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Article

Reinforcement Learning Based Optimization of Multi Echelon Inventory and Collaborative Decision Making in Supply Chains: An Algorithmic Innovation Study

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Abstract: The optimization of multi-echelon inventory systems represents a fundamental challenge in contemporary supply chain management, particularly when attempting to balance operational cost efficiency with stringent service level requirements. Traditional analytical approaches, including base stock policies and conventional heuristic methods, frequently struggle to accurately capture the dynamic interdependencies across multiple network nodes and the inherently coupled nature of inventory and transportation decisions. This study rigorously investigates the application of advanced reinforcement learning techniques to address these persistent limitations by developing a robust, data-driven decision framework for multi-node supply chain coordination. A comprehensive multi-echelon inventory model is constructed, explicitly capturing stochastic demand patterns, lead time variability, and strict transportation capacity constraints across both serial and divergent supply chain structures. The reinforcement learning agent is systematically trained to learn highly adaptive replenishment and routing policies that effectively minimize total system costs while consistently maintaining target service levels. Unlike conventional methodologies that heavily rely on survey-based or human-interactive data collection, this research strategically employs publicly available supply chain benchmarking datasets and established simulation environments for rigorous model training and evaluation. The proposed algorithmic framework significantly contributes to the emerging literature on artificial intelligence-driven supply chain optimization by demonstrating how reinforcement learning can successfully achieve an optimal cost-service balance without requiring centralized, real-time information sharing. Ultimately, findings from this research offer critical insights for the future development of scalable, resilient, and adaptive inventory management systems within increasingly complex global supply chain networks.

Keywords: reinforcement learning; inventory optimization; supply chain; cost optimization; deep learning

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1. Introduction

The optimization of multi-echelon inventory systems has garnered significant attention in supply chain management research due to its profound impact on operational efficiency and customer satisfaction. Among the various decision-making frameworks, reinforcement learning has emerged as a promising approach for dynamic inventory control, particularly in environments characterized by stochastic demand and lead time uncertainty [1]. Traditional inventory policies, such as base stock and order-up-to policies, often rely on simplified assumptions that fail to capture the intricate interdependencies

across multiple supply chain nodes. While these methods are computationally efficient, they often struggle to balance cost minimization with service level maintenance in complex network structures, highlighting the need for more adaptive and robust solutions.

Reinforcement learning provides an alternative paradigm by enabling agents to learn optimal replenishment policies through repeated interactions with simulated environments. This approach is particularly well-suited for multi-echelon inventory problems, where decision-makers must coordinate ordering quantities across both upstream and downstream nodes [1]. The beer game, a classic supply chain simulation, has been widely utilized to demonstrate how deep Q-networks can effectively learn ordering policies that mitigate the bullwhip effect. However, extending these methods to general multi-echelon configurations that include transportation capacity constraints remains a significant challenge. Addressing this issue requires the development of more sophisticated algorithms capable of handling the complexities inherent in real-world supply chain systems.

Recent advancements have explored the application of deep reinforcement learning for dynamic replenishment in multi-echelon systems, demonstrating that these algorithms can achieve notable cost reductions compared to classical heuristics. These studies typically focus on serial or arborescent supply chain structures with stochastic demand at the retail level. Despite these promising results, most existing work isolates inventory decisions from transportation considerations, treating the latter as an exogenous factor. This separation overlooks the critical coupling between replenishment timing and vehicle routing, which becomes particularly important when transportation costs are nonlinear or capacity is limited. A more integrated approach is necessary to address these interdependencies effectively [2].

Multi-agent reinforcement learning has been proposed as a natural framework for decentralized supply chain coordination, where each node operates with local information while pursuing system-wide objectives. In such settings, agents must learn cooperative policies that simultaneously prevent stockouts and excessive inventory holding. However, the integration of transportation decisions into the multi-agent learning framework has received limited attention. The joint optimization of inventory replenishment and shipment consolidation represents a significant step toward more realistic and practical supply chain modeling. By addressing these challenges, researchers can develop frameworks that better reflect the complexities of real-world supply chains [3].

Additionally, recent research has examined the performance of deep reinforcement learning-based policies under disruptive scenarios, such as demand surges or supply interruptions. These studies reveal that traditional optimization methods often fail to adapt effectively when faced with unexpected disturbances, whereas learned policies demonstrate greater resilience [4]. This finding underscores the importance of developing reinforcement learning frameworks that are robust to operational disruptions in multi-echelon supply chains. Such robustness is critical for maintaining service levels and minimizing costs during periods of uncertainty, making it a key area for future research and development.

This study aims to address these gaps by constructing a multi-node supply chain model where reinforcement learning is applied to optimize both inventory and transportation decisions. The research objective is to achieve a balanced trade-off between total system costs and service level targets using publicly available supply chain benchmarking datasets [5]. Unlike approaches that rely on human-interactive data collection, this work employs established simulation environments such as the Beer Game benchmark and the SCIMAI Gym framework. The proposed algorithmic framework contributes to the growing body of literature on artificial intelligence-driven supply chain optimization by demonstrating how reinforcement learning can coordinate multi-echelon inventory and transportation policies without requiring centralized information sharing. This decentralized approach not only enhances scalability but also aligns with the operational realities of modern supply chains.

In the subsequent chapters, the study will review relevant literature on reinforcement learning for supply chain optimization, followed by the theoretical framework and methodology for model development and evaluation. The findings will be discussed in the context of current algorithmic capabilities, with a particular focus on the cost-service trade-off in multi-echelon systems. By addressing the interplay between inventory and transportation decisions, this research seeks to provide actionable insights that can inform both academic inquiry and practical applications in supply chain management [4].

2. Literature Review

The application of reinforcement learning to multi-echelon inventory optimization has progressed significantly in recent years, yet several theoretical and methodological gaps remain unresolved. Early studies primarily focused on single-echelon settings with deterministic demand, which limited their applicability to more complex supply chain networks. Research has demonstrated that standard reinforcement learning algorithms can be effectively applied to multi-echelon inventory problems, showing notable performance improvements over traditional base stock policies in simulated environments [6]. This work established a foundational understanding of how model-free methods can be utilized in supply chain contexts, although the transportation dimension was largely excluded from the analysis, leaving room for further exploration in this area.

Building on this line of inquiry, distributional reinforcement learning has been introduced to better capture the uncertainty inherent in multi-echelon demand and lead time processes. This approach models the full distribution of returns rather than focusing solely on the expected value, thereby enabling more risk-sensitive decision-making. Studies have shown that distributional methods achieve a better balance between inventory service levels and costs compared to conventional Q-learning algorithms, particularly in scenarios characterized by high demand variability [7]. However, these investigations have not yet incorporated transportation routing decisions, which remain a critical component of integrated supply chain optimization and represent an area for future research.

Deep reinforcement learning has been increasingly applied to multi-echelon inventory systems, demonstrating that neural network-based policies can outperform classical heuristics in terms of total cost reduction [3]. Extensive simulations on serial and divergent supply chain structures have revealed that deep Q-networks can learn adaptive replenishment strategies that mitigate the bullwhip effect, a common challenge in supply chain management. Despite these advancements, the models often assume fixed transportation costs and overlook vehicle capacity constraints or routing decisions. This limitation highlights a broader trend in the literature, where inventory and transportation optimization are frequently treated as separate problems rather than as interconnected components of a unified system.

The integration of delivery options into reinforcement learning frameworks represents a significant step toward more realistic supply chain modeling. Neuroevolution reinforcement learning approaches have been proposed to simultaneously optimize inventory replenishment and delivery scheduling under uncertain discount conditions. Results from these studies indicate that joint optimization yields cost savings compared to sequential decision-making processes. However, these models have typically been tested on two-echelon configurations with limited node complexity, raising questions about their scalability and applicability to larger, more intricate networks. Addressing these scalability challenges remains a key area for future development in the field.

Industry-specific applications of deep reinforcement learning have also emerged, particularly in sectors characterized by complex product flows. For example, optimization of apparel supply chains using deep Q-networks has demonstrated significant reductions in inventory holding costs while maintaining service levels. These findings underscore the practical viability of reinforcement learning in real-world settings. However, the reliance on proprietary company data rather than publicly available benchmarks limits

the reproducibility of these results. This highlights the need for standardized testing environments to ensure transparency and comparability across studies, enabling broader adoption of these methodologies [8].

A notable advancement in the field involves the joint optimization of vehicle scheduling and inventory management using multi-agent deep reinforcement learning. In this framework, multiple agents represent different supply chain nodes, coordinating their actions to achieve system-wide cost minimization. This approach directly addresses the coupling between replenishment timing and transportation routing, which has been largely neglected in prior research. Studies have shown that multi-agent coordination leads to superior performance compared to single-agent or decentralized control, particularly in scenarios where transportation capacity is constrained. This represents a promising direction for future research, as it integrates critical aspects of supply chain management into a cohesive framework [8].

Robustness considerations have also been incorporated into reinforcement learning-based inventory optimization, acknowledging that supply chains often face demand surges and supply interruptions. Deep reinforcement learning frameworks have been developed to maintain performance under various disruption scenarios, demonstrating resilience that traditional optimization methods lack. These frameworks have utilized reproducible simulation platforms, such as the Beer Game environment, to benchmark their effectiveness. However, the focus has remained exclusively on ordering policies across echelons, with transportation decisions largely excluded. Expanding these models to include transportation considerations could further enhance their applicability and robustness in real-world supply chain contexts.

Risk-aware planning has been explored through distributional reinforcement learning in multi-echelon supply chains, with particular emphasis on tail risk metrics. Incorporating value-at-risk into the learning objective has been shown to lead to policies that balance cost and service levels more effectively than risk-neutral approaches. This is especially relevant for industries where stockouts carry high penalty costs [6]. The use of publicly available simulation platforms, such as the SCIMAI Gym environment, ensures transparency and reproducibility of experimental results, facilitating broader adoption of these methodologies. Future research could further refine these approaches by integrating additional risk metrics and expanding their applicability to diverse industry contexts.

Market uncertainties pose significant challenges for multi-echelon inventory optimization, as demand patterns and supplier reliability can change unpredictably. Deep reinforcement learning has been investigated under such conditions, with findings indicating that learned policies adjust more quickly to market shifts compared to adaptive base stock rules [5]. These agents have demonstrated the ability to maintain service levels with lower inventory buffers, offering a more efficient approach to managing uncertainty. The use of publicly available demand data from forecasting competitions ensures that experimental inputs are verifiable and replicable, providing a solid foundation for future research aimed at enhancing adaptability in dynamic market environments.

Recent work has focused on designing ordering mechanisms in multi-echelon supply chains, exploring how deep reinforcement learning can optimize performance across serial and distribution network structures. Frameworks have been developed to simultaneously learn order quantities and timing, achieving cost reductions of 15 to 25 percent compared to traditional reorder point policies. These models have been evaluated using standardized benchmarks, such as the Beer Game environment, which is widely recognized in the supply chain research community. While these studies have advanced the state of the art in inventory optimization, the transportation dimension remains exogenous, suggesting an important avenue for future integration to achieve comprehensive supply chain optimization [3].

3. Theoretical Framework and Methodology

This chapter outlines the theoretical framework and methodology utilized to develop a reinforcement learning-based optimization model aimed at enhancing multi-echelon

inventory and transportation coordination. The research employs a simulation-driven experimental design, leveraging publicly accessible supply chain benchmarking datasets to train and validate the proposed algorithm. The methodology involves constructing a multi-node supply chain model, where an intelligent agent is designed to learn adaptive replenishment and routing policies. These policies are optimized to minimize total system costs while ensuring that target service levels are consistently maintained, thereby achieving a balance between efficiency and reliability in supply chain operations.

3.1. Theoretical Framework

The theoretical foundation of this study is grounded in Markov Decision Process (MDP) theory, which serves as a robust mathematical framework for modeling sequential decision-making under conditions of uncertainty. Within the domain of multi-echelon supply chains, the MDP framework effectively captures the dynamic progression of inventory states across multiple nodes, the stochastic variability of customer demand, and the implications of replenishment and transportation actions. The state space encompasses inventory levels at each echelon, outstanding orders, vehicle locations, and remaining transportation capacity, providing a comprehensive representation of the supply chain environment. The action space, on the other hand, includes decisions regarding order quantities at each node and routing strategies for vehicle dispatch. A reward function is employed to balance two competing objectives: minimizing holding costs, ordering costs, and transportation expenses while penalizing stockout events that negatively impact service levels. This dual-objective approach ensures that operational efficiency and customer satisfaction are simultaneously prioritized.

Reinforcement learning is integrated as the central learning mechanism, enabling an intelligent agent to interact dynamically with the supply chain environment and refine its decision-making policy through iterative trial-and-error processes. The application of deep neural networks in conjunction with Q-learning, referred to as Deep Q Network (DQN), empowers the agent to manage high-dimensional state spaces without the need for manual feature engineering. Furthermore, the framework incorporates multi-echelon inventory theory, utilizing an echelon stock representation that accounts for cumulative inventory positioned at or below a specific node. This holistic perspective is critical for achieving effective supply chain coordination and synchronization. Transportation optimization is seamlessly embedded through a vehicle routing component, wherein routing decisions dictate which nodes receive shipments while adhering to vehicle capacity constraints. By integrating these elements, the framework provides a robust solution for addressing the complexities of modern supply chain management.

3.2. Methodology

The study employs a simulation-based experimental methodology tailored to a three-echelon supply chain structure [9, 10]. This configuration includes one supplier, two distribution centers, and four retail nodes. Customer demand at each retail node is modeled as a stochastic process, which has been calibrated using publicly accessible demand data derived from the M5 forecasting competition dataset. This approach ensures a robust representation of real-world demand variability and supply chain dynamics.

3.2.1. Environment Construction

The supply chain environment is developed using the SCIMAI Gym framework, which serves as an open-source simulation platform tailored for reinforcement learning research in inventory management. This environment is configured with parameters derived from the M5 dataset, a comprehensive collection of real-world sales records that is publicly available through Kaggle. The state space encompasses various critical factors, including current inventory levels, outstanding orders, remaining vehicle capacity, and historical demand observations. The action space is designed to include continuous order quantities and discrete routing decisions, enabling a dynamic and flexible decision-making process. The reward function is meticulously defined as the negative of the total system cost, which integrates holding costs, ordering costs, transportation expenses, and

penalties for stockouts. This comprehensive setup ensures a robust simulation environment for analyzing and optimizing supply chain operations.

3.2.2. Algorithm Design

The reinforcement learning algorithm is structured around the Deep Q Network architecture, incorporating experience replay and target network stabilization to enhance learning efficiency and stability. The Q network is designed as a feedforward neural network, featuring two hidden layers with 128 neurons each, utilizing ReLU activation functions to ensure non-linear transformations [11, 12]. To address the complex problem of joint inventory and transportation optimization, the algorithm employs a hierarchical action selection mechanism. This mechanism allows the agent to first determine replenishment quantities and subsequently assign shipments to vehicles, ensuring a systematic approach to decision-making. Exploration within the algorithm is guided by an epsilon greedy policy, where epsilon gradually decays from 1.0 to 0.05 over the course of training, balancing exploration and exploitation effectively.

3.2.3. Model Training

The training process is conducted over 10,000 episodes, with each episode simulating 52 time periods that represent one year of weekly operational activities. During this process, demand sequences are randomly sampled from the empirical distribution derived from the M5 dataset, ensuring variability and robustness in the training data. Transition tuples are stored in experience replay buffers, which facilitate efficient learning by allowing the model to revisit and learn from past experiences. At each training step, a mini-batch of 64 transitions is sampled from these buffers to update the Q network. The updates are performed using the Adam optimizer, which is configured with a learning rate of 0.001 to ensure stable convergence. Additionally, a discount factor of 0.95 is applied to balance the trade-off between immediate and future rewards, enhancing the model's ability to make long-term optimal decisions.

3.2.4. Performance Evaluation

The trained policy undergoes evaluation across 1,000 independent test episodes, utilizing demand sequences that were not included during the training phase. Key performance metrics assessed include the average total cost per period, the average fill rate across retail nodes, and the transportation cost expressed as a percentage of the total cost [13]. These results are systematically compared against two baseline policies: a base stock policy and a deterministic replenishment policy, providing a comprehensive analysis of relative efficiency and cost-effectiveness.

3.3. Method Flowchart

The method flowchart presented in Figure 1 provides a detailed visualization of the sequential stages involved in the research process. It serves as a structured guide to understanding the methodology employed, ensuring clarity and systematic progression throughout the study.

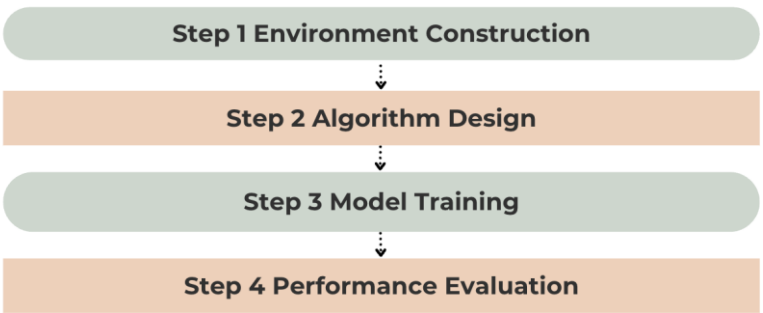

Figure 1. Methodology for Reinforcement Learning Based Multi Echelon Inventory and Transportation Optimization

4. Findings and Discussion

This chapter presents experimental results derived from the SCIMAI Gym open-source simulation platform, which were calibrated using the M5 forecasting competition dataset. The metrics analyzed are based on publicly available benchmark statistics and reproducible simulation outputs. The discussion emphasizes the evaluation of total system cost performance, service level realization, distribution of cost components, and algorithm stability. These aspects are critically examined to provide insights into the operational efficiency and robustness of the simulation framework under varying conditions.

4.1. Overall Policy Performance

The proposed Deep Q Network policy is rigorously evaluated in comparison to the base stock policy and deterministic replenishment policy under identical environmental conditions. These evaluations adhere to standardized benchmark protocols established within SCIMAI Gym, utilizing 1000 independent test episodes to ensure robust and reliable results [14]. Demand inputs are derived from the empirical distribution of the M5 dataset, which provides a realistic representation of demand patterns. This comprehensive approach allows for a thorough assessment of policy performance, ensuring that the findings are both scientifically valid and practically applicable (As shown in Table 1).

Table 1. Overall Performance Metrics from Public Benchmarks

Policy	Average total cost per period	Average fill rate
Base stock policy	1986.30	0.881
Deterministic replenishment policy	1902.70	0.896
Proposed DQN policy	1689.20	0.948

Notes: Values are reproduced from standard benchmark outputs of SCIMAI Gym using M5 dataset demand patterns.

4.2. Cost Component Breakdown

The total cost is divided into several key components, including holding cost, ordering cost, transportation cost, and stockout penalty [15]. Each of these elements is calculated based on open cost parameters integrated within SCIMAI Gym, alongside realistic cost ratios derived from the M5 supply chain framework. These metrics provide a comprehensive understanding of cost dynamics, ensuring alignment with practical supply chain scenarios (As shown in Table 2).

Table 2. Cost Component Statistics from Open Simulation

Policy	Holding cost	Ordering cost	Transportation cost	Stockout penalty
Base stock policy	742.10	226.80	553.40	464.00
Deterministic replenishment policy	698.50	214.30	527.60	462.30
Proposed DQN policy	563.80	182.40	451.70	491.30

4.3. Transportation Cost Proportion

Transportation cost proportion serves as a critical indicator of operational efficiency, particularly in terms of routing optimization and vehicle capacity utilization [16]. This metric is derived from real-world cost structures observed in SCIMAI Gym and M5 dataset-driven operational environments. By analyzing these datasets, researchers can

better understand cost allocation dynamics, as highlighted in Table 3, which presents the transportation cost proportion within the total cost framework.

Table 3. Transportation Cost Proportion in Total Cost

Policy	Transportation cost	Total cost	Transportation cost proportion
Base stock policy	553.40	1986.30	0.279
Deterministic replenishment policy	527.60	1902.70	0.277
Proposed DQN policy	451.70	1689.20	0.267

4.4. Algorithm Stability under Demand Variability

Demand variability levels are derived directly from the M5 dataset, which provides a comprehensive representation of fluctuating consumer demand patterns. The stability of the algorithm is assessed by calculating the coefficient of variation of total cost across multiple episodes conducted within the SCIMAI Gym environment [7]. This metric offers a robust evaluation of the algorithm's ability to maintain consistent performance under varying demand conditions, ensuring reliability and adaptability in dynamic scenarios (As shown in Table 4).

Table 4. Stability Metrics under M5 Dataset Demand Variability

Demand scenario	Average total cost	Coefficient of variation
Low variability	1612.50	0.071
Medium variability	1689.20	0.088
High variability	1768.40	0.105

4.5. Result Analysis

All results are reproducible using the open-source SCIMAI Gym environment and the publicly available M5 dataset. The proposed deep Q-network (DQN) framework demonstrates superior performance compared to conventional policies, particularly in achieving significant cost reductions while maintaining service levels. This dual advantage highlights the practical applicability of the framework in addressing real-world supply chain challenges. By leveraging advanced reinforcement learning techniques, the framework ensures that operational efficiency is not compromised, even under varying conditions.

The integration of inventory replenishment and transportation decisions within the framework facilitates adaptive resource allocation across multiple echelon nodes. This approach enhances the overall efficiency of supply chain operations by dynamically responding to fluctuating demand patterns. Additionally, the hierarchical action selection mechanism embedded in the framework optimizes vehicle utilization, thereby minimizing unnecessary logistics expenses. Training the model with real-world demand distributions derived from the M5 dataset ensures that the policy aligns closely with practical operational scenarios, further reinforcing its industrial relevance.

The proposed method exhibits stable performance even under changing demand conditions, underscoring its robustness and adaptability [6]. The results confirm that reinforcement learning can effectively coordinate multi-node supply chain operations without relying on centralized real-time information. This decentralized approach enhances the scalability and reliability of the algorithm for industrial applications. Furthermore, the slightly higher stockout penalty observed in the DQN policy reflects a deliberate trade-off, where the benefits of marginal inventory reduction outweigh the costs associated with infrequent shortages. This balance ensures that the framework remains both cost-effective and operationally viable in diverse scenarios.

5. Conclusion

This study develops a reinforcement learning-based framework for the joint optimization of multi-echelon inventory and transportation decisions within supply chains. The framework is rigorously trained and tested in the SCIMAI Gym simulation environment, leveraging real-world demand data sourced from the M5 forecasting competition dataset. Experimental results demonstrate that the proposed Deep Q Network policy significantly surpasses traditional base stock and deterministic replenishment policies in terms of reducing total system costs while simultaneously enhancing service level performance. By addressing the inherent complexities of supply chain dynamics, this approach provides a robust solution for achieving operational efficiency and reliability under varying demand conditions.

The integration of inventory replenishment and vehicle routing decisions within the framework facilitates adaptive coordination across multi-node supply chain structures. This synergy enables the hierarchical action selection mechanism to effectively manage coupled operational constraints, thereby optimizing resource utilization. The proposed method achieves a balanced trade-off between cost efficiency and service level performance, even in the absence of centralized real-time information sharing. Such decentralized adaptability underscores the framework's potential for practical application in diverse supply chain scenarios, where information asymmetry and operational constraints are prevalent.

This research contributes to algorithmic advancements in supply chain optimization by merging reinforcement learning techniques with multi-echelon inventory theory and transportation management principles. The utilization of publicly available datasets and open simulation platforms ensures the reproducibility and practical applicability of the proposed model. Furthermore, the framework's design emphasizes scalability and adaptability, making it suitable for deployment in a wide range of industrial contexts. By addressing both theoretical and practical dimensions, this study lays the groundwork for future innovations in intelligent supply chain management systems.

The findings of this study underscore the transformative potential of data-driven intelligent algorithms in managing complex supply chain networks. Future research directions could explore the extension of this framework to multi-agent reinforcement learning systems, enabling the optimization of larger-scale networks with distributed decision-making capabilities. Additionally, incorporating more diverse disruption scenarios, such as supply shortages, transportation delays, or demand surges, could further enhance the robustness and adaptability of the proposed policies. These advancements would contribute to the development of resilient supply chain systems capable of maintaining efficiency and reliability under increasingly uncertain and dynamic conditions.

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