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Optimization of Inventory Management in the Presence of Demand Volatility with Advanced Stochastic Models

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Abstract

The volatility of demand makes it difficult for businesses to maintain a balance between ensuring products are available and the costs and operations associated with carrying inventory. Fixed safety-stock rules and traditional forecasting methods can be inadequate when demand distributions vary, lead times are variable and sales data is censored by stockouts. This paper proposes a decision framework for inventory optimization in the presence of a stochastic demand, a dynamic programming approach, a Monte Carlo simulation and distributionally robust optimization. Demand is treated as a random variable whose distribution can be different from season to season, product to product, and external condition to external condition. The replenishment quantities are determined as those that minimize the expected ordering, holding, shortage, and obsolescence costs with service and risk constraints. A conceptual methodology is outlined as well as an illustrative numerical comparison of fixed safety-stock, classical stochastic and volatility-responsive policies. The numerical example is not an actual scenario, and it represents the process of evaluation, not proving actual empirical results. The framework emphasises the importance of considering cost, service and downside risk all at once, rather than a point forecast. The paper identifies advanced stochastic models where the incorporation of reliable data and regular monitoring, transparency in decision rules and human oversight is most useful. Implementation must start with a small number of SKUs, apply back-testing and stress-testing and only roll out if there is operational advantage.

Keywords: Inventory optimization, Demand volatility, Stochastic programming, Safety stock, Monte Carlo simulation, Distributionally robust optimization, Supply chain resilience.

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Journal of Technological Information, Management & Engineering Sciences (2021),2(2), 1-16

Introduction:

Inventory is a productive asset, and a cost. Having enough stock helps to ensure that customers receive their orders, production is not interrupted, and the company is not caught off guard in case of unpredictable replenishment. Surplus stock is the cost of tying up working capital, using up warehouse space and risking damage, expiry or obsolescence. When demand fluctuates quickly, due to promotions, seasonal trends, competitor reactions, macroeconomic conditions or unexpected events, these competing forces are more difficult to manage.

The volatility of demand is not just an increase in the size of the forecast error. It may include a shift in the mean, variance, skewness, autocorrelation or the likelihood of extreme peaks. A forecasting method that works well in a non-disruption period may be misleading when forecasting during a disruption period. The same holds true for a fixed safety-stock multiplier: It may be overly conservative for slow moving products and not sufficiently large for products which are demanded intermittently or have an uncertain replenishment lead time.

Stochastic inventory models overcome the problem of uncertainty by using a probability distribution for the demand and, if present, the lead time instead of deterministic values. The classical newsvendor model is a model that compares the underage and overage costs for a single decision period. Multi-period systems are an extension of the problem that includes inventory carryover, inventory order lead time, order constraints and service targets. Newsvendor models research has warned that an increase in uncertainty does not always mean a higher optimal order quantity as the results are dependent on the shape of the distribution and the relative cost of shortfall and overstock (Qin et al., 2011).

This paper is therefore suggesting an integrated approach for managers who are in a situation where the demand volatility is considerable and there is a risk of model failure. Connects probabilistic forecasts to cost-based replenishment decision making and continuous performance monitoring. The framework does not treat a sophisticated algorithm as a replacement for operations management, it rather lays open assumptions and trade-offs.

1.1 Problem statement

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Several firms restock based on average demand, fixed reorder points or judgmental reorder points. These policies will fail if there is a shift in demand or if there are periods of stock-outs, where sales data will not reveal demand. The main challenge is to determine cost-effective buffer sizes and replenishment orders that can be maintained while satisfying the service levels that are agreed upon while covering a range of realistic demand scenarios.

1.2 Research questions

How can the volatility of the demand be modeled stochastically in the useful ways? (2) What are the useful ways of representing the volatility of the demand stochastically? and (3) How can the volatility of the demand be modeled stochastically in the useful ways? (2) How can replenishment policies find a balance? What evaluation process can determine if a volatility-responsive policy is better than the simple baselines?

The objectives and significance of research.

2.1 Objectives

The main goal is to develop a realistic stochastic decision model to optimize inventory levels in the presence of fluctuating and unpredictable demand. The specific objectives are to model demand using probability distributions and time-varying information, to account for ordering, holding, shortage and obsolescence costs, to compare ordering policies of fixed safety stock and classical stochastic policies and perform a cost comparison of the two, to include risk controls for ordering policies, including service targets and tail-loss measures, and to provide an implementation roadmap for validation and governance.

The study aims to investigate the significance of the study.

The framework applies to retail, e-commerce, spare-parts management, food distribution, pharmaceuticals and manufacturing. Depending on the industry, the impact of stockout of a critical spare part is the disruption of production, while overstocking of a perishable product represents a loss. These differences can be accounted for by optimizing the cost parameters, service constraints and demand assumptions with a common optimization structure.

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In a managerial sense the research is also important. It takes a different view on replenishment as a decision under uncertainty and not a mechanical reaction to a forecast. If one product has intermittent peaks or a longer and less certain lead time, then despite having the same average demand, different policies may be required. A risk-aware process translates the trade-offs into insights for stakeholders to approve service and working-capital goals.

2.3 Scope and assumptions

The paper is about finished goods or components where demand and replenishment can be measured. The model can be applied to one item, or to many items – and indeed the one item example is given with a deliberately small number of items. It also assumes that a reasonable approximation of costs can be made to support this decision making and that information from the past exists to predict future demand. The framework assumes that these are not perfect and contains sensitivity analysis and model monitoring. Paper is methodologically and illustratively designed. It doesn't claim to be a field experiment or proven savings from an actual company.

3. Literature Review

The newsvendor model is a basic stochastic inventory model. It decides the quantity of goods to be ordered for one period by considering the marginal cost of holding an excess as well as the marginal cost of holding a deficiency in the inventory. The optimal amount is related to a critical fractile based on underage and overage costs in the standard form. The model is useful because it provides an economic interpretation of the decisions on services, but it makes the assumption of one decision period and relies on the distribution of the demand or on the estimated quantiles of the demand distribution.

Qin et al. (2011) provides a survey of extensions of the newsvendor problem with demand, supplier costs, supply-chain contracts and risk profiles of decision makers. This literature reveals that the choices of the inventory must be made in parallel with the economic environment. High shortage penalties or a high margin can support a higher service level, while high holding or obsolescence costs can support a more conservative order.

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3. Literature Review (continued)

Stochastic inventory systems research has considered uncertainty in demand and/or supply. Schmitt, Snyder, and Shen (2010) investigate systems where the supplier is impacted by disruption and the demand or yield is uncertain over time. They show that in cases where discrete disruption events occur simultaneously with ordinary variation, a single forecast-error buffer can possibly prove to be inadequate. Uncertainty policies should take into consideration the nature and the occurrence of uncertainty, rather than simply the average size of the uncertainty.

Another difficulty is that demand might be partially observed. When a product is sold out, recorded sales are less than customer demand. Censoring can cause a biased estimate of the demand distribution and reduce the estimated likelihood of future shortages. In practice, stockouts should be identified and accounts should be made for lost sales, backorders, substitution, or documented imputation.

Data-driven optimization links predictive models straight to decisions. Cao et al. (2024) consider the newsvendor problem for unknown distribution of demand and yield based on historical data and contextual features. These methods are promising if the distribution cannot be precisely specified, but need to be carefully evaluated out of sample. Learning approaches also allow the consideration of uncertainty and time varying costs instead of only fixed parameters.

One way to address model uncertainty is through distributionally robust optimization (DRO). A DRO model does not rely on a single estimated probability distribution, but rather takes into account a family of distributions and works out the best performance for the worst distribution in the family. This can help to mitigate sensitivity to estimation error, but if the ambiguity set is too large it can produce overly conservative inventory. The uncertainty in the forecast should be included in the ambiguity set, as should business risk costs and the number of samples.

3.1 Research gap

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Individual tools found in the literature are effective in some respects, such as the newsvendor analysis, multi-period stochastic programming, machine learning, and robust optimization, but when forecasting, replenishment and evaluation are developed separately, implementation can be problematic. Even if a model is a good predictor of demand, it can still make bad inventory decisions if it fails to consider shortage costs, order constraints or lead-time uncertainty. In this paper, we fill this gap in integration by defining a decision pipeline that connects probabilistic demand estimation with cost-based optimization, scenario testing and continuous monitoring.

3.2 Conceptual framework

The proposed framework assumes that the demand information, cost parameters and supply conditions are input. A stochastic forecasting layer generates a range of possible demand results. The order quantity is determined by an optimization layer considering operational constraints. Through simulation assesses cost, service, and risk, based on scenarios. The forecasts and parameters are updated based on feedback from actual demand and inventory outcomes.

4. Methodology

4.1 Research design

A model-development and simulation-based design is suggested. It makes sense when the objective is to compare inventory decision rules under controlled uncertainty prior to deployment in the field. The workflow involves Data preparation, Probabilistic demand estimation, Optimization, Simulation, Baseline comparison and Sensitivity analysis. The workflow should be applied to a documented company dataset and reproducible code for a formal empirical study, and contains a defined observation window.

4.2 Data requirements

Some of the useful variables for a useful dataset include daily or weekly demand, sales, on-hand stock, stockout flags, purchase orders, actual receipt dates and supplier lead times, order quantities, unit purchase costs, holding costs, shortage

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Journal of Technological Information, Management & Engineering Sciences (2021),2(2), 1-16

or lost-sales penalties, returns, promotions, prices and calendar variables. In cases where it is possible, the data set should separate actual demand and fulfilled sales. Data should be checked for duplicates, inconsistent units, missing dates, unusual price changes, and changes in product identifiers.

Data field: Purpose: Common risk:

Demand / sales history Estimate level, variability, seasonality Sales censored by stockouts

Lead-time history: Only planned dates preserved; Model replenishment uncertainty:

Holding and shortage costs Translate service into economics Costs considered the same for all items

calendar Explain demand regime changes Events missing or poorly coded Promotions

Adjustments to inventory and receipts Reconstruct position of inventory Timing and unit mismatch

4.3 Demand modelling

The easiest approach is an estimate of demand through a "seasonal" or "moving-average" model. In a stochastic approach, a predictive distribution is estimated, for example a normal distribution for approximately symmetric demand, a Poisson or negative binomial distribution for counts and an empirical distribution if there are enough comparable observations. When the demand for an item is intermittent, a model may be needed that deals with the probability that the demand is not zero along with the size of the demand, if it occurs.

Use rolling windows to estimate volatility; Run a test for regime changes. If available at the point of decision, contextual variables can enhance forecasts (e.g. price, promotion, holidays, weather and macroeconomic indicators). Forecasts must be evaluated based on chronological holdout periods and not random periods in order to avoid future observations from being leaked in when training the model.

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4.4 Stochastic inventory formulation

Define the following terms with respect to the protection period:Assess the following terms with respect to the protection period: The protection period can cover the interval in which the review was made as well as the lead time. An simple single period cost function is:

$C(q, D) = c_o q + h \max(q - D, 0) + p \max(D - q, 0)$

In this case, c_o represents the ordering or acquisition cost, h is the cost of holding surplus inventory, and p is the cost of a shortage. Normally in a multi-period system, acquisition cost is included in replenishment, not in each unit in the target level, and holding cost is added to inventory carried over time. It is then a simple one period equation; a live implementation should not double count the purchase cost.

The classical newsvendor with underage cost Cu and overage cost Co has an optimal order quantity q^* for which $F(q^*) = Cu / (Cu + Co)$ where F is the cumulative distribution function of the demands. This outcome is a clear yardstick. In the case of multi-period replenishment, a base-stock or reorder-point policy can be optimized using dynamic programming, stochastic programming, or simulation-based search.

4.5 Modelling demand and lead-time uncertainty

Assume that the demand during the period is statistically independent with a mean of μ and a variance of σ^2, and that the lead time is constant for each period, L, then the demand in the lead time is statistically independent with a mean of Lμ and a variance of $L\sigma^2$. A normal approximation can be used to define a target, for example $\mu L + z\sigma\sqrt{L}$, where z is the service quantile chosen. When the lead time is random and independent of the demand, the variance of the lead-time demand contains both the variance of the demand and the variance of the lead time, which is about $E[L]\sigma^2 + Var(L)\mu^2$, subject to certain assumptions. The simulation/estimation is more complicated in the presence of correlation, seasonality, and heavy tails, necessitating a richer simulation or a direct empirical estimate of the lead-time demand.

4.6 Risk-aware optimization

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Journal of Technological Information, Management & Engineering Sciences (2021),2(2), 1-16

Rare but severe shortages can be masked by expected cost alone. An objective incorporating conditional value at risk (CVaR) could be added, which is a measure of average loss in the upper tail. A generic formulation is to minimize the expected cost and λ times the CVaR, while satisfying minimum cycle-service or fill-rate constraints. The parameter λ is the risk aversion and should be determined jointly with the managers and not only to maximize a back-test score.

4.7 Constraints

Operational constraints can be minimum order quantities, case packs, supplier capacity, shelf life, budget constraints, storage capacity, and order calendars. With several products, the allocation selection might clash with one another regarding the resources of capital or storage. The restrictions may be programmed into an optimization model or applied as a post optimization feasibility check.

5. Proposed Optimization Algorithm

The proposed approach is a probabilistic approach to demand forecasting, coupled with an inventory optimization process that considers costs, along with scenario-based verification. This is not a one-off calculation but a continuous process.

1.1. Data collection and validation – Reconcile sales, inventory, purchase orders, stockouts, costs and lead times.

2.2. Estimate the distribution of demands — Make the candidate models and create predictive samples for the protection period.

3.3. Estimate holding, shortage, obsolescence and ordering costs; define service constraints and then calculate economic parameters.

4.4. Optimize replenishment—Seek the best order quantity or base-stock levels that minimize expected cost and risk.

5.5. Stress test decisions — Consider normal, high demand, low demand, and delayed supply situations.

6.6. Approve and execute — Use business rules and manager review prior to replenishment orders.

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Journal of Technological Information, Management & Engineering Sciences (2021),2(2), 1-16

7.7. Monitor and update — Track and adjust forecasts with actual results; adjust if performance slips.

5.1 Monte Carlo evaluation

The Monte Carlo simulation method estimates the range of potential inventory results by taking a sample of demand and lead time values randomly drawn from fitted or empirical distributions, etc. The simulation records the number of stocks on hand for each candidate policy, number of backorders or lost sales, number of arrivals of the replenishment, holding cost, shortage cost, and cost of expiry or disposal for each candidate policy. The same random scenarios must be used to compare competing policies so as to minimize the noise in the difference between their results.

A practical design provides a distinction between model development and evaluation. A training period is used to estimate parameters, decisions are made on future periods not used for the training. Evaluate during ordinary periods and contingencies, include uncertainty intervals if possible, and record if there has been a response to demand when the product was unavailable. Where products differ significantly, the results should be reported by product class and not just as an average.

5.2 Pseudocode

For each review period:

Update the demand and lead time information

estimate predictive distribution P(D, L | available information)

Produce possible candidate order quantities.Produce possible candidate order quantities.

for each candidate q:

SIMULATE: a program that simulates the demand, arrivals, inventory, and total cost.

Calculate the mean cost, service level and tail risk

Choose feasible q that minimizes the objective function with lowest risk reward

Approve order and apply approval rules

Record and track outcomes and model performance

5.3 Performance measures

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Journal of Technological Information, Management & Engineering Sciences (2021),2(2), 1-16

These key measures are total inventory cost, average inventory value, fill rate, cycle-service level, stockout frequency, lost sales, inventory turns, forecast calibration, and the frequency of emergency orders. Average inventory must be interpreted in conjunction with cost and service: less average inventory can be a tradeoff for a higher number of stockouts than may be acceptable to the organization. Monitoring also needs to include the ability to determine if there are actual demands within the forecast intervals at the forecast rates.

6. Illustrative Numerical Analysis

The following paragraphs illustrate the type of reporting that could take place for the proposed comparison. All of the numbers mentioned below are assumed and not based on any company information. They show the evaluation format but do not imply that there is any statistical significance or real world savings.

6.1 Example setup

Suppose a distributor is checking the stock weekly of one product. The average value of the demand over the weeks is 100 units, demand fluctuates significantly from week to week and the supplier lead time is 2 weeks on average. A fixed buffer policy with a historical average buffer size, a classical stochastic reorder policy that relies on an estimate of the demand distribution, and a volatility-responsive policy that adjusts the demand distribution and includes a risk penalty when demand volatility is high are compared. The issues being considered for each policy are identical on the same sets of hypothetical demand scenarios.

Illustrative input Assumed value Interpretation

Baseline expected demand 100 units

Standard deviation of weekly demands 30 units Variation of materials around average demand per week

Replenishment delay2 days

Capital proxy $2,500/unit Capital costs

Shortage penalty is calculated as a percentage of the service cost.The shortage penalty is calculated as $4.00 per unit of shortage multiplied by the service cost.

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Avoiding backups: target fill rate At least 95% Service constraint for comparison

6.2 Illustrative policy results

The table below provides some examples of possible output of the decisions, which can be summarized. These values need to be replaced by the measured outputs of a repeatable simulation prior to any empirical conclusions.

A. Fixed buffer	B. Stochastic	C. Volatility-responsive
Average time on hand (days)	36	32	31
Fill rate	92.0%	95.1%	96.0%
Stockout events per 100 weeks	18	11	8
Relative total cost index	100	92	88

Corrective measures that should be taken to address the vulnerability of the stress performance as identified above.

Given these assumed outputs, policy C has the smallest level of inventory among the policies being compared and the policy's fill rate is the largest. The outcome is not guaranteed in all environments: a volatility-sensitive policy might hold more stock when the tail demand or service penalties are more important, and a poorly tuned model could have worse performance than a simple policy. The example illustrates the importance of examining the cost-performance-stress relationships together.

6.3 Sensitivity analysis

The measurements of shortage penalties, holding costs, lead time variability, demand dispersion and the size of any ambiguity set should be varied in a robust study. As the costs associated with having unmet demand rise, the optimizer will typically give more importance to minimizing unmet demand. As holding or obsolescence costs increase, the desired stock level could decrease. An increase in lead-time variability can lead to a higher level of protection stock, the amount of which will depend on the shape of the demand, the service constraints, and the options available for expediting.

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7. Discussion

7.1 Interpretation

This proposed framework focuses on the fact that inventory optimization is a joint forecasting and decision problem. Point forecasts provide a handy summary, but cannot give a sense of the likelihood of the high demand outcomes. Probability distributions, quantiles, and scenario sets render uncertainty visible and enable the inventory decision to incorporate the economic impacts of getting it wrong. The classic newsvendor has a well understood basis that is easy to interpret, while the dynamic and robust models solve the multi-period and model-uncertainty problems.

The difference between the illustrative scenarios indicates that there may be a benefit to a policy that is flexible to volatility, depending on the results assumed. Performance in a real study may differ between item category, supplier and demand regime. The overall result should not be an average in which failures are blended in with the critical products. Different policies can be adopted for different classes of demands on the basis of intermittence, value, lead time, perishability and criticality.

7.2 Managerial implications

But, managers should first work on data quality, before they invest in complex software. The Stockout flag and Stockout date are particularly critical because the lack of these pieces of data can be problematic in the estimation of demand and lead-time. Second, a review of cost parameters should be done with finance, sales, operations and customer service. The numbers given as penalties for a shortage should reflect what the business loses, rather than an arbitrary number chosen to obtain the desired response from the model.

Third, adoption should be carried out via a pilot. The planned policy can be compared with the existing rule in the shadow mode using a small set of high impact stock-keeping units. The organization can assess recommendations without necessarily putting them into practice, examine odd orders and determine if forecast distribution is calibrated. Automation should be scaled up only after stable performance is achieved.

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Journal of Technological Information, Management & Engineering Sciences (2021),2(2), 1-16

7.3 Limitations

This paper offers a conceptual framework instead of an empirical field study, and a hypothetical numerical example. Performance data is illustrative and is not intended to be an indicator of savings. The model also assumes that relevant costs can be calculated and that past experience provides information on future results. These assumptions may be breached by structural shocks, new products, supplier failures, or policy changes. There are systems that need to be modeled more complexly—multi-echelon systems, substitution between products, shared capacity, and strategic customer behaviour.

7.4 Ethics and governance issues

Decisions regarding inventories may be responsible for access to necessary goods, wasted inventory and distribution of scarce products to locations. A systematic under-allocation of models to smaller branches or smaller customer groups, especially if they previously had stockouts as a result of sales patterns, should be monitored in models. Decision logic should be documented; override procedures should be defined; automated recommendations must be aligned and comply with safety, regulatory and contractual requirements.

8. Implementation Roadmap

Phase Key activity Exit criterion

2. Process, costs and data gaps identified and agreed baseline and business case

Data preparation includes data cleaning of history, data identification of censored demand and data identification of lead-time errors, which makes up 2.The data preparation consists of data cleaning of history, data identification of censored demand and data identification of lead time errors which makes up 2.

3. Build model Fit distributions and optimize candidate policies Reproducible model and documented assumptions

4. Validate Back-test, stress-test, compare with baseline Acceptable cost/service trade-off

5. pilot – Run in shadow mode, controlled rollout – Operational approval and user training

6. Monitor Monitor drift, overrides, service and realised costs Established review and recalibration cycle

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Journal of Technological Information, Management & Engineering Sciences (2021),2(2), 1-16

9. Conclusion

When prices fluctuate, inventory management is not simply a problem of forecasting one price, but balancing the risk of multiple prices. Fixed safety-stock rules can continue to be useful, but they might not provide the necessary response in the event of changes in the distribution of demand or lead time. The paper has presented an integrated solution that combines stochastic demands estimation, cost-sensitive optimization, simulation and risk controls for supporting replenishment decisions.

The framework adds a practical sequence that includes the testing of decisions under various real-world scenarios, the optimization of the process under operating constraints, the translation of consequences of services and shortages into economic parameters, and the validation of data and estimation of a predictive distribution, as well as updating the process based on realized outcomes. The traditional newsvendor paradigm serves as a clear benchmark, and techniques, such as distributionally robust, Monte Carlo simulation and dynamic programming, can tackle the multi-period setting and uncertainty in the model.

The main managerial lesson is that the complexity of the algorithm is not the only criterion for selecting advanced models for making decisions. All the cost review points should be considered simultaneously, including total cost, fill rate, stockout frequency, inventory value and tail-risk measures. The next research step is the testing of the framework on a real data set in which chronological holdouts, explicit cost assumptions and reproducible simulation are used. Model extensions for future studies include (but are not limited to) multiple warehouses, correlated demand, supply disruptions, product substitution, sustainability costs, and human-in-the-loop decision support.

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