it becomes imperative to emphasize the overarching goal of ensuring that essential items are consistently available to address the pressing needs of patients and communities during crises.

Furthermore, the need for collaborative strategies, such as pooling and sharing, and the implementation of transshipment policies among healthcare facilities during crises has to be highlighted. This cooperative approach ensures a collective response to emergencies, promoting resource efficiency and equitable access to medical supplies. By delving into deterministic and stochastic optimization models, dynamic programming, simulation, and heuristics, this chapter has provided invaluable insights into enhancing healthcare resilience. Applications in both healthcare facilities and humanitarian operations underscore the versatility of these techniques, emphasizing their potential to address the dual challenges of minimizing deprivation and optimizing resource allocation to develop strategies that prioritize the collective well-being of communities.

See also

▶ Continuous Review Inventory Models: (Q, R) Policy
▶ Dynamic Programming: Inventory Control
▶ Inventory Management in Supply Chains

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