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# Research on demand response strategy for multi-echelon supply chain inventory optimization based on data analysis

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**Abstract:** Inventory management in multi-echelon supply chains is increasingly challenged by severe demand volatility, dispersed stock across various echelons, and highly unstable replenishment lead times. Although modern enterprise informatization has successfully produced rich operational records—such as sales transactions, inbound and outbound movements, procurement plans, and detailed shelf-life records—these valuable datasets are often significantly underused for demand-responsive decision-making. Consequently, the negative outcomes, including frequent stockouts, costly overstocks, and slow inventory turnover, remain well documented within the extensive bullwhip-effect literature. To address these critical inefficiencies, this paper develops a comprehensive four-component framework designed for translating routinely collected warehouse data into actionable demand-response strategies across all supply chain echelons. The proposed framework comprises: (i) a unified demand-data collection schema that extends far beyond basic inventory registration to systematically include lead time, supplier, and consumption attributes; (ii) a robust upstream–downstream information-sharing protocol that effectively reduces feedback lag and mitigates information asymmetry; (iii) a hierarchical inventory-classification scheme combining traditional ABC analysis with dynamic shelf-life and turnover criteria; and (iv) an advanced dynamic replenishment mechanism featuring multi-condition alert triggers that replaces rigid fixed-cycle replenishment with agile, event-driven adjustments. We empirically illustrate the practical viability of this framework using four distinct case examples drawn from manufacturing, maintenance, and consumer-goods warehouses. By reporting baseline practices, targeted interventions, and observed performance outcomes for each scenario, the framework contributes a highly practitioner-oriented integration of established inventory-control principles with optimized information-flow design for complex multi-echelon settings.

**Keywords:** supply chain; inventory optimization; demand response; data analysis; information sharing

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## 1. Introduction

Inventory in a multi-echelon supply chain is shaped by the joint dynamics of procurement, production, logistics, and sales decisions taken at every node, from the supplier to the end customer. When demand signals are not transmitted and acted on quickly across echelons, three failure modes recur: stockouts of fast-moving items, overstocking and obsolescence of slow movers, and excessive turnover times for working capital. These failures are economically significant—inventory carrying costs are routinely estimated at 20–30% of inventory value annually—and they are also structural. Variability in orders amplifies as it moves upstream from end demand, a phenomenon termed the bullwhip effect, and a substantial body of subsequent research has documented its causes and countermeasures [1].

Two parallel developments have changed what warehouses can plausibly do about these problems. First, enterprise resource planning, warehouse management systems, and barcode/RFID instrumentation now make it routine to capture entry, exit, lead-time, and supplier-status data at line-item granularity. Second, the operations-research literature on

multi-echelon inventory control and on the value of information sharing provides a well-developed theoretical basis for using this data [2]. Yet practitioner-facing accounts continue to report that data collection in warehouses is fragmented, that upstream–downstream information sharing is slow and informal, that inventory classification stops at coarse categories, and that replenishment follows fixed cycles rather than responding to demand signals.

This paper addresses that gap. Rather than proposing a new theoretical model, it develops a four-component operational framework that connects routinely collected warehouse data to demand-response decisions, drawing on established inventory-control principles and adapting them for the multi-echelon setting. The contributions are: a data-collection schema that specifies the operational fields needed for demand forecasting beyond simple stock counts; an information-sharing protocol explicitly designed for the chain of supplier → purchaser → warehouse → customer; a hierarchical classification rule combining ABC analysis with shelf-life and turnover criteria; and a dynamic, alert-driven replenishment mechanism. Four case examples—personal protective equipment, maintenance spare parts, manufacturing parts/consumables, and food-packaging materials—illustrate how the framework is applied in practice and what outcomes can be observed [1].

The remainder of the paper is organised as follows. Section 2 reviews the structural characteristics of multi-echelon inventory systems and the data representation of demand fluctuations. Section 3 describes the research methodology, including case-selection criteria and analytical approach. Section 4 identifies four recurring problems in current practice. Section 5 develops the four-component framework, presenting each component alongside an illustrative case. Section 6 concludes with limitations and directions for further research [3].

## 2. Basic Analysis of Multi-Echelon Supply Chain Inventory Optimization Demand Response Based on Data Analysis

### *2.1. Characteristics of Multi-Echelon Supply Chain Inventory Structure*

A multi-echelon supply chain consists of a series of stocking points arranged in tiers from supplier through enterprise warehouse and distribution center to the end customer, with each tier holding its own inventory and placing orders on the tier immediately upstream. The relationships between adjacent nodes are characterized by four parameters: the replenishment cycle, the transportation lead time, the purchase batch size, and the safety stock held at each location. These parameters are not independent: a change in one—a longer supplier lead time, a larger batch size to capture a quantity discount, or a tighter safety-stock policy upstream—propagates downstream and alters the effective inventory position at every subsequent tier. The empirical and analytical literature on the bullwhip effect shows that order variability is systematically amplified as signals travel upstream from end demand, so that the inventory state at any single node cannot be evaluated in isolation from the parameters and behavior of its upstream and downstream neighbors. For warehouse management, this structural property has two practical consequences [4]. First, the information set required for inventory decisions extends beyond the current warehouse's own stock counts to include the supply capacity and lead times of the upstream tier and the consumption demand and order plans of the downstream tier. Second, the operational signals routinely captured by warehouse-management systems—total inventory volume, turnover rate, validity period, number of stockouts, and number of repeat purchases—can be aggregated into an index system that measures inventory state at the node level and serves as input to the demand-response strategies developed in subsequent sections.

### *2.2. Data Representation of Inventory Demand Fluctuations*

The changes in inventory requirements typically involve variations in the number of shipments, the quantity of orders placed, seasonal shifts in usage, temporary increases in purchases, and the accumulation of excess inventory. Simply relying on subjective

experience to make judgments is often insufficient to uncover the underlying patterns [2, 5]. By analyzing historical inventory entry and exit records, sales vouchers, production plans, purchase time cycles, and changes in customer demands, it is possible to distinguish between high-frequency materials, long-cycle materials, and special fluctuating materials. The demand information also reveals how inventory pressure varies across time periods, product categories, and supply-chain stages. Clearer data fluctuations facilitate inventory forecasting and enable more reasonable replenishment time points.

*2.3. The Management Value of Demand Response for Inventory Optimization*

Demand response refers to an operation management approach that can respond to changes in demand and promptly adjust inventory allocation, procurement plans, and replenishment frequencies [6]. In a diversified supply chain environment, it can reduce the waste of funds caused by excessive reserves and also lower the supply risks resulting from shortages of key materials. Based on information mining analysis, the inventory detection method for warehouse management can be transformed from the traditional fixed type to a mobile type, and more reasonable settings can be made for the upper and lower limits of inventory, safety stock quantities, and replenishment points. It can also enhance the communication relationship among suppliers, warehouses, and customers, and improve the inventory turnover rate. For different varieties and batches of goods, demand response has the significance of improving management accuracy and ensuring stable supply.

## 3. Research Methodology

This study develops a practitioner-oriented framework for demand response in multi-echelon supply-chain inventory management [7]. Because the framework is intended to be applicable across diverse warehouse settings rather than tuned to a single dataset, a case-illustrated design-science approach is adopted, in which conceptual artefacts—here, a four-component framework—are developed iteratively against problem patterns observed in practice and refined through illustrative cases.

*3.1. Research Design*

The study proceeds in three stages [8].

Stage 1: Problem identification. Four recurring problems in multi-echelon inventory management were identified from (a) a structured reading of the operations-research literature on multi-echelon inventory and the bullwhip effect, and (b) practitioner accounts published in recent supply-chain and warehouse-management literature [9, 10]. The four problems—incomplete demand-data collection, upstream-downstream information lag, inefficient inventory classification, and inflexible replenishment—are the ones most frequently cited as obstacles to data-driven inventory management.

Stage 2: Framework development. For each problem, a corresponding strategy was developed by combining (i) the relevant established inventory-control principle (e.g., ABC analysis for classification; reorder-point/(s, S) policies for replenishment); (ii) the data and information-system capabilities now routinely available in instrumented warehouses; and (iii) the specific demands of the multi-echelon setting, in which a local decision propagates across echelons. The result is the four-component framework presented in Section 4.

Stage 3: Case illustration. Four warehouse cases were selected to illustrate the framework's application: a personal-protective-equipment (PPE) warehouse, a mechanical-spare-parts maintenance warehouse, a manufacturing-enterprise warehouse holding parts and consumables, and a food-packaging materials warehouse. The cases were chosen for diversity along three dimensions: product category (industrial vs. perishable vs. spare parts), demand pattern (seasonal, event-driven, steady-with-spikes), and the dominant inventory problem each is most exposed to. For each case, baseline practice, the framework intervention, and observed outcomes are described.

*3.2. Data Sources*

The case examples draw on operational records typically maintained by warehouse-management systems: entry/exit ledgers, sales vouchers, purchase orders, supplier delivery records, and shelf-life logs [4, 11]. A single integrated dataset is not reported because the cases originate in distinct organizational contexts. Instead, the cases serve as parallel illustrations of how the framework's data requirements align with practical applications.

*3.3. Scope and Limitations of the Methodology*

The framework is developed and illustrated, but it has not been empirically validated against a controlled benchmark. Parameters are not estimated, demand-forecasting models are not fitted, and cost savings are not quantified against a counterfactual. The metrics reported in the case examples are descriptive rather than derived from a controlled comparison. This leads to three implications. First, the framework's external validity is limited to settings broadly similar to the illustrative cases, such as warehouse-managed multi-echelon supply chains with available transaction data. Second, the effect sizes of each component cannot be inferred from this study; they require empirical testing on multi-period operational data, which is identified as a priority for future research. Third, the framework is complementary to, rather than a replacement for, formal multi-echelon optimization models, such as Clark–Scarf base-stock policies or METRIC for repairable parts. It addresses the operational and informational preconditions necessary for such models to function, rather than the optimization itself.

## 4. Problems in Multi-Echelon Supply Chain Inventory Optimization Driven by Data Analysis

*4.1. Incomplete Collection of Demand Data Affects the Accuracy of Inventory Forecasting.*

Multi-echelon supply chain inventory forecasting requires a complete, continuous, and accurate information source [12, 13]. However, in daily operations, challenges such as a narrow scope of information collection, inconsistent record standards, and insufficient update speed often arise. The warehouse entry and exit ledger cannot fully reflect terminal demand quantities, procurement cycle lengths, supplier supply capabilities, the status of goods in transit, special loss conditions, and other critical factors. Some products only record changes in quantity, lacking specific details such as batch numbers, shelf life, usage units, and usage locations, making it difficult to accurately identify demand change patterns. Without a robust data foundation, forecasting models are prone to deviations from actual demand, leading to scenarios of either excess supply or shortages in the material supply plan.

*4.2. The Lag in Information Transmission between Upstream and Downstream Stages Reduces the Efficiency of Inventory Coordination.*

To achieve the goal of optimizing multi-echelon supply chain inventory, consistency of information among suppliers, purchasers, warehousing centers, and customers is necessary. In actual management, situations such as slow information transmission, long feedback chains, and insufficient shared information often occur. If the delivery time of the upper level is delayed and the warehousing center is not informed in time, it may lead to inaccurate shipment quantity and safety stock settings; the downstream demand changes cannot be responded to in time, which may result in deviations in the selection of storage reserves. The information systems, counting methods, and review processes used by each node are different, which increases the difficulty of information confirmation. The inability to receive timely feedback on inventory information makes it impossible for each level of the supply chain to make correct judgments, affecting the allocation of goods, changes in procurement, and the speed of replenishment rate.

*4.3. Inefficient Classification Management of Inventory Increases the Pressure on Warehouse Turnover.*

The materials in the warehouse are diverse in type and numerous in batch. If management is conducted solely by distinguishing them based on names, models, or

storage locations, it cannot meet the inventory optimization requirements of a high-level supply chain. For materials that are frequently used, updated infrequently, have a cycle, and require supply assurance, the absence of corresponding management systems may lead to omissions of key materials and prolonged occupation of storage locations by unsold items. Some inventories have not been classified and analyzed according to factors such as frequency of entry and exit, validity period distribution, demand stability, and capital occupation. This results in a lack of targeted and precise inventory counting and replenishment. Poor classification reduces warehouse efficiency and increases the workload associated with searching, transporting, repairing, and cleaning.

### *4.4. The Inflexibility of the Demand Response Mechanism Leads to Delayed Replenishment Decisions.*

The core of the demand response mechanism lies in promptly adjusting inventory allocation and replenishment strategies based on changes in demand. Many warehouses conduct replenishment activities according to pre-defined time intervals, batch sizes, and experience. However, when there are sudden increases in orders, changes in production plans, extended supply cycles, or decreased terminal demand, it becomes challenging to dynamically adjust storage thresholds and replenishment locations in real time. Some products lack immediate alarm standards, and the inventory status is only identified during inventory checks or material shortages, which impacts the timeliness of replenishment decisions. Weaknesses in the ability to respond promptly to demand result in procurement plans failing to meet actual business conditions, leading to passive inventory adjustments and an inability to support the stable operation of multi-echelon supply chains.

## 5. Demand Response Strategy for Multi-echelonSupply Chain Inventory Optimization Based on Data Analysis

### *5.1. Improve the Demand Data Collection System to Enhance the Accuracy of Inventory Forecasting*

The demand data should be expanded from the inventory registration to include various dimensions such as order quantity, purchase frequency, supplier delivery status, in-transit materials, inventory changes, recipients, and losses. These data serve as the original basis for inventory formation, circulation, consumption, and replenishment. The warehouse management can establish a unified data entry template, setting items such as material codes, material names, batches, entry times, storage locations, uses, usage frequency, minimum inventory quantity, maximum inventory quantity, purchase lead time, supplier names, and frequency of stockouts as fixed items. After data entry, the inventory quantity and shipment quantity should be counted daily, the material consumption trend analyzed weekly, and the demand change rate, inventory age structure, and purchase interval time analyzed monthly to achieve the transformation of inventory planning from empirical estimation to data analysis.

For instance, when managing personal protective equipment in a warehouse, only the quantities of labor protection gloves, goggles, protective shoes, etc. were recorded. Replenishments were provided on a fixed schedule. It was common to encounter situations where there was a shortage of rainproof shoes during the rainy season and a long-term accumulation of ordinary gloves. After the rectification, the warehouse collected data such as the employers, the number of employees, the types of work, seasonal changes, historical consumption, and procurement cycles. It continuously tracked the frequency of usage, the locations of collection, and the inventory days of various types of personal protective equipment. The results showed that the demand for rainproof shoes and rainproof gloves increased significantly within one month before the rainy season, and the usage of gloves by maintenance personnel was much higher than that of administrative staff. Based on the above data, the warehouse advanced the replenishment time of the rainproof series products by 15 days and reduced the purchase

quantity of ordinary gloves by one-third. It also established monthly inspection regulations for products with lower usage, making the inventory forecast clearer.

*5.2. Establishing a Seamless Information Link between Upstream and Downstream to Enhance Inventory Collaboration Levels*

To ensure smooth information flow, a top-down chain-like information transmission channel needs to be established, namely a continuous sharing mechanism among suppliers, the purchasing department, the warehousing department, and customers. This enables timely transmission of demand changes, purchasing processes, delivery times, inventory quantities, and various emergencies. The warehouse should establish a public inventory list, registering the current inventory of key materials, in-transit inventory, estimated delivery times, pending-approval purchase requests, important planned orders, supplier supply situations, etc., to reduce the occurrence of repeated inquiries, manual verification, and repeated modifications [14]. In cases where suppliers fail to deliver samples on time, users increase the quantity, or the purchasing plan changes, there should be a fixed feedback process. The warehouse is responsible for updating inventory information, the purchasing department follows up on the order progress, and the user provides the required time to prevent any lag in a certain link from affecting overall inventory control.

For example, the maintenance warehouse of a mechanical equipment component is responsible for the management of spare parts such as bearings, sealing rings, and lubricating oil. When the maintenance team temporarily repairs and debugs, the maintenance warehouse is usually informed by telephone, making it difficult for the purchasing department to grasp the changes in relevant materials in time, and some urgently needed parts cannot arrive on time. After optimization, the warehouse established a shared demand table for spare parts, entering the expected quantity, usage time, and urgency that maintenance personnel are expected to take after completing the maintenance plan. Then, the purchasing department uses this information to check the purchasing progress and learn about the production progress, delivery time, and possible reasons for delays of the products from the suppliers. Before the routine maintenance of a large machine, the system shows that the inventory quantity of a certain type of bearing is 8 pieces, while the demand is 20 pieces, and the manufacturer's delivery period is 10 days. To avoid the shortage, the warehouse issued a replenishment notice in advance. The purchasing department adopted the form of multiple arrivals, first allocating 6 pieces from the nearest warehouse, and then urging the supplier to replenish the remaining quantity as soon as possible.

*5.3. Refine the Classification and Control Methods for Inventory to Optimize the Turnover Efficiency of the Warehouse.*

Hierarchical inventory classification is a long-established practice; the single-criterion ABC method based on consumption value dates to the 1950s and remains the most widely used scheme in warehouse practice, with multi-criteria extensions developed to capture dimensions that pure value-based ranking misses [15]. The strategy proposed here builds on this tradition in two ways suited to the multi-echelon setting. First, it combines three criteria simultaneously—the ABC value rank, the remaining shelf life of the item, and its turnover rate—rather than applying any one of them in isolation; this is important because items with similar consumption value can nonetheless have very different perishability and movement profiles, and treating them identically produces either premature stockouts (for high-turnover B items) or unnecessary obsolescence (for low-turnover A items with short shelf life). Second, each resulting class is mapped to a concrete set of operational responses rather than left as a categorical label, so the classification has direct consequences for inventory policy across the chain.

Concretely, the three-criterion rule yields three operational classes [16]. "Priority attention" items combine high consumption value with either rapid turnover or short shelf life: they receive additional approval steps for issuance and receipt, separate accounting, more frequent stock counts, and the safety-stock parameters discussed in Section 5.4.

"Routine supervision" items are those with moderate value or stable, predictable consumption: they are managed on standard replenishment cycles with limit-based reorder rules. "Reduction and elimination" items are slow-moving stock with low value or near-expiry shelf life: they are subject to inventory drawdown, cross-warehouse redistribution, or removal from the active purchasing plan. Each class maps to a distinct inventory cycle, purchase quantity, shelf location, and storage protocol. Compared with single-criterion ABC, this combined scheme reduces the risk that valuable but slow-moving items occupy prime storage while fast-moving lower-value items are placed in inaccessible locations—the operational misallocation reported in the manufacturing case described next.

For instance, in a manufacturing enterprise, the warehouse stores various parts, packaging materials, maintenance tools, and consumables. Previously, they were arranged by regions [17]. Some packaging materials that were not frequently used were placed near the entrances and exits, while screws and connectors that were frequently used were placed in more secluded locations, which increased the time cost for searching and transporting. After the warehouse was reorganized, it analyzed the records of entries and exits over the past six months, the validity periods, and the financial proportions. It was found that nearly 20% of the materials accounted for the majority of the outbound volume. Some packaging materials had not been used for over a year and occupied a large amount of storage space. The warehouse placed the frequently used but in small quantities materials near the entrance, established a scanning and borrowing mechanism and a weekly replenishment system; valuable electrical machinery parts were managed separately and a monthly inventory check system and a limited purchase system were implemented; packaging materials that had not been used for a long time were included in the transfer list and distributed to other factories with higher usage volumes, and the purchase plan for this type of products was suspended. Such meticulous division and control made the storage locations more reasonable.

### *5.4. Establish a Dynamic Demand Response Mechanism to Enhance the Timeliness of Replenishment Decisions*

A dynamic demand response mechanism replaces fixed-cycle replenishment with event-driven adjustment of the replenishment location, purchase quantity, and safety-stock level in response to observed changes in demand, inventory cover, purchase lead time, and supply risk. The underlying logic generalizes the continuous-review reorder-point family of policies that has long been standard in inventory control: when monitored inventory or demand crosses a threshold, the policy triggers a replenishment action rather than waiting for the next scheduled review. The mechanism proposed here adapts this logic to the multi-echelon, warehouse-management context in three ways. First, the warning system uses heterogeneous trigger conditions rather than a single inventory threshold—current cover below the safety level, abnormal sales fluctuation, supplier delay, insufficient in-transit quantity, and sudden order-plan increase are each treated as independent alarms, since each captures a different mode of failure [18, 19]. Second, an explicit human-verification step is interposed between trigger and action: warehouse staff, purchasing, and the customer-facing function jointly confirm that the observed signal reflects genuine demand rather than a data artifact or one-off event, addressing the rationing and order-batching causes of bullwhip distortion identified in the literature. Third, the response is tiered rather than binary—based on current inventory, in-transit products, historical consumption, and remaining replenishment lead time, the warehouse can select among temporary replenishment, cross-warehouse allocation, emergency procurement, or order-splitting and distributed fulfillment. The dynamic approach should also periodically review historical data to update the safety stock level, replenishment location, and order quantity parameters.

For instance, a certain warehouse is used for storing food packaging materials, including cartons, labels, and seals, and the management of these materials is involved. The demand is relatively high before holidays. Previously, goods were replenished on a

monthly basis. During peak order periods, there was a shortage of seal supplies, and the purchase price was high, which affected the efficiency of product packaging [19]. After a pre-festival production plan was raised, the shipment volume of the sealing film continued to increase within three days, and the system showed that it would be lower than the safety stock after a week. The warehouse immediately checks the production schedule, determines the trend of increasing demand, orders two batches of goods from the manufacturer, and transfers part of the inventory from other warehouses.

## 6. Conclusion

This paper has developed a four-component operational framework for demand response in multi-echelon supply-chain inventory management, connecting routinely collected warehouse data to demand-response decisions across echelons. The contribution is not a new theoretical model but a practitioner-oriented integration: a data-collection schema that extends beyond inventory registration to lead-time, supplier, and consumption attributes; an information-sharing protocol that opens the upstream-downstream channel and shortens the feedback chain; a three-criterion classification rule combining ABC value, remaining shelf life, and turnover rate, each mapped to specific operational responses; and a multi-condition alert-driven replenishment mechanism that generalizes reorder-point logic for the multi-echelon setting. The four case examples illustrate how each component manifests in distinct warehouse contexts and what failure modes it addresses.

Three limitations should be acknowledged. First, the framework is developed and illustrated rather than empirically validated against a controlled benchmark: the metrics reported in the case examples are descriptive rather than the output of a counterfactual comparison, so effect sizes for each component cannot be inferred from this study. Second, the cases are drawn from distinct organizational contexts and used as parallel illustrations, which means external validity is limited to settings broadly like those described—warehouse-managed multi-echelon chains with available transaction data and a single managing organization. Third, the framework is complementary to, not a replacement for, formal multi-echelon optimization models; it addresses the operational and informational pre-conditions for such models rather than the optimization itself.

Three directions for further work follow from these limitations. The first is empirical validation: applying the framework to a multi-period operational dataset from a single multi-echelon warehouse network and reporting before/after metrics—stockout rate, days-of-supply, turnover, fill rate—against a pre-intervention baseline. The second is integration of modern demand-forecasting methods: the data-collection schema and alert system in this framework provide the inputs needed by machine-learning and deep-learning forecasting approaches, and a natural next step is to replace the rule-based alert thresholds in the framework with model-based forecasts of stockout probability. The third is sensor- and IoT-level instrumentation: as RFID, barcode, and weight-sensor coverage in warehouses expands, the data-collection schema can be enriched with item-level real-time signals, which would allow the human-verification step in the response mechanism to be tightened and, in some routine cases, automated. Each of these directions would strengthen empirical confidence in the framework while preserving the basic structure of the four components developed here.

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