# Demand Forecasting Models and Inventory Optimization Strategies in the Context of E-Commerce Promotional Scenarios

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**Abstract.** E-commerce promotions can lead to significant fluctuations in traffic and sales in a short period of time, which poses higher demands for demand forecasting and inventory management. This paper focuses on demand forecasting models and inventory optimization strategies in the context of e-commerce promotions, proposing a feasible systematic solution. The solution firstly separates the trend and seasonality of baseline demand using time series methods, and then quantifies elements such as promotional rules, price trajectories, coupon distribution, traffic allocation, and external events into features introduced into machine learning models, in order to capture short-term nonlinear disturbances and adjust the baseline accordingly. Based on the forecast outputs and uncertainties, it designs layered stock replenishment, regional multi-warehouse allocation, and real-time allocation rules to balance the risks of stockouts and inventory holding costs. The paper further discusses key points regarding feature engineering, data update cadence, and system deployment, including automated data pipelines, short-cycle retraining trigger mechanisms, and organizational support for operational and supply chain collaboration. This solution emphasizes methodology and implementation pathways, aiming to provide actionable references for platforms to enhance forecasting reliability and inventory decision-making efficiency during large-scale promotional periods.

**Keywords:** E-commerce; promotion; demand forecasting; inventory optimization.

## 1. Introduction

Driven by the tide of the digital economy, e-commerce has transformed from a traditional retail supplementary channel into an important force driving consumer growth. Particularly in China, the annual e-commerce promotion event like Singles' Day can generate tremendous consumer enthusiasm and create astonishing sales figures in a very short time. However, this concentrated demand explosion presents unprecedented challenges to enterprises' operational management systems, especially in supply chain management. The rapid surge in demand, changes in consumer behavior patterns, and cross-category sales correlation effects triggered by promotions render traditional operational decision-making models based on historical data no longer applicable. Therefore, effectively addressing the operational complexity in promotional scenarios has become a critical issue that e-commerce enterprises urgently need to resolve.

This study focuses on the integration and application of demand forecasting models and inventory optimization strategies in the context of e-commerce promotions. These two elements are core aspects of e-commerce operations, and the quality of decisions made in these areas directly impacts a company's service level, operational costs, and profitability. Although existing literature has extensively researched these areas, most studies tend to emphasize optimization from a single dimension and lack in-depth exploration of the synergistic relationship between the two. This research aims to bridge the gap between theory and practice by constructing a comprehensive framework that views demand forecasting and inventory optimization as an organic whole, providing e-commerce companies with more systematic and forward-looking solutions.

Previous research has laid a foundation for this study in multiple aspects. One study explored how optimizing inventory paths and pricing can enhance corporate profits within an omnichannel retail model, highlighting the interdependent effects of inventory and pricing decisions [1]. Another

study analyzed the strategies of omnichannel retail enterprises in distributing coupons online, indicating that high-value coupons can benefit offline channels [2]. In terms of demand forecasting, researchers have validated the effectiveness of deep learning frameworks for retail demand prediction, emphasizing the importance of integrating promotional rules as key features in forecasting models [3]. Additionally, one study established an inventory model that considers promotional efforts and memory effects, proposing an optimal replenishment strategy [4]. These studies generally agree that the demand uncertainty brought about by promotional activities is a core challenge in inventory management. Furthermore, a study focused on Alibaba indicated that integrating operational research algorithms related to demand forecasting, inventory management, and pricing can lead to cost savings of millions of dollars [5]. These studies provide significant theoretical and methodological support for this topic.

Based on a systematic review of the aforementioned literature, this paper proposes an integrated operational management strategy. This study views demand forecasting and inventory optimization as a closely related whole, aiming to provide new perspectives and methods for operational decision-making in the context of e-commerce promotional scenarios through an in-depth analysis of their collaborative mechanisms. The paper is divided into five chapters: the first chapter is the introduction, which elaborates on the research background, objectives, and significance, and reviews relevant literature; chapters two to four will provide a detailed analysis of the characteristics of e-commerce promotional activities, construct forecasting models, explore inventory optimization strategies, and discuss the technical and organizational support required for the implementation of these strategies; the fifth chapter concludes and looks ahead, summarizing the research findings and proposing future research directions.

## 2. Core Characteristics of E-Commerce Promotion Scenarios and Key Factors for Forecasting Models

### 2.1. Typical Characteristics of E-Commerce Promotion Scenarios

E-commerce promotions like Singles' Day usually led to a concentrated surge in demand within a short period, with single-day sales potentially reaching more than ten times the daily sales, putting tremendous pressure on the supply chain. During the promotional period, consumers' price sensitivity obviously increases, and impulsive buying and stockpiling behaviors become more common. Promotional methods such as discounts, coupons, bundling deals, and flash sales can change users' purchasing rhythm and decision-making. In addition, promotions often trigger cross-category linkages, where promotions for main products boost the sales of complementary products simultaneously. This makes it challenging to accurately predict the actual demand during the promotional period based solely on the historical sales of individual products, so forecasting models need to consider promotional rules and category correlations as important features [6].

Promotions pose a strong challenge to the supply system, and companies must make stocking decisions and respond to peak fulfillment demands within a limited preparation period. Warehouse and sorting capabilities often approach their limits during peak promotion times, with delivery delays and localized overstocking weakening fulfillment efficiency. Suppliers and upstream capacity are generally difficult to significantly increase in the short term, and emergency replenishments are constrained by production cycles and transportation timing. Therefore, replenishment and allocation strategies need to be planned in advance of promotions, reserving sufficient redundancy. Alibaba achieved cost savings during the promotional period by integrating demand forecasting, inventory management, price optimization, and recommendation systems, which indicates that closely coupling demand forecasting with supply-side scheduling can effectively alleviate the supply pressure brought about by promotions in practice [5].

### 2.2. Key Factors that Forecasting Models Should Consider

Building a predictive model for promotional scenarios needs to consider multiple influencing factors at the same time. Historical promotional activity data, especially the sales of the same products during previous promotional events like Singles' Day, is the most direct and crucial reference for predicting future demand. By analyzing historical data, businesses can identify sales patterns and seasonal characteristics of products during promotional periods. Second, the promotion rules need to be quantified, such as the type and depth of discounts, the scale of coupon distribution, the threshold for minimum purchases to receive discounts, and whether there are any limitations in terms of quantity or time. These rules can influence consumers' purchasing decisions in various ways. Third, product attributes and lifecycles have a vital moderating effect on promotional responses. Fast-moving consumer goods are more likely to be stockpiled during promotions, while durable goods tend to exhibit a more stable promotional elasticity. New products lack historical data and rely on market popularity, whereas classic products can refer to past trends. Fourth, external environmental variables should not be overlooked. The promotional intensity and strategies of competing products during the same period will directly affect the sales of this brand's products. The model needs to consider the actions of competitors and make dynamic adjustments. The macroeconomic environment, industry development trends, and changes in consumer preferences will all have a long-term impact on product demand. Moreover, unpredictable events such as weather, social news, and policies may severely affect commodity demand in a short period of time, so the model should possess a certain degree of robustness to cope with the shocks brought by sudden events. Systematically incorporating these factors into feature engineering helps to improve the stability and interpretability of promotion period forecasting [3,7].

## 3. Model Formulation

### 3.1. Overall Modeling Approach and Implementation Workflow

In order to respond to the rapid fluctuations in demand and various factors during promotional periods, adopting a hybrid modeling framework is both practical and robust. First of all, apply time series methods to identify and separate long-term trends, seasonal components, and cyclical elements to obtain the underlying demand. Subsequently, input promotional rules, price trends, coupon distribution, traffic allocation, and external events as exogenous variables into machine learning or lightweight deep learning models to study the nonlinear effects of these factors on short-term demand. Ultimately, by means of model integration or weighted fusion, the results of time series and machine learning corrections are combined to output point predictions and uncertainty intervals for use in inventory decision-making. It is necessary to automate the processes of data cleaning, feature construction, model training, and deployment, while also supporting rapid model updates during promotional periods [3,8].

Data quality matters. It is essential to adequately address missing values and outlier data to ensure the consistency of the time series. Many key features require hourly updates, such as the traffic and order speed for the current day. For data that is prone to delays, for example in-transit transportation volume, methods for compensation or delay modeling need to be designed. Once the model is deployed, monitoring should be in place to observe errors and bias direction in real-time, with the capability for automatic retraining or manual review in case of significant errors [3,7].

Experiments and testing should be closely aligned with real business operations. Use the past several promotions to test how the model performs under different promotion intensities and competition situations. Testing should not only consider statistical errors but also calculate the losses caused by stockouts and inventory holding costs, so that they can assess the model's actual contribution to the business. Then continuously adjust the model and safety stock parameters through testing.

### 3.2. Feature Engineering and Data Strategy

Feature engineering refers to the process of transforming business information into signals that models can utilize. Required features include historical sales lag, changes in price and discounts, the deployment of coupons, traffic and exposure statistics, existing inventory in warehouses, weather, as well as holidays. For new products, substitute signals such as pre-sales, reservations, and search trends should be utilized for launching. Organizing these features by hours and days enables the model to better reflect short-term changes [3,7].

The rhythm of data updates should match the promotion phase. Conduct in-depth historical feature engineering and test multiple scenarios before promotions. During promotions, perform rolling forecasts with an hourly granularity, and retrain in short cycles if necessary. After promotions, compare actual sales with forecast results and provide feedback on the causes of deviations to the features and model. This rhythm ensures that the model is both robust and can respond quickly to actual changes [3,8].

### 3.3. Key Modeling Points for Different Promotion Types

The overall promotional campaign requires prior forecasting of the platform's total traffic, which should then be allocated to various categories and stock-keeping units. This approach allows for consideration of competition among different categories and traffic distribution, thereby avoiding an isolated judgment of a single stock-keeping unit. In this regard, a hierarchical model can be utilized to connect the platform, categories, and products [6,9].

High-frequency forecasting is essential for popular individual items, focusing on peak intensity and out-of-stock times. It is indispensable to ensure that data pipelines and calculations can update at an hourly or even minute level, so that inventory and allocation decisions can keep pace with changes. A familiar approach is to combine short-window forecasting with simple bidding or queueing models to estimate trading rates within a limited time frame [10].

Since there is no historical data for new product launches, demand must be estimated based on pre-sales, reservations, and market response. After the launch, they need to closely monitor the situation within the first hour and the first day to quickly adjust replenishment plans, avoiding prolonged stockouts or excessive inventory buildup. Moreover, operations and suppliers must have efficient communication and execution channels [3].

### 3.4. Evaluation and Production Deployment Suggestions

When evaluating models, they should not just rely on MAE or RMSE but also incorporate business impact. It is recommended to convert stockout costs and holding costs into the same monetary unit and include them as part of the optimization objective. This allows them to directly observe the effect of model improvements on profit. During deployment, rollback and A/B testing mechanisms should be implemented. Monitoring should extend beyond error metrics to include business indicators such as order fulfillment rate and on-time delivery performance. If a decline in business metrics is detected due to the model, they should promptly revert to a stable version and investigate the cause [8].

At the engineering level, a reproducible modeling process and automated deployment should be implemented. This enables them to conduct multiple experiments rapidly before promotions, iterate quickly during promotions, and efficiently review results after campaigns to incorporate outcomes into the next optimization cycle.

## 4. Inventory Optimization Strategies Based on Demand Forecasts

### 4.1. Total Inventory Planning and Stratified Stocking

When determining total inventory quantity, use the median or average of the forecast as a baseline and then make adjustments based on prediction uncertainty and business goals. If user

experience and avoiding stockouts are prioritized, increase the safety stock level. If capital efficiency is prioritized, lower the safety stock level. A common practice is to manage products by tier. Increase inventory for important bestsellers, while using a more conservative inventory strategy for long-tail products, along with planning post-promotion inventory clearance [1,4].

Decision-making should also take the supplier's minimum order quantity and replenishment cycle into account. Don't push inventory too low just for the sake of reducing stock. Otherwise, it might lead to widespread shortages in the next promotion. Actually, they need to find a balance between the costs of stocking and the costs of stockouts.

### 4.2. Inventory Allocation and Multi-Warehouse Coordination

When distributing inventory to different warehouses, arrangements should be made based on the demand and delivery timeliness in each region. Fast-moving products that need to arrive quickly should be placed in front warehouses, while bulk replenishment and low-frequency demand items should be stored in the central warehouse. Pre-sales and historical regional distribution can serve as a basis for allocating inventory before promotions, which can reduce the need for temporary transfers during promotional periods [1,2].

The inventory information for online and offline should be interconnected, so that when a particular warehouse is out of stock, nearby stores or third-party warehouses can be prioritized for replenishment. Connecting the inventory requires a unified inventory view and clear prioritization rules to avoid duplication or conflicts.

### 4.3. Real-Time Transfers and Replenishment during Promotions

During the promotional period, it is essential to establish simple and clear warning rules. Whenever the inventory of a certain stock-keeping unit in a warehouse falls below the threshold, it should trigger a transfer or replenishment. The transfer decision needs to consider the costs of allocation as well as the opportunity costs of stockouts, prioritizing stock-keeping units that significantly impact platform traffic and repurchase rates. The system should automatically generate transfer instructions and coordinate with the delivery providers for prioritized execution to minimize replenishment time [4,10].

In practice, the system can integrate the rule engine and the optimization program for use. The rule engine addresses the necessary priorities and constraints, while the optimization program calculates the optimal allocation amount under cost and service level constraints. This approach guarantees both real-time responsiveness and improved decision-making quality [4,10].

### 4.4. Post-Promotion Clearance and Post-Mortem

Handle the remaining inventory as soon as possible after the promotion ends. Discounts and bundled promotions should first be applied to flexible products, and if needed, some inventory can be transferred to other channels or subjected to secondary promotions. The combination of pricing and promotions should consider the brand's impact, avoiding short-term clearance efforts that could damage long-term customer trust [6].

During the review process, prediction errors should be broken down by specific stock- keeping units and time point to determine whether the issue stems from the model or operational execution. The findings should be translated into concrete improvement measures, such as updating features, adjusting model parameters, or optimizing the replenishment process. These improvements must be validated before the next promotion to ensure effectiveness [3].

### 4.5. Organizational and Technical Enablers

To implement the above strategies, collaboration among data platforms, computing capabilities, and organizational processes is indispensable. It is necessary to establish a reliable data pipeline to guarantee the timely availability of sales, inventory, and promotional event data. Additionally, an automated model deployment and monitoring system should be set up to support rapid iteration

during promotional periods. The supply chain and operations teams must work closely with the data team to practice replenishment and allocation processes in advance, ensuring swift execution during promotions [5,10].

## 5. Conclusion

This article proposes a systematic approach and implementation recommendations for demand forecasting and inventory optimization in the context of e-commerce promotional scenarios. It constructs a hybrid forecasting framework that is based on time series decomposition and driven by promotional features and external variables through machine learning corrections. The article emphasizes that the forecasting output should include point estimates and uncertainty intervals to support inventory decisions with risk perception. Based on forecasts and uncertainty, it suggests layered stocking, regional multi-warehouse allocation, and real-time allocation rules to reduce stockout risks while controlling inventory holding costs. Furthermore, the article discusses feature engineering, data update rhythms, model monitoring and automation retraining trigger mechanisms, as well as key points for collaboration with supply chain and operations teams, thereby providing organizational support for the implementation of the model in a production environment.

The contributions of this article are primarily reflected in the integration of methodology and implementation pathways, providing actionable references for e-commerce platforms to enhance the reliability of forecasts and the efficiency of inventory decision-making during large promotional events. Future research can be conducted in three aspects: first, by expanding and refining the feature system, particularly enhancing the correlation between products and the expression of dynamic competitive signals; second, by exploring real-time adaptive learning algorithms and more advanced model structures to improve responsiveness during extreme fluctuations; and third, by extending the methods to multi-platform or omnichannel scenarios to tackle the complexities of cross-channel traffic allocation and inventory coordination. Additionally, it is essential to validate the performance of the methods through practical cases or production deployment and to collect runtime data to support continuous optimization.

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