mathematics

MDPI

Article

Supply Chain Inventory Management from the Perspective of "Cloud Supply Chain"—A Data Driven Approach

Yue Tan [1], Liyi Gu [1], Senyu Xu [2,*] and Mingchao Li [2]

1 College of Business, Southern University of Science and Technology, Shenzhen 518055, China; 12133011@mail.sustech.edu.cn (Y.T.); guly@sustech.edu.cn (L.G.)
2 School of Business, Shenzhen Institute of Technology, Shenzhen 518000, China; limingchao@zcst.edu.cn
* Correspondence: xusenyu@ssti.net.cn; Tel.: +86-1552-117-3263

Abstract: This study systematically investigates the pivotal role of inventory management within the framework of "cloud supply chain" operations, emphasizing the efficacy of leveraging machine learning methodologies for inventory allocation with the dual objectives of cost reduction and heightened customer satisfaction. Employing a rigorous data-driven approach, the research endeavors to address inventory allocation challenges inherent in the complex dynamics of a "cloud supply chain" through the implementation of a two-stage model. Initially, machine learning is harnessed for demand forecasting, subsequently refined through the empirical distribution of forecast errors, culminating in the optimization of inventory allocation across various service levels.The empirical evaluation draws upon data derived from a reputable home appliance logistics company in China, revealing that, under conditions of ample data, the application of data-driven methods for inventory allocation surpasses the performance of traditional methods across diverse supply chain structures. Specifically, there is an improvement in accuracy by approximately 13% in an independent structure and about 16% in a dependent structure. This study transcends the constraints associated with examining a singular node, adopting an innovative research perspective that intricately explores the interplay among multiple nodes while elucidating the nuanced considerations germane to supply chain structure. Furthermore, it underscores the methodological significance of relying on extensive, large-scale data. The investigation brings to light the substantial impact of supply chain structure on safety stock allocation. In the context of a market characterized by highly uncertain demand, the strategic adaptation of the supply chain structure emerges as a proactive measure to avert potential disruptions in the supply chain.

Keywords: cloud supply chain; machine learning; inventory optimization

MSC: 90B06

check for updates

Citation: Tan, Y.; Gu, L.; Xu, S.; Li, M. Supply Chain Inventory Management from the Perspective of "Cloud Supply Chain"—A Data Driven Approach. *Mathematics* **2024**, *12*, 573. https://doi.org/10.3390/math12040573

Academic Editor: Andrea Scozzari

Received: 10 January 2024
Revised: 31 January 2024
Accepted: 8 February 2024
Published: 14 February 2024

1. Introduction

With the continuous evolution of e-commerce, the market demand is burgeoning, further propelled by the advancements in Industry 4.0 and digital technologies. This progress has given rise to new business models, including those based on cloud platforms and intelligent manufacturing organizations. The broad concept of a cloud supply chain offers a novel perspective on operational management. It is a business model that leverages a cloud-supported network based on certain third-party physical and digital assets for designing and managing supply chain networks [1]. Currently, an increasing number of major corporations, such as Amazon, JD.com, and Cainiao Logistics, are adopting this model. However, despite its practical application in the industry, there is a paucity of research specifically addressing this new paradigm.

This paper aims to investigate inventory management issues within the context of the cloud supply chain. The cloud supply chain heavily relies on the digitized operations of Industry 4.0, with big data playing a crucial role in decision-making. In the realm of inventory decision-making, data-driven methodologies hold the potential for achieving superior outcomes. Although there has been a continuous stream of research in the field of inventory management in recent years, literature specifically focused on data-driven inventory decision methods has also accumulated. However, an examination of existing literature reveals that some studies merely engage in pure demand forecasting, using the predicted demand as the basis for inventory decision-making without correcting for forecast errors. On the optimization front, much of the research remains confined to the optimization of inventory for individual nodes, overlooking the potential impact of other nodes and the supply chain structure on inventory allocation.

The operational management of a cloud supply chain necessitates a holistic consideration of issues from a supply chain perspective. The intricate structure of this system requires concurrent evaluation of the collaborative effects among multiple nodes and the overarching structure of the supply chain. However, existing literature displays a significant gap in research concerning this particular aspect.This study endeavors to fill these identified research gaps and contribute to the expanding literature on inventory management within the context of the cloud supply chain. Through a thorough exploration of data-driven inventory decision methodologies, we aim to enhance the understanding of how the unique characteristics of the cloud supply chain influence inventory management practices.

To address the inventory allocation challenges within the cloud supply chain using a data-driven approach, this paper introduces a two-stage model, particularly adopting the "demand forecasting-inventory optimization" framework. In comparison to ensemble methods, the intuitiveness and higher interpretability of this approach are advantageous for practical applications. The selection of a multiple linear regression model over a neural network aligns with the belief that fundamental machine learning models are more suitable for our problem, supported by practical examples. This study refrains from assuming demand distribution, mitigating potential decision biases and their consequential impacts. In the inventory optimization phase, the research delves into the allocation issues under two supply chain structures–one allowing same-level replenishment and the other prohibiting it.

Leveraging the newsvendor model as the foundational model, this study extends its application, drawing inspiration from the data-driven newsvendor model [2] and expanding upon their work. Different models are provided for two supply chain networks with distinct structures, offering applicable solutions for these models. The validation of the proposed model is conducted using real data from a Chinese logistics company operating within the cloud supply chain from 2018 to 2019. This company provides end-to-end solutions for transportation, warehousing, distribution, delivery, installation, and after-sales service for household appliances, serving entities throughout the supply chain process. The methodology presented in this paper receives positive feedback from real-world data, affirming its utility in practical decision-making scenarios.

In comparison to previous research, this study introduces a novel perspective by considering inventory issues in supply chain management from the vantage point of the cloud supply chain. Utilizing a data-driven approach, we propose a practical inventory decision-making method that accounts for the interactive relationships among multiple nodes and the structure of the supply chain. This method dynamically adjusts inventory decisions based on different service levels, addressing a research gap in this domain.

In summary, the primary contributions of this paper include the following:

1. The study offers a data-driven inventory decision-making method from the perspective of the cloud supply chain.
2. Emphasis is placed on the superior performance of data-driven inventory decision solutions in cases of sufficient data volume.
3. The study highlights that, in certain scenarios, the predictive performance of deep learning models may not surpass that of machine learning models.
4. The study discusses multi-node inventory decisions under different cloud supply chain structures, elucidating the impact of supply chain structure on inventory decisions.

However, it is essential to acknowledge the limitations of the proposed approach. Firstly, in situations where data volume is insufficient, the methods employed in this study may not yield optimal results. Secondly, for specific industries characterized by fixed product demand and products prone to supply chain interruptions, the model proposed in this study may no longer be applicable. Consequently, in subsequent models, certain restrictions will be imposed to ensure the model's applicability within a reasonable scope.

2. Relate Literature

The advent of the digital era, marked by Industry 4.0 and advancements in digital technology, has profoundly reshaped traditional supply chain management strategies. Within these transformative shifts, the emergence of the cloud supply chain has garnered considerable attention in recent years. Leukel et al. [3] has adopted the basic idea of cloud computing and proposed to represent the supply chain as a set of service offerings and to present customer needs as service requests from the system service concept. Surucu et al. [4] systematically elucidated the pivotal role of digital transformation in enhancing supply chain information sharing and processing. They revealed the dynamic capabilities, driving factors, and impediments associated with digital information sharing based on blockchain and cloud platforms. The study emphasized the methods and theories applied in its supply chain applications. This research provides robust theoretical support for investigating inventory management issues in cloud supply chains, underscoring the significance of digital information sharing and highlighting the reliability of data-driven approaches within cloud supply chain contexts. Chauhan et al. [5] deliberated on the sustainable development potential inherent in intelligent supply chains. They underscored the imperative of intelligent supply chain management, placing particular emphasis on the future elements of sustainability. The discussion highlighted the need to consider environmental, social, and economic factors in intelligent supply chain management to achieve sustainable development. Ivanov et al. [1] through the analysis of practical cases, have deduced some common features of the cloud supply chain, constructing a comprehensive model for this paradigm. Simultaneously, they have identified future research directions for the cloud supply chain. Inventory management within the context of the cloud supply chain stands out as a crucial area of contemporary supply chain research. The integration of cloud technology, data analytics, and digital platforms heralds a new era in supply chain operations, presenting both opportunities and challenges for effective inventory management. This chapter will conduct a retrospective review of previous literature from three dimensions, elucidating the research gaps and contributions of this study compared to prior research.

Table 1 provides a visual representation of the literature related to the developed model. It also highlights succinct research gaps identified in the relevant studies.

2.1. Demand Forcasting

In the realm of inventory management within the cloud supply chain, a pivotal challenge lies in the necessity for precise demand forecasting. Through the integration of abundant real-time data and the incorporation of machine learning algorithms, the cloud supply chain holds the potential to significantly enhance the accuracy of demand forecasting.

The history of demand forecasting dates back several decades. In the previous century, Silver et al. [6] highlighted the normalization of demand distribution in mainstream inventory management models, such as assuming demand follows a normal or gamma distribution. Random algorithms were then employed to determine the required inventory levels, and this approach continues to hold a prominent position in inventory management. Also, Eppen et al. [7] addressed the deviations between forecasted and actual demand. They considered exponential smoothing and probability models, using the variance of forecast errors in lead time to establish safety stock levels. Drawing inspiration from this research, we incorporated considerations of deviations between forecasted and actual demand in our model construction to mitigate decision biases.Furthermore, Kleywegt et al. [8] employed a sample average approximation method, replacing the assumption of demand distribution with empirical data. They discussed the convergence speed, stopping rules, and computational complexity of this approach.Wang et al. [9] introduced an error compensation mechanism for demand forecasting and assessed the necessity of compensation using individual and moving range (I-MR) control charts. This evaluation aimed to leverage predictive models in addressing current bottleneck issues. These work provided valuable insights for our study. In our model, an empirical distribution will be utilized to adjust forecast errors.

The advancement of machine learning technologies has provided additional tools for demand forecasting. Carbonneau et al. [10] discussed the application of machine learning techniques in supply chain demand forecasting, specifically investigating the suitability of Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and Support Vector Machines (SVM) for predicting distorted demand at the end of the supply chain. The study compared these methods with traditional time series models, revealing that machine learning technologies generally exhibit better predictive performance. Kilimci et al. [11] improved demand forecasting models using machine learning and proposed comprehensive strategies for supply chain decision-making. Kharfan et al. [12] employed machine learning to forecast new seasonal products, demonstrating the effectiveness of data-driven approaches in inventory management and providing support for this study.

Villegas et al. [13] introduced a novel model selection approach based on SVM for prediction. This method offered a set of candidate models rather than considering individual criteria, resulting in failure when faced with high demand fluctuations. Allowing model changes when the fit is high reduced technical risks when handling large datasets. Similarly, in demand forecasting, this study adopted a multi-criteria approach, presenting different predictive models to further reduce forecasting biases.

The application of deep learning methods in cloud supply chain is also within our scope of consideration, showcasing promising results in various studies. For instance, Bandara et al. [14] unified cross-sequence information in e-commerce using Long Short-Term Memory (LSTM). Abbasimehr et al. [15] proposed a demand forecasting method based on multi-layer LSTM, demonstrating its strong ability to capture nonlinear patterns in time series data and outperforming other standard techniques empirically. Falatouri et al. [16] trained and evaluated Seasonal Autoregressive Integrated Moving Average (SARIMA) and LSTM on over 37 months of actual retail data from an Austrian retailer. Both models yielded reasonable to good results, indicating that LSTM performs better for products with stable demand, while SARIMA performs better for products with seasonality. These studies highlight the efficacy of neural networks in demand forecasting. However, neural networks have certain drawbacks, including high requirements for data scale and paradigm, as well as a lack of interpretability. Although this study considers neural networks, when machine learning methods exhibit similar accuracy to neural networks, it is argued that machine learning methods with higher interpretability should be preferred.

2.2. Inventory Optimization

Due to its dynamic and interconnected nature, cloud supply chains introduce unique complexities to inventory management. Unlike traditional supply chain models, cloud supply chains rely on real-time data sharing and collaboration across multiple nodes. This interconnectivity necessitates a reevaluation of conventional inventory management strategies to adapt to the nuanced differences in the cloud environment. Simultaneously, the interconnected nodes and dynamic characteristics of cloud supply chains require innovative approaches to balance inventory levels, minimize stockouts, and optimize order fulfillment processes. Therefore, in cloud supply chains, it is crucial to consider the mutual influence among nodes, adjusting inventory strategies based on demand forecasts to optimize inventory management.

Research on inventory optimization under uncertain demand is a classic problem, and scholars have approached this issue from various perspectives. Carlson et al. [17] addressed scenarios involving stochastic demand, determining safety stock for each component in the product structure. They proposed a heuristic upper-bound solution considering a systematic production plan. Datta et al. [18] investigated the dynamic pricing of the newsvendor model under price-sensitive stochastic demand, incorporating geometric Brownian motion. They employed the Black-Scholes equation for solving this, presenting a highly meaningful contribution. This work introduced novel perspectives into cost calculations within dynamic systems, addressing a gap in the existing literature. Similarly, our study utilizes an extended newsvendor model to contemplate optimal inventory decisions within dynamic systems. The methodology proposed in this paper offers a fresh direction for subsequent research. Bahroun et al. [19] used Monte Carlo methods to determine the dynamic safety stock for cyclic production plans under non-stationary demand patterns. These studies are significant, highlighting the importance of optimization under stochastic demand conditions.

Buffa and Frank [20] , combining demand forecasting models, presented a goal programming problem to determine safety stock in a multi-product environment. It is acknowledged that generating accurate demand forecasts remains a considerable challenge, particularly without considering exogenous factors in the forecasting process. They incorporated a demand regression function into a news vendor model, creating a data-driven safety stock framework. This article is interesting as it integrates external factors influencing demand estimation, such as weather and seasonality, into the prediction, proposing a comprehensive data-driven framework. Inspired by this research, our study incorporates factors like weather and seasonality into the forecasting model to enhance prediction accuracy.

Furthermore, Huber et al. [2] introduced a solution based on machine learning and quantile regression that does not assume specific demand distributions, demonstrating significantly improved performance with sufficiently large datasets. Oroojlooyjadid et al. [21] integrated neural networks into a newsvendor model, comparing this integrated model with other methods and finding superior performance in specific environments. While these studies inspired our research, they primarily focused on optimizing inventory at individual nodes, neglecting the interaction among nodes in the supply chain structure. In our study, we consider the supply chain structure and dynamic market changes to align with the requirements of cloud supply chains.

2.3. Supply Chain Structure

Certainly, the impact of cloud supply chain structures on inventory allocation is an additional dimension that warrants exploration. For instance, Chinelloren et al. [22] employed simulation techniques to optimize multi-tier supply chains; Jiang et al. [23] established a cost model for ordering and supplying distributed material warehouses, employing an improved Genetic Algorithm-Simulated Annealing (IGA-SA) to address the optimization problem of distributed material warehouses; Hammler et al. [24] assessed various optimization algorithms to determine the applicability of deep reinforcement learning in multi-level inventory optimization frameworks, leading to the development of fully dynamic reordering strategies. Kumar et al. [25] considered a multi-warehouse model, utilizing the Rain Optimization Algorithm to design optimal replenishment strategies and evaluating the model using data from footwear inventory management. Pirhooshyaran et al. [26] proposed a framework that utilizes deep neural networks to optimize inventory decisions in complex multi-tier supply chains. Li et al. [27] discussed the optimization of product inventory distribution in a large-scale logistics network comprising up to hundreds of distribution center warehouses. The authors constructed a scenario-based distributed robust optimization model, transforming the original problem into a large-scale linear programming problem for rapid resolution, thereby enhancing computational efficiency.

While these studies considered the interconnectivity among multiple nodes and provided numerous intriguing solutions, there is a paucity of literature incorporating demand forecasting into the models. Moreover, the dynamic changes in inventory management resulting from different configurations in cloud supply chains, such as allowing or restricting replenishment between nodes, have not been adequately addressed. In this study, we incorporate these factors into consideration and propose a feasible solution, intending to make a modest contribution to research in this area.

2.4. Research Gap

While existing literature extensively explores the impact of cloud technology on supply chain management, a significant research gap remains in the specific domain of cloud-based inventory management within the supply chain. The current body of knowledge primarily focuses on the macro-level, highlighting the general advantages and challenges brought about by cloud computing in supply chain environments. However, there is a lack of in-depth research into the nuanced differences in inventory control and optimization specifically tailored to cloud-based supply chain environments. This paper addresses this gap by starting from specific models and delving into inventory management methods in cloud supply chain environments at a micro-level, thus filling this void.

Existing research on inventory management provides broad insights into cloud supply chain inventory management and offers excellent inspiration for implementing specific aspects. However, most articles do not integrate demand forecasting accuracy and dynamic optimization of inventory strategies, often focusing solely on either forecasting or optimization. This paper delves into both aspects, providing concrete implementation plans and making a minor contribution to this area of research.

Moreover, the existing literature on data-driven inventory management predominantly overlooks the structure of the supply chain or remains confined to a single node. Another portion of the research focuses solely on a single supply chain structure. However, the impact of cloud supply chain structure on inventory allocation is another dimension that requires exploration; different configurations in cloud supply chains (such as allowing or restricting replenishment between nodes) lead to dynamic changes in inventory management. This paper provides distinct inventory management methods for two supply chain configurations, addressing a gap in this area of research.

Table 1. Contribution of previous authors.

Author	Demand Forecasting Methods	Optimization Methods	Supply Chain Structure Type	Replenishment
Buffa and Frank (1977) [20]	Linear regression	Goal Programming	Single Node	
Carlson et al. (1986) [17]		Heuristic upper-bound algorithm		
Eppen et al. (1988) [7]	Exponential smoothing and probability models			
Silver et al. (1998) [6]	Assuming demand distribution			
Kleywegt et al. (2002) [8]	Sample average approximation			
Carbonneau et al. (2008) [10]	ANN; RNN; SVM			
Villegas et al. (2018) [13]	SVM			
Huber et al. (2019) [2]	Machine learning	Quantile regression	Single Node	
Kilimci et al. (2019) [11]	Machine learning			
Bandara et al. (2019) [14]	LSTM			
Bahroun et al. (2019) [19]	Assuming normal distribution	Monte Carlo simulation	Single Node	
Abbasimehr et al. (2020) [15]	Multi-layer LSTM Networks			
Oroojlooyjadid et al. (2020) [21]	Deep learning	Neural network integration	Single Node	
Chinello et al. (2020) [22]		Simulation	Multi-echelon supply chain	
Jiang et al. (2020) [23]	Assuming normal distribution	Genetic Algorithm-Simulated Annealing (IGA-SA)	Multiple Nodes	
Pirhooshyaran et al. (2020) [26]		Deep neural networks	Multi-echelon supply chains	
Kumar et al. (2021) [25]		Rain Optimization Algorithm	Multiple Nodes	
Li et al. (2021) [27]	Assuming demand distribution	Robust optimization	Multiple Nodes	
Kharfan et al. (2021) [12]	Machine learning			
Ivanov et al. (2022) [1]				Introducing a notion of cloud supply chain
Falatouri et al. (2022) [16]	SARIMA; LSTM			
Wang et al. (2022) [9]	Hybrid LSTM-ARMA Demand-Forecasting Model			
Hammler et al. (2022) [24]		Deep Reinforcement Learning	Multi-echelon supply chain	
Chauhan et al. (2023) [5]				Sustainable development in smart supply chains
Surucu et al. (2024) [4]				Application of digital information sharing in supply chain
Datta et al. (2024) [18]		Geometric Brownian motion		
This study	Machine learning	Quantile regression; PSO algorithm	Multi-echelon supply chains(two types)	

3. Methodology

3.1. Problem Description

This study examine a prominent logistics company operating within the framework of the "cloud supply chain", as illustrated in Figure 1. Initially, the manufacturer directly dispatches products to the logistics company, bypassing the retailer on the platform. Subsequently, when the platform receives an order request from a customer, it forwards the order to the logistics company, which then processes the order. Upon dispatch, the goods are readied and sent directly to the customer. Throughout this entire process, the platform remains uninvolved in the logistics operations and instead outsources the complete supply chain.

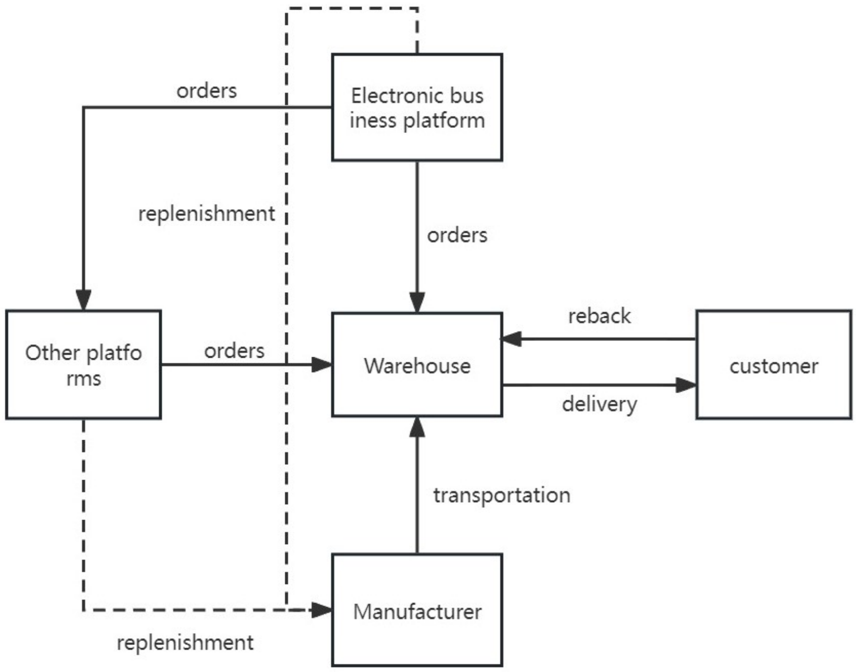

Figure 1. Distribution process in cloud supply chain model.

In this model, the warehouse is not singular but rather constitutes a distributed warehouse comprising multiple facilities to cover the customer area adequately. The configuration of safety stock in this model cannot be confined to a single warehouse; instead, it necessitates considering the inventory arrangement across multiple warehouses simultaneously. Inadequate safety stock may result in insufficient warehouse inventory, leading to extended logistics times and diminished customer satisfaction. Conversely, excessive stock may lead to inventory backlogs, incurring additional inventory costs.

In the actual production process, specific market demand for each warehouse is unknown. However, historical information and data acquired from external sources, such as past order records, warehouse details, temperature information, and external sources' discount information, are available. Leveraging this information aids in making informed decisions.

In the following model discussion, this study assumes the following: (1) Demand is stochastic; (2) Products undergo various stages, including production, warehousing, and transportation, and can be delivered within specified timeframes; (3) There is no physical loss of products during warehousing and transportation. These assumptions aim to streamline the model configuration and delineate the applicable scope of the proposed model.

In the subsequent section of this chapter, This study will delineate the methodologies employed, as illustrated in Figure 2. These methodologies encompass demand forecasting techniques, inventory optimization methods within a configuration that prohibits cross-replenishment among peers (independent replenishment inventory optimization method), and inventory optimization methods within a configuration that permits cross-replenishment among entities at the same hierarchical level (relying on replenishment inventory optimization methods). Ultimately, we propose solutions for inventory optimization models operating under distinct structural constraints.

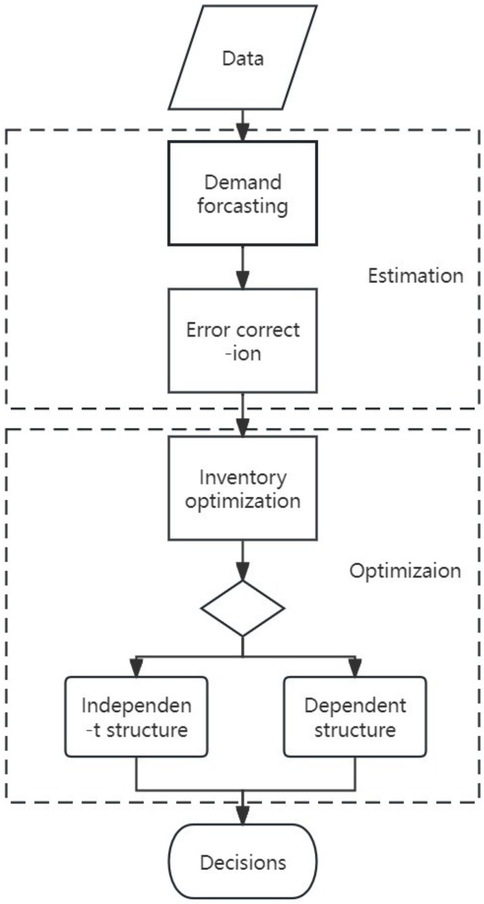

Figure 2. Methodology process in cloud supply chain model.

3.2. Demand Estimation

In many instances, the selection of a suitable predictive model holds paramount significance, contingent upon factors such as the data source, data volume, and data characteristics. Employing data-driven methodologies for prediction involves a judicious, fact-driven choice. Within the scope of this paper, we opt for the utilization of multiple linear regression, a machine learning method, as the primary predictive approach based on the available data. We undertake a comparative analysis with alternative methods to substantiate this choice.

Multiple linear regression models, as a statistical method, are frequently employed to establish a linear relationship involving multiple independent variables and a single dependent variable. This method assumes a specific linear relationship between the independent and dependent variables, utilizing multiple linear functions to articulate this connection. In the context of multiple linear regression, model parameters can be estimated by minimizing the sum of squared residuals, where residuals represent the disparities between observed and predicted values. This process allows for the straightforward establishment of the relationship between parameters and data characteristics, which can be expressed as:

$$min||Y - X\theta||, \tag{1}$$

where X represents the input features, Y represents the actual output, and θ represents the parameters that need to be learned. The solution to this problem is simple, and we can easily obtain the optimal solution for the parameters:

$$\theta = (X^T X)^{-1} X^T Y. \tag{2}$$

In this study, particular emphasis is placed on scrutinizing the disparities between the model's predictive outcomes and the actual results. It is acknowledged that all forecasting models must exhibit a degree of generalization to forestall overfitting, particularly in markets characterized by highly uncertain demand. In such contexts, forecasting models often capture demand trends but struggle to provide precise quantity estimates. While exploring the distribution of errors in traditional safety stock optimization is a valid research avenue, the conventional approach involves making initial assumptions about the error distribution, typically assuming a normal distribution. Subsequently, an optimization model is constructed based on these assumptions. While this traditional method can address general scenarios and yield optimal solutions if the assumed distribution holds true, accurately pinpointing the actual error distribution proves challenging in practical production settings. The true error distribution may exhibit temporal variations, posing additional complexities. To circumvent these challenges, our approach employs empirical distribution as a substitute for assuming the error distribution. This strategy effectively mitigates assumption errors and, over time, aligns the empirical distribution more closely with the true distribution as additional data becomes available. We assume that the historical errors are ϵ_1, ϵ_2, ..., ϵ_n, then the empirical error distribution can be expressed as:

$$\overline{F}(p) = \frac{1}{n} \sum_{i=1}^{n} I(\epsilon_i \leq p), \tag{3}$$

where $\overline{F}(p)$ represents the empirical error distribution, $I(x)$ is an indicative function, assuming that the full set is R, for any set $A \subset R$, when $x \in A$ take 1, when $x \notin A$ take 0. We use this method to characterize the error distribution, and correct the demand forecast through the error distribution to prepare for the next part.

3.3. Independent Structure Inventory Optimization

This study initially explores a two-level supply chain structure. In this arrangement, the primary tier comprises a Regional Distribution Center (RDC), tasked with transporting goods to the subsequent tier, known as the Local Transshipment Center (LTC). The second tier encompasses a total of nLTCs, as illustrated in Figure 3.

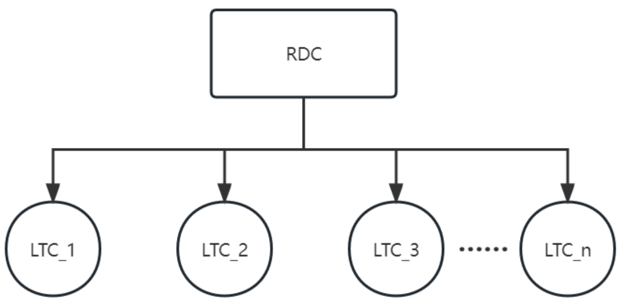

Figure 3. Two-level independent replenishment structure.

In this model, the warehouses at each level operate independently, without mutual replenishment between them. Specifically, when one of the LTCs depletes its stock, it can only request replenishment from the higher-level RDC, even if other LTCs still have stock. Similarly, when the RDC exhausts its inventory, it must replenish goods to the higher-level warehouse. Therefore, each LTC's ordering decision is based on its individual optimal ordering strategy. Huber et al. [2] also adopted a data-driven approach in their article to construct the newsvendor model, where the optimal inventory decision for the single-node model can be expressed as:

$$q^* = d_f + inf\left\{p : \overline{F}(p) \geq \frac{c_l}{c_l + c_h}\right\}, \tag{4}$$

where $F(p)$ represents the demand distribution, c_l represents the unit shortage cost, c_h represents the unit inventory cost, d_f represents the forecast demand, and $\overline{F}(p)$ represents the use of empirical error distribution.

Assuming the optimal safety stock for each LTC is denoted as q_i^*, and the total demand of RDC is represented by D_R. For the RDC, its demand originates from the downstream LTC. Given that each downstream LTC optimally determines its safety stock, it follows that each LTC will transmit its optimal order request to the RDC based on its own optimal safety stock, resulting in the formulation of the demand distribution for the RDC as follows:

$$F_R = \sum_{i=1}^{n} q_i^* + \overline{F}_R(p). \tag{5}$$

where $\overline{F}_R(p)$ denotes the historical empirical distribution of replenishment from the RDC forecast of total downstream demand versus actual downstream demand with a random variable greater than 0. It is unlikely that the RDC will have negative replenishment.

For each LTC, we have acquired the forecasted demand and its empirical error distribution through the forecasting model. Consequently, the demand distribution for each LTC can be formulated as follows:

$$F_i(p) = d_{f_i} + \overline{F}_i(p). \tag{6}$$

where d_{f_i} denotes the forecasted demand for the ith LTC obtained using the data-driven approach, and $\overline{F}_i(p)$ denotes the empirical error distribution between the actual and forecasted demand for the *i*th LTC, which differs from $\overline{F}_R(p)$ in that the random variable of the distribution differs from the historical experience of replenishment of RDCs, and the error may be positive or negative.

For the entire supply chain, our objective is to minimize the overall cost. Therefore, this problem can be expressed as an optimization problem:

$$\begin{aligned} min \sum_{i=1}^{n} \mathbb{E}[c_l^i(F_i(p) - q_i)^+ + c_h^i(q_i - F_i(p))^+] + \\ \mathbb{E}[c_l^R(F_R(p) - q_R)^+ + c_h^R(q_R - F_R(p))^+]. \end{aligned} \tag{7}$$

where c_l^i, c_h^i denote the unit shortage cost and unit inventory cost of the *i*th LTC, and c_l^R, c_h^R denote the unit shortage cost and unit inventory cost of the RDC, respectively. In addressing this optimization problem within the independent model, each LTC, being independent, will autonomously make the most optimal inventory decision. As for the RDC, it is aware of the optimal inventory decisions of each LTC, and the demand distribution of the RDC is predetermined. Consequently, the RDC is treated as a single-node scenario, enabling it to make the most advantageous decision for itself. Therefore, the optimal solution for the RDC and each LTC can be formulated as:

$$q_i^* = d_{f_i} + inf\left\{p : \overline{F}_i(p) \geq \frac{c_l^i}{c_l^i + c_h^i}\right\}, \tag{8}$$

$$q_R^* = \sum_{i=1}^{n} q_i^* + inf\left\{p : \overline{F}_R(p) \geq \frac{c_l^R}{c_l^R + c_h^R}\right\}, \tag{9}$$

where d_{f_i} represents the predicted demand of the ith LTC, c_l^i, c_h^i represent the shortage cost and inventory cost of the ith LTC respectively, c_l^R, c_h^R represent the shortage cost and forecast cost of RDC respectively. The comprehension of this solution is intuitive. Each LTC independently makes its optimal decision, and for its parent RDC, it only needs to be aware of the optimal decisions made by each downstream LTC to determine its own optimal decision. Thus, in this network of independent warehouses that cannot replenish each other, the optimal inventory strategy entails each warehouse formulating its individual optimal inventory strategy.

3.4. Dependent Structure Inventory Optimization

This study will elaborate on the scenario that permits mutual replenishment of goods between entities at the same hierarchical levels. In this configuration, the top tier comprises a regional distribution center (RDC), responsible for delivering goods to the lower-tier local transfer centers (LTCs), constituting the second level with n LTCs. The distinctive feature is that this structure facilitates LTCs to replenish each other's goods, as depicted in Figure 4.

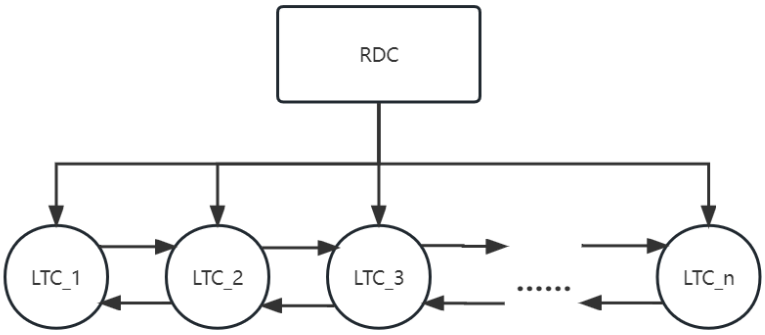

Figure 4. Two-level dependent replenishment structure.

In this model, a decision must be made when an LTC faces stockouts. It can either directly send a replenishment request to the upstream warehouse or request replenishment from a same-level warehouse that has available stock. In this scenario, each LTC is no longer considered an independent entity, introducing complexity to the entire model.

Suppose we know that the optimal decision of each LTC is q_i^*, then for RDC, its optimal decision can be expressed as:

$$q_R^* = \sum_{i=1}^{n} q_i^* + inf\left\{ p : \overline{F}_R(p) \geq \frac{c_l^R}{c_l^R + c_h^R} \right\}. \tag{10}$$

The problem is reformulated to minimize the total cost incurred by all LTCs while permitting replenishment. We assume that each LTC incurs a fixed transfer cost, which is linearly correlated with the average distance between itself and the other LTCs within the network. This assumption is justifiable, given the strong linear relationship between transfer costs and distance in practical scenarios. Employing the average distance to ascertain the transshipment cost of LTCs is deemed feasible, particularly when numerous transshipments are required over an extended period. The problem is then mathematically expressed as a constrained objective optimization problem:

$$min \sum_{i=1}^{n} \mathbb{E}\Big[(q_i - F_i(p) - S_i)^+ c_h^i + \lambda_i (F_i(p) - q_i)^+ c_t^i + (1 - \lambda_i)(F_i(p) - q_i)^+ c_l^i\Big], \tag{11}$$

$$\text{s.t:} \quad \sum_{i=1}^{n} \lambda_i (F_i(p) - q_i)^+ \leq \sum_{i=1}^{n} (q_i - F_i(p))^+, \tag{12}$$

$$0 \leq \lambda_i \leq 1, \tag{13}$$

$$q_i \geq 0. \tag{14}$$

where $F_i(p)$ represents the demand distribution obtained using a data-driven approach. c_t^i represents the transfer cost generated by scheduling between warehouses of the same level. q_i represents the safety stock of each LTC. S_i represents the quantity expected to be used for replenishment by other LTCs, and this data can obtain the average value or its empirical distribution through historical data. λ_i represents the proportion used for scheduling from other warehouses in the decision. The main problem is to minimize the sum of the costs of all LTCs. The first term represents the inventory cost of the i-th warehouse; The second term represents the cost of scheduling the i-th warehouse between the same levels. The specific meaning is expressed as the ratio of λ_i is used to request replenishment between the same levels in case of shortage during the cycle; The third term indicates the out-of-stock cost for the i-th warehouse, which is specifically expressed as the cost incurred by requesting replenishment from the RDC using a ratio of $(1 - \lambda_i)$ when out-of-stock occurs during the cycle. The first constraint indicates that the number of all LTCs scheduled at the same level should be less than or equal to the number of excess inventory in all warehouses. The second constraint indicates that the scheduling rate must be between 0 and 1, and the third constraint indicates that all quantities and unit costs must be greater than or equal to 0.

The solution to this problem is evidently intricate. To address this challenge, we employ the particle swarm optimization algorithm as our primary tool. The particle swarm optimization algorithm is a nature-inspired metaheuristic algorithm that has been extensively utilized as a robust optimization tool since its inception. Below Algorithm 1 is the pseudo-code for the particle swarm optimization algorithm.

Algorithm 1: Particle swarm optimization

Data: particle i, position x_i, velocity v_i, fitness f_i
Result: Optimal position and find minimum fitness
for *each particle i* **do**
    Initial position x_i randomly within search space;
    Initial velocity v_i randomly wtihin (v_{min}, v_{max});
    evalute fitness f_i of particle i;
    set pbest position $p_i = x_i$;
    set pbest fitness $f_{p_i} = f_i$;
end
Find global best position g = x_i with minimum fitness f_i among all particles;
while *not termination criterion* **do**
    for *each particle i* **do**
        Update velocity v_i;
        Update position x_i;
        Evaluate fitness f_i of particle i;
        if $f_i < f_{p_i}$ **then**
            Set pbest position $p_i = x_i$;
            Set pbest fitness $f_{p_i} = f_i$;
        end
    end
    Find global best position g = x_i with minimum fitness f_i among all particles;
    Record global best position and minimum finess;
end
Return global best position g and minimum finess f(g)

This study employs the particle swarm optimization algorithm to address the inventory optimization problem within a dependent replenishment structure, yielding favorable outcomes. Further empirical analysis will be presented in the fourth chapter.

4. Empirical Analysis

To assess the feasibility and impact of the methods proposed in this paper across different levels, empirical analysis of the aforementioned data-driven approaches will be conducted. This chapter will encompass the following aspects: (1) Comparison of forecasting models; (2) Inventory optimization analysis; (3) Supply chain structure analysis; (4) Comparison of traditional and data-driven approaches. The effectiveness of our model will be demonstrated through an analysis of a major home appliance logistics company in China.

4.1. Data

To validate the reliability of the predictive model, This study utilize warehouse order data from a prominent domestic logistics company in China, specializing in the management of home appliance business. This dataset comprises nearly 14 million records of orders generated by various warehouses throughout the calendar year. Information includes the order generation timestamps, origins, destinations, and shipping methods. Leveraging this data, we can discern the daily order count, along with the origins and destinations of the orders.

As an illustrative example, this study selected four warehouses, analyzed their daily order volumes, and illustrated the trends in order volumes from December 2018 to July 2019 using line graphs (refer to Figures 5–8). Remarkably, the order demand for each warehouse displays substantial fluctuations between different months, indicative of an overall non-stationary trend.

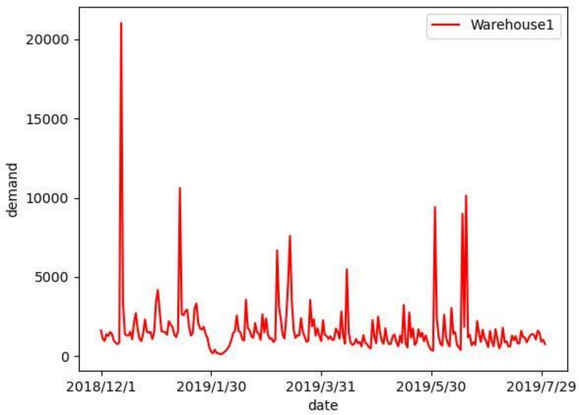

Figure 5. LTC1 demand line chart.

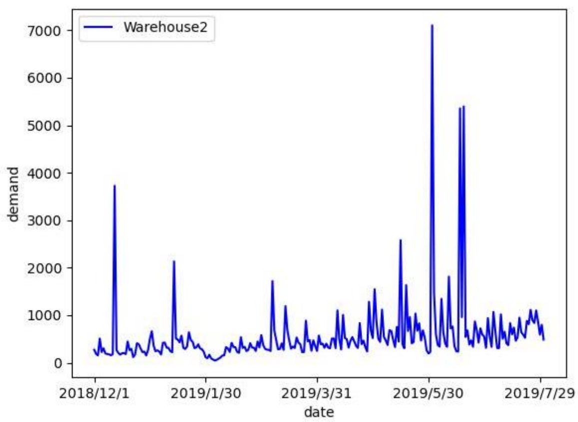

Figure 6. LTC2 demand line chart.

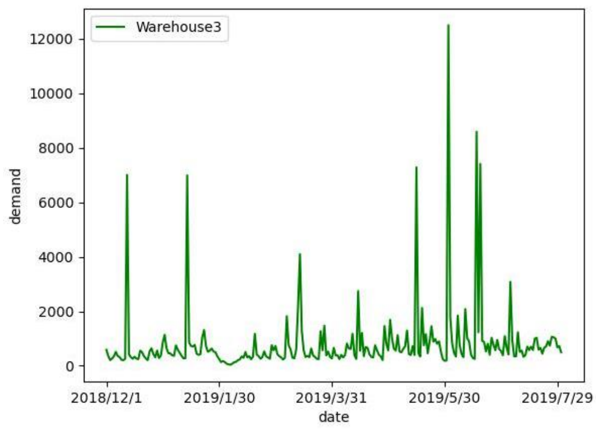

Figure 7. LTC3 demand line chart.

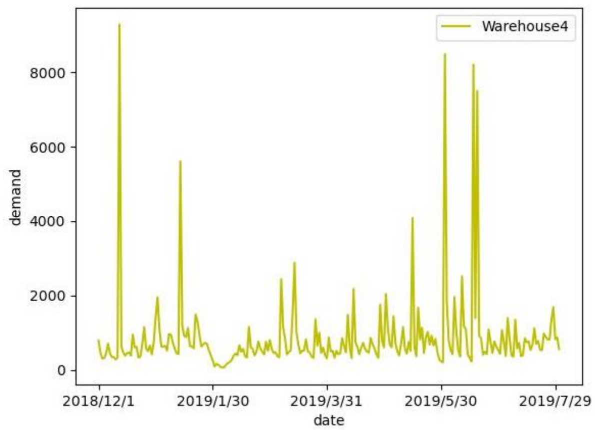

Figure 8. LTC4 demand line chart.

These four warehouses belong to the same level of LTCs, and thus, they exhibit a roughly similar fluctuation trend. However, variations in order demand from different LTCs can still be discerned. Additionally, it is noticeable that the number of orders experiences spikes during specific time periods, often coinciding with e-commerce holidays such as "6.18 Shopping Day" and "12.12 Shopping Day". The temperature season is also a significant influencing factor. As evident from the graph, there is a discernible seasonal tendency, with lower demand in winter compared to summer.

4.2. Predictive Model Analysis

This study meticulously considered e-commerce platform discount information spanning the years 2018 to 2019, subjecting it to transformation based on predetermined weights. Additionally, we conducted a comprehensive processing of the features essential for forecasting. Beyond incorporating their individual daily order volumes and warehouse details, we took measures to ensure the accuracy of data collection for these features. Subsequently, a filtration process was applied, and the primary features were singled out as our input variables. Predominantly, these input variables consist of five features: temperature, season, discount, holiday, and location. It is noteworthy that the location feature primarily serves the purpose of distinguishing between warehouses in different regions and is not utilized as an input variable. The season, being a categorical variable, underwent conversion into a dummy variable for regression analysis. The deliberate selection of these characteristics took into account not only their significance in relation to inventory requirements but also the availability and accuracy of the data for forecasting purposes.

The chosen features were selected for their simplicity and ease of accuracy in actual forecasting. Meteorological predictions and early release of discounts by platforms are aspects that can be readily captured. The dataset was partitioned into two segments, with data spanning from December 2018 to July 2019 allocated for model training, while data from August 2019 served as the test set. Employing the dummy variable method for analysis, where the spring season acted as the control group, regression analysis was applied to gauge the relationship between our selected features and order demand. The results of this analysis are presented in Tables 2 and 3. Upon scrutinizing the outcomes of the regression analysis, a robust correlation emerged between the chosen characteristics and the quantity demanded, a correlation we will endeavor to elucidate.

Table 2. Feature description of Multiple linear regression.

Feature	Description	Scope	Example
lowtemp	The minimum temperature of the day	$[-50, 50]$	lowtemp = 23
hightemp	The maximum temperature of the day	$[-50, 50]$	hightemp = 37
discount	E-commerce platform discount strength	$[0, 1]$	discount = 0.1
season	The season of the day, set as a dummy variable	win,spr,sum,	season = spr
holiday	Indicate whether the day is a holiday	0,1	festival = 1

Table 3. The result of regression analysis for all LTC.

Warehouse	LCT1	LCT2	LCT3	LCT4
summer	617.1840 **	227.0788 **	417.6497 **	384.9574 **
winter	−869.8527 ***	−250.3708 **	−407.0030 **	−363.3952 **
lowtemp	−250.7641 ***	−56.2812 ***	−134.9787 ***	−109.2522 ***
hightemp	118.9390 ***	60.1963 ***	119.6490 ***	81.5322 ***
discount	1.335×10^{-4} ***	5548.0741 ***	9417.4020 ***	8962.4242 ***
holiday	−456.9492 **	−163.2782 **	−298.4687 **	−256.6419 **
R-squared	0.383	0.441	0.367	0.412

*: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01

The first aspect of consideration is the correlation between the season and demand. In this study, the dummy variable method was employed with spring designated as the control group. The regression analysis revealed that the demand for orders tends to increase during the summer season and decrease during the winter season. This pattern is attributed to the company's primary focus on the logistics of large home appliances, including air conditioners, refrigerators, and washing machines. Notably, there exists a discernible seasonal trend for home appliances like refrigerators, air conditioners, and electric fans in these stores. Consumer demand for such appliances tends to surge in the summer months and decline in winter, thereby influencing demand fluctuations with changing seasons.

The second aspect is the correlation between temperature and household appliances. Both maximum and minimum temperatures were taken into account. Typically, the maximum temperature occurs during the day, and the minimum temperature occurs at night. An increase in maximum temperature during the day tends to prompt people to purchase appliances for maintaining physical comfort. Conversely, at night, as most people begin to sleep, an increase in the minimum temperature is conducive to achieving an ideal sleeping temperature. Therefore, a rise in the minimum temperature is associated with a decrease in appliance demand, aligning with the outcomes highlighted by the regression analysis.

The third aspect concerns the association between discounts and demand. It is crucial to acknowledge that discounts constitute the most influential factor affecting demand. The magnitude of discounts significantly impacts the demand quantity. Beyond major e-commerce events such as "11.11 Shopping Day", "12.12 Shopping Day", and "6.18 Shopping Day", various other festive promotions exert a substantial influence on demand.

The rationale for the impact of discounts is apparent—as discounts increase, demand experiences a notable rise, a correlation evident in the regression analysis results.

Finally, this study posits that there exists a relationship between holidays and demand, albeit less intuitively discernible than the previously discussed features. Given that the order data is derived from e-commerce platforms, it is evident that people often lack the time for offline shopping on weekdays, thereby turning to the convenience of online shopping, resulting in an increased demand for e-commerce platforms. Conversely, during holidays, individuals tend to engage in offline purchases, particularly for significant items like home appliances, due to the ample time available. In such instances, e-commerce platforms may experience a decline in orders. The results of the regression analysis further confirm that holidays exert a dampening effect on demand.

It is essential to emphasize that our objective is to employ multiple linear regression for forecasting, necessitating the pre-acquisition of chosen features. While there are other features demonstrating correlation with demand, such as the national economic index, these data are not available in advance, and accurate access is a prerequisite for our feature selection. Despite the "R-squared" of the multiple linear regression indicating that its accuracy in this paper is not particularly high, and utilizing forecast data directly for setting safety stock may lead to decision errors, the performance of multiple linear regression remains superior compared to other models, as will be elaborated in the subsequent analysis. Consequently, This utilize empirical errors to rectify model errors and then optimize based on this correction to derive more accurate decisions.

In summary, the finding of this part include the following:

1. Compared to neural networks, machine learning methods exhibit greater interpretability, facilitating data analysis for practitioners.
2. In the home appliance industry, factors such as seasonality, temperature, discounts, and holidays can influence the quantity of online orders.
3. In the home appliance industry, the factors associated with holidays may potentially suppress the quantity of online orders.

5. Predictive Performance Analysis

For the performance evaluation of forecasting models, this study employed the median method (Median), Autoregressive Integrated Moving Average model (ARIMA), artificial neural network (ANN), and long short-term memory neural network (LSTM). The selected methods encompass basic models, time series models, and machine learning models, which currently dominate the field of forecasting. The median model is considered first, as it is frequently employed in production. In this case, the forecast is generated using the median of the data from 30 days before the forecasting date. The ARIMA model holds a crucial role in time series forecasting. Its autoregressive component represents a linear combination of past values, while the moving average component is a linear combination of past errors, and temporal sequences are stabilized through differencing. In this study, the auto.arima() function from the pmdarima package in Python is directly utilized to determine the most suitable model for each time series.The ANN model is one of the most widely employed models in machine learning. In our approach, we utilize 8 months of data as input, apply the sigmoid function as the activation function, and employ a backpropagation algorithm for training. The predicted values for August 2019 are generated after completing the training process. LSTM, designed specifically for time series data, is constructed using the Tensorflow framework. In this model, five-dimensional features primarily serve as input variables, and the backpropagation method is employed for training, followed by the output of predicted values. We conducted statistical analysis on the prediction results, employing RMSE, MAE, and MAPE as evaluation metrics for model performance. Lower values for these metrics indicate better prediction performance and higher accuracy. A comprehensive evaluation and comparison of the aforementioned models were conducted, forecasting order data for August. Figures 9–12 compares the forecast results.

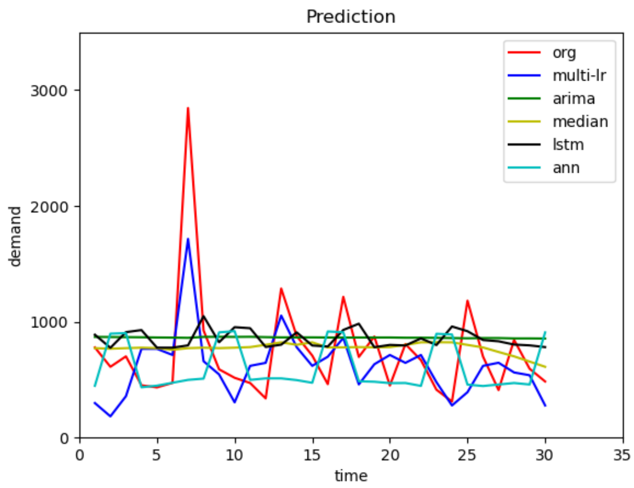

Figure 9. LTC1 demand line chart.

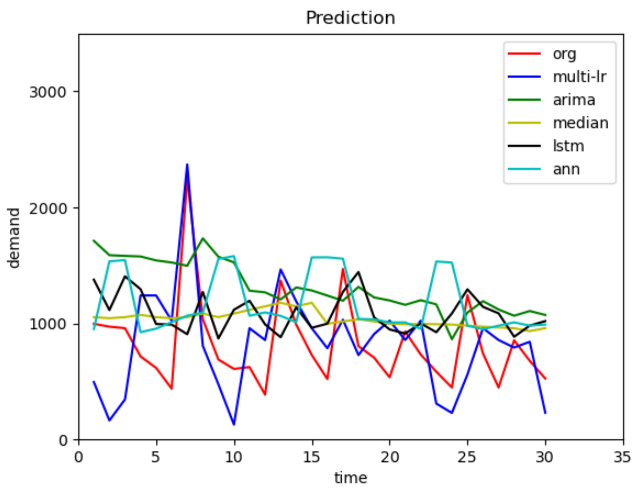

Figure 10. LTC2 demand line chart.

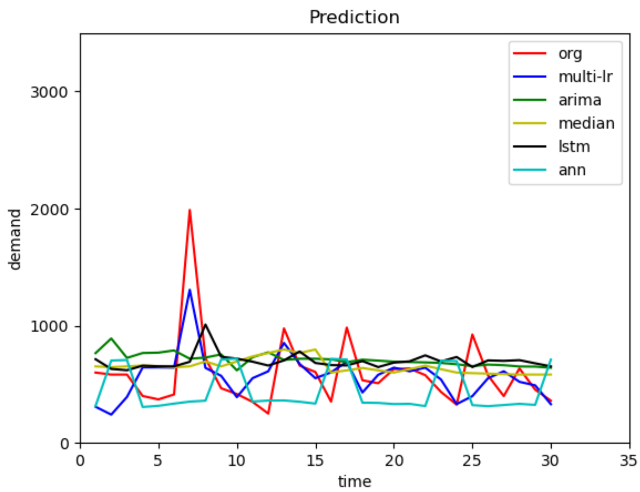

Figure 11. LTC3 demand line chart.

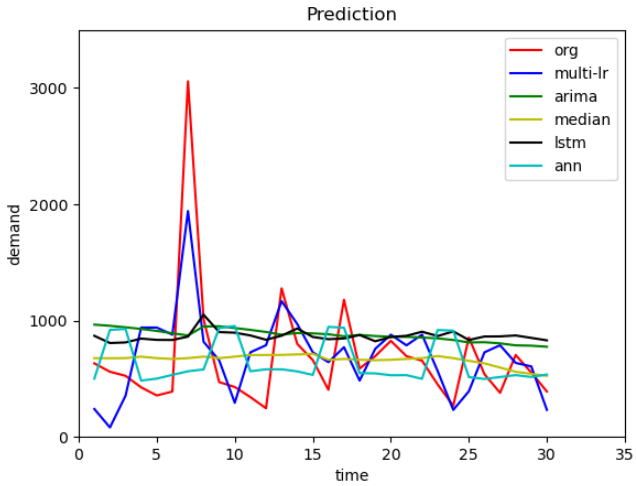

Figure 12. LTC4 demand line chart.

From these figures, both multiple linear regression and LSTM can capture the overall demand trend, with multiple linear regression showing a slight superiority. Notably, multiple linear regression exhibits distinct advantages in capturing holiday effects, particularly during e-commerce events such as the "88 Shopping Festival" and "8.14 Green Valentine's Day", where strong discounts are prevalent. Multiple linear regression effectively reflects the demand on those specific days, whereas the LSTM model demonstrates a somewhat lesser performance. The ANN model fails to effectively reflect the trend and exhibits a lag in capturing it. The ARIMA model displays mediocre characteristics without clear distinguishing features. The median model, on the other hand, demonstrates minimal fluctuations and lacks any discernible trend characteristics. Table 4 will present variations in different indicators across the various forecasting models.

Table 4. Comparison of predictive model metrics.

Method	Multi-LR	LSTM	ANN	ARIMA	MEDIAN
LCT1-RMSE	392.77	475.74	580.13	630.88	431.26
LCT1-MAE	339.7	401.83	471.4	583.37	359.53
LCT1-MAPE	49.8	59.47	73.61	88.86	55.14
LCT2-RMSE	231.98	335.19	410.2	345.26	324.48
LCT2-MAE	169.77	251.53	294.43	261.2	217.46
LCT2-MAPE	31.87	49.02	47.45	52.76	42.40
LCT3-RMSE	357.8	535.39	556.78	546.28	502.31
LCT3-MAE	273.53	384.37	344.73	398.3	280.8
LCT3-MAPE	51.99	73.78	55.47	77.07	45.48
LCT4-RMSE	346.02	484.69	552.81	481.84	464.31
LCT4-MAE	265.1	330.4	362.97	337.1	291.33
LCT4-MAPE	37.84	53.87	47.48	55.92	44.92

Upon comparing various metrics, multiple linear regression emerges as slightly superior to other models in either LTC, aligning with our intuitive observations from the graphical representations. This paper asserts that the multiple linear regression model exhibits higher prediction accuracy. Multiple linear regression is widely favored as a forecasting method due to its advantages in simple model construction, easy implementation, and high interpretability. Nevertheless, it is crucial to note that the efficacy of multiple linear regression heavily depends on data accuracy and effective feature selection. Consequently, the application of multiple linear regression mandates ensuring data correctness and possessing extensive experience in feature selection.

It is noteworthy that upon comparing metrics, the neural network exhibits poor performance in our example. Specifically, the Artificial Neural Network (ANN) ranks among the least effective models in our comparison. A noticeable lag in predictions, as depicted in the figures, contributes to the suboptimal performance observed in the metric analysis. Long Short-Term Memory neural networks (LSTM) perform comparatively better than ANN and fall within the mid-to-upper range of performance among the selected models. As a neural network framework tailored for time series data, LSTM outperform general-purpose neural networks like ANN. The primary reason for the neural network's suboptimal performance is attributed to the limited data size. The training set utilized for the neural network model comprises only 8 months of data, and neural networks may not excel at such a modest scale. It is anticipated that the neural network's performance will improve in future application scenarios as the volume of available data continues to grow.

Remarkably, the conventional median method exhibits commendable performance in model metrics. Solely based on indicators, the median method ranks second only to the multiple linear regression method. However, upon visual inspection, the median method fails to capture the predicted trend. This implies that while the median method holds an advantage in terms of metrics, it struggles to respond promptly to demand surges or abrupt declines. In terms of outcomes, the median method proves to be straightforward to operate and serves as a suitable choice in scenarios where substantial data support is lacking, and swift decision-making is imperative. However, it is not advisable to employ the median method when ample data support is available.

In summary, the finding of this part include the following:

1. In demand forecasting, neural networks do not necessarily outperform machine learning methods.
2. Professionals should choose models based on the characteristics of the dataset, conduct tests and comparisons of different models, and select the best-performing model as the demand forecasting model.

5.1. Predictive Error Analysis

In this study, we aligned the empirical error distribution with both the demand forecast data and the actual demand data for August 2019. Subsequently, we computed the discrepancy between the actual and forecasted demand, subjecting it to the Shapiro-Wilk test. The outcomes of this test are presented in Table 5.

Table 5. The result of Shapiro-Wilk test.

Warehouse	LCT1	LCT2	LCT3	LCT4
p-value	3.15×10^{-1}	1.01×10^{-1}	9.9×10^{-2}	2.9×10^{-2}

It is evident that the p-values for LTC1, LTC2, and LTC3 are all greater than 0.05, suggesting that LTC1, LTC2, and LTC3 can be considered to follow a normal distribution. However, the p-value for LTC4 is less than 0.05, indicating that we lack sufficient evidence to conclude that it adheres to a normal distribution. This also implies that the error distribution generated by the data-driven method varies across different warehouse distribution centers, potentially influenced by numerous factors.

In traditional approaches, it is common to assume that the error distribution follows a specific distribution (often assumed to be normal). However, such assumptions are not always reliable, and errors in assumptions can lead to significant biases in decision-making, subsequently increasing enterprise costs. In this case, assuming a traditional method where each long-term cycle follows a normal or other specific distribution is not dependable. Therefore, we employ an empirical distribution method for estimation.

While this empirical distribution method is contingent on the size of the data, it is more persuasive than assuming a normal distribution. As the data volume continues to expand, the accuracy of the empirical error distribution improves, offering better corrections to our demand forecasting model.

In summary, the finding of this part include the following:

1. The distribution between actual demand and forecasted demand may not necessarily adhere to a normal distribution. Employing a normal distribution to adjust the demand may introduce biases in the correction process.
2. In cases where there is sufficient historical data, employing an empirical distribution instead of a normal distribution for correcting forecasted demand might yield better performance.

5.2. Inventory Optimization Analysis

In this section, the study aims to underscore the necessity of inventory optimization following the forecasting process through the use of simulations. A comparative analysis will be carried out to assess inventory allocation costs in different supply chain structures. This evaluation will involve a comparison between the direct utilization of forecast results and the incorporation of inventory optimization after forecasting. Additionally, the study will delve into the variations in total inventory costs across diverse supply chain structures and offer an explanation for these discrepancies.

This study will focus on a segment of the company's supply chain network as the primary subject of investigation. Based on delivery data from the logistics company, we observe that 99.3% of the company's orders are fulfilled within a week, indicating a high level of service. Given the distinctive characteristic of the "cloud supply chain" with its emphasis on rapid delivery and superior service, our analysis will consider service levels of 0.8, 0.85, 0.9, and 0.95. Furthermore, it is reasonable to assume uniformity in service levels between LTCs and RDC in this structure. Similar service targets and service areas among LTCs at the same level result in identical service level requirements, while the RDC, serving LTC, maintains an equivalent service level. According to industry surveys, the average replenishment cycle for home appliances typically ranges from 10 to 30 days. We opt for a 15-day replenishment cycle to ensure comprehensive consideration of other factors such as weather, season, discounts, etc., within this timeframe.

This study assumes a linear relationship between LCT and RDC inventory costs and shortage costs. We consider three scenarios where RDC costs are lower than LTC, equal to LTC, and higher than LTC. For the sake of simulation convenience, we explore three cases with linear coefficients of 0.5, 1, and 2. In the dependent structure, we presume a linear relationship between the transshipment cost and LTC. Additionally, the transshipment cost is strictly assumed to be lower than the out-of-stock cost, as transshipment among peers would be unnecessary otherwise. We assess variations in inventory quantities for safety stock under different structures and discuss the values across four service levels, as illustrated in Table 6.

Table 6. Comparison of inventory quantities under different structures.

Method	LTC1	LTC2	LTC3	LTC4	RDC
ORGNUMBER	13,364	10,632	13,866	14,906	52,768
PRENUMBER	14,265	9169	11,778	10,357	45,569
PRE + OPT (IND, SL = 0.8)	18,690	11,029	14,343	14,572	78,434
PRE + OPT (D, SL = 0.8)	18,619	11,412	12,906	13,273	56,210
PRE + OPT (IND, SL = 0.85)	21,143	12,792	16,173	15,592	89,377
PRE + OPT (D, SL = 0.85)	21,216	10,989	12,599	13,287	58,091
PRE + OPT (IND, SL = 0.9)	21,795	13,549	17,898	16,777	97,229
PRE + OPT (D, SL = 0.9)	21,193	12,406	12,476	13,675	59,750
PRE + OPT (IND, SL = 0.95)	24,000	15,679	18,836	19,882	112,289
PRE + OPT (D, SL = 0.95)	21,884	11,125	16,369	13,059	76,027

To delve deeper into the necessity of inventory optimization, this study conducted a comparison between the total costs accrued by utilizing forecast results directly as safety stock and the total costs associated with inventory optimized following the forecast, as depicted in Table 7.

Table 7. Comparison of total cost of forecasting-inventory optimization and direct forecasting.

Method	SL = 0.8	SL = 0.85	SL = 0.9	SL = 0.95
PREDICT (IND, $a = 0.5$)	47,699	67,198.2	106,196.5	223,191.5
PREDICT (IND, $a = 1$)	62,097	87,595.3	138,592	291,582
PREDICT (IND, $a = 2$)	90,893	128,389.7	203,383	428,363
PREDICT (D, $a = 0.5$)	43,950.8	61,948.3	98,943.3	205,928.3
PREDICT (D, $a = 1$)	58,348.8	82,345.5	130,338.8	274,318.8
PREDICT (D, $a = 2$)	87,144.8	123,139.8	195,129.8	411,099.8
PRE + OPT (IND, $a = 0.5$)	20,369	31,236.7	39,481.5	55,389.8
PRE + OPT (IND, $a = 1$)	33,202	49,541.5	61,712	85,150.5
PRE + OPT (IND, $a = 2$)	58,868	86,151	106,173	144,672
PRE + OPT (D, $a = 0.5$)	11,916.2	15,266.2	16,803.1	23,603.6
PRE + OPT (D, $a = 1$)	13,637.2	17,927.6	20,294.1	35,233.1
PRE + OPT (D, $a = 2$)	17,079.2	23,250.6	27,276.1	58,492.1

As observed in the comprehensive cost analysis table, across all scenarios, there is a consistent upward trend in total costs with the escalation of service levels. Notably, as the service level advances from 0.9 to 0.95, the total cost experiences a substantial increase, almost doubling or achieving a twofold increase in all instances. This unequivocally indicates that the expenses associated with upholding a high service level are notably higher, a trend vividly demonstrated in our simulations.

A noteworthy observation from the data lies in the substantial contrast in total costs incurred when utilizing forecasts directly for safety stock allocation versus employing forecasting followed by inventory optimization. This substantiates our hypothesis, emphasizing that relying on forecasts directly for allocation can result in considerable decision-making discrepancies and, consequently, substantial costs. Particularly in the context of highly uncertain markets and inadequately large datasets, the inherent limitations of forecasting models may lead to inaccuracies in predicting actual demand. These inaccuracies tend to escalate as the service level increases, potentially resulting in significant losses. The optimization strategy post-forecasting effectively addresses this issue. As the service level rises, the optimization approach leans towards increasing inventory, adeptly mitigating the risk of stockouts and thereby yielding considerable cost savings.

This study also conducts a comparison based on inventory volume, as presented in Table 7. It is evident that there are discrepancies between the predicted and actual values for each LTC, with notable errors observed for LTC3 and LTC4. This discrepancy implies that utilizing the forecast result directly for inventory allocation would result in significant out-of-stock costs. Furthermore, since our prediction model does not account for the service level, the forecast result remains constant as the service level changes. Consequently, under high service levels, the losses due to stockouts become substantial, leading to an increase in costs.

Now, turning our attention to the optimized inventory allocation, we observe that, when the service level is 0.8, the inventory levels for all LTCs increase compared to the predicted result, and this trend continues as the service level rises. The rationale behind this is that as the service level increases, decision-makers lack knowledge about the actual inventory levels in the future, necessitating an increase in inventory quantity to avert shortages. Hence, inventory optimization post-forecasting proves to be indispensable.

In light of our analysis, this study contends that optimization based on demand forecasting is crucial, particularly within the context of the "cloud supply chain" where a high service level is of utmost importance. For decision-makers, a more accurate predictive model yields superior outcomes. However, confronted with highly uncertain market demand, compounded by limitations in data size and other factors, the reliable assurance of the model's predictive accuracy and effectiveness becomes challenging. In such circumstances, optimization serves as an additional auxiliary tool for enhancing inventory allocation decisions.

In summary, the finding of this part include the following:

1. Utilizing demand forecast results directly for inventory decisions may lead to significant deviations in decision-making.
2. In the context of a cloud supply chain environment, it is essential to dynamically adjust inventory decisions based on market service levels.

5.3. Supply Chain Structure Analysis

Moreover, this study recognizes that diverse supply chain structures can influence safety stock allocations. In this subsection, we will analyze these structures by examining inventory quantities and costs, referring to Tables 6 and 7.

It is evident that, for each warehouse, the inventory levels under the non-independent replenishment structure are lower than those under the independent replenishment structure. Furthermore, as the service level increases, the disparity in inventory levels among LTCs under both structures widens. This discrepancy arises from the interdependence among LTCs in the non-independent structure, where each LTC serves as a buffer for the others, unlike the independent structure. Examining the RDC data reveals that the inventory of dependent RDCs is significantly lower compared to that of standalone structures. This is attributed to the fact that, under the independent structure, if an LTC is out of stock, it must restock directly from the RDC, prompting the RDC to maintain higher inventory levels to accommodate LTC restocking needs. Under the dependent structure, when an LTC faces a stockout, it replenishes its stock from the LTC at the same level, leading to a proportionate reduction in safety stock allocation for the RDC. However, it is crucial to note that, with high service levels, the RDC also augments its inventory significantly to mitigate potential disruptions. The data indicates a substantial increase in RDC inventory when the service level rises from 0.9 to 0.95. This elevation is attributed to the heightened risk of stockouts at higher service levels, prompting both LTC and RDC to bolster their inventories substantially to avert any potential shortages due to uncertain future demand.

From a cost perspective, the total cost of the dependent replenishment structure is lower than that of the independent replenishment structure at the same service level, as indicated in Table 6. Notably, this cost difference is more pronounced when the cost of the RDC exceeds that of the LTC ($a = 2$). This amplification occurs because a higher operating cost for the RDC necessitates increased inventory to accommodate LTC's replenishment requests, resulting in a wider gap in total costs. Therefore, the dependent replenishment structure emerges as a preferable option, particularly in scenarios with elevated upstream operating costs.

Considering service levels, the total cost disparity between the two structures expands with higher service levels. Despite both structures opting to augment safety stock to prevent stockouts as service levels increase, the rate of increase in the independent structure is comparatively lower than that in the dependent structure. Consequently, in terms of total cost, the dependent structure exhibits superior performance, especially at higher service levels.

Confronted with highly uncertain market demand, adjusting the supply chain structure in a timely manner becomes crucial. This adjustment could involve transitioning from an independent replenishment structure to a dependent replenishment structure, contingent upon meeting specific conditions. Such an adaptation ensures the availability of ample buffer space to mitigate the risk of potential stockouts.

In summary, the finding of this part include the following:

1. In inventory management within the context of the cloud supply chain, the structure of the supply chain can have an impact on inventory decisions.
2. In specific circumstances, practitioners can mitigate supply chain risks and prevent disruptions by adjusting the structure of the supply chain.

5.4. Comparative Analysis of Methods

To further elucidate the effectiveness of the data-driven approach, this study conducts a comparative analysis with the traditional approach. We provide comprehensive details regarding the data-driven method and the acquisition of each parameter. The normal distribution is applied as the demand distribution to capture the normal parameters from the data, while considering the seasonality of these parameters. The optimization model employed in the traditional approach is in line with that of the data-driven approach. However, in the traditional approach, the study resorts to the normal distribution to model errors, deviating from the empirical distribution used in the data-driven approach. Specifically, in the traditional approach, we relies on the assumption of a normal distribution for demand forecasting instead of embracing the machine learning approach. The simulation of inventory data is carried out using software, and the results are presented in Table 8.

Table 8. Comparison of traditional and data-driven approaches to inventory levels.

Method	LTC1	LTC2	LTC3	LTC4	RDC
ORGNUM	13,364	10,632	13,866	14,906	52,768
PRENUM	14,601	9776	12,294	11,569	48,240
TRA (IND, SL = 0.8)	18,194	13,590	17,260	17,863	86,359
TRA (D, SL = 0.8)	15,597	12,870	14,168	14,529	66,924
PRE + OPT (IND, SL = 0.8)	18,690	11,029	14,343	14,572	78,434
PRE + OPT (D, SL = 0.8)	18,619	11,412	12,906	13,273	56,210
TRA (IND, SL = 0.85)	19,428	14,608	18,792	19,316	94,038
TRA (D, SL = 0.85)	17,699	11,887	13,970	18,694	73,747
PRE + OPT (IND, SL = 0.85)	21,143	12,792	16,173	15,592	89,377
PRE + OPT (D, SL = 0.85)	21,216	10,989	12,599	13,287	58,091
TRA (IND, SL = 0.9)	20,984	15,873	20,719	21,143	103,647
TRA (D, SL = 0.9)	15,793	14,913	19,494	14,349	78,219
PRE + OPT (IND, SL = 0.9)	21,795	13,549	17,898	16,777	97,229
PRE + OPT (D, SL = 0.9)	21,193	12,406	12,476	13,675	59,750
TRA (IND, SL = 0.95)	23,285	17,748	23,578	23,851	117,887
TRA (D, SL = 0.95)	18,478	15,053	17,248	18,120	85,788
PRE + OPT (IND, SL = 0.95)	24,000	15,679	18,836	19,882	112,289
PRE + OPT (D, SL = 0.95)	21,884	11,125	16,369	13,059	76,027

In the initial analysis, this study focuses on the independent replenishment structure. Our research compares the inventory levels resulting from the two methods across four service levels. We observed that at a service level of 0.8, the traditional method effectively prevents stockouts, while the data-driven method incurs a slight but acceptable shortfall. However, with increasing service levels, the data-driven approach demonstrates a more pronounced advantage, particularly at high service levels. The gap between the data-driven approach and the traditional approach is substantial. This difference is primarily attributed to the highly uncertain nature of markets, where the actual distribution may not necessarily adhere to a normal distribution. Assuming a normal distribution of demand can introduce bias into decision-making.

This study further compares the inventory levels between the two methods across four service levels. The data-driven approach consistently outperforms the traditional method, and this advantage becomes more pronounced with higher service levels. At a service level of 0.8, both methods exhibit reasonable inventory allocation at the LTC level; however, at the RDC level, the data-driven method clearly outperforms the traditional approach. This is attributed to the data-driven method's utilization of an empirical distribution for replenishment, contrasting with the normal distribution employed by the traditional method. The error introduced by this distribution assumption results in higher inventory levels for the traditional method in RDC decisions. In instances of high service levels, the traditional method demonstrates inferior performance at both the LTC and RDC levels when compared to actual demand.

As evident from the table, the data-driven approach leads to more rational inventory decisions than the traditional approach. To conduct a comprehensive comparison of their performance, this study will analyze them from the perspective of total cost. The total cost incurred by the traditional safety stock allocation method is compared with that of the data-driven method, as shown in Table 9.

Table 9. Total cost of ownership comparison of traditional and data-driven approaches.

Method	SL = 0.8	SL = 0.85	SL = 0.9	SL = 0.95
TRA (IND, a = 0.5)	30,934.5	40,011	51,390.5	68,253.5
TRA (IND, a = 1)	47,730	60,646	76,830	100,813
TRA (IND, a = 2)	81,321	101,916	127,709	165,932
PRE + OPT (IND, a = 0.5)	20,369	31,236.7	39,481.5	55,389.8
PRE + OPT (IND, a = 1)	33,202	49,541.5	61,712	85,150.5
PRE + OPT (IND, a = 2)	58,868	86,151	106,173	144,672
TRA (D, a = 0.5)	12,079	19,971.5	25,201.6	32,641
TRA (D, a = 1)	19,157	30,461	37,927.1	49,151
TRA (D, a = 2)	33,313	51,440	63,378.1	82,171
PRE + OPT (D, a = 0.5)	11,916.2	15,266.2	16,803.1	23,603.6
PRE + OPT (D, a = 1)	13,637.2	17,927.6	20,294.1	35,233.1
PRE + OPT (D, a = 2)	17,079.2	23,250.6	27,276.1	58,492.1

From a cost perspective, it is evident that both structural data-driven methods are significantly superior to the traditional method. The data-driven approach eliminates the assumed distribution of the traditional method, allowing it to capture the distribution more accurately. When the operating cost of RDC is low (a = 0.5), the difference between the traditional method and the data-driven method is not pronounced, with the data-driven method showing a slight advantage. As operating costs increase, this gap widens due to the greater accuracy of the data-driven approach in capturing the replenishment distribution. With the rise in service levels, the data-driven approach consistently outperforms the traditional approach, although the gap does not widen further at higher service levels, indicating that the traditional approach remains somewhat reliable. In situations with a small data size or inaccurate data, opting for the traditional method is a reasonable choice.

In summary, the finding of this part include the following:

1. In situations with insufficient data volume, utilizing traditional methods for inventory decision-making is a viable solution.
2. In the context of cloud supply chains, leveraging the data collection capabilities of cloud platforms, employing a data-driven approach for inventory decision-making is a superior choice.

5.5. Additional Example

To enhance the persuasiveness of the methods proposed in this paper and demonstrate the reliability of the data-driven framework, we applied the model to sub-product data within the same company. Numerical experiments were conducted on a local network in another region, yielding results similar to the analysis mentioned earlier. Due to length constraints, the primary numerical results are presented in Appendix A. The supplementary examples corroborate the main findings, affirming the necessity of optimization after forecasting. These examples illustrate the impact of different supply chain structures on safety stock allocation, consistently showing that the data-driven method outperforms the traditional approach in most scenarios. The comparison between traditional and data-driven methods is substantiated by the supplementary examples, further reinforcing the arguments presented in this paper.

6. Conclusions

In conclusion, this study provides an in-depth exploration of inventory management within the context of cloud supply chains. The investigation into inventory management in the cloud supply chain environment offers valuable insights into the dynamic interaction between cloud technology and inventory control. Our research adopts a micro-level perspective, thoroughly examining inventory allocation issues under different supply chain structures and proposing data-driven solutions. The study has yielded unique findings, elucidated certain limitations, and laid the groundwork for future research directions.

One of the notable contributions of this study lies in its meticulous exploration of inventory management within the framework of cloud supply chains at the micro-level. Through a detailed examination of the characteristics of diverse supply chain structures and the application of machine learning and optimization techniques, this research introduces a specific data-driven model, offering a novel perspective on inventory management from the vantage point of cloud supply chains. To validate the reliability of the proposed methodology, this paper utilizes data from a major domestic logistics company as a case study, conducting analyses encompassing predictive performance, forecast errors, inventory optimization, supply chain structure, and comparisons with traditional methods. Empirical results underscore the significant impact of supply chain structure on safety stock, with distinct safety stock allocations observed under different supply chain structures. A comparative analysis between traditional methods and the data-driven approach proposed in this study reveals the superior decision-making capabilities of the data-driven method. Simultaneously, intriguing phenomena emerge in the empirical analysis: firstly, the case study in this paper illustrates that in situations with insufficient data, deep learning may not necessarily outperform other models; secondly, regression results from the empirical analysis suggest that holidays exert a certain inhibitory effect on online orders, presenting a noteworthy observation; finally, the study emphasizes the influence of supply chain structure on inventory management, underscoring that practitioners should adopt different inventory decision-making strategies when confronted with diverse supply chain structures.

However, it is essential to acknowledge the inherent limitations of this study. The generalizability of the strategies proposed in this research may be contingent upon specific industry sectors, organizational structures, and the maturity of cloud adoption within the supply chain, making them not universally applicable across all industries. Additionally, the model presented in this paper relies on the scale and accuracy of the data; the performance of the method significantly diminishes when the data quality falls below the required standards. Furthermore, while our focus on demand forecasting and inventory optimization is crucial, it only represents one facet of the broader domain of cloud supply chain management.

To broaden the impact of this research, future studies can explore several promising avenues. Firstly, research focused on the integration of real-time data sharing mechanisms in cloud supply chains could enhance the responsiveness of inventory management systems. Secondly, investigating the impact of emerging technologies such as blockchain on inventory traceability and transparency holds promise for improving the overall efficiency and reliability of supply chain operations [4]. Additionally, future research efforts can extend our findings by examining the applicability of the proposed inventory management strategies in different industry contexts and supply chain configurations. This may involve conducting case studies in specific sectors to validate and refine the proposed models. Given the increasing importance of sustainability in supply chain management, future research could delve into how cloud-based inventory management aligns with sustainable practices. Examining the environmental, social, and economic feasibility of these approaches would be a promising avenue [5].

In summary, while our study has advanced the understanding of cloud supply chain inventory management, there remains ample room for further exploration. Addressing these research gaps and extending our findings to different contexts will contribute to the ongoing development of supply chain management practices in the era of cloud technology.

Author Contributions: Conceptualization, Y.T. and L.G.; methodology, Y.T.; software, Y.T.; validation, L.G., S.X. and M.L.; formal analysis, L.G.; investigation, S.X.; resources, L.G.; data curation, M.L.; writing—original draft preparation, Y.T. and L.G.; writing—review and editing, M.L. and S.X.; supervision, L.G.; project administration, S.X.; funding acquisition, S.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Achievements of Key Research Base of Humanities and Social Sciences in Shenzhen: Skilled Society Research Center of Shenzhen Institute of Technology.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following symbols and abbreviations are used in this manuscript:

RDC	Regional Distribution Center
LTC	Local Transportation Ceter
MAE	Mean absolute error
MAPE	Mean absolute percentage error
RMSE	Root mean square error
Multi-Lr	Multiple linear regression model
Armia	Autoregressive integrated moving average
Median	Median model
ANN	Artificial neural networks
LSTM	Long short-term memory model
X	Input features
Y	Actual output
θ	Parameters to be learned
ϵ_i	Historical errors
$I(x)$	Indicator function
q^*	Optimal inventory quantity
inf	Lower bound of set
c_l	Unit shortage cost
c_h	Unit holding cost
d_f	Demand forecasting using machine learning methods
d_{f_i}	Demand for the i-th LTC predicted using machine learning methods
q_i^*	Optimal inventory quantity of the i-th LTC
c_l^i	Unit shortage cost of i-th LTC
c_h^i	Unit holding cost of i-th LTC
D^R	Total demand of RDC
q_R^*	Optimal inventory quantity of RDC
c_l^R	Unit shortage cost of RDC
c_h^R	Unit holding cost of RDC
S_i	Transshipment quantity distribution function of the i-th LTC
λ_i	The proportion of cargo transshipped by the i-th LTC from other LTCs
q_i	The inventory quantity of the i-th LTC

c_t^i	The transshipment cost of replenishing the i-th LTC from other LCTs
$(x)^+$	An operation;when x is greater than 0, take x; otherwise, take 0
a	Cost proportionality coefficient between LTC and RDC
$F(p)$	Demand distribution function
$\bar{F}(p)$	Error distribution function between forecast demand and actual demand
$F_R(p)$	Total demand forecast distribution function of RDC
$F_i(p)$	Total demand forecast distribution function of the i-th LTC
$\bar{F}_i(p)$	Error distribution function of the i-th LTC
$\bar{F}_R(p)$	Replenishment distribution function of RDC

Appendix A

Table A1. Comparison of inventory quantities under different methods and supply chain structures.

Method	LTC5	LTC6	LTC7	LTC8	RDC2
ORGNUM	13,989	11,966	19,714	26,213	71,882
PRENUM	10,804	8600	18,896	21,344	59,644
PRE + OPT (IND, SL = 0.8)	16,939	13,970	25,421	33,149	120,124
PRE + OPT (IND, SL = 0.85)	17,689	15,035	27,326	33,877	129,440
PRE + OPT (IND, SL = 0.9)	19,339	16,160	27,881	37,109	137,254
PRE + OPT (IND, SL = 0.95)	21,259	17,803	30,941	41,639	161,285
PRE + OPT (D, SL = 0.8)	15,137	13,129	25,748	28,610	113,269
PRE + OPT (D, SL = 0.85)	17,149	13,138	26,147	28,609	120,585
PRE + OPT (D, SL = 0.9)	15,234	19,488	26,901	27,526	125,914
PRE + OPT (D, SL = 0.95)	19,009	14,655	25,235	39,753	148,294
TRA (IND, SL = 0.8)	17,479	12,658	29,573	35,252	115,755
TRA (IND, SL = 0.85)	18,676	13,480	31,490	37,640	128,821
TRA (IND, SL = 0.9)	20,182	14,514	33,901	40,645	145,260
TRA (IND, SL = 0.95)	22,413	16,046	37,476	45,099	169,625
TRA (D, SL = 0.8)	13,568	12,752	27,875	34,088	109,076
TRA (D, SL = 0.85)	17,235	13,511	26,232	35,862	120,415
TRA (D, SL = 0.9)	13,770	14,524	31,865	34,263	130,440
TRA (D, SL = 0.9)	18,833	14,831	32,683	39,234	154,172

Table A2. Comparison of total costs under different methods and supply chain structures.

Method	SL = 0.8	SL = 0.85	SL = 0.9	SL = 0.95
PRE (a = 0.5)	78,828	111,673	177,363	374,433
PRE (a = 1)	108,704	153,997.3	244,584	516,344
PRE (a = 2)	168,456	238,646	379,026	800,166
PRE + OPT (IND, a = 0.5)	41,718	51,094	61,293	84,461.5
PRE + OPT (IND, a = 1)	65,839	79,873	93,979	129,163
PRE + OPT (IND, a = 2)	114,081	137,431	159,351	218,566
TRA (IND, a = 0.5)	45,116.5	57,873.5	74,049	98,023.5
TRA (IND, a = 1)	67,053	86,343	110,738	146,895
TRA (IND, a = 2)	110,926	143,282	184,116	244,638
PRE + OPT (D, a = 0.5)	31,435.5	37,362.5	44,283	64,976
PRE + OPT (D, a = 1)	52,129	61,564	71,299	103,182
PRE + OPT (D, a = 2)	93,516	109,967	125,331	179,594
TRA (D, a = 0.5)	35,371.8	38,772.5	52,257	65,156
TRA (D, a = 1)	53,968.8	63,039	81,536	106,301
TRA (D, a = 2)	91,162.8	111,572	140,094	188,591

References

1. Ivanov, D.; Dolgui, A.; Sokolov, B. Cloud supply chain: Integrating industry 4.0 and digital platforms in the "Supply Chain-as-a-Service". *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *160*, 102676. [CrossRef]
2. Huber, J.; Müller, S.; Fleischmann, M.; Stuckenschmidt, H. A data-driven newsvendor problem: From data to decision. *Eur. J. Oper. Res.* **2019**, *278*, 904–915. [CrossRef]
3. Leukel, J.; Kirn, S.; Schlegel, T. Supply chain as a service: A cloud perspective on supply chain systems. *IEEE Syst. J.* **2011**, *5*, 16–27. [CrossRef]

4. Surucu-Balci, E.; Iris, Ç.; Balci, G. Digital information in maritime supply chains with blockchain and cloud platforms: Supply chain capabilities, barriers, and research opportunities. *Technol. Forecast. Soc. Chang.* **2024**, *198*, 122978. [CrossRef]
5. Chauhan, R.; Majumder, A.; Kumar, V. The impact of adopting customization policy and sustainability for improving consumer service in a dual-channel retailing. *J. Retail. Consum. Serv.* **2023**, *75*, 103504. [CrossRef]
6. Silver, E.A.; Pyke, D.F.; Peterson, R. *Inventory Management and Production Planning and Scheduling*; Wiley: New York, NY, USA, 1998; Volume 3.
7. Eppen, G.D.; Martin, R.K. Determining safety stock in the presence of stochastic lead time and demand. *Manag. Sci.* **1988**, *34*, 1380–1390. [CrossRef]
8. Kleywegt, A.J.; Shapiro, A.; Homem-de Mello, T. The sample average approximation method for stochastic discrete optimization. *SIAM J. Optim.* **2002**, *12*, 479–502. [CrossRef]
9. Wang, C.C.; Chang, H.T.; Chien, C.H. Hybrid LSTM-ARMA Demand-Forecasting Model Based on Error Compensation for Integrated Circuit Tray Manufacturing. *Mathematics* **2022**, *10*, 2158. [CrossRef]
10. Carbonneau, R.; Laframboise, K.; Vahidov, R. Application of machine learning techniques for supply chain demand forecasting. *Eur. J. Oper. Res.* **2008**, *184*, 1140–1154. [CrossRef]
11. Kilimci, Z.H.; Akyuz, A.O.; Uysal, M.; Akyokus, S.; Uysal, M.O.; Atak Bulbul, B.; Ekmis, M.A. An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain. *Complexity* **2019**, *2019*, 9067367. [CrossRef]
12. Kharfan, M.; Chan, V.W.K.; Firdolas Efendigil, T. A data-driven forecasting approach for newly launched seasonal products by leveraging machine-learning approaches. *Ann. Oper. Res.* **2021**, *303*, 159–174. [CrossRef]
13. Villegas, M.A.; Pedregal, D.J.; Trapero, J.R. A support vector machine for model selection in demand forecasting applications. *Comput. Ind. Eng.* **2018**, *121*, 1–7. [CrossRef]
14. Bandara, K.; Shi, P.; Bergmeir, C.; Hewamalage, H.; Tran, Q.; Seaman, B. Sales demand forecast in e-commerce using a long short-term memory neural network methodology. In *Neural Information Processing, Proceedings of the 26th International Conference, ICONIP 2019, Sydney, NSW, Australia, 12–15 December 2019*; Proceedings, Part III 26; Springer: Cham, Switzerland, 2019; pp. 462–474.
15. Abbasimehr, H.; Shabani, M.; Yousefi, M. An optimized model using LSTM network for demand forecasting. *Comput. Ind. Eng.* **2020**, *143*, 106435. [CrossRef]
16. Falatouri, T.; Darbanian, F.; Brandtner, P.; Udokwu, C. Predictive analytics for demand forecasting—A comparison of sarima and lstm in retail scm. *Procedia Comput. Sci.* **2022**, *200*, 993–1003. [CrossRef]
17. Carlson, R.C.; Yano, C.A. Safety stocks in MRP—Systems with emergency setups for components. *Manag. Sci.* **1986**, *32*, 403–412. [CrossRef]
18. Datta, A.; Sarkar, B.; Dey, B.K.; Sangal, I.; Yang, L.; Fan, S.K.S.; Sardar, S.K.; Thangavelu, L. The impact of sales effort on a dual-channel dynamical system under a price-sensitive stochastic demand. *J. Retail. Consum. Serv.* **2024**, *76*, 103561. [CrossRef]
19. Bahroun, Z.; Belgacem, N. Determination of dynamic safety stocks for cyclic production schedules. *Oper. Manag. Res.* **2019**, *12*, 62–93. [CrossRef]
20. Buffa, F.P. A Model for Allocating Limited Resources when Making Safety-Stock Decisions. *Decis. Sci.* **1977**, *8*, 415–426. [CrossRef]
21. Oroojlooyjadid, A.; Snyder, L.V.; Takáč, M. Applying deep learning to the newsvendor problem. *IISE Trans.* **2020**, *52*, 444–463. [CrossRef]
22. Chinello, E.; Herbert-Hansen, Z.N.L.; Khalid, W. Assessment of the impact of inventory optimization drivers in a multi-echelon supply chain: Case of a toy manufacturer. *Comput. Ind. Eng.* **2020**, *141*, 106232. [CrossRef]
23. Jiang, H.; Wu, Y.; Zhang, Q. Optimization of Ordering and Allocation Scheme for Distributed Material Warehouse Based on IGA-SA Algorithm. *Mathematics* **2020**, *8*, 1746. [CrossRef]
24. Hammler, P.; Riesterer, N.; Mu, G.; Braun, T. Fully Dynamic Reorder Policies with Deep Reinforcement Learning for Multi-Echelon Inventory Management. *Inform. Spektrum* **2023**, *46*, 240–251. [CrossRef]
25. Kumar, S.; Mahapatra, R.P. Design of multi-warehouse inventory model for an optimal replenishment policy using a rain optimization algorithm. *Knowl.-Based Syst.* **2021**, *231*, 107406. [CrossRef]
26. Pirhooshyaran, M.; Snyder, L.V. Simultaneous decision making for stochastic multi-echelon inventory optimization with deep neural networks as decision makers. *arXiv* **2020**, arXiv:2006.05608.
27. Li, C.; Liu, S.; Qi, W.; Ran, L.; Zhang, A. Distributionally Robust Multilocation Newsvendor at Scale: A Scenario-Based Linear Programming Approach. *Available at SSRN* **2022**. [CrossRef]