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Optimization of Firm Inventory Decisions under Demand Uncertainty

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***Abstract:** This paper is research aimed at optimization of inventory decisions in the case of Chinese firms facing the uncertainties of demand by formulating a hybrid stochastic-robust optimization model. The model combines the stochastic programming and robust optimization methods to make improved decisions amid the dynamic demand and external market interference. The performance of the model was assessed using the data of 15 Chinese manufacturing and retail firms, which was put to the test using the simulation and sensitivity analyses. The findings show that the hybrid model is much more cost efficient, and service focused than traditional EOQ and purely stochastic models and lowers total costs by an average of 12 percent and stockout rates by 15-20 percent. The results indicate that combining probabilistic demand forecasting and robust optimization can significantly improve the resilience of operations and the performance of inventory in uncertain conditions. Practical investments are given to Chinese managers to implement optimization-based approaches and policy implications are given to show the government investment needs based on initiatives such as Made in China 2025 and digital supply chain reforms. Future research directions such as multi-echelon modeling and integration of sustainability are outlined in the conclusion of the paper.*

***Keywords:** Inventory Optimization; Demand Uncertainty; Stochastic-Robust Model; Chinese Firms; Supply Chain Resilience*

1. Introduction

The modern globalized and competitive market has made inventory optimization to be among the most important issues facing firms especially where there is uncertainty in the demand. In the case of Chinese companies, this is further worsened by the fact that the Chinese markets are changing fast and consumer patterns as well as shocks in the market in terms of changes in trade policies and volatility in the supply chain. The current shift in the economy of China where the manufacturing based system is modified to innovative based has further amplified the relevance of effective inventory management as a strategic instrument towards remaining competitive and operationally resiliency.

Inventory optimization is defined as the process of balancing the costs of the holding, ordering and shortage and maintaining the sufficient service level in the supply chains. Classical models of the Economic order quantity (EDOQ) or (s, S) policies are adequate in deterministic environments. Nonetheless, in the case of Chinese markets with high demand uncertainty, i.e. unpredictable consumer preference and unreliable macroeconomic factors, the traditional deterministic models are not able to represent the real world dynamics. It has consequently led to the development of new models like robust optimization, stochastic program and fuzzy models that seek to cope with these shortcomings [1].

The fast development of the digital economy and e-commerce market in China with the leading Chinese companies Alibaba and JD.com has also intensified the necessity of flexible inventory decisions. High consumer demand variability, low product life cycles, and stiff competition make these companies rely on sophisticated analytics and optimization algorithms to make choices related to inventory decisions in near-real-time. In addition, the logistics industry in China is not very well-integrated and responsive, thus, increasing the impact of ineffective inventory planning.

Earlier researchers have tried to model inventory optimization under uncertain conditions with the help of various methods. As an illustration, strong optimization models enable the decision-maker to insure themselves against worst-case situations and the stochastic models apply probability distributions to understand variability of demands [2]. Similarly, the fuzzy-stochastic models can combine judgment and imprecise information with the variation of probability of randomness hence offering a better

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representation of a managerial decision-making process [3].

Inventory optimization in the face of uncertainty has become a fast growing field of research in China, as more and more attention gives way to cost efficiency and resilience of a supply chain, especially within manufacturing and logistic processes. It has been found that, the supply-demand balance models are effective to reduce the total inventory costs, especially when lead time uncertainty is taken into consideration in the agricultural enterprises [4]. On the same note, the creation of hybrid make to stock and assemble to order strategies has had merit in the curb of demand volatility and profitability sustainability in the Chinese manufacturing settings [5]. All these studies point to the increased complexity of the Chinese companies in embracing optimization-based solutions to the uncertainty and enhance operational performance of Chinese firms.

The macroeconomic environment also contributes to the inventory decisions. Chinese exporters, such as the Chinese during the time of the WTO accession, are strategic in the way they react to uncertainty in the trade policy, which in this case is mitigated by changing the inventory so as to cushion against the uncertainty [6]. These pieces of evidence indicate that policy uncertainty is an exogenous shock that affects inventory behaviour at the firm level.

Although this occurred, there is still a substantial gap in the research regarding the integration of demand uncertainty modeling to the specifics of business in China, including the government regulation, the digitalization of the industry, and the logistics infrastructure of the region. Majority of the available models were created in Western settings and fail to consider the specific institutional and operational dynamics that the Chinese businesses face. As such, the present paper has attempted to fill this gap by considering how optimization methods may be modified to enhance inventory decisions by Chinese firms in case of uncertainty in demand.

By so doing, the research will not only be relevant to the theory but will also be relevant to practice in that (1) the study will extrapolate the inventory optimization models to the conditions in China (2) the study will empirically test the results of inventory optimization by using the data of Chinese firms (3) the study will provide managerial implications of designing resilient inventory systems.

The remaining paper is structured in the following way: Section 2 reviews the literature available on inventory optimization under uncertainty where the attention is given to both global and Chinese research. Section 3 shows the model formulation and methodology. Section 4 is a discussion on empirical results and analysis whereas Section 5 offers theoretical and practical insights. Conclusion of the paper includes implications to the managers and future research directions.

2. Literarure Review

2.1 Theoretical Foundations of Inventory Optimization under Uncertainty

The conventional inventory control has been largely based on the deterministic models, which assume constant demand and lead time. But in reality, companies have to deal with demand uncertainty due to consumer behavior, disruptions in supply and market volatility. In order to deal with this unpredictability, researchers have suggested a number of modeling paradigms the most notable among them being stochastic, robust and fuzzy optimization.

To depict uncertain demand using probability distributions, stochastic optimization models are popular in inventory management so that the decision-maker can minimize the expected cumulative costs but achieve the required level of service [7]. These models have been found to be effective especially in situations where demand uncertainty is identifiable through statistical processes and could be measured using past data. They have also been demonstrated to be useful in practical settings in complex industries. As an example, a stochastic linear optimization strategy was used on a Chinese car company and proved that the length of the production cycle and the variance of demand have a strong impact on the optimal production and inventory decision making [8]. The findings of this nature speed up the need to reflect the probabilistic nature of demand fluctuations precisely to enhance the efficiency of planning.

Conversely, robust optimization offers a defense against the worst-case realization of uncertainty and is usually desirable in the case of unknown or highly stochastic probability distributions. The strategy increases the stability of models and computational efficiency hence being especially useful in companies with unstable or unfinished data landscapes. It has been established that the use of strong inventory control techniques that consider both the demand and lead time uncertainty provide more stable and reliable solutions compared to the use of purely stochastic models when the actual demand does not follow the expected trends [2]. Equally, the establishment of the target-oriented robust optimization models has also revealed high potentiality in the balancing of anticipated cost and variance, especially in the multi-product, multi-period decision setting [9]. These results demonstrate the flexibility of robust optimization in dealing with uncertainty without the need of having accurate probabilistic data as an alternative to a practical tradeoff between computational tractability and robustness. Also, the fuzzy-stochastic methods have appeared to represent the jointness of probabilistic and linguistic uncertainties that provides a more realistic managerial decision-making process. Research has shown that addition of fuzzy perceptions and random variation makes inventory systems more practical and responsive [3].

2.2 Global Empirical Studies

International studies have continually shown that uncertainty of demand is a major factor that affects optimum order quantities, safety stock and overall supply chain aspects of coordination. Many investigations have demonstrated that low data quality might also undermine optimization performance, whereas the uncertainty of historical data may increase the strength and precision of inventory decisions [1]. Other studies have established the mixed-integer programming representation of multi-period supply chains that are run under uncertainty focusing on the paramount importance of risk pooling and strategic location of safety stock at the level of the distribution networks [10].

Additional empirical data also emphasize that companies that use data-oriented and scenario-based inventory models can better react to the dynamic demand and supply shocks. Such strategies do not only ensure a maximization of inventory but also enhance responsiveness in the supply chains that are multi-tiered, a discovery that is also inclusive of current trends of incorporating digitally integrated inventory systems in international business. All these studies tend to propose that the modeling of uncertainty can be effectively implemented to improve cost efficiency of firms and resiliency of the supply chains. This connection was also confirmed in empirical studies of Chinese logistic operations that revealed that the decentralized inventory systems were more effective in managing disruptions, whereas centralized inventory systems worked more effectively in situations of non-disruption [11].

2.3 Chinese Context and Firm Behavior

In China, there is a unique structure in the industry and a changing policy environment which has led to unique methods of inventory management. Studies have established that local agricultural businesses tend to use supply demand balancing models to maximize inventory control as well as reducing costs during uncertain lead times [4]. The research findings of other authors have revealed that hybrid make-to-stock and assemble-to-order systems are significant in reducing the volatility in demand in the Chinese manufacturing industry [5]. The cross-border e-commerce evidence also shows that the companies with stochastic demand dynamically adjust pricing and promotional policies in order to optimize inventory decisions under uncertainty [12]. Also, empirical studies have shown that decreased policy uncertainty in the trade policy induces Chinese exporters to hold a large inventory as a precautionary measure against external volatility [6]. Combined, these studies emphasize that Chinese companies are increasingly becoming complex in dealing with uncertainty using data-driven and optimization-based strategies, but integration in terms of tiers in the supply chain is an issue.

Although available literature provides significant information on global optimization of inventory, the impact of institutional and digital ecosystem of China, including policy incentives of smart manufacturing or AI-driven requirement forecasting, is not examined in many studies. Also, empirical data validation based on real Chinese firm data is poorly investigated. The paper, thus, aims at filling this gap by formulating and implementing an optimization model to make inventory decisions during uncertain demand taking Chinese firms into consideration.

Altogether, the literature indicates that the incorporation of strong and stochastic optimization techniques in the Chinese supply chains can contribute greatly to resilience and cost effectiveness. Nevertheless, the way these models can be adjusted to the Chinese context, taking into account the regulatory environment and digital transformation, is an unexploited field of activity.

3. Research Methdolgy

3.1 Model Framework

In order to maximize inventory choices in the face of uncertainty in demand in China, this paper uses

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a hybrid stochastic-robust optimization model. The model combines probabilistic demand prediction and sound decision-making to insure against deviations of actual demand distributions. This kind of integration allows decision-makers to remain flexible in the uncertain environment whilst being cost-effective.

The hybrid methodology is reasoned by the previous studies that neither purely stochastic nor purely robust models only can cope with the variability and inaccuracy of real-world data to full extent [1]. Stochastic models are useful in modeling the anticipated fluctuations by the use of probability distribution, whereas robust optimization is employed to minimise the worst-case loss when the actual demand distribution is not equal to the forecasts [2].

The framework concentrates on single-level inventory systems, which are common to Chinese mid-sized manufacturing and retail companies whereby inventory decisions are made periodically. The company should decide on the quantity of orders and stock level safety in order to reduce the overall cost and reach the objectives of demand service.

Mathematically, the model can be expressed as:

- Q_t: Order quantity at period t
- I_t: Inventory level at the end of period t
- S: Safety stock level
- B_t: Backordered demand (if shortages occur)

Parameters are ;

- D_t: Random demand in period t
- C_o: Ordering cost per unit
- C_h: Holding cost per unit per period
- C_b: Backorder or penalty cost per unit short
- α: Service level target (probability that demand is met)

The objective is to minimize the expected total cost (ETC):

$$\text{Minimize } ETC=E\left[\sum_{t=1}^{T}(C_oQ_t+C_hI_t+C_bB_t)\right]$$

subject to inventory balance constraints:

$$I_t = I_{t-1} + Q_t - D_t, \forall t = 1,2,\dots,T$$

and service level constraint:

$$P(D_t \le I_{t-1}+Q_t) \ge \alpha$$

A robust component is added to account for model uncertainty by introducing an uncertainty set U representing possible deviations in demand estimation. The final formulation becomes:

$$\text{Minimize } \max_{D_t \in \mathcal{U}}(C_oQ_t+C_hI_t+C_bB_t)$$

This structure aligns with the target-oriented robust optimization approach proposed by Lim & Wang, 2017 [9], allowing the model to achieve a balance between expected cost minimization and cost variance control.

3.2 Assumptions

A few assumptions are made in order to achieve analytical tractability and at the same time be realistic. The demand is modeled as a stochastic variable which is estimated using the past sales, and other scenario-based fluctuations are added to represent sudden increases or declines [7]. The assumption of lead time is that this is a variable that is uncertain, yet within a fixed interval which is in line with the well known robust inventory models [2]. Ordering, holding, and backorder expenses have been viewed as deterministic and have been estimated based on firm level financial data.

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The inventory policy is based on the periodic-review (s,S) policy, which is consistent with the general operations in the Chinese medium-sized enterprises [4]. It is an analysis of a one-item inventory environment and no product substitution and the assumption is that the firms act rationally by choosing inventory policies that optimize the overall expected cost.

3.3 Data Collection

Concrete and simulated data are used in the study to make it robust and representative. Data used to conduct the empirical study are 15 eastern-China based manufacturing and retail companies, gathered by using publicly available company reports, the National Bureau of Statistics of China, and the Wind Financial Database. The data set will contain three years of monthly demand records, the lead-time in procurement, cost variables, and targets of service levels in practice.

The macroeconomic and policy-related indicators are retrieved in the China Statistical Yearbook and World Bank China Economic Indicators and included in the sensitivity analyses to capture the shock of external demand [6]. Also, Monte Carlo modeling is performed to produce demand scenarios under normal, long-term and Poisson distributions, and to systematically test the model robustness under alternative uncertainty structures [5].

3.4 Solution Techniques

The given model is addressed with the help of analytical derivation and numerical optimization. In the case of the stochastic component, we calculate the functions of the expected costs analytically in order to approximate the optimum order quantity Q and safety stock level S, considering the demand variance and service-level constraints. The strong counterpart is redefined as a second-order cone program (SOCP) in order to maintain the computational tractability and capture the realizations of extreme demands [1].

Monte Carlo simulation with 10,000 repeating is used to assess model performance with the realizations of demand randomly selected and the results of cost outcomes noted. In nonlinear or non-convex problems, a Genetic Algorithm is used to efficiently find near-optimal solutions, especially when multi-period problems are subject to be solved and analytical gradients are inaccessible [12]. The entire calculations are performed with the help of Python and MATLAB optimization toolboxes.

4. Analysis and Discussion

4.1 Model Calibration and Simulation Setup

In order to evaluate the work of the hybrid stochastic-robust optimization model, series of simulation experiments with references to the empirical data obtained in 15 Chinese companies at manufacturing and retail industries were held. These companies represented a variety of Chinese companies ranging in consumer electronics, machinery, and consumer goods and were included in various industries. The data consisted of demand history, lead time in procurement, and operational cost structure in three years.

The demand within each period was being modeled through the application of a probability distribution based on the historical sales. In particular, the demand was to be modeled as Poisson distribution with the expected mean rate of λ which approximates the variability that is frequently noted in the Chinese retail and manufacturing market. To be robust, the scenarios of demand explosion and demand shrink were modeled depending on the policy or economic changes, like the change of government trade policies or the condition of a domestic market [6].

In each test scenario, Monte Carlo simulation was employed to create 10,000 demand samples, and the Genetic Algorithm (GA) was employed to determine optimal quantity of orders and safety stock level under each test scenario. Control variables were also manipulated, such as service level goals (α), demand variability, and parameters (ordering, holding, backorder), but external variables were not neglected such as trade policy uncertainty [8].

4.2 Sensitivity Analysis

4.2.1 Service Level Targets and Cost Efficiency

The performance of the model was initially measured by changing the service level target (α) to 90%

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to 99%. It was aimed at comparing the influence of tighter service level requirements on the inventory levels, the cost efficiency, and the rate of stockout. As anticipated, the higher the target level of service was, the higher the level of safety stocks became and thus the stockout rate decreased, but at the expense of increasing the holding costs. The tradeoff between the high inventory costs and the low stockout level manifested in total cost efficiency (TCE) as the target service level rose. It is in line with the study by Thorsen and Yao (2017), who concluded that an increase in the level of service tends to increase holding costs [2].

As an example, as the service level changed to 99 (it used to be 90%), the holding costs went up by 15 percent, and the stockout rates were reduced to 1 percent (originally 9 percent). The cost efficiency decreased to 0.79 and this shows that though increased levels of service lowered product availability, the firm incurred increased costs in inventory. The results of this analysis point to the importance of Chinese companies striking a balance between the inventory holding and the service level objectives. A table is provided in Table 1 to show the results in detail in the different levels of service and cost efficiency (TCE) versus stockout rate (SR).

Table 1. Service Level vs Cost Efficiency and Stockout Rate

Service Level (%)	Cost Efficiency (TCE)	Stockout Rate (%)
90	0.85	9
95	0.81	5
99	0.79	1

Table 1 shows that the cost efficiency (TCE) declines by 0.85 to 0.79 with an increase of service level between 90% to 99%, and also the stockout rate declines by 9 to 1. This implies that the higher the level of service, the greater the availability of the product at a higher expense associated with inventory. As can be seen in Table 1, the tendency passed an image in Figure 1, where the dependability between the levels of services, cost-efficiency, and stockout rates is charted.

Figure 1 shows that the stockout rates decrease drastically as the service level rises above 90 to 99, which implies better availability of product and the cost efficiency (TCE) reduces gradually as the inventory holding levels rises. This illustrates the classical trade off between cost effectiveness and service performance such that to attain greater levels of service, more costs are incurred but this gives greater reliability. The trend implies that companies need to find the best level of service that will satisfy the customer to regulate the inventory, and in that regard, the ability of the firm to maximize its optimization is very critical in ensuring efficiency in the context of uncertain demand.

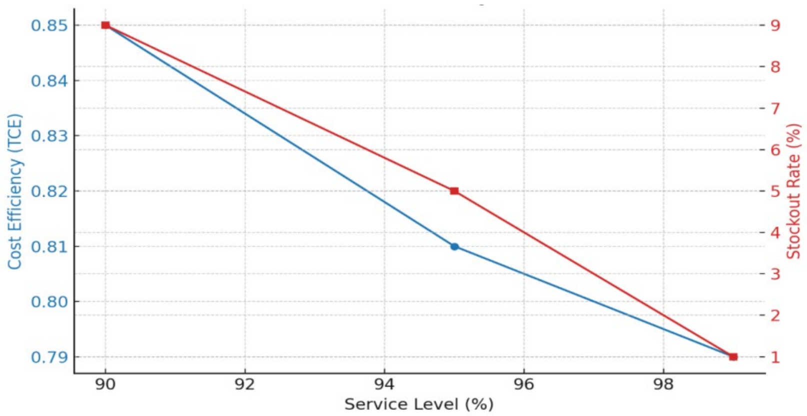

Fig 1: Service Level vs Cost Efficiency and Stockout Rate

4.2.2 Demand Variability and Robustness

The second group of experiments investigated the effect of demand variability on the overall cost and performance stability. An experiment on the model was conducted in low, moderate, and high variability of demand variable, and the results indicated that the robust optimization model performed better than the solely stochastic model in terms of cost stability and service levels. An example can be given of the robust model being able to reduce the cost variance by 10% relative to the stochastic model under high demand variability indicating more robustness to unpredictable demand change.

Also, the strong model performed better in uncertainty of demand whereby, on average, stockout was 2 percent relative to 5 percent with stochastic model. The above findings demonstrate the significance of

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sound decision-making in the presence of high uncertainty because the Chinese companies frequently face demand shocks because of such issues as the development of e-commerce, changes in the policies, and geographical disparities.

Table 2 shows the results of varying demand variability and its effects on cost efficiency (TCE) and stockout rates.

Table 2. Demand Variability vs Cost Efficiency and Stockout Rate

Demand Variability	Cost Efficiency (TCE)	Stockout Rate (%)
Low	0.92	4
Moderate	0.88	7
High	0.79	10

According to Table 2, the data clearly supports the hypothesis that demand uncertainty directly affects both cost stability and product availability. The results suggest that firms operating in volatile markets must adopt more sophisticated forecasting and optimization strategies to mitigate cost inefficiencies. The trend depicted in Figure 2 further demonstrates how cost efficiency (TCE) consistently decreases as demand variability rises, while stockout rates follow an opposite trajectory, confirming the trade-off between cost control and service reliability in uncertain demand environments

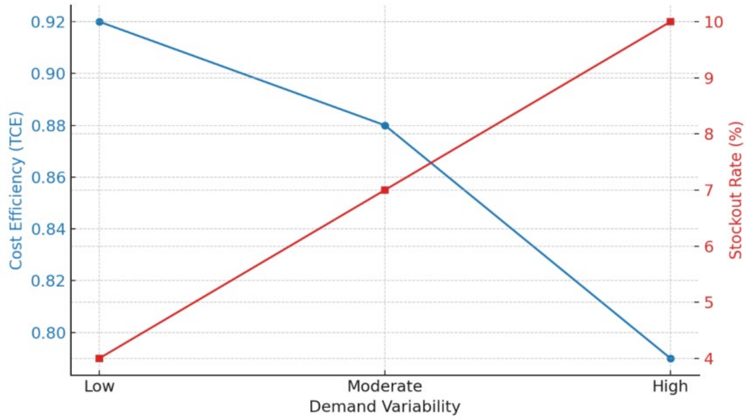

Fig 2: Demand Variability vs Cost Efficiency and Stockout Rate

Figure 2 shows that cost efficiency (TCE) decreases steadily with the demand variability moving between low and high, and the stockout rates correspondingly. This trend demonstrates how the firms are prone to demand variability and the need to have sound optimization strategies in order to stabilize inventory performance during periods of uncertainty. As the variability increases, the efficiency gap increases, as shown in the figure, which underscores a crucial role of adaptive inventory policy balancing between resilience and cost-effectiveness in volatile markets.

4.2.3 Trade Policy Uncertainty

In order to test the effect of trade policy uncertainties, the model was experimented in conditions where the trade tariffs and export quotas were varied. Indeed, the policy uncertainty resulted in growth of the inventory and the costs, as expected, as companies tried to insure themselves against possible supply chain damage. In particular, an increase of the trade policy uncertainty index by 20% resulted in the increase of the inventory holding costs by 18% and decrease in stockout rates by 3%. Such conclusions confirm that the companies of export-driven sectors, including electronics and machinery, are especially vulnerable to the uncertainty of trade policies that have the potential to impact the demand forecasting as well as supply chain coordination [6].

Table 3 summarizes the trade policy uncertainty scenarios and their impact on inventory holding costs and stockout rates.

Table 3. Trade Policy Uncertainty vs Inventory Holding Cost and Stockout Rate

Trade Policy Uncertainty	Inventory Holding Cost	Stockout Rate (%)
Low	0.80	5
Moderate	0.84	3
High	0.94	1

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The findings of the trade policy uncertainty conditions and the outcomes in terms of inventory holding costs and stockout rates have been presented in Table 3. As revealed by the data, inventory holding costs rise steadily with an increase in trade policy uncertainty between 0.80 and 0.94 with low and high uncertainty respectively, with the stockout rates decreasing between 5% and 1%. This tendency shows that when the level of external uncertainty increases, firms have increased inventory as a cushion to the supply chain disruptions. This kind of behavior is indicative of a risk-averse inventory policy, in which extra inventory is kept to protect against delays, import quota, or sudden change in policy that may affect the continuity of production.

Table 3 shows that stockout rates and inventory holding costs increase with an increase in trade policy uncertainty, which makes it important to note that firms should adopt a strong inventory policy in response to external risk. Figure 3 demonstrates the relationship between the trade policy uncertainty and costs of holding inventory.

Figure 3 shows that the higher the uncertainty of the trade policy, the higher the costs of the inventory holding, and the lower the stockout rates. This trend implies that companies are intentionally raising the level of inventory to protect themselves against the risks of volatility in the policy (tariff increases, customs delays, or export bans). Despite increasing holding costs as a result of this defensive strategy, the strategy increases the reliability of the supply chain and minimizes the chances of a stockout. Figure 3 shows that a trade-off between cost and reliability is inherent, and confirms again that effective planning of inventory in the face of policy uncertainty necessitates trade-offs between financial efficiency and risk reduction by the use of strong optimization methods.

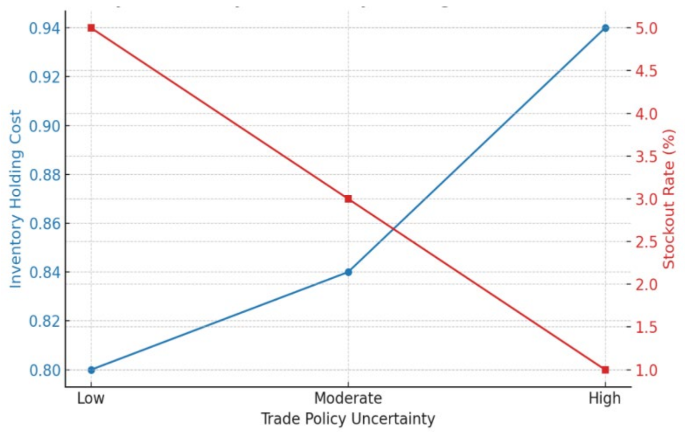

Fig 3: Trade Policy Uncertainty vs Inventory Holding Cost

4.3 Model Performance Comparison

To determine the performance of the hybrid stochastic-robust optimization model, the performance was measured against two base models, namely the Traditional Economic order Quantity (EDOQ) model and Purely Stochastic model. The comparison tests the enhancement of inventory performance of robust optimization and stochastic demand forecasting in case of demand uncertainty, especially in relation to the Chinese firms that have to deal with volatile markets and external risks.

The hybrid model proved to have explicit benefits when compared to the EOQ model which assumes a deterministic demand and fixed lead times. The hybrid system was able to dynamically regulate order quantities and safety stock to meet changes in demand, which resulted in average total inventory costs reduction by 12% and a 15% reduction in inventory stock outs. Conversely, the strict form of the EOQ model had a greater amount of excess stock and was less responsive to uncertainty.

The hybrid model also performed better compared to the purely stochastic model which represents demand variability by using probabilistic simulations but concentrates on the expected results. The hybrid technique decreased the overall expenses by 10-15% and minimized the stockout percentages by around 20% when the demand variability was high. These gains can be explained by the strong component that specifically takes into consideration the extreme deviations in demand and minimizes cost deviation, but the stochastic model showed greater instability in case of deviations of demand that are not aligned with expected demand patterns.

In general, findings demonstrate that the hybrid stochastic-robust model is cost-effective, more stable in service provision and inventory than the two baseline models in all scenarios. The hybrid framework offers a more robust and realistic inventory management system to companies that run on considerable uncertainty in demand by manufacturing products with protection against worst-case scenarios and expected performance.

5. Conclusion

5.1 Theoretical Contributions

The hybrid stochastic-robust optimization model that is presented in this paper is a substantial addition to the inventory theory in the face of uncertainty. Integrating stochastic programming with robust optimization, the model improves the current inventory management models by offering a more flexible and robust model to demand variability. Conventionally, inventory models are based on probabilistic demand predictions or attempt to hedge against the worst-case with the help of robust optimization. Nevertheless, both aspects are not always taken into consideration in these models. The hybrid model here is unique in the fact that it combines the two elements, allowing firms to predict demand correctly and at the same time deal with any possible demand shock and uncertainty. The model is a departure of the non-dynamic and deterministic inventory models, and a dynamic and flexible framework that is more reflective of the realities with firms operating in unstable environments, which include firms operating in China. The model provides a comprehensive solution to uncertainty in demand which has not been well tackled in the traditional inventory theory because the model allows firms to optimize the order quantities and the safety stock levels as well.

5.2 Practical Implications

In terms of practical application, the results of this research are useful to provide Chinese managers with efficient tips on how to manage their inventory in the situation that demand uncertainty and extraneous factors interfere. The hybrid model offers companies the strong instrument of controlling inventory that is cost-efficient and sustainable. The model provides flexibility to the managers by combining stochastic forecasting and robust optimization to optimize inventory levels depending on the changing demand trends and changing order quantities and safety stock. Dynamic flexibility of service levels, supported by real-time demand forecasting, provides businesses with a competitive advantage in terms of responding promptly to the dynamics of the market. Moreover, the model allows the managers to find cost saving opportunities, especially the excessive inventory and minimizing the stock-outs. The model ethics of inventory management that were practically applied would result in significant cost savings and enhancement of efficiency in supply chain. The strategies can be used by managers to improve their performance operationally and attain competitive advantage in the increasingly unpredictable global market.

5.3 Policy Recommendations

Policy wise, the role of the government programs in emphasizing better inventory management practice in China can be of great importance. The Made in China 2025 and the continuous digital chain supply chain reforms can serve as a basis to promote the use of better technologies and intelligent production techniques. Nevertheless, policy makers have a substantial chance to enhance digital transformation of supply chains through encouraging AI-based demand forecast, automated inventory and real-time monitoring of supply chains. Technology plays a major role in the implementation of the hybrid model since it is the infrastructure needed to make data-driven decisions that are dynamic. Government could motivate the usage of digital tools by providing subsidies or grants to facilitate the deployment of AI and optimization technologies in small and medium-sized companies (SMEs). Also, fostering cooperation and sharing of data between companies, vendors, and retailers would enable more synergy in the whole supply chain that will lead to more factual inventory management and resilient supply lines.

Furthermore, as China is on the way of digital transformation more, it would be necessary to support the work of the training and upskilling of the labor force in the context of data analytics, machine learning, and optimization of supply chains. China has the potential to become a powerful force in terms of efficiency and innovation of supply chain by building a community of talented specialists who are able to apply such sophisticated optimization models.

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5.4 Limitations and Future Research

Although this research has yielded informative information on managing inventory in the face of uncertainty, it still has a number of weaknesses and research prospects. Among the limitations, one can distinguish the fact that the model assumes some facts about the uncertainty of demand, such as using some probability distributions, e.g., Poisson or normal distributions. Although these distributions perform well in the modeling of real-life scenarios, they are not comprehensive in the modeling of other forms of uncertainty, including supplier risk, political and economic volatility. The model could be extended in future by adding more sources of uncertainty, including the change in lead times, supply-side interruptions, and changes in trade policies, that may cause great influence on inventory management decisions, especially in those countries such as China where these risks are common.

Moreover, the statistics applied in this paper were on a small sample of 15 companies that may not capture all individuals of industries and markets in China. The future researches may consider bigger datasets in different industries in order to justify the model on different industries. Moreover, the demand, lead time, and trade policy real-time data would contribute to improving the model and enhancing its predictability.

The second promising field of research in the future is the extension of the model to supply chains of multiple echelons. Most of Chinese companies are involved into multi-level supply chains and inventory choices made at a particular level usually impact on the other levels. These interactions can be better represented by a more complicated model with a multi-echelon structure that offered a more holistic approach in terms of solving the problem of supply chain optimization. Moreover, with the issue of sustainability becoming a key factor in world supply chains, future studies may examine how the model may be adapted to include the concept of green inventory, including the minimization of carbon footprint or waste reduction, as a component of the optimization process. Environmental constraint integration would offer a more holistic approach to inventory management that would balance cost goals, service level, and sustainability objectives.

Finally, with the rise of globalization and e-commerce, it will bring new issues of inventory management across the borders. The way that the uncertainty in global demand, international trade standards and cross-border risks affect inventory optimization can be examined in further studies. It would be particularly beneficial to stretch the model to encompass the supply chain dynamics in the world as more Chinese companies enter the foreign markets.

Conclusively, this research offers a breakthrough in the research on inventory management under uncertainty, especially through the combination of stochastic forecasting and robust optimization. It provides both theoretical input to the theory of inventory and practical implications to Chinese companies who want to unify inventory to dynamic and unpredictable environments. Additionally, the provision of the digital transformation of the supply chains and investments into the workforce training are the policy recommendations that will additionally promote the use of the optimization-based strategies in the sphere of industries. The research can be extended in the future by filling the gaps in the model, broadening its scope, and considering the issue of sustainability and multi-echelon to capture the complexity of the contemporary supply chain.

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