# Research On Multi-level Supply Chain Inventory Optimization Based On Particle Swarm Optimization Algorithm

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**Abstract:** In the context of global digitalization and intelligent transformation, supply chain management is undergoing fundamental restructuring. Within multi-level supply chain systems, traditional inventory control strategies often fail to achieve overall system optimization due to challenges such as numerous nodes, information transmission delays, and amplification of prediction errors. Particle Swarm Optimization (PSO), a representative swarm intelligence optimization method, has gained widespread application in solving complex constraint-based and multi-variable interactive problems through its structural simplicity and high search efficiency. This study focuses on multi-level supply chain inventory optimization by developing a collaborative model involving suppliers, manufacturers, distributors, and retailers. An enhanced PSO optimization strategy is proposed, incorporating dynamic inertia weights, local fine-grained search, and multi-objective fitness functions to significantly improve convergence efficiency and robustness in multi-level supply chain inventory optimization.

**Key words:** Multi-level Supply Chain; Inventory Optimization; Improved PSO Algorithm

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## Introduction

In the context of increasingly complex global supply chain systems, achieving inventory cost minimization, service level assurance, and optimal resource allocation across multi-tier supply chain nodes has become critical for enterprise operations. Particularly under current market conditions marked by frequent demand fluctuations and heightened logistics timeliness requirements, traditional inventory control methods such as Economic Order Quantity (EOQ) models and quantitative/periodic ordering strategies can no longer meet the real-time responsiveness, collaborative efficiency, and dynamic adaptability demands of multi-level supply chain systems. Concurrently, issues like information delays, forecasting deviations, and node response time lags within multi-tier structures have emerged, further exacerbating uncertainties and risks in inventory management. Against this backdrop, Particle Swarm Optimization algorithm (Hereinafter referred to as PSO algorithm)—known for its non-dependence on mathematical analysis and capability to handle nonlinear and multi-constraint problems—is adopted in this study to explore improvements in the algorithm.

## 1 The application theory of PSO algorithm in multi-level supply chain inventory optimization

The PSO algorithm, a stochastic optimization method rooted in swarm intelligence, operates through information exchange and collaborative learning among particles to efficiently search for global optimal solutions within the solution space. Using population as its fundamental unit, this algorithm enables particles to continuously update their states during exploration. By dynamically adjusting search directions based on individual and collective experiences, it achieves optimal solutions for complex problems. Key features include minimal parameters, simple implementation, strong global search capabilities, and excellent parallel processing performance, making it particularly suitable for solving nonlinear, multi-objective, and high-dimensional optimization challenges.

In supply chain inventory optimization, multi-level structures exhibit hierarchical complexity, uncertain market demand fluctuations, and interdependent decision variables. These factors make traditional analytical methods struggle to obtain satisfactory solutions within reasonable timeframes. The PSO algorithm, however, can efficiently handle large-scale variable systems and non-convex objective functions without relying on gradient information, demonstrating strong problem adaptability and optimization efficiency. Inventory optimization is often constrained by supply cycles, service levels, safety stock requirements, and other factors. When addressing constraint optimization problems, the PSO algorithm effectively handles these complexities through embedded penalty mechanisms or fitness function transformation strategies, ensuring its applicability to real-world complex scenarios.

From the perspective of technological evolution, the PSO algorithm has gradually developed a series of variants adapted to dynamic environments, such as Adaptive PSO, Hybrid PSO, and Distributed PSO. These versions can be integrated into supply chain systems to achieve real-time optimization of inventory strategies, multi-node collaborative adjustments, and multi-objective decision support[1]. Additionally, the PSO algorithm can interface with supply chain simulation models or ERP systems, enabling algorithmic, model-based, and intelligent approaches in inventory decision-making processes.

## 2 Design of multi-level supply chain inventory optimization model based on PSO algorithm

### 2.1 Multi-level supply chain structure modeling and inventory control objective setting

The multi-level supply chain structure consists of four fundamental tiers: suppliers, manufacturers, distributors, and retailers. Each tier contains nodes with inventory capabilities, including parameters such as safety stock, maximum inventory levels, and replenishment cycles. These nodes maintain regular order interactions and transportation delays with upstream/downstream counterparts. Inventory demand originates from end retailers and propagates upward through the hierarchy, creating a classic bullwhip effect scenario. The optimization model focuses on minimizing total system inventory costs while incorporating service level constraints and stockout rate control mechanisms to ensure business viability. The cost function encompasses holding costs, ordering costs, transportation expenses, and stockout penalties, with standardized parameter quantification achieved through [2]. To enhance dynamic adaptability, the model incorporates rolling cycle control principles that enable periodic re-optimization in response to demand fluctuations, thereby improving inventory management flexibility. The final optimization framework provides a well-structured search space foundation for the PSO algorithm, ensuring clear objectives and efficient resource allocation.

### 2.2 Improve the inventory control variable coding and adaptation mechanism of PSO algorithm

In multi-level supply chain inventory optimization, each particle's code must be accurately mapped to inventory decision variables at various supply chain nodes. This study employs a multidimensional vector structure for particle encoding, dividing the dimensions into multiple inventory sub-blocks corresponding to critical control parameters from suppliers to retailers, including reorder points, safety stock levels, and order quantities. To address the incompatibility of standard PSO algorithms with high-dimensional inventory constraints, an adaptability correction mechanism is designed to ensure particles remain within feasible solution space. Specific measures include dynamic boundary adjustment strategies, rebound mapping for particle boundary violations, penalty factors based on inventory cost functions, and enhanced steady-state control of inventory levels during particle search. Considering supply chain discontinuity cycles and transportation delays, the algorithm synchronously updates delayed inventory status during iterations, ensuring the particle evaluation function accurately reflects system lag effects. This encoding-adaptability mechanism guarantees efficient optimization within search space while adhering to operational constraints at each node, thereby improving the business executability of inventory optimization solutions.

### 2.3 Intelligent coupling design of information sharing and collaboration mechanism

The particle swarm optimization framework incorporates information sharing and collaborative mechanisms among supply chain nodes, leveraging modern inventory management strategies such as VMI (Variable Management Inventory) and CPFR (Continuous Process Flow Replenishment) to enable real-time exchange of inventory status and demand forecasting data across nodes. During each iteration, the inventory strategies of particles in the swarm influence upstream and downstream nodes while integrating global and local optimal solutions to establish a dynamic feedback loop that ensures controlled and transparent information flow. A collaborative response threshold mechanism is implemented: when a node's inventory approaches critical levels, it triggers upstream nodes to initiate early-warning ordering behavior, simulating agile collaborative responses in real-world scenarios. This mechanism enhances systemic coupling between particles, shifting inventory optimization from local optimization toward global coordination, thereby mitigating risks of redundant stockpiling and stockouts caused by "island-style" inventory control.

### 2.4 Dynamic recalculation mechanism and simulation verification process of optimization scheme

The PSO algorithm incorporates a dynamic recalculation mechanism that automatically updates demand data and transportation delay parameters after each rolling cycle. By resetting the current inventory status as a new initial solution and reactivating the particle swarm optimization process, the system dynamically adjusts inventory strategies through periodic iterations and fitness re-evaluations, preventing policy failure caused by external disturbances. Implementation involves conducting system-level simulations using a supply chain modeling platform to validate optimization outcomes. These simulations evaluate inventory response effectiveness across various scenarios, generating key metrics including average inventory levels, inventory turnover rates, stockout rates, and total costs to assess the system's stability and robustness in real-world operations. A control group is established for comparative experiments, demonstrating the proposed solution's advantages and applicability across multiple scenarios and timeframes. This ultimately achieves a transition from static configuration to dynamic strategy in inventory optimization, establishing a practical and continuously improving intelligent decision-making system for inventory management.

## 3 Formulation of multi-level supply chain inventory optimization scheme based on PSO algorithm

### 3.1 Optimization of particle update mechanism based on dynamic adaptive strategy

In multi-level supply chain inventory optimization, traditional PSO algorithms often encounter premature convergence and local optima stagnation due to high variable dimensions, nonlinear objective functions, and complex search spaces. To address this challenge, a dynamic adaptive inertia weight adjustment strategy is introduced. By continuously monitoring population fitness trends, the algorithm dynamically adjusts inertia weights to enable differentiated search behaviors across phases[3]. Specifically, when global fitness improvement slows, the system automatically increases inertia weights to enhance exploration capabilities. When potential optimal regions are identified, inertia weights are gradually reduced to improve local search precision. This dynamic approach effectively resolves particle clustering issues in early iterations while enhancing the algorithm's ability to escape multiple local minima in complex inventory functions. Additionally, a position perturbation mechanism is incorporated during each iteration, introducing minor disturbances to particles to prevent stagnation. These improvements boost the algorithm's robustness and dynamic adaptability, providing a more flexible search foundation for multi-variable decision-making in complex inventory environments.

### 3.2 Introduce local fine search module to improve inventory optimization accuracy

The inventory scheduling between nodes across multi-level supply chains exhibits complex nonlinear interactions. Near critical inventory thresholds (e.g., safety stock lower limits or transportation cycle constraints), traditional PSO's standard particle update formula struggles to capture the fine-grained structure of solution space. To address this, we integrate a Local Exploitation Module (LEM) into the standard PSO framework. This module selects representative high-quality particles after each iteration for small-scale multi-point perturbations and micro-step searches, enabling high-density sampling and local optimization in adjacent regions. The LEM employs mutation operators to construct local search grids, dynamically adjusting disturbance step sizes based on gradient direction and cost function feedback to enhance search precision and guidance. Additionally, multi-threaded parallel execution of local fine-search tasks ensures algorithmic runtime remains within operational tolerance. This optimized approach enables accurate identification of "optimization-sensitive zones" near inventory boundaries, significantly improving the reliability and cost control capabilities of end-user inventory strategies in practical applications.

### 3.3 Design of fitness function driven by multi-objective collaboration

Traditional PSO algorithms primarily focus on optimizing single-objective functions. However, in practical multi-level supply chain inventory control, it is essential to balance multiple metrics including holding costs, stockout losses, batch sizes, and inventory turnover rates, demonstrating significant multi-objective decision-making characteristics. To accommodate diverse operational requirements, we developed a multi-objective collaborative fitness function system. This system integrates multiple objective functions into a dynamically adjusted comprehensive fitness metric through weight transformation strategies. The weights of each objective are not fixed but dynamically adjusted in real-time based on the current iteration phase, system status, and particle distribution[4]. For instance, during inventory overstock phases, the system automatically increases the weight of holding costs, while during periods of intense demand fluctuations, it enhances the weights of stockout rate and response speed to strengthen short-term supply resilience. Additionally, the fitness function incorporates fuzzy logic mapping functions to convert quantitative indicators into comparable membership values, enhancing the algorithm's robustness and interpretability when resolving nonlinear conflicts between objectives.

## 4 Case study on inventory improvement of multi-level supply chain based on PSO algorithm

### 4.1 Case Background

Company A, an electronics manufacturer specializing in high-performance smart wearables, operates through a supply chain spanning raw material suppliers, core component manufacturers, provincial distribution centers, and retail outlets. Amid market volatility and cross-border logistics uncertainties, the company's inventory management system has encountered multiple challenges. Firstly, unstable upstream supplies have led to frequent production schedule changes. Secondly, severe inventory overstock at provincial distribution centers has caused cash flow strain. Thirdly, persistent high product shortages and declining customer satisfaction highlight the limitations of traditional ERP-based inventory management systems that rely on rigid replenishment rules. To address these issues, Company A has implemented an intelligent inventory optimization project centered on the PSO algorithm. The initiative aims to dynamically adjust multi-tier supply chain parameters through algorithmic models, achieving efficient alignment between inventory structures and demand fluctuations while enhancing overall supply chain resource allocation efficiency and responsiveness.

### 4.2 Deployment programme

Building upon Company A's existing ERP and WMS systems, the project integrates an embedded PSO algorithm module without replacing core business platforms. This module establishes centralized modeling for critical inventory decision parameters across supply chain nodes, including safety stock levels, reorder points, order quantities, and replenishment thresholds at each tier. To ensure model sensitivity to multi-source data, the algorithm incorporates 14 dynamic metrics including historical sales data, manufacturing lead times, supplier punctuality rates, and return rates as input variables. The optimization model employs a "rolling window + hierarchical update" mechanism, retraining inventory parameter models every 48 hours to achieve local fine-tuning while maintaining overall strategy stability. To resolve information silos between manufacturers and distribution nodes, the system synchronizes with sales forecasting platforms to perform machine learning predictions for weekly order expectations from retail outlets, transmitting these predictions as external feedback factors for particle fitness functions. The deployment plan establishes three inventory status warning levels and incorporates local disturbance modules before particle swarm optimization convergence to handle emergencies like supply disruptions. The two-month implementation phase comprises three phases: algorithm tuning, joint debugging and operation, and full-scale deployment. The entire process maintains user interface integrity while preserving all original replenishment and approval workflows, focusing solely on optimizing decision parameter generation modules.

### 4.3 Implementation effect

The specific implementation effect is shown in Table 1.

Table 1 Implementation effect

| Indicator items | Optimize the previous value | Optimized values | Improvement margin |
|---|---|---|---|
| Average inventory cost (10,000 yuan/month) | 126.3 | 98.5 | ↓22.0% |
| Terminal shortage rate (%) | 8.40% | 3.10% | ↓63.1% |
| Distribution inventory turnover days (days) | 47 | 32 | ↓31.9% |
| Order response time during peak hours (hours) | 27.4 | 14.8 | ↓46.0% |
| Safety stock warning trigger rate | 13.60% | 4.70% | ↓65.4% |

While maintaining the same level of order service quality, Company A has significantly reduced inventory costs in its midstream and upstream operations. Notably, it achieved substantial improvements in both end-user stockout rates and peak-period response efficiency. Key outcomes include: optimized inventory structures at distribution centers with marked reduction in excess stock; more stable manufacturing planning; and markedly reduced supply chain volatility. These improvements collectively demonstrate the dual objectives of cost reduction and efficiency enhancement. Overall, this algorithm-driven inventory management optimization successfully integrates data analytics, computational frameworks, and business operations, showcasing broad industry applicability with significant potential for widespread adoption.

## 5 Conclusion

To address the practical needs of multi-level supply chain inventory optimization, this study proposes a systematic solution based on an enhanced PSO algorithm. By constructing a multi-tiered, dynamically feedback-enabled supply chain inventory control model, the proposed approach integrates particle encoding adaptation, information coordination mechanisms, and dynamic recalculation strategies to achieve intelligent optimization throughout the inventory scheduling process. Building on this foundation, the algorithm further incorporates dynamic inertia weights, a local fine-tuning module, and a multi-objective adaptive fitness function to enhance its search capabilities and robustness in nonlinear complex solution spaces. The research demonstrates that the improved algorithm not only effectively reduces system inventory costs and stockout rates but also improves coordination efficiency among multi-level nodes, demonstrating significant practical value for real-world applications.

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