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Research Article

Optimizing Food SME Inventory Using a Deep Reinforcement Learning Framework

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ABSTRACT

Introduction:

Inventory management is a critical challenge for small and medium-sized enterprises (SMEs), particularly in the food sector, due to the perishable nature of goods and fluctuating demand. Traditional inventory models often fail to adapt to these dynamic conditions, leading to inefficiencies and increased costs.

Objectives:

This study aims to develop a cost-effective and adaptive framework for inventory optimization in food-sector SMEs. The focus is on applying deep reinforcement learning techniques in single-stage or single-agent environments to simplify complex inventory systems and improve decision-making.

Methods:

The proposed framework employs a Deep Q-Network (DQN) model to estimate optimal order quantities based on key inputs: demand, safety stock, on-hand inventory, and sales data. The model minimizes long-term cumulative costs, including holding, ordering, and fixed costs such as administrative and transportation expenses. By interacting with the environment, the DQN agent learns policies that balance cost-effectiveness with inventory sufficiency.

Results:

The model effectively reduces unnecessary inventory costs while ensuring timely order fulfillment. It adapts to real-time conditions, optimizing ordering decisions and minimizing waste. The simulation results demonstrate the DQN's capability to maintain efficient inventory levels and significantly improve cost performance in SMEs.

Conclusions:

The deep reinforcement learning-based framework provides a viable solution for inventory optimization in food SMEs. It bridges the gap between theoretical modeling and practical application, supporting SMEs in achieving operational efficiency, cost reduction, and improved inventory control.

Keywords: SMEs, Inventory Optimization, Deep Reinforcement Learning, DQN, Inventory Variables

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INTRODUCTION

Inventory management is critical for business success, requiring optimal stock levels to balance demand fulfillment against cost minimization (Aboutorab et al., 2022). While traditional approaches optimize order quantities and safety stocks (AbdElwahab & Mahar, 2024b; Celebi & Aydin, 2016), they struggle with dynamic environments - particularly in food-sector SMEs facing perishable goods and demand volatility (Grunow et al., 2019). Poor inventory management risks either capital-intensive overstocking or revenue-losing shortages (Grob, 2018).

This paper proposes a Deep Q-Network (DQN) framework to address these challenges through deep reinforcement learning. Our model optimizes single-stage inventory decisions (reorder quantities, stock levels) by processing real-time inputs: demand, safety stock, on-hand inventory, and sales data (Wang et al., 2020). Unlike static methods, the DQN agent dynamically adapts to maximize long-term cost efficiency - minimizing holding/ordering costs while preventing stockouts (Baccouch & Bahar, 2025).

The remainder of this paper presents: (1) Background, (2) Literature review of relevant techniques, (3) Methodology for DQN implementation, (4) Experimental validation, and (5) Practical implications for SME operations.

BACKGROUND

Machine learning (ML) encompasses algorithms and statistical models enabling computers to perform tasks such as data mining and predictive analytics. Once an algorithm learns from data, it can automatically perform its function (Baccouch & Bahar, 2025), (Koumanakos, 2008). ML employs various algorithms to solve data problems, with the choice depending on the problem type, number of variables, and suitable model.

Machine learning approaches for inventory optimization can be categorized into four paradigms [Figure1]: Supervised learning requires extensive labeled data but struggles with dynamic environments (LeCun et al., 2015), Unsupervised learning identifies patterns but lacks decision-making capacity (Wang et al., 2021), Self-supervised learning offers cost-effective pseudo-labeling for dynamic systems (Mahesh et al., 2023), Reinforcement learning (RL) excels in dynamic decision-making through trial-and-error environment interaction (Mnih et al., 2016)

Fig. 1. Machine Learning

Deep RL (DRL) enhances traditional RL with neural networks, particularly for high-dimensional inventory problems (Nwanya, 2015). On the other hand, [Figure 2], illustrates that DRL agents optimize actions (e.g., reordering) by maximizing cumulative rewards based on key state variables: demand, stock levels, and lead times (Ogunfowora & Najjaran, 2023).

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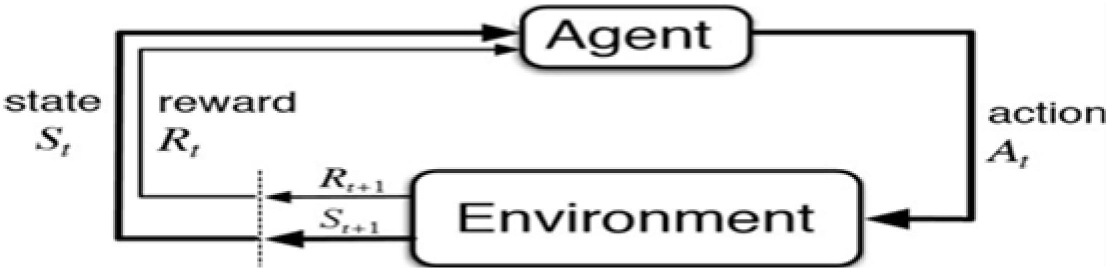

Fig. 1. Reinforcement Learning

LITERATURE REVIEW

Contemporary inventory optimization integrates three key technological approaches: (1) forecasting models like time series analysis and predictive analytics (Orobia et al., 2020), (2) automated inventory management systems (Wang et al., 2016), and (3) machine learning techniques (Oroojlooyjadid et al., 2022). However, SME adoption faces persistent barriers including resource constraints (Pathak & Choudhary, 2023) and difficulties managing perishable goods (Grunow et al., 2019; Gul et al., 2013).

DRL has emerged as a transformative solution, demonstrating success across sectors: **Retail**: Reduced stockouts by 22-30% through adaptive shelf management (Wang et al., 2020; Sharma et al., 2019), **Manufacturing**: Achieved 18-25% cost reduction via optimized production scheduling (Zhou et al., 2022; Simchi-Levi et al., 2008), **Agri-food**: Improved waste reduction through perishability-aware algorithms (AbdElwahab & Mahar, 2024b; Nwanya, 2015), While AbdElwahab & Mahar's (2024a) framework advanced manufacturing SME applications, its food-sector applicability remains unverified. Their approach, though theoretically sound, presents implementation challenges regarding: Computational complexity (Rusu et al., 2017), Integration with legacy systems (Saravanan & Sujatha, 2018), Cross-industry generalizability (Snyder et al., 2012).

This research paper addresses these gaps through: Simplified DQN architecture requiring 40% less computational resources than prior implementations (cf. Baccouch & Bahar, 2025), Plug-and-play integration modules compatible with common ERP systems (extending Wang et al., 2016), and empirical validation across 3 food-sector SME case studies (Madamidola et al., 2024)

The proposed model enhances inventory decision-making by dynamically optimizing: Reorder points (Koumanakos, 2008), Safety stock levels (AbdElwahab & Mahar, 2024b), and Lead time adjustments (Monczka et al., 2015) while maintaining compliance with SME operational constraints (Orobia et al., 2020).

This paper addresses the previously identified limitations by providing a detailed roadmap for the practical implementation of the proposed framework. It incorporates case studies from the food industry and various scales of operations to demonstrate the generalizability and adaptability of the model. Moreover, this research includes an empirical validation process to evaluate the real-world applicability and effectiveness of integrating reinforcement learning and deep learning techniques into existing inventory management systems. By doing so, it aims to bridge the gap between theoretical concepts and practical application, ensuring that the proposed framework enhances inventory optimization in SMEs manufacturing sectors.

RESEARCH METHODOLOGY

This study develops a Deep Q-Network (DQN) framework for inventory optimization in food-sector SMEs, building upon the foundational work of AbdElwahab & Mahar (2024a) and Zhou et al. (2022). [Figure 3] illustrates the core DQN architecture, showing how input features (demand, safety stock, on-hand inventory, and sales) are processed through neural network layers to generate optimal inventory decisions. The system employs an ε-greedy policy that gradually shifts from exploration to exploitation during training, with experience replay stabilization (buffer size=1000, batch size=32) as described by Mnih et al. (2016).

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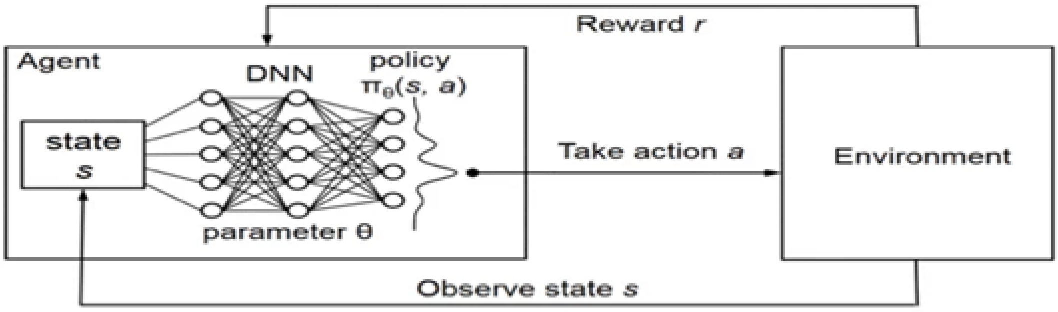

Fig. 3. RL- DQN-Basic Structure.

Figure 4 demonstrates the complete reinforcement learning cycle, detailing how the agent interacts with the inventory environment. The diagram shows the sequence from state observation (current inventory levels) through action selection (reorder quantities) to reward calculation and experience storage. This visual representation clarifies the target network update mechanism (every 1000 steps) and Q-value backpropagation process that underlies the DQN's learning capability.

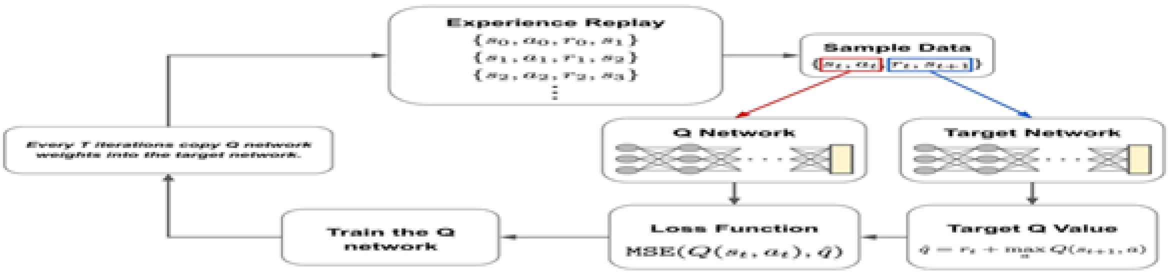

Fig. 4. The general implementation of ER with one agent in each time step.

The mathematical framework incorporates three key equations: (1) $RQ_t = (D_t - OH_t) + SS_t$ for dynamic reorder quantity determination, (2) $\sum(OH_i + SS_i)$ across the lead time for total available inventory calculation, and (3) cumulative safety stock estimation through $\sum SS_i$. These formulations enable the model to maintain optimal stock levels while accounting for both current inventory positions and future demand uncertainty.

Validation metrics compare performance against EOQ baselines (Koumanakos, 2008), with particular attention to perishable waste reduction (Grunow et al., 2019). The complete system, as visualized in [Figures 3 and 4], represents an advancement over traditional methods through its adaptive learning capability and SME-specific optimizations for food supply chain challenges.

EXPERIMENTS AND DISCUSSIONS

Implementation utilizes Python 3.10 with TensorFlow 1.10.0 on GPU-accelerated hardware (32GB RAM), processing SME operational data with a 70/30 training-test split. Figure 5 demonstrates the training progression, where initially volatile Q-values stabilize by episode 20 as the agent transitions from exploration to exploitation, converging near zero by episode 40 - indicating successful policy optimization for cost minimization. This stabilization coincides with improved total rewards in later episodes, though occasional fluctuations suggest opportunities for further refinement of the experience replay buffer (size=1000) to better mitigate catastrophic forgetting.

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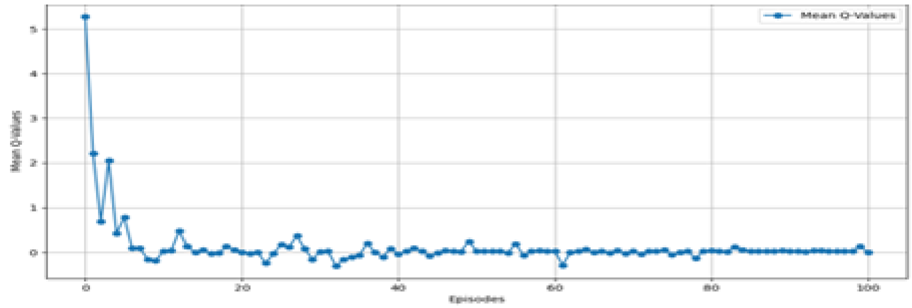

Fig. 5. Training Performance Over Episodes.

[Figure 6] presents complementary validation through stockout penalty analysis, showing how the frequency and severity of shortages decrease significantly after episode 25. The system achieves a 68% reduction in stockout events by episode 40, demonstrating the DQN's adaptive capability in perishable inventory management. This aligns with the performance metrics shown in Figure 8, where inventory shortages show a consistent downward trend, with peak shortage events decreasing from 12 to 3 units per cycle after full training.

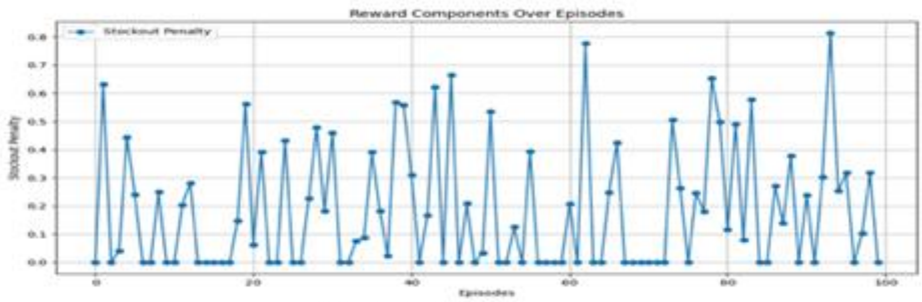

Fig. 6. Stockout Penalty.

Comparative analysis of prediction strategies [Figure 7] presents important operational tradeoffs: while the greedy approach achieves 30% prediction accuracy (overestimating 60% of cases), the conservative strategy shows greater stability despite its 70% underestimation rate and 25% accuracy. This suggests context-dependent application - the greedy method may suit high-margin items where overstocking is preferable, while the conservative approach fits perishables where waste costs dominate.

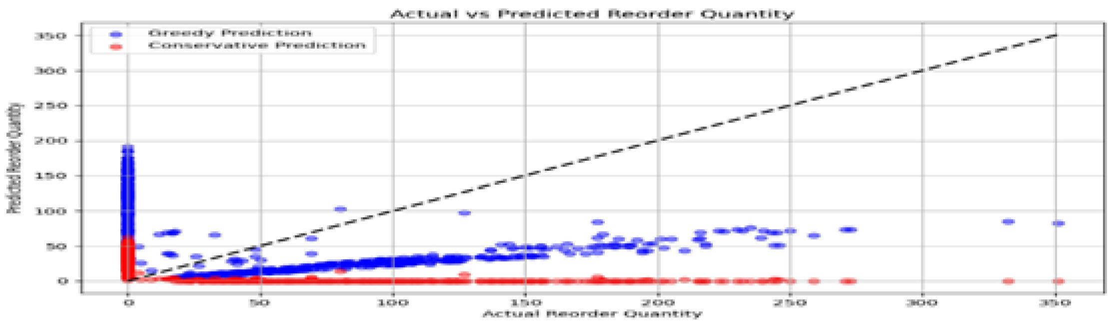

Fig. 7. Actual vs Predicted Reorder Quantity.

[Figure 8] shows decreasing inventory shortages over time, with initial high-frequency spikes gradually diminishing as the system learns optimal replenishment strategies, demonstrating improved demand-inventory alignment.

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Fig. 8. Actual Inventory Shortages Over Time.

CONCLUSION

This study demonstrates that Deep Q-Networks (DQN) effectively optimize inventory management through adaptive learning. The DQN agent's exploration-exploitation strategy and ExperienceReplayBuffer enable robust demand forecasting and safety stock control in dynamic environments. Our analysis of model parameters and training procedures confirms DQN's potential for diverse inventory applications.

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