**Enhancing Decision-Making under Uncertainty: A TRIZ-Inspired Robust Optimization Framework with Machine Learning**

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**Abstract**

Effective inventory management under uncertain demand is a critical challenge in supply chain operations, where traditional methods relying heavily on historical data often fail to capture dynamic and unpredictable variations. This research introduces a novel TRIZ-driven, data-driven robust optimization framework that integrates Machine Learning (ML), stochastic optimization, and TRIZ (Theory of Inventive Problem Solving) principles to address these limitations and seize emerging opportunities. By leveraging ML techniques, the framework enhances demand forecasting by combining historical data with real-time predictive models, capturing variability in demand patterns more effectively. TRIZ inventive principles, such as Local Quality, Equipotentiality, Parameter Change, and Composite Materials, are incorporated to resolve contradictions in system design, optimize decision-making processes, and improve robustness.The proposed framework constructs uncertainty sets by dynamically balancing historical and predictive data, providing a comprehensive and adaptive representation of future demand scenarios. Robust optimization techniques are then applied to formulate multistage stochastic models, enabling businesses to minimize inventory costs, maintain service levels, and navigate trade-offs between forecasting accuracy, computational efficiency, and decision-making robustness. Numerical experiments validate the proposed approach, demonstrating its superiority in addressing real-world challenges and advancing inventory management practices. This research provides a systematic, innovative solution for enhancing decision-making under uncertainty, with broad applicability across industries and significant potential for improving operational efficiency and customer satisfaction.

**Keywords:** *TRIZ, Robust Optimization, Machine learning, demand forecasting, inventory management*

1. Introduction

Inventory management is a critical component of supply chain operations, directly influencing a company’s operational efficiency and customer satisfaction (Chopra & Meindl, 2019). The primary challenge in inventory management lies in balancing the trade-off between holding sufficient inventory to meet demand and minimizing the costs associated with excess stock (Silver, Pyke, & Thomas, 2016). Traditional inventory control models, often based on deterministic or stochastic frameworks, rely heavily on historical demand data, which may not adequately capture future demand variations caused by dynamic market conditions (Fildes et al., 2008).

The unpredictability of real-world demand presents a significant limitation for these traditional models, as they struggle to adapt to unforeseen fluctuations or external disruptions (Tang, 2006). Recent advancements in machine learning (ML) offer new opportunities to improve inventory forecasting by leveraging large datasets and predictive algorithms to generate more accurate demand predictions (Choi, Wallace, & Wang, 2018). By integrating ML with inventory management, businesses can gain better insights into future demand patterns, enabling them to make more informed and proactive decisions (Makridakis, Spiliotis, & Assimakopoulos, 2018).

However, even with the enhanced forecasting capabilities of ML, uncertainty remains an inherent challenge in inventory decision-making, particularly in volatile markets (Huang, 2020). To address this issue, robust optimization has emerged as a powerful tool for developing solutions that can perform well across a range of potential demand scenarios (Bertsimas & Sim, 2004). Robust optimization methodologies incorporate uncertainty into the decision-making process, ensuring that inventory strategies are not only cost-effective but also resilient to variability (Ben-Tal, El Ghaoui, & Nemirovski, 2009).Moreover, the integration of the Theory of Inventive Problem Solving (TRIZ) into inventory management frameworks provides a structured approach to resolve contradictions and optimize system design (Altshuller, 1999). By applying TRIZ principles, such as Local Quality, Parameter Change, and Composite Materials, decision-makers can develop innovative solutions that balance the trade-offs between accuracy, computational efficiency, and operational robustness (Mann & Domb, 2003).

This research proposes a novel framework that combines ML, robust optimization, and TRIZ to enhance inventory decision-making under uncertainty. By leveraging ML for advanced demand forecasting and TRIZ to address system contradictions, the proposed framework aims to improve the adaptability and effectiveness of inventory management practices (Wang & Sarkis, 2013). The integration of these approaches not only advances inventory management but also provides practical solutions for businesses to reduce costs, enhance service levels, and navigate the complexities of uncertain demand (Lemke, Gabryelczyk, & Nowicka, 2020).

1. **Literature Review**

Effective inventory management is a cornerstone of supply chain operations, with a rich body of literature exploring methodologies to address demand uncertainty, optimize costs, and improve service levels. This section reviews relevant research on machine learning for demand forecasting, robust optimization techniques, the application of TRIZ principles, and emerging opportunities through the integration of these approaches.

**2.1 Demand Forecasting with Machine Learning**

Demand uncertainty remains a persistent challenge in supply chain management. Traditional inventory control methods, such as the Economic Order Quantity (EOQ) model, rely on assumptions of stable demand, which limits their applicability in dynamic market conditions (Silver et al., 1998; Chopra & Meindl, 2019). Stochastic optimization has addressed some of these limitations by incorporating probabilistic demand forecasts, but its reliance on accurate probability distributions remains a bottleneck (Simchi-Levi et al., 2014).

Machine learning techniques provide a promising alternative to traditional methods by analyzing historical data and identifying complex demand patterns. Models like time series analysis, recurrent neural networks (RNNs), and ensemble methods have proven effective in enhancing forecasting accuracy, particularly for volatile demand (Makridakis, Spiliotis, & Assimakopoulos, 2018). For instance, Choi, Wallace, and Wang (2018) showed that ML can integrate external factors—economic indicators, weather, and market signals—to generate precise forecasts. Long short-term memory (LSTM) models further address temporal dependencies in time-series data, improving predictions for time-sensitive inventories (Brownlee, 2017).

Despite its advantages, ML faces challenges related to overfitting, computational complexity, and data preprocessing. Hyndman and Athanasopoulos (2018) highlighted that integrating ML predictions into optimization models enhances their robustness and adaptability to real-time data, which is crucial for dynamic supply chain systems.

**2.2 Robust Optimization in Inventory Management**

Robust optimization (RO) has emerged as a powerful methodology for managing uncertainty in inventory systems by constructing uncertainty sets that account for a range of possible scenarios (Ben-Tal, El Ghaoui, & Nemirovski, 2009). Unlike stochastic optimization, which relies on probabilistic distributions, RO ensures resilience under worst-case demand conditions (Bertsimas & Sim, 2004).

For example, Goh and Sim (2010) introduced an adjustable RO model that dynamically adapts to evolving uncertainties, improving inventory cost-efficiency. Agrawal and Seshadri (2000) demonstrated the benefits of RO in multi-stage systems, minimizing costs while accommodating uncertain demand. However, the trade-off between computational efficiency and model complexity remains a critical challenge for large-scale applications (Mulvey, Vanderbei, & Zenios, 1995).

Robust optimization provides flexibility for integrating ML-based demand forecasts, ensuring that optimization models remain feasible and effective under evolving uncertainties. Zhao et al. (2023) emphasized that combining ML predictions with RO frameworks allows supply chains to respond proactively to demand fluctuations, minimizing risks of stockouts and overstocking.

**2.3 Application of TRIZ Principles to Inventory Management**

The Theory of Inventive Problem Solving (TRIZ) provides a systematic approach to resolving contradictions and fostering innovation in inventory management. TRIZ principles, such as Local Quality, Parameter Change, and Composite Materials, have been applied to optimize system design and enhance decision-making processes (Altshuller, 1999).

For instance, Mann and Domb (2003) explored the application of TRIZ principles in supply chain optimization, demonstrating how Local Quality can be used to tailor inventory policies to specific market segments. Similarly, the principle of Parameter Change has been utilized to dynamically adjust inventory control parameters in response to changing demand patterns (Souchkov, 2007). The principle of Composite Materials has also been applied to integrate diverse data sources and resources, enabling more robust and adaptive inventory strategies (Ikovenko & Litvin, 2016).

TRIZ has also been integrated with optimization techniques to address contradictions in multi-objective decision-making. For example, Wang and Sarkis (2013) combined TRIZ with robust optimization to resolve trade-offs between cost minimization and service level maximization in supply chain management. However, the practical implementation of TRIZ in inventory management requires careful consideration of contextual factors and a deep understanding of system dynamics (Mann, 2007).

The Theory of Inventive Problem Solving (TRIZ), developed by Altshuller (1984), is a systematic methodology for addressing contradictions and fostering innovation. TRIZ principles, such as Local Quality, Equipotentiality, Parameter Change, and Composite Materials, have been applied to optimize inventory management systems (Mann & Domb, 2003).

For example, Local Quality divides complex inventory problems into smaller, manageable segments, enabling tailored solutions for specific demand patterns (Souchkov, 2007). Parameter Change dynamically adjusts system parameters, such as reorder points and safety stock, to respond to real-time demand variability (Ikovenko & Litvin, 2016). The principle of Composite Materials integrates multiple resources—such as ML forecasts and robust optimization frameworks—to develop adaptive and resilient strategies (Kuo & Lin, 2020).

TRIZ has also been applied alongside optimization frameworks to resolve contradictions, such as minimizing costs while maintaining high service levels (Wang & Sarkis, 2013). However, its practical implementation requires specialized expertise to align TRIZ principles with supply chain dynamics, which has limited its widespread adoption in inventory management (Mann, 2007).

**2.4 Emerging Opportunities and Integration**

Recent studies emphasize the need for hybrid approaches that integrate ML, robust optimization, and TRIZ principles to address the multifaceted challenges of inventory management under uncertainty. By leveraging ML-based forecasts, robust optimization frameworks can incorporate accurate demand predictions while maintaining resilience against uncertainty (Bertsimas et al., 2011). TRIZ principles further enhance this integration by resolving systemic contradictions and fostering innovative decision-making strategies (Lemke, Gabryelczyk, & Nowicka, 2020).

For example, Zhao et al. (2023) demonstrated the effectiveness of combining ML and robust optimization in minimizing inventory costs while adapting to real-time demand variability. TRIZ principles, such as Equipotentiality and Parameter Change, can enhance this synergy by balancing trade-offs between cost minimization, service level optimization, and computational efficiency (Altshuller, 1999; Mann, 2007).

This integrated approach represents a significant advancement over traditional models, offering adaptive and resilient solutions for inventory management in uncertain environments. However, research on the combined application of TRIZ, robust optimization, and ML remains limited, highlighting the need for further exploration to validate its scalability and practical applicability across industries (Chopra & Meindl, 2019; Gupta et al., 2023).

**2.6. Research Gap**

Despite significant advancements in machine learning, robust optimization, and TRIZ, their integration in inventory management remains underexplored. Existing studies often address these methodologies in isolation, neglecting the opportunity to leverage their complementary strengths to tackle demand uncertainty holistically (Zhao et al., 2021; Kuo & Lin, 2020).

A unified framework that integrates ML for demand forecasting, robust optimization for decision resilience, and TRIZ for innovation holds significant potential for improving inventory management strategies. Such a framework could provide transformative solutions for balancing trade-offs, improving operational efficiency, and enhancing resilience in uncertain environments (Mann, 2007; Lemke et al., 2020). This research aims to bridge this gap by developing and validating an integrated approach that addresses the limitations of traditional inventory management models.

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