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AN INTEGRATED APPROACH TO DEMAND FORECASTING AND INVENTORY OPTIMIZATION IN E-COMMERCE

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Abstract. This study investigates demand forecasting and inventory optimization in an e-commerce environment with a large assortment of products and highly variable demand. The research focuses on SKU-level demand modeling based on transactional data from an online retail store. The proposed approach combines machine learning methods with a stochastic inventory model. Demand forecasting is performed using regression-based and ensemble models with engineered temporal features, including calendar variables, lagged values, and rolling statistics. Demand uncertainty is estimated based on forecasting errors and adjusted using a robust capping procedure. The results show that the gradient boosting model provides the highest forecasting accuracy (MAE = 23.97, RMSE = 311.70). The average weekly demand across products is approximately 158 units, while demand variability differs significantly between SKUs. The application of the Newsvendor model leads to an average optimal order quantity of 236 units, which reflects the impact of demand uncertainty on safety stock formation. However, unconstrained solutions exceed the available budget by more than 14 times. To address this issue, a budget constraint is incorporated, and a proportional scaling procedure is applied. As a result, the average order size is reduced to 16 units, and the total procurement cost (119.3 thousand monetary units) satisfies the budget constraint (122.8 thousand). The achieved service level is approximately 0.94. The study demonstrates that integrating machine learning forecasting with stochastic inventory optimization provides an effective decision-support tool for e-commerce, enabling balanced consideration of demand uncertainty, service level, and financial constraints.

Keywords: demand forecasting, inventory optimization, e-commerce, machine learning, Newsvendor model, supply chain management, stochastic optimization, time series forecasting, ensemble learning, gradient boosting, demand uncertainty, safety stock, inventory manage

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ИНТЕГРИРОВАННЫЙ ПОДХОД К ПРОГНОЗИРОВАНИЮ СПРОСА И ОПТИМИЗАЦИИ ЗАПАСОВ В ЭЛЕКТРОННОЙ КОММЕРЦИИ

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Аннотация. В работе рассматривается задача прогнозирования спроса и оптимизации запасов в системе электронной коммерции, характеризующейся широким ассортиментом товаров и высокой вариативностью спроса. Объектом исследования являются временные ряды спроса на уровне отдельных товарных позиций (SKU), сформированные на основе транзакционных данных интернет-магазина. Предложен интегрированный подход, объединяющий методы машинного обучения и стохастическую модель управления запасами. Прогнозирование спроса осуществляется с использованием регрессионных и ансамблевых моделей с применением календарных, лаговых и скользящих признаков. Неопределённость спроса оценивается на основе ошибок прогнозирования с использованием процедуры ограничения выбросов. Результаты эксперимента показали, что наилучшую точность демонстрирует модель градиентного бустинга (MAE = 23.97, RMSE = 311.70). Средний недельный спрос составляет около 158 единиц, при значительной неоднородности между товарами. Применение модели Newsvendor приводит к среднему оптимальному объёму заказа 236 единиц, что отражает влияние неопределённости спроса на формирование страхового запаса. При этом суммарная стоимость закупки без ограничений превышает бюджет более чем в 14 раз. Для учёта финансовых ограничений введено бюджетное ограничение и применена процедура пропорционального масштабирования заказов. В результате средний объём заказа снижается до 16 единиц, а итоговая стоимость закупки (119.3 тыс.) не превышает заданный бюджет (122.8 тыс.). Достигнутый уровень обслуживания составляет около 0.94. Полученные результаты показывают, что интеграция методов машинного обучения и стохастической оптимизации является эффективным инструментом управления запасами в электронной коммерции.

Ключевые слова: прогнозирование спроса, оптимизация запасов, электронная коммерция, машинное обучение, модель ньюсвендор, управление цепочками поставок, стохастическая оптимизация, прогнозирование временных рядов, ансамблевые методы, градиентный бустинг

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Introduction

Modern e-commerce systems are characterized by high demand volatility and significant uncertainty in consumer behavior. For online retailers, one of the key challenges is efficient inventory management, which enables simultaneous minimization of holding costs and reduction of the risk of lost sales due to stockouts. A wide product assortment combined with highly variable demand significantly complicates decision-making regarding inventory replenishment.

Classical inventory management approaches have been extensively studied in the literature. One of the most well-known models is the Newsvendor model, which determines the optimal order quantity under stochastic demand and given cost parameters associated with shortages and excess inventory (Arrow et al., 1951). Further developments and modifications of this model are discussed in studies devoted to stochastic inventory control and supply chain optimization (Khouja, 1999; Qin et al., 2011; Choi, 2012).

In recent years, considerable attention has been paid to the application of machine learning methods for demand forecasting in retail. Modern machine learning algorithms enable the identification of complex nonlinear relationships in sales data and improve forecasting accuracy (Makridakis et al., 2018; Fildes et al., 2019; Shirokova et al., 2025; Svetunkov and Petropoulos, 2019; Ferreira et al., 2016). A number of studies demonstrate that ensemble methods, including gradient boosting techniques, achieve high performance in time series forecasting tasks in e-commerce (Benidis et al., 2022; Lim and Zohren, 2021; Januschowski et al., 2020; Makridakiset al., 2022).

Despite the large body of research on demand forecasting, the integration of machine learning techniques with inventory optimization models remains relatively underexplored. Several studies investigate approaches that combine predictive models with optimization methods to support decision-making in supply chains (Bandara et al., 2020; Salinas et al., 2020; Bentejac et al., 2021; Prokhorenkova et al., 2018). However, many existing works either focus exclusively on forecasting tasks or consider inventory control models without leveraging modern data-driven techniques.

Particular interest lies in the development of integrated approaches that combine machine learning-based demand forecasting with stochastic inventory optimization models. Such approaches make it possible to account for demand uncertainty alongside economic parameters of inventory control, which is especially important for e-commerce systems with a large assortment of products (Carbonneau et al., 2008; Babai et al., 2012; Huberty, 2018; Syntetos and Boylan, 2006).

In the previous study, a formulation of the inventory optimization problem for a hybrid warehouse configuration in e-commerce was proposed (Ermochenko, 2025). However, the practical implementation of the proposed model requires computational experiments based on transactional data and modern forecasting methods.

The aim of this study is to develop and experimentally validate an integrated approach to demand forecasting and inventory optimization in e-commerce using machine learning methods and stochastic inventory models.

To achieve this goal, the following research objectives are formulated:

1. Preparation and preprocessing of an online retail transaction dataset.
2. Development of machine learning models for demand forecasting at the SKU level.
3. Estimation of demand uncertainty based on forecasting errors.
4. Application of the Newsvendor model to determine optimal order quantities.
5. Incorporation of a budget constraint into the inventory replenishment plan.
6. Conducting computational experiments and analyzing the obtained results.

Materials and Methods

The study is based on an open transactional dataset of an online retail store available on the Kaggle platform (Chen, 2017). The dataset contains detailed information on sales transactions and is widely used in research on demand analysis and forecasting in e-commerce. Each record includes the transaction date, product identifier, quantity sold, and price. Each entry corresponds to an individual sales transaction.

The original dataset contains more than one million transaction records covering a period of approximately two years. Prior to analysis, a data preprocessing procedure was performed.

Transactions corresponding to product returns and records with negative quantities were removed. To begin with, records corresponding to situations with the return of goods and transactions with a negative quantity of products were deleted from the original data set, then records with missing values of key parameters were excluded. In the next step, the data was aggregated by date and product identifier to form a time series of daily demand for each item. Then, in order for the analysis to be carried out correctly, a complete time grid of observations was formed, including all dates in the period under review. If there was no sales information for a particular product, the values were set to zero. As a result of the preliminary data processing, a dataset was formed that contained more than 350,000 observations of daily demand, and 500 items with the largest sales volume were selected from it. The proposed framework allows focusing on the most significant products while reducing computational complexity.

To improve forecasting accuracy, additional features describing the temporal structure of the data were generated. These include calendar-based features such as day of the week, month, and week of the year, which capture seasonal patterns in demand. In addition, lagged features representing demand values from previous periods were constructed. Specifically, lags of 1, 7, 14, and 28 days were used. Such lag structures enable machine learning models to capture short-term fluctuations as well as weekly seasonal effects commonly observed in retail data.

Furthermore, rolling statistics were computed, including moving averages and standard deviations over previous time windows. These features help capture local trends and reduce the impact of random fluctuations. The resulting feature set allows machine learning models to account for both seasonal patterns and temporal dynamics of demand.

Several machine learning models were used for demand forecasting (Makridakis et al., 2018; Fildes et al., 2019; Svetunkov and Petropoulos, 2019; Ferreira et al., 2016). Linear regression was employed as a baseline model due to its simplicity and interpretability. In addition, ensemble learning methods (Benidis et al., 2022; Lim and Zohren, 2021; Januschowski et al., 2020; Makridakiset al., 2022) were applied, including Random Forest and HistGradientBoosting models. These approaches are capable of capturing nonlinear relationships between input features and the target variable.

Model training was performed using the constructed time series and feature set. The dataset was split into training and test subsets based on time in order to reflect the real-world forecasting scenario. The first 80% of observations were used for training, while the remaining 20% were reserved for testing. Model performance was evaluated using standard regression metrics, including mean absolute error (MAE) and root mean squared error (RMSE).

An important stage of the study is the estimation of demand uncertainty. Even highly accurate forecasting models inevitably produce errors that must be taken into account in inventory management decisions. Forecast errors for each SKU were defined as the difference between the actual demand and the predicted value:

$$\varepsilon = D - \widehat{D}$$

where D denotes the actual demand and $\widehat{D}$ is the predicted demand obtained from the machine learning model.

Based on these errors, the standard deviation of forecast errors was calculated for each SKU, representing the variability of demand. But unfortunately, when analyzing forecast errors, I found that for some products there are "outliers", very large deviations associated with rare and sharp spikes in demand. To avoid distorting the overall estimate, it was decided to limit the extreme values of the standard deviation to the 99th percentile. This made it possible to make the assessment of the uncertainty of demand more resilient to such situations and to prevent an overestimation of the insurance stock for certain items of goods. The next step, after the forecast parameters were determined and the uncertainty of demand was assessed, was the construction of a stochastic demand model. Demand for each SKU was modeled as a normally distributed random variable:

$$D_i \sim N(\mu_i, \sigma_i)$$

where μ_i represents the expected demand obtained from the forecasting model, and σ_i denotes the estimated standard deviation of forecast errors. To determine optimal order quantities, the classical Newsvendor model was applied. The optimal order quantity is given by:

$$Q_i^* = \mu_i + z_i\sigma_i$$

where Q_i^* is the optimal order quantity, μ_i – the expected demand, σ_i is the standard deviation of demand, and z_i is the quantile of the standard normal distribution corresponding to the desired service level. The service level is determined by the critical ratio:

$$CR = \frac{C_u}{C_u - C_o}$$

where C_u represents the cost of understocking (lost sales or penalty costs), and C_o denotes the holding cost per unit. The value of z_i is obtained from the inverse standard normal distribution corresponding to the critical ratio. In addition to the stochastic inventory model, a budget constraint was incorporated to reflect real-world financial limitations. Based on the approach used in this work, the cost of purchasing goods should not be more than the budget allocated for this purpose. Mathematically, this can be written as the following expression:

$$\sum_{t=1}^{n} c_i Q_i \leq B$$

where C_i is the purchase price of a unit of the product *i*, Q_i is the order volume for this item, and *B* is the total purchase budget. If the total cost of orders calculated using the Newsvendor model exceeds the limits of the finances available in the budget (122,763 monetary units), then the order volumes are additionally adjusted. For this, a scaling factor is used, which proportionally reduces orders for all products. As a result, the total cost of the purchase remains within the specified economic constraints, and the ratio between the volumes of orders for different items remains. Based on the above, the sequence of steps of the proposed solution is presented in the form of a block diagram in Fig. 1.

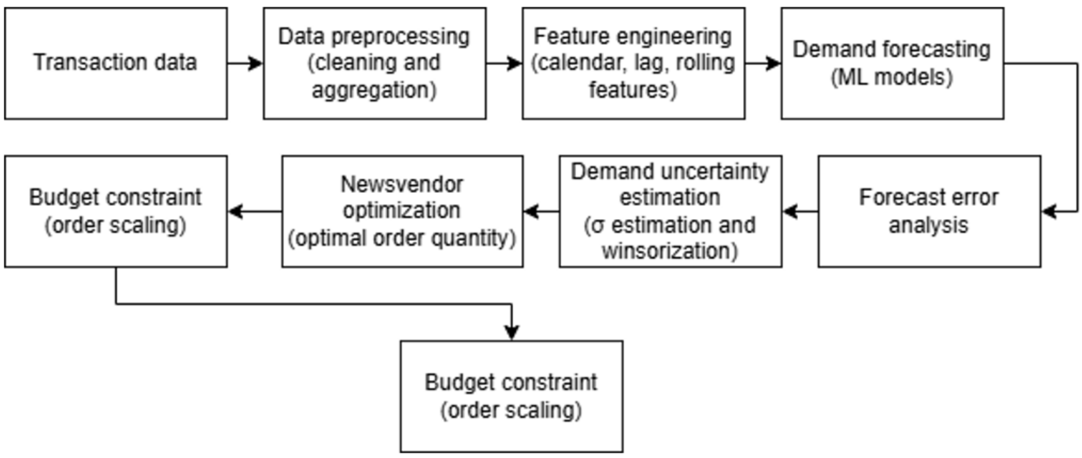

Fig. 1. Workflow of the proposed demand forecasting and inventory optimization framework.

Results and Discussion

This section presents the results of the computational experiment aimed at evaluating the effectiveness of the proposed approach to demand forecasting and inventory optimization in an e-commerce system. The experiment consists of several sequential stages: demand forecasting using machine learning models, analysis of forecasting errors and estimation of demand uncertainty, application of a stochastic inventory optimization model, and incorporation of a budget constraint in the procurement planning process.

At the first stage, the forecasting accuracy of the machine learning models was evaluated. Three models were considered in the experiment: linear regression, Random Forest, and HistGradientBoosting. Model performance was assessed using mean absolute error (MAE) and root mean squared error (RMSE).

Table 1. Forecasting model performance.

Model	MAE	RMSE
Linear Regression	24.15	311.40
Random Forest	25.92	315.71
HistGradientBoosting	23.97	311.70

The results indicate that the gradient boosting model demonstrates the best forecasting performance among the considered approaches. The MAE value for this model is 23.97 units, which is lower than that of the alternative models. Linear regression shows comparable performance in terms of RMSE but is inferior to gradient boosting in terms of MAE. The Random Forest model exhibits the lowest accuracy among the evaluated methods. These findings are consistent with existing studies highlighting the effectiveness of ensemble learning techniques for demand forecasting in retail and e-commerce environments (Benidis et al., 2022; Lim and Zohren, 2021; Januschowski et al., 2020; Makridakiset al., 2022).

At the next stage, a detailed analysis of forecasting errors was conducted. For each SKU, key statistical characteristics of the errors were computed, including MAE, standard deviation of errors, and bias. The average MAE across all products was 23.97 units, while the average standard deviation of forecasting errors reached 61.42 units.

The analysis revealed substantial heterogeneity in error distributions across different products. The minimum standard deviation of errors was approximately 6 units, whereas the maximum value exceeded 6700 units. Such extreme values are associated with occasional demand spikes observed for certain products and reflect the highly irregular nature of demand in e-commerce systems. This behavior is typical for datasets with a wide assortment of products, where demand patterns may differ significantly between items.

To mitigate the influence of extreme values, a capping procedure was applied at the 99th percentile of the error distribution. This approach allows obtaining a more robust estimate of demand variability and prevents excessive overestimation of safety stock levels for products with rare but extreme demand fluctuations.

Further analysis focused on demand characteristics. The average weekly demand across the selected SKUs was approximately 158 units. At the same time, demand values ranged from 23 to 953 units per week, indicating significant variability across products. This confirms the heterogeneous structure of demand in online retail, where some products exhibit stable demand patterns while others experience high sales intensity and variability.

Based on the estimated demand parameters and uncertainty measures, a stochastic inventory optimization model was applied. The Newsvendor model was used to determine optimal order quantities for each SKU, taking into account both expected demand and its variability (Arrow, 1951; Khouja, 1999; Qin et al., 2011; Choi, 2012).

The results show that the average optimal order quantity is approximately 236 units. The minimum values are around 31 units, while the maximum values exceed 1400 units. In most cases, the optimal order quantity exceeds the expected demand. This is explained by the presence of safety stock, which compensates for demand uncertainty. In the Newsvendor framework, the safety stock level is directly influenced by the standard deviation of demand and the target service level. Consequently, products with higher demand variability require larger safety stocks to reduce the risk of stockouts.

However, applying the Newsvendor model without additional constraints leads to order quantities that significantly exceed available financial resources. In the conducted experiment, the total cost of optimal orders amounted to approximately 1.76 million monetary units. At the same time, a budget constraint of 122,763 monetary units was imposed. Thus, the unconstrained optimal solution exceeded the available budget by more than 14 times.

In real-world inventory management systems, such discrepancies require additional adjustment of decision variables. In order for the purchase volume plan to meet budget constraints, it is necessary to carry out a procedure for proportional scaling of order volumes. This solution allows you to reduce the volume of purchases for all products in proportion to their initial and optimal values, while maintaining the overall order structure. After the budget restriction was introduced, the average order volume decreased to about 16 units of goods, while the total purchase cost was about 119.3 thousand monetary units, that is, it did not exceed the established budget of 122.8 thousand. These results suggest that financial constraints are really important to consider when making inventory replenishment decisions. Without such a limitation, the Newsvendor model forms a solution based only on the balance of losses from a shortage of goods, as well as excess inventory. In fact, the company is always limited in available financial resources, so the final procurement plan must be consistent with the actual capabilities of the company. In addition to the above, the level of service was additionally considered, which is essentially the ratio of deficit costs to inventory storage costs. On average, its value in the sample was about 0.94, which tells us about the high probability of meeting demand and also about the desire of the system to reduce the possible risk of shortage of goods. It can be said that the results show that the proposed integrated approach makes it possible to form a realistic procurement plan that simultaneously takes into account the forecast of demand, its uncertainty and the financial constraints of the enterprise. The approach simultaneously accounts for predicted demand, demand uncertainty, and financial constraints. The integration of machine learning methods with stochastic inventory optimization models can therefore be considered an effective decision-support tool for inventory management in e-commerce systems.

Conclusion

This study proposes and experimentally validates an integrated approach to demand forecasting and inventory optimization in e-commerce systems. The approach is based on the combination of machine learning methods for demand prediction and stochastic inventory models for decision-making under uncertainty.

Within the study, an online retail transaction dataset was used to construct demand time series for individual products. A comprehensive data preprocessing procedure was performed, including data cleaning, aggregation, and feature engineering. Additional features capturing temporal patterns in demand, such as calendar variables and lagged values, were generated to improve forecasting performance.

Several machine learning models were developed and evaluated for demand forecasting at the SKU level. The results of the computational experiment demonstrate that ensemble methods are capable of capturing nonlinear relationships in sales data and provide higher forecasting accuracy compared to baseline models. In particular, the gradient boosting model showed the best performance among the considered approaches.

A key component of the proposed framework is the estimation of demand uncertainty based on forecasting errors. The analysis revealed significant variability in demand across different products, as well as the presence of extreme values associated with irregular demand patterns. To reduce the sensitivity of the uncertainty assessment of demand, the possible emissions were limited, showing its possible extreme spikes. Then the Newsvendor model was applied, based on the forecasts obtained, which showed that the optimal stock level depends not only on the expected demand, but also on the level of its uncertainty, and as a result, an insurance reserve is formed to compensate for possible fluctuations in demand. In addition, a budget constraint was introduced into the optimization model to reflect real-world financial limitations. The results show that unconstrained optimal solutions may significantly exceed available financial resources. The application of a proportional scaling procedure made it possible to obtain a feasible procurement plan that satisfies the budget constraint while preserving the relative structure of optimal decisions.

Thus, all research objectives formulated in the introduction have been successfully addressed. The study demonstrates that the integration of machine learning techniques with stochastic inventory optimization models provides an effective framework for supporting inventory management decisions in e-commerce. The proposed approach allows balancing demand uncertainty, service level requirements, and financial constraints, making it applicable to real-world retail environments.

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