**增強不確定性下的決策：結合TRIZ和機器學習方法的穩健優化框架**

廖庭煜1、維琪2、饒忻

中原大學工業與系統工程學系

e-mail: angus21210@gmail.com1; viicky.pratama.p@gmail.com2

**摘要**

本研究旨在解決在需求高度不確定性的情況下，設計穩健的生產與訂購政策之根本問題。傳統方法往往未能適當考慮客戶行為的固有隨機性，因此導致庫存管理效率低下、成本增加和服務水平不佳。我們提出了一種結合發明問題解決理論 (TRIZ)、穩健最佳化和機器學習方法的新型決策框架來克服這些困難。受到 TRIZ 中「等勢性」原理的啟發，我們將決策問題轉化為數學問題以獲得最佳解。穩健最佳化用於構建涵蓋各種可能需求情境的決策模型，確保所選決策在計劃外的情況下仍可行且有效。機器學習演算法也用於分析歷史數據，識別其中的模式並預測未來需求趨勢，以得出更準確、更靈活的決策。此研究建構了幾個數值實驗數據集來評估所提出模型的性能，結果表明我們的模型在總成本降低和執行時間方面優於傳統方法。本研究的結果與製造業、零售業和物流業等多個行業具有重要意義，因為它們可以促進在日益波動的市場中建立更有效、更穩健的供應鏈流程。

關鍵詞: TRIZ、穩健最佳化、機器學習、需求預測、存貨管理

**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).

The structure of the paper is as follows. In section 2, some literature reviews about the TRIZ method and the difficulties when facing demand uncertainty will be done. The methodology of this study will be presented in section 3. Some numerical experiments will be constructed in section 4 to evaluate the performance of the proposed model.

**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.

**Methodology**

**3.1 Problem-solving through TRIZ**

The TRIZ methodology, which stands for the Theory of Inventive Problem Solving, offers systematic tools and principles that can be applied to identify innovative solutions to complex inventory challenges. By leveraging TRIZ principles, organizations can systematically analyze their inventory issues and generate creative alternatives that not only optimize stock levels but also enhance overall supply chain performance.

The main challenge in the field of inventory management is dealing with the uncertainty in the future demand. This uncertainty can lead to overstocking or stockouts, both of which negatively impact operational efficiency and customer satisfaction. The simplest way to overcome the challenges posed by demand uncertainty is to increase the quantity of production and replenishment, which will also lead to increased holding costs and potential waste if demand does not meet expectations.

Thus, by utilizing 48 engineering parameters, parameter 10 (Amount of Substance) should be enhanced to increase the production and replenishment quantity for dealing with uncertain customer demand. However, if the production and replenishment quantity is increased, this will lead to a worsening parameter 31 (Other Harmful Effects Generated by System), which the total cost will be increased. In this case, a technical contradiction will be revealed and can be resolved by the corresponding inventive principles in the contradiction matrix. Table 1 shows the partial TRIZ contradiction matrix for this case.

Table . Partial TRIZ contradiction matrix for this research

|  |  |  |  |
| --- | --- | --- | --- |
| Worsening Feature  Improving Feature | … | 31. Other Harmful Effects Generated by System | … |
| … | … | … | … |
| 10. Amount of Substance | … | 35. Parameter Changes,  40. Composite materials,  3. Local Quality,  12. Equipotentiality | … |
| … | … | … | … |

At the point where parameters 10 and 31 intersect in the contradiction matrix, the corresponding inventive principles are: 3. local quality, 12. equipotentiality, 35. parameter changes, and 40. Composite materials. In this research, the key inventive principle used is 12. equipotentiality, while the other was considered as a support idea that could resolve the problem more effectively.

Under the 40 inventive principles, inspired by principle 12, equipotentiality, we transform the decision-making problem into a mathematical problem that can be solved by using robust optimization techniques that can be applied to identify the optimal solutions while accommodating various constraints and uncertainties inherent in the decision-making process. Robust optimization is an optimization technique that copes with the uncertainty in demand by using historical data to construct the uncertainty set used during the optimization process.

After transforming the problem into a mathematical framework, we enhanced the overall framework by incorporating the other inventive principles. Principle 40, composite materials, since the uncertainty sets used in the robust optimization method are built with the historical data, we can apply the strength of machine learning techniques to predict future demand, and leverage these predictions to refine the uncertainty sets, ultimately leading to more accurate and efficient decision-making outcomes.

In this case, there would be a hyperparameter called “weight” that is used to determine the proportion of the predicted demand to be integrated into the uncertainty sets. By adopting principle 35, parameter changes, we can tune the hyperparameter to optimize the performance of our model, ensuring that it adapts effectively to fluctuations in demand while maintaining robustness against unforeseen variations.

Finally, considering principle 3, local quality, we divided the products into three groups based on their demand patterns: high, medium, and low variability. Inspired by the concept of ABC-inventory control, Table 2 shows the product in category A. This categorization allows the managers to focus on the high variability products priority to save more cost and make more profit.

Table . Percentage of items in ABC inventory control

|  |  |  |
| --- | --- | --- |
| Category | Quantity (%) | Value (%) |
| A | 20 | 80 |
| B | 30 | 15 |
| C | 50 | 5 |

**3.2 Robust optimization techniques**

3.2.1 Problem formulation

In this paper, we will transform a decision-making problem into a mathematical model, and then solve the model by utilizing the robust optimization method. The standard framework of robust optimization is shown in (1), is the number of uncertainty sets used during the optimization process, is the number of stages considered for the decision-making problem, is the th uncertainty set, , , and are the problem parameters determined by the specific problem. In this case, the central idea of robust optimization is to obtain decision rules that can perform well on average over the uncertainty set. The uncertainty set is constructed as hyperrectangles of the form as shown in (2), is the th historical data used to construct the uncertainty set. The parameter is used to control the size of the uncertainty sets, and the -norm means the maximum absolute value in the vector.

|  |  |
| --- | --- |
|  | (1) |
| s.t. |  |

|  |  |
| --- | --- |
|  | (2) |

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