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Supply chain inventory control of company Xinghua based on predictive analytics

by

Tiejian Sun

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Acknowledgment

A year passed in a hurry. During the year in Erasmus, I completed the transformation from an undergraduate in industrial engineering to a master in MEL. During this period, I constantly broadened my vision, learned a lot of valuable professional knowledge, and had a clearer career development direction.

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Abstract

As the development as delivery and industry, big company takes more orders from relatively small companies, especially in furniture companies. It seems to be an oligopoly.

However, Xinghua is this kind of small companies. To compete with companies, it needs to make more profit or save cost. As a result, this thesis put focus on how to save cost for the company.

The thesis is made of two main parts. First, an accurate prediction model of material needs to be made. There are three possible models which are LSTM model, ARIMA model, and Holt-Winters model for prediction. The best model is the model which could fit the last 11 years' data best, finally, it concludes that the LSTM model is the best fit model for the data, though there is still much difference between the prediction value and real value.

Because of the existence of the difference, accurate prediction for material A usage is possible. As a result, we need to prepare appropriate safety stock in order to avoid the situation that out of stock. However, too much safety stock will lead to extra cost to the company, so it would be of great importance for us to balance the amount of safety stock. In this part we use EOQ model to calculate appropriate reorder point which includes safety stock for the company.

Although we help Xinghua company calculate safety stock, reorder point and make a prediction model, and these data work indeed, the company could not totally depend on these data. It is because that there is still some random error in the data

1.Introduction

Furniture refers to a large category of appliances and facilities necessary for human beings to maintain normal, engage in production practice and carry out social activities. Furniture also keeps developing and innovating with the pace of the times. Nowadays, it has a wide range of categories, different materials, and different usage ways. It is an important foundation for establishing a working and living space. With the rapid development of China's social economy, the output of China's furniture industry will reach 1.12 billion pieces in 2021, with a year-on-year increase of 23.1%. At present, China has become one of the major furniture manufacturers. In 2021, the export value of China's furniture and its parts reached 5.8 billion euros, with a year-on-year increase of 18.2% (gongyan, 2022). Although China's furniture market is showing a prosperous state, for small and medium-sized furniture enterprises, they still face the “sale winter”. It is because that they could not compete with those big companies which have production efficiency. As a result, for the small companies, they need to get more profit. However, more importantly, they need to save cost.

There are three major profit sources of enterprises, which are resources, labor, and logistics. With the rapid development of the economy, the promotion space of resources and labor as the first and second profit sources is getting smaller and smaller. Therefore, logistics as the "third profit source" has become the focus of people's attention. Research shows that logistics has a great space for improvement in reducing costs. As a result, we could find that logistics plays a significant role in making more profit and saving costs, so for the small company, the ultimate goal of development is to reduce logistics costs to the maximum extent, thus reducing the total cost of each manufacturing enterprise.

Small manufacturing businesses have always had a big problem with the inventory issue. When there is not enough inventory, production cannot proceed, wasting both labor and equipment. Because the order cannot be completed in time, it will also result in a reduction in customer orders, a reduction in revenue, and possibly even a loss of customers. A large amount of inventory will also result in late material waste, insufficient storage space, higher inventory management costs, and a large amount of money. An organization's lifeblood is its working capital. Due to the difficulty in capital turnover, an enterprise may close if both working capital and inventory are overly occupied. Additionally, businesses can make use of working capital. Additionally, businesses can use working capital for other purposes such as construction and investment, and the less money that is used for inventory, the better. More importantly, inventory hides numerous issues with management. An organization must innovate its products, increase its sales market, and manage its production costs if it wants to grow steadily over time. Along with the costs of labor, raw materials, machinery, factory buildings, intellectual property rights, management, and other expenses, there is one more expense that is simple to overlook but impossible to do so: the cost of inventory. There is a lot of room for improvement since inventory costs currently range from 20% to 40% of the value of the inventory items.

The cost of inventory is closely related to the cost of logistics. Inventory is directly related to the objectives of businesses as a crucial link in the supply chain. As a result, one of the keys focuses of each node enterprise's benefit decision-making is how to efficiently reduce the cost of the inventory. Safety stock has a crucial role to play in inventory control. Describe safety stock. There are frequently a lot of unpredictable factors in the actual production or sales of businesses, such as shortages or late deliveries of upstream businesses, changes in downstream businesses' demand, unexpectedly large orders or early deliveries, etc. The pre-set insurance reserve to guard against these uncertain factors is called a safety stock. Safety inventory is a separate category from the enterprise's core inventory. Holding safety inventory has become one of the most effective ways to deal with emergencies because it is impossible to fully realize the ideal "zero inventory" production and sales under real-world social conditions.

The setting of safety stock has a direct impact on the cost of inventory management. There will be some disadvantages if the setting of the safety stock is too high or too low.

If the safety stock is set too high, it will naturally increase the cost of inventory management, and at the same time, it will cause a large amount of funds to be used for purchasing materials, resulting in the non-circulation of funds; On the contrary, if the setting is too low, it will not be able to respond to the uncertain problems or demands of the upstream or downstream of the enterprise in a timely manner, which will lead to out of stock costs, affect the reputation of the enterprise, and increase transportation costs. Traditional inventory control methods include ABC classification method, mathematical statistics method, utility value method and so on. However, most of these methods are based on mathematical statistics and economic knowledge, and artificially formulate safety inventory, which is inefficient and lacks accuracy. Therefore, it is urgent to seek a new inventory control method.

Due to the fiercer market competition, service time has emerged as one of the crucial competition-related factors for businesses, and a short lead time is one of the essential elements for securing orders. By streamlining the internal service process and supply chain management, we can achieve quick and efficient customer response while cutting the length of the customer service response cycle, so that the predicted demand is greater than the actual demand, or the predicted demand time is later than the actual demand time, inventory will be generated. Production by order means that the enterprise arranges production according to the received orders and arranges the purchase of raw materials according to the orders. According to the definition, this production method does not need to make demand forecast and will not lead to inventory due to inaccurate demand forecast. However, in actual production, in order to cope with emergency orders, especially those important customers, the enterprise has added its own stock preparation mechanism under the production by order method, that is to say, the mixed order-based and stock-based production will be adopted. Once the forecast of this mode is not accurate, it will lead to a large amount of inventory just like the stock-based production. A good prediction result can effectively improve the service level of the enterprise and save the cost of the enterprise. However, demand forecasting is based on historical data and decision makers' judgment of the future, and there will always be errors. Different prediction models will have different prediction results, and the same prediction model will have different prediction results with different data sets. In order to do a good job in demand forecasting, it is necessary for enterprises in the upstream and downstream of the supply chain to cooperate closely and make collaborative forecasting, rather than individual enterprises making demand forecasting in isolation. This is because if an enterprise makes a forecast in isolation, it will easily lead to a shortage of goods or an excessive inventory. Traditional inventory control is basically limited to a certain enterprise, without considering the situation of upstream and downstream enterprises. This closed-door approach is difficult to achieve inventory optimization. In today's supply chain management environment, the inventory problem of an enterprise not only affects the interests of an enterprise, but also affects its related upstream and downstream enterprises. When every enterprise in the supply chain can operate healthily and efficiently, the supply chain will have strong competitiveness, so that the member enterprises in the supply chain can realize the supply chain. Therefore, how to forecast demand and control inventory from the perspective of supply chain is an important content of supply chain management.

Capital flow is the blood of enterprises, logistics is the object of production operations, and information flow is an important guarantee for capital flow and logistics. Within the enterprise, efficient information flow can improve the operation efficiency of the enterprise; Among the member enterprises of the supply chain, the efficient information flow can effectively integrate the discrete enterprises, maximize the operational efficiency of the whole supply chain, reduce the operation cost of the enterprises in the supply chain, improve the income, and improve the core competitiveness of the supply chain. High-quality information transmission and sharing is the premise to ensure the coordinated and efficient operation of the supply chain.

Due to the fiercer market competition, service time has emerged as one of the crucial competition-related factors for businesses, and a short lead time is one of the essential elements for securing orders. By streamlining the internal service process and supply chain management, we can achieve quick and efficient customer response while cutting the length of the customer service response cycle. Improving the accuracy of supply chain demand forecast, realizing information sharing among enterprises in the supply chain and shortening the lead time, and establishing an effective supply chain inventory control mechanism will help all enterprises in the supply chain reduce unnecessary inventory costs and excessive production costs caused by market demand fluctuations, reduce unnecessary waste, achieve win-win results, and improve the competitiveness of the entire supply chain.

This thesis put focus on a small furniture company that has serious problem on inventory. It usually occurs that the material is out of stock, which block the process of production. Apart from that, the company will also order too much one kind of material in one time, which means there is no space for other material. The goal of the research is to help the company make an accurate prediction for make reasonable inventory strategies to avoid unexcepted accidents.

2. Literature Review

2.1 Concepts Related Inventory

2.1.1 Inventory

Inventory refers to the goods and commodities in storage state, which is to meet the demand for raw materials or finished products in production, manufacturing, or sales. Whether it is a supplier, manufacturer or seller in the supply chain, a certain amount of inventory can help to ensure the normal, continuous, and stable operation of the supply chain, and can also meet the requirements of customers in a timely manner, improve customer satisfaction, to enhance the market competitiveness of enterprises.

The functions of inventory held by enterprises are as follows:

(1) To balance enterprise production, inventory plays a "regulating valve" role in enterprise production. Before an enterprise conducts production, it needs to purchase the raw materials required for production. The purchased raw materials need to be stored in the designated warehouse. Similarly, finished products that have been produced but have not yet reached the sales phase also need to be stored. Enterprises can control their own production volume according to the quantity of raw materials and finished products in the warehouse.

(2) To balance enterprise sales, inventory plays a similar role in commodity sales and production. It can also adjust the product sales status of an enterprise. The sales volume of commodities is more affected by uncertain factors such as weather, season and holidays. Especially in the peak sales season of this commodity, the enterprise needs to prepare a large amount of commodity inventory in advance to meet the purchase behavior of customers; Even in peacetime, it is necessary to prepare a certain amount of inventory for unexpected needs. Therefore, inventory can alleviate the shortage of goods caused by uncertain factors in the sales process.

(3) To balance enterprise logistics, inventory includes not only available inventory stored in the warehouse, but also in transit inventory and inventory to be inspected. The

logistics link involves the production, procurement, processing, sales and other links of the supply chain. The raw materials, semi-finished products or finished products transported in each link belong to in transit inventory. In the existing logistics links of the transit warehouse, it plays a role in connecting other supply chain links. In addition to in transit inventory, which can regulate enterprise logistics, preparing a certain amount of available inventory can appropriately reduce the number of purchases, thereby reducing the number of transportation and balancing logistics.

According to the role of inventory, we can divide inventory into the following three categories: turnover inventory refers to the inventory necessary to maintain the normal operation of enterprise business; Safety stock refers to the inventory demand caused by solving uncertain factors; Excess inventory, also known as sluggish inventory, is the excess inventory caused by batch purchase due to plan change and forecast failure.

2.1.2 Safety stock

In order to avoid the risk of supplier supply interruption, manufacturers will generally refer to historical data and experience when ordering and add a certain "buffer" quantity on the basis of each order to reduce the possibility of material shortage and increase the company's inventory holding cost. After years of operation, Xinghua company gradually realized that the inventory cost restricts the further development of the company. It not only needs to meet the needs of customers but also needs to control the inventory strictly. The company adjusted the supply chain strategy: make to order (production according to order), that is, the preparation of raw materials with solid versatility should be relatively large, while the preparation of modular finished products and semi-finished products should not be too extensive, Xinghua will arrange materials and production schedule only when the customer has an order intention. Considering the new strategy, Xinghua will establish a safety inventory for auxiliary materials, materials with high defect rates and some key components.

Safety stock (SS) is also called safety storage. The larger the safety stock, the less likely it is to be out of stock; However, the more extensive the inventory, the remaining list will appear. The shortage shall be kept at an appropriate level according to the use of different items and the requirements of customers, and a certain degree of deficiency is allowed.

2.1.3"Zero Inventory" Management

The real meaning of zero inventory is that in multiple operating environments such as material supply, production, and manufacturing, sales and logistics, materials (including raw materials, work in process, and finished products) do not exist in a single warehouse, and inventory form but are in a state of continuous consumption and replenishment. As early as the 1960s, Toyota company realized the state of "zero inventory." At that time, to comprehensively improve the internal operational efficiency and at the same time focus on the core operation links to reduce the waste of funds in unnecessary links, Toyota company used the idea of JIT operation management to timely understand the market demand and control it, to prepare for the implementation of unit production management, constantly optimize the beat of prediction, procurement, production and supply, and improve the turnover rate of materials, So that the company's inventory has reached a "zero inventory" state, making preparations for the development of efficient production. Not long after, more and more scholars from developed countries analyzed this concept and expanded it. They applied it to more business areas, such as sales and procurement, and the inventory input decreased to a certain extent.

2.1.4 Supplier-managed Inventory

This management mode may be referred to as VMI(Jia Lina et al., 2017) for short. It is a supply chain solution that realizes resource allocation and replenishment based on predicted or actual market demand and inventory holdings in a complex and changeable supply chain environment. VMI promotes the enterprise's management mode from push to pull. This inventory management mode is in the supply chain environment, transforming some difficult problems into simple ones, that is, single-level inventory management. Using this mode, we can grasp exactly what kind of demand the end-user has generated, define its inventory, and solve the problems of forecasting market demand and replenishing stock. By understanding the market demand according to the sales data, suppliers can respond more quickly to the changing market environment and user demand. In the traditional mode, the enterprise will replenish only after receiving the user's order, which is more passive. VMI has significantly changed this situation and can adjust the business strategy according to the market demand.

2.1.5 Cycle Inventory

Cycle inventory(Siregar et al., 2019), also known as a basic reserve and benchmark inventory, is a component of the average inventory generated in the replenishment process. It can be described by half of the order quantity (if only the order quantity is considered).

Cycle inventory is prepared for daily customer needs and is usually obtained through replenishment procedures. The quantity of each replenishment is also called the order quantity. The average cycle inventory is equivalent to 1 / 2 of the ordered quantity. When the enterprise orders according to the economic order quantity, the sum of the order cost and the storage cost can be minimized.

2.1.6 Machine Learning

Machine learning(Hajek & Abedin, 2020) is an interdisciplinary discipline, covering probability theory knowledge, statistics knowledge, approximate theory knowledge and complex algorithm knowledge. It uses computers as a tool and is committed to simulating human learning in real-time. It also divides the existing content into knowledge structures to effectively improve learning efficiency.

Machine learning has the following definitions:

(1) Machine learning is a science of artificial intelligence. The main research object in this field is artificial intelligence, especially how to improve the performance of specific algorithms in empirical learning.

(2) Machine learning is the study of computer algorithms that can be automatically improved by experience.

(3) Machine learning uses data or experience to optimize the performance standards of computer programs.

Machine learning has existed for decades or centuries. Dating back to the 17th century, Bayesian and Laplace's derivation of the least square method and Markov chain constitute the tools and foundations widely used in machine learning. From 1950 (Allen Turing proposed to build a learning machine) to early 2000 (with the practical application of deep learning and recent progress, such as Alexie in 2012), machine learning has made great progress.

Since the study of machine learning in the 1950s, the research approaches and objectives in different periods are not the same, which can be divided into four stages.

The first stage is from the mid-1950s to the mid-1960s. This period mainly studies "learning with or without knowledge". This kind of method mainly studies the execution ability of the system. During this period, the data fed back by the system is mainly detected by changing the environment of the machine and its corresponding performance parameters, which is like giving the system a program. By changing their free space function, the system will be affected by the program and change its own organization. Finally, the system will choose an optimal environment to survive. The most representative research in this period is samuet's chess program. However, this method of machine learning is far from meeting human needs.

The second stage is from the mid-1960s to the mid-1970s. During this period, the main research is to implant knowledge in various fields into the system. The purpose of this stage is to simulate the process of human learning through machines. At the same time, the knowledge of graph structure and its logical structure is also used to describe the system. In this research stage, the machine language is mainly represented by various symbols. During the experiment, the researchers realized that learning is a long-term process and cannot learn more in-depth knowledge from this system environment. Therefore, the researchers added the knowledge of experts and scholars into the system, The practice proves that this method has achieved certain results. The representative work in this stage is Hayes Roth and Winson's structural learning system method.

The third stage, from the mid-1970s to the mid-1980s, is called the Renaissance period. During this period, people have expanded from learning a single concept to learning multiple concepts, explored different learning strategies and learning methods, and at this stage, they have begun to combine the learning system with various applications and achieved great success. At the same time, the demand of expert system in knowledge acquisition has greatly stimulated the research and development of machine learning. After the emergence of the first expert learning system, the example induction learning system has become the mainstream of research, and automatic knowledge acquisition has become the research goal of machine learning applications. In 1980, the first International Conference on machine learning was held in Carnegie Mellon (CMU) of the United States, marking the rise of machine learning research in the world. Since then, machine learning has been widely used. In 1984, the second volume of the collection of machine learning jointly written by more than 20 artificial intelligence experts such as Simon was published, and the international magazine machine learning was launched, which further showed the rapid development trend of machine learning. Representative works in this stage include Mostow's guided learning, lenat's mathematical concept discovery program, Langley's bacon program and its improvement program.

The fourth stage, in the mid-1980s, is the latest stage of machine learning. Machine learning in this period has the following characteristics:

(1) Machine learning has become a new discipline. It integrates psychology, biology, neurophysiology, mathematics, automation, and computer science to form the theoretical basis of machine learning.

(2) The research of integrated learning systems, which integrates various learning methods and forms, is rising.

(3) A unified view of various basic problems of machine learning and artificial intelligence is being formed.

(4) The application scope of various learning methods has been continuously expanded, and some applied research results have been transformed into products.

(5) Academic activities related to machine learning have never been more active.

2.2 Research Status

2.2.1 Research Status of Safety Stock

As an important part of inventory management, safety inventory is the insurance inventory preset to prevent uncertain factors, which is independent of the basic inventory of the enterprise. The earliest research on inventory management and safety stock started in the United States. The following are some research cases on inventory management and safety stock.

As early as 1973, crowstonl and other scholars studied the production and inventory problem(Zhao et al., 2010) of multi-stage assembly systems with the method of dynamic programming. Schwarz and Schrage proposed the optimization and near-optimal strategy of multi-stage inventory assembly system under the continuous demand within the infinite planning range by using the boundary condition method. The conclusion is that when solving the optimal or near optimal solution, the constraint conditions are added, and by adding a branch algorithm program, it can usually be faster. Kil and other scholars proposed an algorithm for optimizing the batch size of products with complex product structure, Find the optimal solution. Abenaki also uses LaGrange boundary condition relaxation method to study inventory management. Cetinkaya, Aya, leel proposed an analysis model for coordinating inventory and transportation decisions in VMI system. By assuming that the demand from the demander obeys Poisson distribution and using the properties of Poisson distribution to simplify the nonlinear model, the optimal inventory replenishment and scheduling frequency are calculated. Based on BP artificial neural network technology, the ABC inventory classification method is studied and compared with the multiple discriminant analysis (MDA). The results show that the prediction accuracy of ANN model is higher than that of MDA. Bbodtl and other researchers have studied the impact of the difference in uncertain demand on safety stock under MRP.

(Qi & Jing, 2010) proposed a logistics management model based on ABC classification to improve the quality of logistics management. GUI Weihua and other scholars adopted an improved genetic algorithm that can effectively overcome the shortcomings of the traditional genetic algorithm that is easy to fall into the local optimal solution, and applied the improved model to the raw material inventory work of a non-ferrous smelting enterprise. The practice shows that this method is superior to the original inventory method of the plant and can improve the economic efficiency of the enterprise. Based on the quantitative analysis method and the role of safety stock in the supply chain management system, (Ma & Lin, 2008) analyzed and evaluated that the quantitative analysis method can reduce the influence of uncertainty factors and calculate the appropriate safety stock level. Luo Rongwu proposed a production inventory model with the goal of minimizing the total cost under the condition that the products are out of stock and the raw materials have batch discounts. (Shang & Zhang, 2021) proposed a prediction model based on BP neural network for the complex and nonlinear factors affecting safety stock, and optimized the BP neural network by using genetic algorithm. Then, the simulation experiment was carried out through mobile material data. The experimental results proved that the optimized BP neural network model can provide better accuracy and stability.

2.2.2 Research Status of LSTM

LSTM is an improved recurrent neural network (RNN). In the past few years, a recurrent neural network has been widely used in speech recognition, translation, language modeling and other fields, and has achieved certain results. The following is the development and application of recurrent neural networks at home and abroad.

Ssocher and other researchers introduced a prediction model based on recurrent neural networks (Dai & Cong, 2004), which can restore its structure in complex scene images and sentences. At the same time, it can also be used in the syntax parser and outperforms other methods in semantic scene segmentation, annotation and classification. In terms of segmentation and annotation, the algorithm achieves the highest level of performance on the Stanford background dataset. Cardie constructed a new deep recurrent neural network(Brakel et al., 2013) by superimposing multiple recursive layers, and evaluated the model on the fine-grained emotion classification task. The results show that the performance of the deep recurrent neural network is better than the tree structure-based model using the same number of parameters. And the experimental effect of this method on emotion analysis is also better than the previous algorithm. Kolen and kremer proposed that when the time interval between the input and the corresponding information is short or long, the cyclic neural network model(Yang, 2008) is prone to gradient disappearance or gradient explosion. The long-term and short-term memory neural network (LSTM) proposed later can effectively solve the problems of gradient explosion and gradient disappearance in RNN.

LSTM was first proposed by Sepp Hochreiter and schmidhuuber in 1997. It is one of the most widely used models in deep learning. Like RNN, the application of LSTM mostly stays in picture recognition and rpathy the artificial intelligence of image subtitles using LSTM, such as the generation of handwritten characters in Graves. Karpath did training and achieved good results. Fardis and mehdil applied the cyclic neural network to Copper Mine Metallurgical experiments and compared it with radial basis function neural network (RBFNN) and multiple linear regression (mnlr) models. The experimental results show that the performance of the cyclic neural network is better than that of radial basis function neural network and multiple linear regression model.

Liao and Yin of Nanhua Institute of Technology established the rudiment of multi-branch(Yamashita et al., 2003) recurrent neural network learning algorithm and applied it to the field of chaotic time series prediction to solve the problems of network structure and computational complexity in traditional recurrent neural network. Hu applied LSTM's deep learning model to solve the problem of semantic relationship classification and found that this model is suitable for text sequence data. Liang(Zhang et al., 2020) of Zhengzhou University and other scholars extended LSTM to the recursive neural network based on tree structure and introduced the emotional polarity transfer model, which achieved better results than LSTM and RNN in capturing deeper semantic and grammatical information of text. Zhang of the College of electronic engineering of the people's Liberation Army also applied LSTM to feature extraction in captcha recognition and proposed a decoding algorithm, which not only further improved the recognition rate of the model, but also reduced the time complexity.

Throughout the research literature at home and abroad, recurrent neural network (RNN) and long-term and short-term memory artificial neural network are mostly used in language model, translation, speech recognition, picture recognition and artificial intelligence, but not really used in safety inventory prediction.

2.2.3 Research Status of ARIMA

The simple exponential smoothing method was developed in the 1950s by Holt (1957) and Winters, and Brown (1959) expanded on this theory of statistical prediction (1960). Many researchers heavily utilized the development and research of the ARIMA model in the 1970s. The theoretical framework was first described by Box and Jenkins in 1970, and later developed by Box et al. (1994). (Ji et al., 2016)With Holt winters in the form of the multiplication being the only notable exception, most linear exponential smoothing models have equivalent ARIMA models. A large number of academics developed and studied the ARIMA model at the end of the 19th century. Single-stage and multi-stage supply chain models(Felfel et al., 2014) were created by Graves scholars, respectively, studied the effect of sharing demand information on optimizing the total costs of members at all levels by taking into account the inventory storage costs and stock out costs of members at all levels in the supply chain in the model. The trend extrapolation mechanism was added to the ARIMA prediction method by Haiming (2006) and others. In order to predict data without a trend, one must first predict data with a trend using an ARIMA model, then predict data without a trend using a trend line, and finally propose a new prediction method. Finally, a case study demonstrates the benefits of the prediction method(Lin & Lee, 1994). The demand forecasting technique based on the ARMA (1,1) model was studied by Feng and others in 2008, derived the calculation equation of the bullwhip effect of retailers, and discussed the influence of relevant parameters on the bullwhip effect.

2.2.4 Research Status of Inventory Control

When the market demand is subject to normal distribution conditions, Bourland K. (Bourland et al., 1996)investigated the effects of sharing demand information on reducing demand forecasting error and, consequently, safety stock in a supply chain composed of a single supplier and a single retailer. (Silva et al., 2019)and other academics investigated the multi-level inventory system's inventory control. They discovered that the variance of each link's order quantity in the multi-level inventory system of the supply chain is frequently greater than the variance of the actual demand, and that the variance of the distributor is occasionally greater than the variance of the manufacturer's sales volume. The inventory replenishment strategy in the secondary supply chain was studied by(Zeng et al., 2006) and others in 2006. It has been proven through the development of models and numerical analysis that it is advantageous for businesses to adopt the VMI mode in order to get rid of the bullwhip effect(Svensson, 2008) and decrease supply chain inventory.

3.Methodology

In this thesis, two kinds of methods are applied. The first method is a time series method which includes ARIMA and Holt-Winters method. The second method is machine learning which includes LSTM method. Each of these methods have their own advantages and disadvantages as introduced below.

3.1 Time Series Methods

When making time series prediction, there is an obvious idea that the point is closer to the prediction point, the greater the effect is. For example, when we make predictions to the sale volume of products, it is obvious that the data of recent months have a greater influence on the prediction of the sale volume of the next month. Actually, we could assume that the weight decreases exponentially with the time: 0.8 for this month, then 0.8^2 for last month... the weight of the data with a long age will be close to 0 at the end, which is the basic idea of exponential smoothing method. The exponential smoothing method has several different forms: the one-order exponential smoothing method is for the series without trend and seasonality, the quadratic exponential smoothing method is for the series with trend but without seasonality, and the tertiary exponential smoothing method is for the series with trend and seasonality. "Holt winters" sometimes refers to cubic exponential smoothing. All exponential smoothing methods need to update the calculation results of the previous time step and use the new information contained in the data of the current time step. They are realized by mixing new data and old data, which means it is significant to make good use of an adjustable parameter to balance the weight of relevant old and new data.

3.1.1 One-order exponential Smoothing Method

The recurrence relationship of the first-order exponential smoothing method(Schmeja & Klessen, 2004) is as follows:

Prediction equation: $x_{i+1} = s_i$

Smoothing equation: $s_i = \alpha x_i + (1-\alpha)s_{i-1}\ \ 0 \le \alpha \le 1$

s_i: the smoothed value on time step i

x_i: the real value on time step i

α: the weight on new data and old data

According to the relationship, we could know that α which is bigger than 0 smaller than 1, controls the balance between old data and new data. When α is closer to 0, the old data influences the model more; inversely, when α is closer to 1, the new data takes account more.

Quadratic exponential smoothing is an extension of exponential smoothing. The common implementation is Holt Exponential Smoothing, which includes one prediction equation and two smoothing equations (horizontal smoothing equation and trend prediction equation). Among them, the trend part can be divided into additive trend and multiplicative trend, which correspond to Holt linear trend model and exponential trend model. For the prediction of large time steps, the trend may not extend indefinitely, so it is necessary to suppress this trend. The suppression of additive trend and multiplicative trend corresponds to additive suppression (suppression of linear trend) and multiplicative suppression (suppression of exponential trend). In our passage we just adopt additive trend.

3.1.2 Holt linear trend model

Holt extended the simple exponential smoothing model in 1957 to predict the data containing trends.

Prediction equation: $x_{t+i} = s_i + ht_i$

Horizontal equation: $s_i = \alpha x_i + (1-\alpha)(s_{i-1} + t_{i-1})$

Trend equation: $t_i = \beta(s_i - s_{i-1}) + (1-\beta)t_{i-1}$

α: horizontal smoothing coefficient

β: trend smoothing coefficient

s_i: the smoothed value on time step i

x_i: the real value on time step i

Trend equation describes the trend after smoothing. The unsmoothed value of the current trend t_i is the difference between the current smoothed value s_i and the previous smoothed value s_{i-1}. In other words, the current trend tells us how much the smooth signal changed in the last time step. To smooth the trend, we use the exponential smoothing method to process the trend and use the parameter β . It is obvious that the method of dealing t_i is like the way of dealing s_i. The similar ways mean the trend also needs to be smoothed, and we also need another weight for trend. In order to obtain a smooth signal, we mix it once as last time, but we should also consider the previous smooth signal and trend. If the previous trend is maintained in a single step time, the last term of the first equation can estimate the current smoothed signal. If the calculation result is to be used for prediction, the last smoothing value is taken, and then the last smoothing trend is added to the smoothing value every time the time step is increased.

3.1.3 Holt-Winter model

A series is referred to as seasonal if a specific repeated pattern appears in each specified time interval; this period is known as a season. A season's duration k is determined by how many sequences points it has. The third exponential smoothing adds a seasonal component based on the quadratic exponential smoothing's consideration of the series' baseline and trend. The seasonal component should also be exponentially smoothed, much like the trend component. For instance, it is required to smoothly take into account the seasonal component of the third point in the present season while projecting the seasonal component of the third point in the following season.

Prediction equation: $x_{t+i} = s_i + ht_i + p_{i-k+h}$

Horizontal equation: $s_i = \alpha(x_i - p_{i-k}) + (1-\alpha)(s_{i-1} + t_{i-1})$

Trend equation: $t_i = \beta(s_i - s_{i-1}) + (1-\beta)t_{i-1}$

Seasonality equation: $p_i = \gamma(x_i - s_i) + (1-\gamma)p_{i-k}$

α: horizontal smoothing coefficient

β: trend smoothing coefficient

γ: seasonality smoothing coefficient

s_i: the smoothed value on time step i

x_i: the real value on time step i

p_i: periodic value on time step i

3.1.4 ARIMA model

ARIMA is short for Autoregressive Integrated Moving Average model, which is one of the most widely used models in time series analysis. ARIMA is consist of three parts: AR model, MA model and difference method.

AR model

AR (Auto Regression) model describes the relationship between current value and historical value, AR model could predict data with historical data of variable.

General p-order autoregressive model AR:

$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \cdots + \alpha_p X_{t-p} + \mu_t$

X_t: the prediction value of variable at time t

α_p: the coefficient (weight) for X_{t-p}

μ_t: random disturbance term

White noise sequence refers to the sample real name of the white noise process, which is called white noise for short. The characteristic of white noise sequence is that the random variables at any two time points are not related, and there is no dynamic law that can be used in the sequence. Therefore, historical data cannot be used to predict and infer the future.

There are three requirements for the definition of white noise ε :

(1) $E(\varepsilon_t) = \mu$

(2) $Var(\varepsilon_t) = \sigma^2$

(3) $Cov(\varepsilon_t, \varepsilon_s) = 0, t \neq s$

If the residual is white noise, and the sequence is completely random. The past behavior has no impact on the future development, so there is no need for further analysis. If the residual is not white noise, there is something wrong with the model, like inappropriate coefficient. If we could not change the residual to white noise, we need to change the model or make another prediction to the residual.

If the random disturbance term is a white noise （$\mu_t = \varepsilon_t$） , it is called a pure AR (p) process, which is recorded as:

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \cdots + \alpha_p X_{t-p} + \varepsilon_t$$

The autoregressive model first needs to determine an order p, which means the current value is predicted by the historical value of several periods.

There are many limitations for AR model:

(1) AR model needs to be predicted with its own data

(2) Time series data must be stable

(3) AR model is only applicable to predict the phenomena related to the previous periods (autocorrelation of time series)

MA model

In AR model, if μ_t is not white noise, usually we think it as an q-order moving average:

$$\mu_t = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \cdots + \beta_q \varepsilon_{t-q}$$

ε_t: white noise sequence

However, when $X_t = \mu_t$, which means in the time series, the current value has no relationship with historical value but depends on linear combination of historical white noise, so we could get MA model.

$$X_t = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \cdots + \beta_q \varepsilon_{t-q}$$

Historical white noise will influence the current prediction value indirectly.

ARMA model

The formula shows that:

When combining AR(p) model and MA(q) model, we will get a general autoregressive moving average model ARMA (p, q):

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \cdots + \alpha_p X_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \cdots + \beta_q \varepsilon_{t-q}$$

(1) A random time series could be represented by an ARMA model, which means the series can be explained by past value or lag value and random disturbance term.

(2) If the sequence is stable, which means its behavior will not change with time, then we can predict the future through the past behavior of the sequence.

ARIMA model

Combining AR model, MA model and difference method, we get differential autoregressive moving average model ARIMA (p, d, q), where d is the order of data difference.

Basic procedures for producing an ARIMA model:

(1) To determine whether the sequence is stable, making the ADF test and the sequence drawing is necessary; unstable time series should first undergo the d-order difference in order to convert to stable time series.

(2) The stable time series has been acquired after the first step. The best order p and q can be obtained by analyzing the autocorrelation graph and partial autocorrelation graph to obtain the autocorrelation coefficient (ACF) and partial autocorrelation coefficient (PACF) of the stationary time series.

(3) The ARIMA model is obtained from the obtained d, q, and p. The developed model is subsequently subjected to a model test.

3.2 Machine Learning

3.2.1 ANN Model

In essence, ANN (artificial neural network) is a mathematical model. Its method of information transmission resembles that of a biological neural network. There are many processing units connected to it through weighted paths in the form of a directed graph. Neuron is the name of this cognitive structure. Figure 2.2 depicts the basic neuronal structure. The main components of an independent neuron are input and weight parameters. output and activation function. Multiplying and summing numerous inputs with corresponding weight parameters is the basis of ANN operation. Finding the weight parameter values for all inputs at once can be challenging when there are numerous input parameters and large input samples. People suggest a method of continuously adjusting the weight parameters with the addition of training samples in order to achieve the ideal output. This process is known as training. To obtain the desired output, we can randomly initialize the weight parameter values in the experiment and then use the training method to continuously adjust the weight values.

3.2.2 Activation Function

When we are doing ANN training with deep learning, we need make use of activation function, here is several activation functions we will use in the following research.

(1) Sigmoid activation function

Sigmoid activation function is non-linear activation function, which could transform the input value to interval [0, 1]. Sigmoid function is as follow:

$$sigmoid(x) = \frac{1}{1 + e^{-x}}$$

x: input value

(2) Tanh activation function

Tanh activation function is hyperbolic tangent function, which could transform the input value to interval [-1, 1]. Tanh activation function formula is as follow:

$$\tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

x: input value

(3) Relu activation function

In essence, Relu activation function is the function which could take the maximum value. This function will not be activated all the neurons. When the input value is negative, the output is 0, which represents this neuron is disable; When the input value is positive, which represents this neuron is enable. Relu function process is convenient and easy because of high convergence speed. As a result, Relu function is the most widely used activation function for making artificial neural network. Relu function is as follow:

$$relu(x) = \max(0, x)$$

x: input value

3.2.3 RNN Model

RNN (recurrent neural network) is a network, whose input is sequence data. In the hidden layer, there are connections between various nodes in a hidden layer, with the help of these kinds of connections, we could catch memory parameters of recent neural output, and transfer the parameters to the next input. For each neuron, except for the output from the last layer's nodes, the output will also include the memory value before the last output. When we make trend analysis to production by timeline, continuedly updating data and learning would get better prediction appearance. It is because the functions of the environment and climate factors are addictive in long term.

3.2.4 LSTM Model

LSTM is short for long short-term memory. Sepp Hochreiter invent LSTM model to make up for the shortcomings of RNN in 1997. LSTM is widely used in many fields like sale volume prediction, speech recognition and so on. Although RNN could keep the former input data for a while, the RNN model could not store the time series data in long time ago.

However, this is not a unique disadvantage for RNN model, other models will also be disable in this aspect. Model will not be valid enough if models could only load recent input data. LSTM is a branch of RNN, in other words, LSTM is an advanced version at solving plentiful data. The advantage for LSTM is storing and loading data better. According to the LSTM model structure picture, we could find that LSTM and RNN are different on structures. LSTM owns four input and one output. Four inputs include input of LSTM model and three gating units. The three doors are input gate, output gate, and forget gate. The three gating units control input, output, and memory of variables respectively. The LSTM model use sigmoid activation function to transform the input value to the interval [0, 1]. The value between 0 and 1 could represent the degree of door opening.

LSTM model equations are as follow:

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i)$$

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right)$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o)$$
$$\widetilde{c_t} = tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \widetilde{c_t}$$
$$h_t = o_t \odot tanh(c_t)$$

$\odot$: represent elements multiplication

i_t: input gate

f_t: forget gate

o_t: output gate

$\widetilde{c_t}$: current time memory

c_t: memory gate

b_i: bias term of input gate

b_f: bias term of forget gate

b_o: bias term of output gate

b_c: bias term of memory gate

W_{xi}, W_{hi}, W_{ci}: The input gate corresponds to the weight from the hidden layer to the input, the weight corresponding to the last output data and the weight corresponding to the last memory data.

σ: sigmoid function, which could map the input value from each gate to interval [0, 1]. The value between 0 and 1 could represent the degree of door opening. 0 represent that the door is close, and 1 represent that the door is open.

$tanh$: activation function, which could map the input value to interval [0, 1]

h_t: the output value at time t

The result h_t could be output value or could step into next hidden unit.

3.2.5 LSTM Evaluation Standard

In this thesis, we use MSE and RMSE as standard to evaluate whether the results of prediction are accurate or not.

(1) MSE

MSE (Mean Squared Error) is an important indicator of evaluating prediction results.

MSE is the average of the square of difference between prediction value and real value. In other words, MSE is the average of variance. So, the value of MSE could express the difference between real value and prediction value. The small difference means the prediction result is accurate. MSE formula is as follow:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2$$

n: sample size

y_i: real value of dependent variable corresponding to the ith sample

y_i: prediction value of dependent variable corresponding to the ith sample

(2) RMSE

RMSE (Root Mean Squared Error) is also an important indicator of evaluating prediction results. RMSE is the root of the average of the square of difference between prediction value and real value. Similarly, the value of RMSE could also express the difference between real value and prediction value. RMSE formula is as follow:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}$$

n: sample size

y_i: real value of dependent variable corresponding to the ith sample

$\widehat{y_i}$: prediction value of dependent variable corresponding to the ith sample

3.3 Comparison with Methods

According to the former introduction, we have three methods: ARIMA, Holt-Winter, LSTM. For each method, it has its own advantages and disadvantages.

(1) ARIMA model

Advantages:

The model is very easy, only endogenous variables are needed.

Disadvantages:

The time series data is required to be stable or stable after differential differentiation.

In essence, it can only capture linear relationships; nonlinear relationships are not captured.

Calculation is difficult, the model needs lots of data.

(2) Holt-Winter model

Advantages:

The model could be fit for the data sequence that have trend and seasonality. The prediction result is accurate.

Disadvantages:

Calculation is relatively difficult; the model needs much data.

(3) LSTM model

Advantage:

It has certain advantages in sequence modeling and has long-term memory function.

The problems of gradient disappearance and gradient explosion in the process of long sequence training are solved.

Disadvantages:

There are disadvantages in parallel processing. Compared with some of the latest networks, the effect is as good as them.

4. Analysis

4.1 Model Setting

In this experiment, we took components A as an example, the usage amount of A and B is as follows. The goal of the research is to make a model which is accurate. According to the analysis in chapter 3, we have chosen 3 methods that are fit for the usage amount: ARIMA model, Holt-Winters model, LSTM model. For each method, the disadvantages and advantages are all exist. They all might be the best prediction model for usage amount. As a result, we apply all 3 models in this experiment, and find which one is the best according to RMSE. The best model is the one that has the least RMSE.

For these 3 methods, we will apply all of these in python. There are still some other statistic tools like SPSS, R language. Although they could also achieve this goal, even they could have less procedures, convenient method and simple interface, Python environment provide much freedom for adjusting the model, which is the most important reason why we choose Python. And as an open-source language, we could find much resource on the Internet and communicate with other people, which could benefit us find a right way to apply the method, why the way is right and how to improve the process. Take ARIMA method as an example, when we apply this model, we will find that finding appropriate (p, d, q) is relatively significant for the model, and at this point, Python is much better. It is because the result is more intuitive. As a result, we choose to apply all three models in Python

4.2 Lab environment

All lab environments are the same, the environment is as follow

Operation system	Monterey 12.0.1
CPU name	Apple M1
CPU frequency	3.2GHZ

ROM	8GB
Development language	Python
Development integrated environment	PyCharm

Table 1 Lab Environments

4.3 ARIMA Method

Next, we will use ARIMA method to make a model, and predict for the sale volume, we have collected 11 years' usage amount of material A.

(1) install and load packages

```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from statsmodels.tsa.holtwinters import ExponentialSmoothing as HWES
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa import stattools
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima_model import ARMA, ARIMA
import statsmodels.tsa.stattools as st
from scipy import stats, signal, interpolate
from sklearn.metrics import mean_squared_error
import warnings
```

Table 2 ARIMA code section 1

Statsmodels: In Python, statsmodels is the core toolkit for statistical modeling and analysis. It includes almost all kinds of common regression models, nonparametric models and estimates, time series analysis and modeling, and spatial panel models. Its functions are very powerful and easy to use. In addition to building statistical models and calculating data, the toolkit also provides the function of model visualization, such as the visualization of ACF and PACF

SciPy: SciPy is an advanced scientific computing library. SciPy contains modules of linear algebra, optimization, integration, and statistics. The SciPy package contains various toolkits dedicated to common problems in scientific computing. Its main function is based on numpy, so its array uses numpy. Its different sub modules correspond to different applications such as interpolation, integration, optimization, image processing, special functions and so on.

(2) Test seasonality and stationarity

```
def diff_stat(self):
        nor_p = stats.shapiro(self.data)
        if nor_p[1] > 0.05:
            print(f{self.col} can be assumed to be normally distributed')
        else:
            print(f{self.col} cannot be assumed to be normally distributed')
```

Table 3 ARIMA code section 2

The following process needs table data, so we need test the stationarity, and change it to be stable if it is not.

(3) find the order of ARIMA according to ACF and PACF

```
# ACF
        fig, ax = plt.subplots(figsize=(20, 10))
        fig = plot_acf(self.data, alpha=0.05, ax=ax, lags=10, unbiased=True)
        title = f'{self.col} ACF'
        plt.xlabel('Order', fontsize=20)
        plt.ylabel('ACF', fontsize=20)
        plt.title(title, fontsize=20)
        plt.xticks(fontsize=20)
        plt.yticks(fontsize=20)

        # PACF
        fig, ax = plt.subplots(figsize=(20, 10))
        fig = plot_pacf(self.data, alpha=0.05, ax=ax, lags=10)
        title = f'{self.col} PACF'
        plt.xlabel('Order', fontsize=20)
        plt.ylabel('PACF', fontsize=20)
        plt.title(title, fontsize=20)
        plt.xticks(fontsize=20)
        plt.yticks(fontsize=20)

        #
        ts = seasonal_decompose(self.data, freq=12)
        plt.figure(figsize=(20, 10))
        ts.plot()
```

```
        p_value = adfuller(self.data)[1]
        if p_value < 0.05:
            print(f'{self.col} is stationary')
            return 0
        print(f'{self.col} is not stationary')
        i = 1
        p_value = adfuller(diff(self.data, i).dropna())[1]
        while p_value >= 0.05:
            i += 1
            p_value = adfuller(diff(self.data, i).dropna())[1]
        return i


    # find the order for ARMA
    @staticmethod
    def find_order(series):
        order = st.arma_order_select_ic(
                series,
                max_ar=3,
                max_ma=3,
                ic=['aic', 'bic', 'hqic']
            )
        order_min = order.aic_min_order
        p = order_min[0]
        q = order_min[1]
        return p, q
```

Table 4 ARIMA code section 3

(4) set ARIMA prediction model and test RMSE

```
    # predict
    def pre(self):
        predictions_ARMA_diff = pd.Series(
            self.result_ARMA.fittedvalues,
            copy=True,
            index=self.data.index
        )
        plt.figure(figsize=(20, 10))
        if self.arima_order[1] > 0:
            predictions_ARMA = cum_sum(predictions_ARMA_diff,
self.arima_order[1])
        else:
            predictions_ARMA = predictions_ARMA_diff

        temp = pd.concat(
            [self.data, predictions_ARMA], axis=1
        )
        temp.columns = ['original data', 'fitted data']
        colormaps = {
                'original data':'blue',
```

```
            'fitted data':'red'
        }
        for col in temp.columns:
            temp[col].plot(
                style=colormaps.get(col)
            )
        plt.legend(loc=1, fontsize=20)
        title = f'{self.col} ARIMA({self.arima_order[0]}, {self.arima_order[1]},
{self.arima_order[2]})'
        plt.xlabel('Date', fontsize=20)
        plt.title(title, fontsize=20)
        plt.xticks(fontsize=20)
        plt.yticks(fontsize=20)
        return predictions_ARMA.fillna(0) + self.data[self.col].values[0]
arima = ARIMA_auto(df, 'Passengers')
pred = arima.predictions_ARMA
```

Table 5 ARIMA code section 4

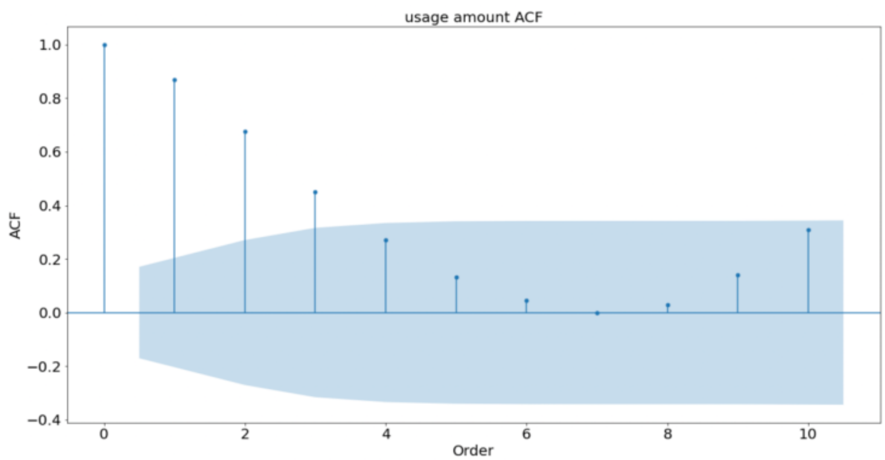

Figure 1 ACF

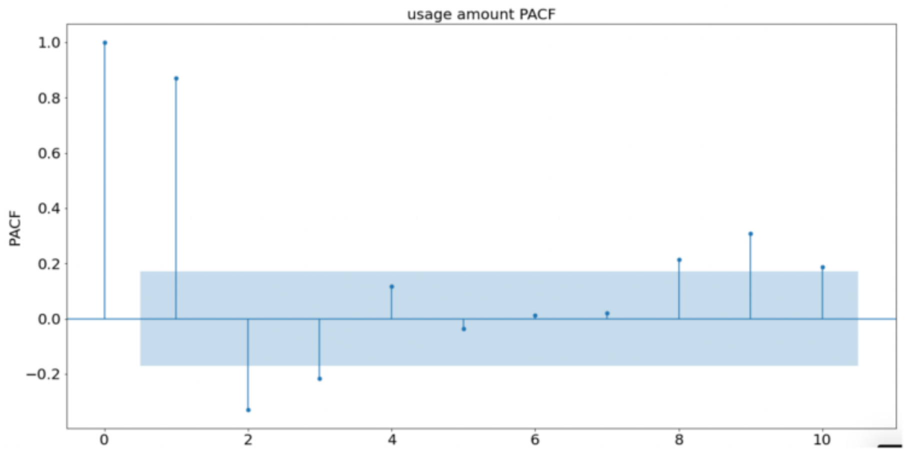

Figure 2 PACF

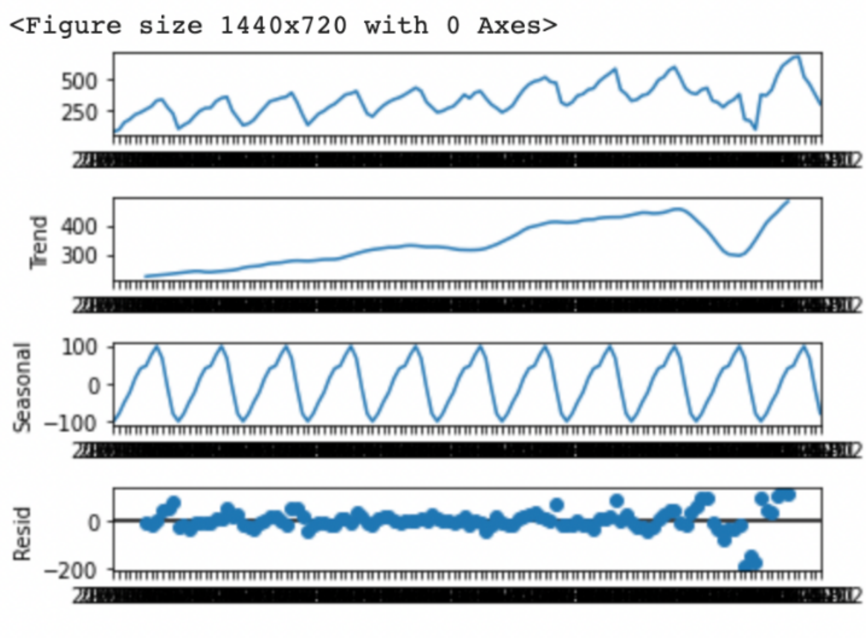

Figure 3 Residual

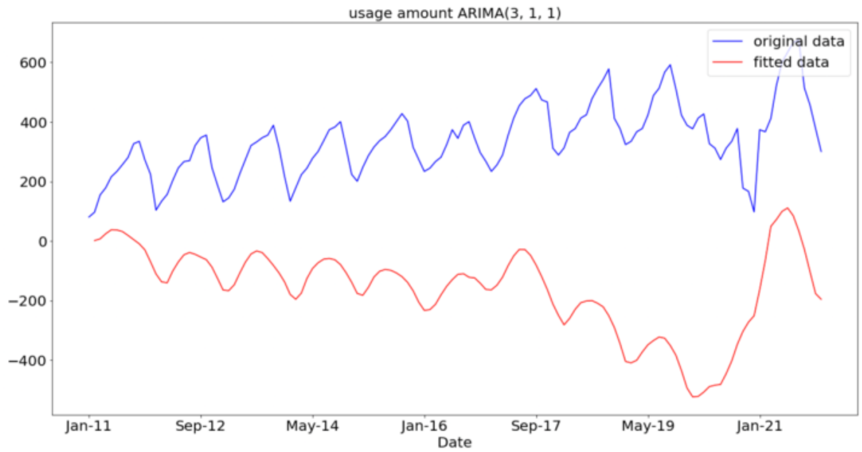

Figure 4 ARIMA model

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:         D.usage amount   No. Observations:                  131
Model:                 ARIMA(3, 1, 1)   Log Likelihood                -697.821
Method:                       css-mle   S.D. of innovations             48.939
Date:                Wed, 07 Sep 2022   AIC                           1407.642
Time:                        22:24:41   BIC                           1424.893
Sample:                             1   HQIC                          1414.652

=========================================================================================
                            coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                     1.8860      0.325      5.803      0.000       1.249       2.523
ar.L1.D.usage amount      1.0105      0.082     12.296      0.000       0.849       1.172
ar.L2.D.usage amount     -0.0213      0.120     -0.177      0.859      -0.257       0.215
ar.L3.D.usage amount     -0.3340      0.083     -4.025      0.000      -0.497      -0.171
ma.L1.D.usage amount     -0.9999      0.025    -40.152      0.000      -1.049      -0.951
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            1.0361           -0.5726j            1.1838           -0.0804
AR.2            1.0361           +0.5726j            1.1838            0.0804
AR.3           -2.1362           -0.0000j            2.1362           -0.5000
MA.1            1.0001           +0.0000j            1.0001            0.0000
-----------------------------------------------------------------------------
```

Figure 5 ARIMA model analysis

RMSE: 456

4.4 Holt-Winter model

Next, we will use ARIMA method to make a model, and predict for the sale volume

```
df.index.freq = 'MS'
#build and train the model on the training data
model = HWES(df, seasonal_periods=12, trend='add', seasonal='mul')
fitted = model.fit(optimized=True, use_brute=True)
```

```
#print out the training summary
print(fitted.summary())



#plot the training data, the test data and the forecast on the same plot
temp = df.copy()
temp['Predicted number of passengers'] = fitted.fittedvalues
temp.plot(figsize=(20, 10))
```

Figure 6 Holt-Winters code section 1

```
                       ExponentialSmoothing Model Results
================================================================================
Dep. Variable:                Passengers   No. Observations:                 132
Model:              ExponentialSmoothing   SSE                        394600.969
Optimized:                          True   AIC                          1088.373
Trend:                          Additive   BIC                          1134.498
Seasonal:                 Multiplicative   AICC                         1094.426
Seasonal Periods:                     12   Date:                Fri, 26 Aug 2022
Box-Cox:                           False   Time:                        18:12:53
Box-Cox Coeff.:                     None
=================================================================================
                          coeff                 code              optimized
---------------------------------------------------------------------------------
smoothing_level               0.5707527                alpha                True
smoothing_trend               0.0001626                 beta                True
smoothing_seasonal            0.4291482                gamma                True
initial_level                 225.74290                  l.0                True
initial_trend                -2.2621710                  b.0                True
initial_seasons.0             0.9557020                  s.0                True
initial_seasons.1             1.0440579                  s.1                True
initial_seasons.2             0.8969626                  s.2                True
initial_seasons.3             1.1295813                  s.3                True
initial_seasons.4             1.3984195                  s.4                True
initial_seasons.5             1.5564690                  s.5                True
initial_seasons.6             1.6500438                  s.6                True
initial_seasons.7             1.8690877                  s.7                True
initial_seasons.8             2.1349428                  s.8                True
initial_seasons.9             2.3151093                  s.9                True
initial_seasons.10            1.9502836                 s.10                True
initial_seasons.11            1.6826308                 s.11                True
---------------------------------------------------------------------------------
```

Figure 7 Holt-Winters model analysis

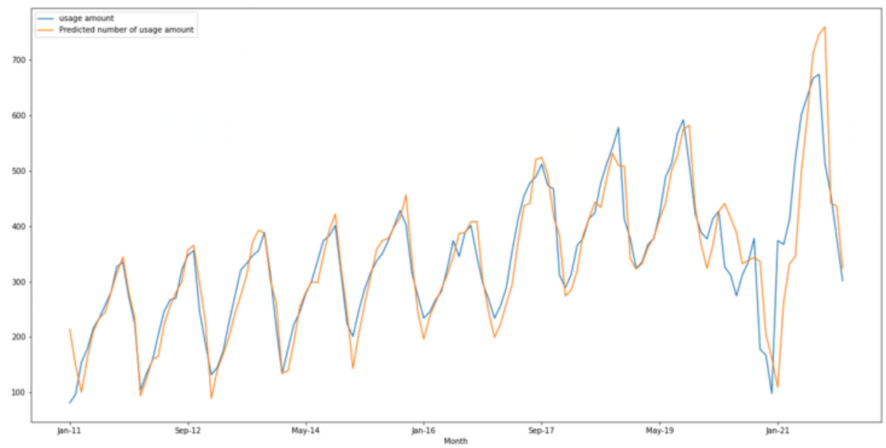

Figure 8 Holt-Winters model

RMSE: 54.67541752183051

4.5 LSTM method

Next, we will use LSTM method to make a model and predict for the sale volume.

(1) install and load packages

```
# LSTM for international airline passengers' problem with regression framing
import numpy as np
import matplotlib.pyplot as plt
from pandas import read_csv
import math
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LSTM
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
```

Table 6 LSTM code section 1

Pandas: Pandas is a powerful tool for Python data analysis. It is an open-source data analysis package. It was originally developed for financial data analysis tools. Therefore, pandas provides good support for time series analysis.

Tensorflow, keras: Google's Tensorflow machine learning framework is known as

Keras. It is a free framework that works with Python to implement algorithms, deep learning applications, and other things. It is employed in both research and production. It is equipped with optimization technology, which can speed up the completion of challenging mathematical operations. It is because it employs multidimensional arrays and "numpy" algorithms. They are also known as "tensors" when they have multiple dimensions. Deep neural networks can be used, according to the framework. It has many well-known datasets and is very scalable. It performs calculations and automatically manages resources using GPU. It is supported well and has a wealth of machine learning libraries. The framework could run a deep neural network model, train it, and create applications that can predict the relevant characteristics of each data set.

Python-based Keras is a deep learning API. It is a high-level API with a useful interface that can assist in resolving machine learning issues. It utilizes the Tensorflow framework for operation. It is intended to facilitate quick experimentation. It offers the fundamental constructs and abstractions that are necessary for creating and packaging machine learning solutions. It is highly scalable and functions across platforms. This means that a TPU or GPU cluster can run Keras. Additionally, the keras model can be exported for use in a web browser or mobile application.

(2) convert data

```
# LSTM for international airline passengers' problem with regression framing
import numpy as np
import matplotlib.pyplot as plt
# convert an array of values into a dataset matrix
def create_dataset(dataset, look_back=1):
    dataX, dataY = [], []
    for i in range(len(dataset)-look_back-1):
        a = dataset[i:(i+look_back), 0]
        dataX.append(a)
        dataY.append(dataset[i + look_back, 0])
    return np.array(dataX), np.array(dataY)
```

Table 7 LSTM code section 2

The data in the form of time series is converted into the form of supervised learning set, which means the previous number is taken as the input and the latter number is taken as the corresponding output.

(3) remove uncertainty

```
# fix random seed for reproducibility
tf.random.set_seed(7)
```

Table 8 LSTM code section 3

For this model, every run will get different result. As a result, to compare the result with other models, we need to use a fixed result to achieve valid comparison.

(4) load data

```
# load the dataset
dataframe = read_csv('airline-passengers.csv', usecols=[1], engine='python')
dataset = dataframe.values
dataset = dataset.astype('float32')
```

Table 9 LSTM code section 4

(5) normalize the dataset

```
# normalize the dataset
scaler = MinMaxScaler(feature_range=(0, 1))
dataset = scaler.fit_transform(dataset)
```

Table 10 LSTM code section 5

Scaling the data in the training set and the test set to [0, 1] can accelerate the convergence. After initialization, the scaler is trained with the training set data, and then the training set and the data set are scaled. This scaler is also used to perform inverse scaling in the subsequent prediction to restore the predicted value to the real dimension.

(6) split into train and test sets

```
# split into train and test sets
train_size = int(len(dataset) * 0.67)
test_size = len(dataset) - train_size
train, test = dataset[0:train_size,:], dataset[train_size:len(dataset),:]
```

Table 11 LSTM code section 6

The data set is divided into training set and test set. The first two-thirds are training sets and the last one-third are test sets. Take the sale data as an example, The first 99 records are training sets and the last 33 records are test sets.

(7) reshape input

```
# reshape input to be [samples, time steps, features]
trainX = np.reshape(trainX, (trainX.shape[0], 1, trainX.shape[1]))
testX = np.reshape(testX, (testX.shape[0], 1, testX.shape[1]))
```

Table 12 LSTM code section 7

Divide the input and output columns in the training set into x and y, and the input columns are converted into three-dimensional arrays.

(8) create LSTM model

```
# create and fit the LSTM network
model = Sequential()
model.add(LSTM(4, input_shape=(1, look_back)))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')
model.fit(trainX, trainY, epochs=100, batch_size=1, verbose=2)
```

Table 13 LSTM code section 8

Initialize LSTM model and start training, set the number of neuron cores, set the format of input data during training, etc. At this time, we could get a trained LSTM model, and use it for the following testing.

(9) make and invert the prediction

Separate the input and output columns of a piece of data, and the input is transformed and transferred to the prediction function for single-step prediction. After obtaining the prediction value, we need inversely scale the value and restore it to the original value range.

```
# make predictions
trainPredict = model.predict(trainX)
testPredict = model.predict(testX)
# invert predictions
```

```
trainPredict = scaler.inverse_transform(trainPredict)
trainY = scaler.inverse_transform([trainY])
testPredict = scaler.inverse_transform(testPredict)
testY = scaler.inverse_transform([testY])
```

Table 14 LSTM code section 9

(10) Visualization of prediction results

Plot the y value and the predicted value of the test set in the same chart, and calculate the RMSE value of the training and test parts

```
# calculate root mean squared error
trainScore = np.sqrt(mean_squared_error(trainY[0], trainPredict[:,0]))
print('Train Score: %.2f RMSE' % (trainScore))
testScore = np.sqrt(mean_squared_error(testY[0], testPredict[:,0]))
print('Test Score: %.2f RMSE' % (testScore))
# shift train predictions for plotting
trainPredictPlot = np.empty_like(dataset)
trainPredictPlot[:, :] = np.nan
trainPredictPlot[look_back:len(trainPredict)+look_back, :] = trainPredict
# shift test predictions for plotting
testPredictPlot = np.empty_like(dataset)
testPredictPlot[:, :] = np.nan
testPredictPlot[len(trainPredict)+(look_back*2)+1:len(dataset)-1, :] = testPredict
# plot baseline and predictions
plt.plot(scaler.inverse_transform(dataset))
plt.plot(trainPredictPlot)
plt.plot(testPredictPlot)
plt.show()
```

Table 15 LSTM code section 10

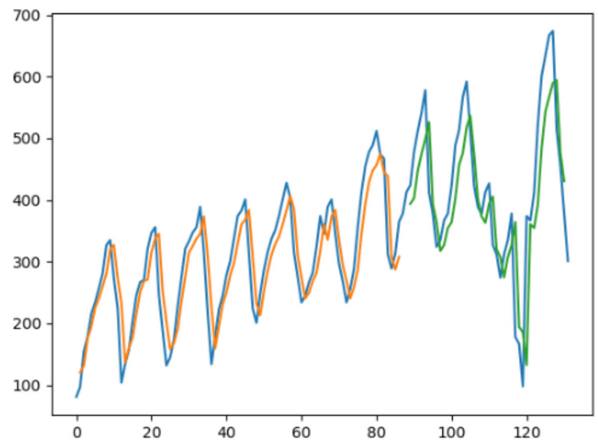

Figure 9 LSTM model

Train Score: 45.00 RMSE

Model Name	ARIMA	Holt-Winters	LSTM
RMSE	456	54.7	45

Table 16 Train Score

4.5 Summary

After comparison, we could find that LSTM is the best method among these methods because of the lowest RMSE. However, we could find that there is still some difference between real value and prediction value according to the graph. The reasons are as follow:

(1) we adopt the data from 2011 to 2021, we could find that there is much difference around 2020, It is because that during 2020 covid-19 affected the logistic and supply chain seriously. First, it will lead less material and components transport to company. It is because that during covid-19, there was less trucks available. As a result, the usage amount decreased. Apart from that, during that time, the furniture orders decreased, less people would like to buy furniture, since during that, people got less money from companies, so they dislike paying for the bill. Finally, during covid-19 labor cost

increased a lot, and labor cost includes transportation cost, worker salary, material cost and so on. In order to control the cost in a reasonable margin, Xinghua company planned to decrease component's usage.

(2) After 2019, the customers would like to buy furniture on the Internet. The assembled furniture which is similar as IKEA attracted lots of people especially young people. It is because that first the way of buying fit young people's interest. Furthermore, the assembled furniture needs customers to assemble furniture by themselves. Although this process will take some time, the assembled furniture will decrease the labor cost because customers assemble furniture by themselves. As a result, customers will get lower price because of lower cost. Although the assembled furniture is convenient and cheap, the assembled furniture only includes some small furniture, which means assembled furniture will only influence orders mainly from small companies like Xinghua.

(3) During eleven-years' time, the company have made some wrong business decisions. For instance, if the company overweigh the material usage in the next period, so in order to make full use of the remained material, the company will try to get more orders and increase the usage in next period to avoid too much inventory cost. Inversely, if the company underestimate the material usage in the next period, so the company will try to get less orders and delay production plan in next period.

Various prediction model including LSTM, ARIMA, Holt-Winters could help company predict the normal situation but not the unexcepted things like covid-19, changing market preferences (assembled furniture), changing customers' demand. For the company, it could not control the market trend, predict customer's preference and urgent accident.

As a result, the most accurate prediction model even not consider unexcepted accident. That is the reason why there is still difference between real value and predict value, so the value predicted by the model may lead company to the wrong way and make wrong business decision. To make up these inevitable errors, we need to prepare appropriate safety stock. Too muck safety stock will lead to cost more resource like warehouse space, labor cost, inventory cost. Inversely, less safety stock may not make up the troubles provided by unexcepted accident. As a result, it would be of great importance to balance the safety stock. Even the model is accurate enough, we still need safety stock as a plan b.

5.Inventory optimization

5.1 Inventory management method

The traditional inventory management is often limited to the enterprise. By classifying materials, it focuses on the ordering frequency, quantity and ordering method of key components to minimize the inventory holding. In this section, we will focus on two common methods:

(1)ABC classification

Villefort Pareto used relevant economic theories to analyze the distribution of personal income. In this process, he proposed the ABC classification method, which is also called Pareto analysis method. The core idea of this analysis method is to distinguish many influencing factors, and select the important factors that play a decisive role in the development of things for focus and research, while most other factors with little impact are secondary. Later, this analysis method was called ABC method by H.F. Dickie and was introduced into inventory management. In the 1960s, Peter Drucker extended the application of ABC classification to the analysis of various phenomena in society, so that ABC analysis gradually evolved into one of the operation methods to improve the comprehensive benefits of enterprises and was widely used.

The core idea of the "two eight principle" in ABC classification is the key minority and the general majority, that is, the key factors accounting for 20% affect the main affairs accounting for 80%. In the enterprise inventory management business, the inventory of class a materials accounts for 5-20% of the total inventory, but it accounts for 65-80% in capital; The proportion of class a materials is completely opposite to that of class C materials. The proportion of capital is only 5-20%, but the proportion of inventory reaches 60-80%; The proportion between these two types of materials is class B materials.

ABC classification, as a traditional inventory management method, is widely used in the basic operation management of enterprises. Its role in the inventory management of enterprises is mainly shown as follows: first, the total inventory holdings are reduced; second, The total amount of funds occupied decreases; third, The proportion of various inventories is more reasonable; fourth, The proportion of human and material resources invested in inventory management is reduced. But at the same time, it also has some shortcomings. It only uses the inventory quantity or type and fund amount as the classification basis, but ignores other factors that have an impact on the enterprise's inventory management. For example, some materials classified as class C may play a key role in the inventory management. However, the enterprise management has the characteristics of diversity and different emphasis. Therefore, it is necessary to introduce other scientific analysis methods and ABC classification to make inventory management decisions more accurately.

(2) EOQ

EOQ is short for economic ordering quantity, which belongs to the quantitative ordering model. This method can accurately grasp the order quantity of the enterprise and effectively control the purchase, ordering and storage costs of the enterprise. The main function of EOQ model is to balance the inventory cost according to the order cost to achieve the goal of reducing the inventory cost. To achieve this goal, it is necessary to ensure the minimum order quantity in the order stage, that is, whenever the enterprise's material inventory level drops to the lowest point (reorder point), the purchase demand with the order quantity of a certain most economic quantity will be triggered immediately.

The economic batch model (EOQ) is a commonly used ordering method for enterprises at present. That is, when the stock of inventory materials gradually decreases to zero with the demand of continuous consumption during the storage period, the order is placed and the goods are supplied immediately. The stock of the materials immediately rises to the maximum stock, and then enters the cycle of the next storage cycle. Under the premise of relatively stable demand, EOQ mode is more effective to improve the inventory turnover rate and reduce the inventory cost. However, in the face of large demand fluctuations, EOQ cannot fundamentally solve the inventory problem.

5.2 Replenishment strategy

Replenishment strategy includes the decision of when to put forward replenishment order and how much to order each time. These decisions determine the product satisfaction rate, cycle service level, turnover stock and safety stock. Replenishment strategies can take many forms. We only focus on the following two types:
(1) Continuous review: this method is to check the inventory at any time. When the inventory drops to the reorder point, the order with batch number Q will be issued. For example, suppose that the inventory manager of Xinghua Company continuously observes the inventory of material A. when the inventory is lower than the reordering point, that is, 200 units, he orders 600 materials a. In this case, the quantity of each order is unchanged. However, when the demand changes, the time interval between two adjacent supplementary orders will change.
(2) Periodic review: this method is to count the inventory regularly according to the predetermined time interval, and then put forward an order to supplement the inventory level to the specified target inventory level. Let us take Xinghua company as an example. In periodic review model, the inventory manager will not check the inventory of material A continuously. Every Thursday, workers will check the inventory of material a, and then inventory management will order enough material a to make the sum of the existing inventory and the replenishment order quantity reach 1000. In this case, the time interval for ordering is fixed. However, in the case of changing demand, the batch size of each order will fluctuate.
Although these two replenishment strategies are not comprehensive enough, they are sufficient to explain the main management issues related to safety stock.

5.3 Measurement of product availability

Product availability reflects the ability of an enterprise to use inventory to meet customer orders immediately. If the customer's order arrives and the enterprise has no inventory, it will lead to shortage. There are many methods to measure product availability. Several important measurement indicators reflecting product availability are listed below.

(1) Product fill rate

Product fill rate refers to the rate at which product demand can be met immediately through inventory, that is, the possibility of using existing inventory to meet product demand. The product satisfaction rate should be based on a specified demand rather than time. Therefore, it is more appropriate to measure the satisfaction rate of demand per million units rather than the satisfaction rate of monthly demand. Assuming that the inventory of Xinghua Company can provide furniture for 90% of customers, the remaining 10% of customers will be lost to competitors due to insufficient inventory. At this time, the product satisfaction rate of Xinghua Company is 90%.

(2) Order fill rate

Order fill rate refers to the rate at which orders are immediately satisfied through inventory. The order fulfillment rate should also be based on a specified order quantity rather than time. In the case of multiple products, only when the inventory can supply all the products of the order can it be said that the inventory meets the requirements of the order.

(3)Cycle service level (CSL)

Cycle service level (CSL) refers to the proportion of replenishment cycle in which all customers' needs are met in all replenishment cycles. Replenishment cycle refers to the time interval between two consecutive replenishments. The periodic service level is equivalent to the probability that there is no shortage in a replenishment period. The periodic service level shall take the specified replenishment cycle times as the reference object. If Xinghua Company orders 600 materials a, the interval between the arrival of two consecutive batches of replenishment is a replenishment cycle.

(4) Expected shortage per replenishment cycle (ESC)

It refers to the average value of the market demand that cannot be met by the existing inventory in each replenishment cycle. Assuming that the order quantity is Q (that is, the average demand in the replenishment period), the demand loss rate is equal to ESC / Q.

In many practical cases, enterprises have their desired level of product availability, and hope to achieve this desired level by designing replenishment strategies. Inventory manager must design corresponding replenishment strategy and reasonable safety stock to achieve this goal. The desired product availability level can be determined by weighing the inventory holding cost and the out-of-stock cost.

5.4 Existing inventory problems in the enterprise

(1) inventory accuracy is low and the account is inconsistent with the actual situation

There are omissions in the inventory management of company a, and errors often occur in the receipt and delivery, which are mainly reflected in two links. Due to the particularity of household appliances, there are many problems that need to be paid attention to in the acceptance entry. However, company a is seriously short of manpower, and only one person is arranged for the acceptance. If the number of goods inspected is large, If the acceptance personnel are in a hurry, errors will occur, but they will not be found at that time, and will not be found until delivery or inventory; On the other hand, after the goods are delivered from the warehouse, it is necessary to timely complete the tasks of replenishing the goods off the shelf and replenishing the goods on the shelf. The error rate in this link is high. Company a arranges employees to scan the code with the handheld terminal. The former is to take down the goods from the location, while the latter is to take down the required goods from the event location and put the remaining goods on the location. In the case of heavy workload, errors in quantity often occur when replenishing goods and putting them on shelves. However, due to the company's technology not being upgraded in a timely manner and a complete accountability system not being formed, even if there is an error, the specific operator cannot be found, and the error will only be found in the monthly inventory.

(2) frequent material shortage and low procurement efficiency.

For many years, the cooperation relationship with suppliers has not attracted the attention of company A. all the strategies adopted by the company are to obtain higher benefits. When purchasing goods from suppliers, company a did not take the same payment measures for all suppliers. Some suppliers have strong strength and large demand. Company a does not pay the full amount at one time, and chooses installment payment out of the pursuit of profit; Some suppliers are small in scale and production scale. Company a will take the form of credit sales and even delay payment. Suppliers are full of complaints and think that the biggest problem in the process of cooperation with company a is payment collection.

The occurrence of these situations has exposed that company a's maintenance of its own interests and pursuit of profits have infringed on the interests of suppliers. The uncertainty of the procurement lead time has been enhanced, and there is no rule to follow for the warehousing of the purchased goods. The small household appliance business department has become a major disaster area of such problems. For example, in early August 2019, the small appliance business department purchased a batch of motors from a motor factory in Changzhou, but the delivery was not completed until the end of December; In September of that year, a batch of motors were purchased from a motor factory in Shandong, and it took nearly two months to complete the delivery. The cooperation time between company a and these two manufacturers is relatively long. After receiving the order from company a, it took two months for both manufacturers to complete the delivery. The time span is relatively large, and it is difficult to grasp the warehousing rhythm. It often occurs that downstream users have strong demand for goods.

5.5 Causes of inventory problems

(1) Impact of purchase lead time on inventory

The lead time mentioned in this article refers to the purchase lead time. In the calculation, the date when company a submits the order is taken as the starting point. The supplier sends all the materials listed in the order to the warehouse designated by company a as the end point. The time period from the starting point to the end point is the purchase lead time. If the materials are from overseas, it should also include the material customs clearance. Company needs to purchase a complete range of products, such as wires, plastic parts, rubber parts, etc. The company has formulated classification principles for these products, which can be divided into two types, domestic and imported, based on the place of origin. The procurement lead time of these two types of products is 5-30 days and 30-90 days respectively. Some raw materials are special and can be extended to 180 days. For imported raw materials, transportation and customs clearance take a long time, while the lead time for procurement is relatively long. It can be seen from the data in Table 4.2 that the procurement lead time of 945 materials in the company exceeds 2 months, accounting for 25% of the total raw materials. In order to control the procurement cost, these materials are basically transported by sea, which is likely to be affected by bad weather, customs clearance control and other factors, and the transportation time is uncertain. The accuracy of forecast depends largely on the purchase lead time, which is the main reason for increasing inventory.

(2) In terms of supplier management, company needs improvement in the following aspects:

First, the information between company and suppliers is not smooth. In the contemporary supply chain management mode, each node should not only form a simple trading relationship or a buying and selling relationship but should be a strong cooperative relationship with the purpose of "win-win". However, company's awareness in this respect is not in place. Not only does it not create a "win-win" situation, but also the information communication is not smooth. It maintains independence in inventory management and cannot arrange orders and distribution according to the actual demand. In this case, suppliers do not know much about orders and sales, and the rationality of production and distribution plans cannot be guaranteed. In the whole supply chain, inventory will fluctuate greatly, too much inventory will occupy capital flow, and too little inventory will lead to shortage.

Second, there are contradictions between a company and multiple suppliers. Import procurement needs to bear heavy cost pressure. In order to achieve the purpose of cost control, company a must strive to realize the local transformation of suppliers. However, in practice, the company ignores the importance of getting along with suppliers harmoniously, only pays attention to its own interests, and frequently selects new suppliers. The suppliers are dissatisfied with this.

Third, many suppliers think that company often issues urgent orders, which is difficult for them to resist. The purchasing personnel will frequently urge the goods, and the supplier can only make the decision of inserting orders when it has no choice. In some cases, in order to meet the needs of the company, the supplier can only ask employees to work overtime or suspend the original plan. In other cases, the logistics company needs to arrange separate delivery, which not only breaks the original plan but also requires more operating costs. The frequent occurrence of this situation will certainly cause strong dissatisfaction from suppliers, who think that company a should adjust its procurement mode.

Fourth, the suppliers of company are scattered and numerous. Before the implementation of VMI, company a cooperated with 222 suppliers, most of which were in eastern provinces and cities.

5.6 Reorder point model

In order to solve those problems, the Xinghua company could adopt re-order point model. In this model, we need to clarify two things. First, we need to know the material consumption in unit time. Second, we need to confirm the safety stock which is appropriate for the company.

For the prediction, we adopt continues review as the Xinghua company's replenishment strategy. Here is picture that describe how replenishment strategy operate.

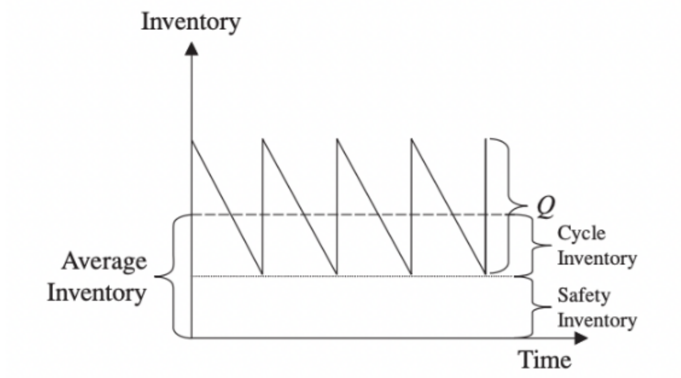

Figure 10 Inventory model

The reorder point calculation formula is as follows:

$$ROP = E(D) * L + ss$$

ROP: reorder point

$E(D)$: usage amount in time unit, the value of $E(D)$ is affected by the unit of lead time

L: lead time

ss: safety stock

We adopt the data of material usage amount for 11 years. We list the data in appendix. After data analysis we could know that the average usage amount of material A is 337, and the standard deviation of the data σ is 121.

The delivery cycle of company a is relatively fixed, generally about one and a half months. In this case, assuming that l remains unchanged, and the customer service level is 95%, the safety stock of the product is calculated on this premise. The calculation formula is as follows:

$$ss = Z\sigma\sqrt{L} = 1.65\text{x}121\text{x}1.5 = 299$$

Depending on the normal distribution, when the customer service level is 95%, Z is 1.65. Meanwhile, the standard deviation of this product σ It is 1329, and l is 1.5 days. By substituting these data into the formula, the calculation results shown in the following formula are obtained:

According to the above calculation, the safety stock of this product is 2868 pieces, and the following formula can be obtained:

$$ROP = ss + E(D) * L = 492 * 1.5 + 299 = 1037$$

Then, according to the calculation formula of economic order quantity, the most economic quantity of material a of Xinghua Company is calculated. The calculation formula of economic order quantity is:

$$EOQ = \sqrt{\frac{2DS}{H}}$$

In order to obtain the economic order quantity in this formula., It is necessary to specify the ordering cost, total demand and storage cost of a single product, which are represented by D, S and H respectively. We know that the total demand D of lcm3.0 products of company a is 5902. In addition, according to the internal data of company Xinghua, the ordering cost S of lcm3.0 products is 250 yuan, and the unit storage cost h is 0.42 yuan. Therefore, the economic ordering batch of material A products is:

$$EOQ = \sqrt{\frac{2DS}{H}} = 765$$

It can be concluded that the reordering point of material A is 765 pieces, that is, company will choose to release orders when the inventory level of material drops to 1037 pieces, and order 765 pieces each time to ensure that there is no shortage risk of products and ensure normal production.

Company a has always insisted on using the above traditional inventory management method to control inventory and ensure production. Although it has made many improvements in the process, such as continuously optimizing the economic order batch, adjusting the order point and the safety inventory level, it has always neglected one point: the reorder point cannot accurately and effectively transmit the demand forecast information. For suppliers, reorder points only transmit one purchase order after another, which is difficult to be converted into accurate prediction. This common purchase order could not guide suppliers to make effective raw material preparation plans and overall capacity planning. This problem is particularly prominent in the environment of multiple supply chains, mainly manifested in that the demand forecast released by reorder points is effectively transmitted among multiple supply chain partners. Therefore, the calculated results can only aid with the enterprise's inventory strategy and replenishment strategy to some extent.

5.7 Company strategies after analysis

From the above analysis, we can find that the selection of demand forecasting model and model parameters has a relatively large impact on the forecasting results, which in turn has a great impact on the inventory level of the enterprise. Similarly, information sharing and order lead time in the supply chain have an important impact on the inventory level of enterprises in the supply chain. In view of the current situation of company Xinghua , this thesis believes that company Xinghua can focus on strengthening the construction of information sharing mechanism with downstream distributors and shortening the production lead time.

(1) *strengthen the construction of information sharing mechanism*

Information sharing can bring the following benefits to company Xinghua :

- restrain the bullwhip effect, reduce the inventory level and inventory cost of enterprises in the supply chain;
- Improve the inventory turnover rate and shorten the lead time;
- Reduce the total cost of supply chain and effectively improve workflow;
- Improve the overall service level of the supply chain;
- Improve the overall competitiveness of the supply chain;
- It is conducive to the allocation of resources, enhancing the competitiveness of enterprises and the flexibility to deal with market changes.

Therefore, company Xinghua must actively take measures to participate in information sharing, so that the decision-making is based on more valuable information.

From the above research, It could be found that the information of downstream distributors is shared with company A. company Xinghua can reduce the inventory level and reduce the inventory cost, but the downstream distributors do not get any benefits. Therefore, company Xinghua compensates the downstream distributors in certain ways, such as offering price discounts to the downstream distributors, improving the service level to the downstream distributors, or conducting more business cooperation. In order to strengthen this harmonious cooperation relationship, company a should establish an effective cooperation mechanism with upstream and downstream enterprises, such as complementing each other's advantages, sharing risks and sharing benefits. The company's leadership should also strengthen exchanges and communication.

(2) *shorten the lead time of supply chain*

In today's market competition environment, time is one of the important factors in the competition, and a short lead time is one of the key factors to successfully obtain orders. To improve the competitiveness of the supply chain, company a must achieve rapid and effective customer response, and shorten the customer service response cycle to the maximum extent by optimizing the internal service process and supply chain management. Therefore, it is very necessary for company a to shorten the lead time of the supply chain. Shortening the production lead time means shortening the logistics lead time and shortening the information lead time. However, the two are not carried out independently and are usually carried out by taking comprehensive time compression measures.

(3) *Optimize business processes.*

Business process has a great impact on logistics lead time and information lead time. Improving business process can greatly shorten the lead time of supply chain. The business process improvement principles include batch processing, parallel processing, cross processing, reducing waiting, deleting non-value-added processes, increasing resources at the bottleneck, etc. for non-bottleneck links, company a can adopt the production mode of small batch and multi batch, so that their inventory level only needs to ensure the material demand at the bottleneck process, thus reducing the inventory lead time.

(4) *Use a deferral strategy.*

The main means include production delay and logistics delay. The basic idea of production delay is just in time, that is, before obtaining the accurate demand and purchase intention of customers, the products are not produced and processed early, but are produced in strict accordance with the orders. The most common means of production delay is to keep the products in the semi-finished state as far as possible, or to adopt modular production means, so that after receiving the order, subsequent processing can be carried out quickly, to produce semi-finished products or modules in batch and obtain economies of scale. Finally, different processes are adopted according to the order requirements, which can not only meet the diversity of demand, but also shorten the delivery lead time. Logistics delay refers to the storage of necessary goods in the central warehouse of the logistics network in advance according to the demand forecast. Once the user's order is received, materials are immediately transferred from the central warehouse and delivered in time. In this way, centralized forecasting and centralized stock preparation can give play to the advantages of scale economy, reduce the overall inventory and improve the service level.

In addition to shortening the production lead time, in order to reduce inventory, company a can also reduce the procurement lead time as much as possible on the premise of ensuring normal production. Premature procurement will not only lead to a large amount of inventory, but also lead to the risk of material deterioration and damage. In addition, once the order is changed, the materials purchased in advance will become obsolete. Therefore, strictly controlling the purchase lead time is also the key to controlling inventory.

6.Conclusion

With the development of computer network and the progress of productivity level, the combination of production and data statistics has become more and more close. How to accurately predict the demand of raw materials by using statistical data has become the focus of research in recent years. The prediction model of output and raw materials has also changed from the traditional supply and demand model to the machine learning model. In recent years, the relevant research on extracting the time series characteristics of the input variables of production prediction using LSTM network has gradually increased. At present, most demand forecasting models based on LSTM only divide the input character sequence into time steps, without considering the influence of internal factors of time steps, which will also lead to inaccurate prediction models. Therefore, compared with Arima, Holt winters, and LSTM to find the most suitable model. The main work of this thesis is as follows:

In view of the characteristics that the factors affecting furniture parts inventory are difficult to determine and non-linear, and the previous prediction of safety inventory of auto parts does not consider the time sequence of data. In this thesis, a recurrent neural network model based on long short-term memory (LSTM) is used to predict the safety stock of auto parts. LSTM model can effectively reduce the error rate of safety stock prediction of auto parts. The main work of this thesis is as follows:

(1) The main influence indexes of safety stock prediction of auto parts are determined. The basic concept of safety stock and several traditional quantitative methods of safety stock are studied and analyzed. Because the factors that affect the safety stock of auto parts are complex and non-linear, this thesis uses a neural network algorithm and time series method to predict the safety stock of auto parts after quantitative analysis. Because the traditional neural network does not consider the timing of data, this thesis uses a recursive neural network LSTM based on long-term and short-term memory to solve the safety inventory prediction problem of auto parts.

(2) This thesis briefly introduces the basic principles of recurrent neural networks (RNN)

and LSTM. The LSTM network model applied to automobile parts safety inventory is analyzed, and the input and output of the LSTM network model, as well as the parameters of activation function, objective function, optimization function and cycle layers are determined.

(3) This thesis introduces the time series method, compares ARIMA, Holt winters and other exponential smoothing methods, finds out the advantages and disadvantages of various methods, synthesizes their advantages and disadvantages, and selects ARIMA and Holt-winters to forecast demand.

(4) This thesis combines demand forecasting theory and inventory control theory to study the supply chain inventory control from the perspective of demand forecasting and inventory management. When both distributors and suppliers adopt ARIMA (3, 1, 1) prediction model, the factors such as inventory cost, out of stock cost, smoothing coefficient of prediction model, ordering lead time of distributors, information sharing, etc. have an impact on the ordering strategy and inventory level of distributors and suppliers, as well as on the inventory level of the whole supply chain. In addition, this thesis takes material A of Xinghua company as the background, and verifies the above conclusions through an example. It is also found that LSTM model has better prediction effect than Holt winters and ARIMA model under the specific conditions of this example

This thesis also has some shortcomings:

(1) The safety stock dataset based on auto parts used in this thesis is simulated by combining the real data of Xinghua furniture company and does not consider the safety stock status of other enterprises, so it is not universal. In the follow-up, we can further study the safety stock prediction problem of parts with universality.

(2) The experimental data used in this thesis are all regression data based on time series, and the LSTM algorithm proposed in this thesis is not applied to classification or other fields. In the future, the effect of LSTM algorithm model in dealing with classification problems could be invented.

(3) This thesis studies a simple second-order supply chain, with only one distributor and one supplier. In real life, the relationship between enterprises in the supply chain is

complex, and each node enterprise has multiple upstream and downstream enterprises. Therefore, facing many upstream and downstream partners, how to formulate effective ordering strategies and inventory strategies is still worth studying.

(4) The research in this thesis assumes that the upstream and downstream enterprises in the supply chain adopt the same prediction model, which may not be true. Therefore, when the upstream and downstream enterprises adopt different prediction models, it remains to be studied.

(5) The research in this thesis assumes that the inventory cost and out of stock cost of the upstream and downstream enterprises in the supply chain are the same, which may not be the case. Then, when the inventory cost and out of stock cost of the upstream and downstream enterprises in the supply chain are different, the ordering strategy and inventory strategy still need to be studied.

(6) The research in this thesis assumes that the order information transfer time of the upstream and downstream enterprises in the supply chain is zero, which may not be the case in real life. Then, how to determine the order strategy and inventory strategy with time windows, especially for multi-object, is a very worthy research topic.

(7) The research in this thesis assumes that suppliers can meet the needs of distributors indefinitely, which may not be the case in real life. Therefore, when there are demand constraints, it is still worth studying how suppliers and distributors formulate ordering strategies and inventory strategies respectively.

(8) Limited by space, this thesis quantitatively studies the factors that affect the inventory level of the supply chain, and briefly explains the improvement ideas in combination with enterprise A. in fact, whether it is to improve the accuracy of demand forecasting, shorten the lead time of the supply chain, or realize information sharing, it is a very complex problem, and these three issues are worth studying in detail.

This thesis combines demand forecasting theory and inventory control theory to study the supply chain inventory control from the perspective of demand forecasting and inventory management. When both distributors and suppliers adopt ARIMA (2, 1, 3) prediction model, the factors such as inventory cost, out of stock cost, smoothing coefficient of prediction model, ordering lead time of distributors, information sharing, etc. have an impact on the ordering strategy and inventory level of distributors and suppliers, as well as on the inventory level of the whole supply chain. The main conclusions are as follows: in addition, this thesis takes material A product of enterprise a as the background and verifies the above conclusions through an example. It is also found that LSTM model has better prediction effect than Holt winters and ARIMA model under the specific conditions of this example

(1) When the out-of-stock cost is greater than the inventory cost, the distributors and suppliers will take the strategy of improving the expected inventory level and maintain a long-term over inventory state, so that the inventory of the whole supply chain can be kept at a high level.

(2) When the inventory cost is less than the out-of-stock cost, in order to minimize their comprehensive cost, distributors and suppliers will reduce their expected inventory, which will be in a negative inventory state in the long run, so that the inventory of the whole supply chain will be kept at a low level.

(3) When the distributor's order lead time increases, the distributor will increase its expected inventory level and increase the order quantity in order to maximize its own income; In order to maximize their own profits, suppliers will also increase their expected inventory level and increase production, thus increasing the inventory level of the entire supply chain. Therefore, it is very advantageous for distributors and suppliers to shorten the lead time. That is, shortening the lead time is conducive to reducing the overall inventory level of the supply chain.

(4) It is very important for member enterprises in supply chain to choose appropriate demand forecasting model for inventory control.

(5) Sharing the demand forecast information of distributors with suppliers is conducive to reducing the inventory level of suppliers. Therefore, information sharing among supply chain member enterprises is conducive to reducing the inventory level of the whole supply chain.

(6) When the prediction accuracy of downstream distributors is low or their order lead time is large, the greater the value of information sharing.

Appendix

(1) Material A usage data from 2011-2021

Months	Years										
	‘11	‘12	‘13	‘14	‘15	‘16	‘17	‘18	‘19	‘20	‘21
January	81	104	132	134	201	234	234	289	324	377	374
February	97	134	145	179	248	245	256	313	335	413	367
March	155	157	174	223	287	267	289	365	367	427	412
April	179	204	227	245	316	282	356	378	378	327	523
May	216	246	274	278	337	324	413	413	423	312	601
June	234	267	321	301	351	374	455	424	489	274	634
July	257	270	333	337	374	345	478	478	513	312	667
August	281	321	347	374	401	389	489	512	567	335	674
September	327	347	356	383	428	401	512	542	592	378	514
October	335	356	389	401	403	346	474	578	512	178	457
November	273	247	314	314	315	297	467	412	423	167	378
December	225	188	217	224	274	268	312	378	389	98	301

References

Bourland, K. E., Powell, S. G., & Pyke, D. F. (1996). Exploiting timely demand information to reduce inventories [Article]. *European Journal of Operational Research*, *92*(2), 239-253. https://doi.org/10.1016/0377-2217(95)00136-0

Brakel, P., Stroobandt, D., & Schrauwen, B. (2013, Aug 25-29). Bidirectional Truncated Recurrent Neural Networks for Efficient Speech Denoising.*Interspeech* [14th annual conference of the international speech communication association (interspeech 2013), vols 1-5]. 14th Annual Conference of the International-Speech-Communication-Association (INTERSPEECH 2013), Lyon, FRANCE.

Dai, Y., & Cong, S. (2004, May 29-Jun 01). Convergence analysis of recurrent neural networks. [Proceedings of 2004 chinese control and decision conference]. 16th Chinese Control and Decision Conference, Huangshan, PEOPLES R CHINA.

Felfel, H., Ayadi, O., & Masmoudi, F. (2014, Dec 17-19). A Multi-site Supply Chain Planning Using Multi-stage Stochastic Programming.*Applied Condition Monitoring* [Multiphysics modelling and simulation for systems design and monitoring]. 1st International Conference on Multiphysics Modelling and Simulation for Systems Design (MMSSD), Sousse, TUNISIA.

Hajek, P., & Abedin, M. Z. (2020). A Profit Function-Maximizing Inventory Backorder Prediction System Using Big Data Analytics [Article]. *Ieee Access*, *8*, 58982-58994. https://doi.org/10.1109/access.2020.2983118

Ji, S. J., Yu, H. Y., Guo, Y. N., Zhang, Z. R., & Acm. (2016, Dec 23-25). Research on Sales Forecasting Based on ARIMA and BP Neural Network Combined Model. [Proceedings of the 2016 international conference on intelligent information processing (iciip'16)]. International Conference on Intelligent Information Processing (ICIIP), Wuhan, PEOPLES R CHINA.

Jia Lina, L., Jia, L., Zhu, M., & Tu, B. B. (2017). T-VMI: Trusted Virtual Machine Introspection in Cloud Environments. *2017 17TH IEEE/ACM INTERNATIONAL SYMPOSIUM ON CLUSTER, CLOUD AND GRID COMPUTING (CCGRID)*, 478-487.

Lin, G. F., & Lee, F. C. (1994). ASSESSMENT OF AGGREGATED HYDROLOGIC TIME-SERIES MODELING. *Journal of Hydrology*, *156*(1-4), 447-458. https://doi.org/10.1016/0022-1694(94)90089-2

Ma, L. H., & Lin, M. (2008, Dec 20-22). Determination of Safety Stock for Power Enterprises Under Uncertainty. [Iscsct 2008: International symposium on computer science and computational technology, vol 1, proceedings]. International Symposium on Computer Science and Computational Technology, Shanghai, PEOPLES R CHINA.

Qi, Y., & Jing, K. D. (2010, Apr 17-18). Theory and Practice of Regional Industry Development-Analysis on Port Industrial Cluster's Influence on the Regional Economy. [Proceedings of 2010 international conference on regional management science and engineering]. 2010 International Conference on Regional Management Science and Engineering, Jinan, PEOPLES R CHINA.

Schmeja, S., & Klessen, R. S. (2004). Protostellar mass accretion rates from gravoturbulent fragmentation [Article]. *Astronomy & Astrophysics*, *419*(2), 405-417. https://doi.org/10.1051/0004-6361:20034375

Shang, Y. Q., & Zhang, Q. H. (2021). A SUBGRID STABILIZING POSTPROCESSED MIXED FINITE ELEMENT METHOD FOR THE TIME-DEPENDENT NAVIER-STOKES EQUATIONS. *Discrete and Continuous Dynamical Systems-Series B*, *26*(6), 3119-3142. https://doi.org/10.3934/dcdsb.2020222

Silva, A. D. E., Pertille, A., Barbosa, C. G. R., Silva, J. A. D., de Jesus, D. V., Ribeiro, A., Baganha, R. J., & de Oliveira, J. J. (2019). Effects of Creatine Supplementation on Renal Function: A Systematic Review and Meta-Analysis [Review]. *Journal of Renal Nutrition*, *29*(6), 480-489. https://doi.org/10.1053/j.jrn.2019.05.004

Siregar, K., Supriyanto, S., Rani, D. S., Nurdiansyah, Y., & Wijayanto, F. (2019, Nov 07-08). Conceptual Design of Inventory Analysis Software to Support the Life Cycle Assessment in Palm Oil Production.*E3S Web of Conferences* [1st international conference on bioenergy and environmentally sustainable agriculture technology (icon beat 2019)]. 1st International Conference on Bioenergy and Enviromentally Sustainable Agriculture Technology (ICoN-BEAT), Univ Muhammadiyah Malang, Malang, INDONESIA.

Svensson, G. (2008). The Industrial / Societal Bullwhip Effects and Supply Chain Performance [Article]. *Journal of Global Scholars of Marketing Science*, *18*(2), 1-18. <Go to ISI>://WOS:000409725300001

Yamashita, T., Hirasawa, K., Hu, J. L., & Ieee. (2003, Aug 04-06). Multi-branch neural networks with Branch Control. [Sice 2003 annual conference, vols 1-3]. SICE 2003 Annual Conference, Fukui, JAPAN.

Yang, X. S. (2008). 3-D cellular neural networks with cyclic connections cannot exhibit chaos [Article]. *International Journal of Bifurcation and Chaos*, *18*(4), 1227-1230. https://doi.org/10.1142/s0218127408020951

Zeng, H., Zhao, X., & Wu, Y. (2006, Aug 12-14). Revenue sharing contract under JIT environment (ID : 8-121).*International Conference on Industrial Engineering and Engineering Management IEEM* [Proceedings of the 13th international conference on industrial engineering and engineering management, vols 1-5: Industrial engineering and management innovation in new-era]. 13th International Conference on Industrial Engineering and Engineering Management, Shandong Univ, Weihai, PEOPLES R CHINA.

Zhang, Y. J., Xu, B., & Zhao, T. J. (2020). Convolutional multi-head self-attention on memory for aspect sentiment classification [Article]. *Ieee-Caa Journal of Automatica Sinica*, *7*(4), 1038-1044. https://doi.org/10.1109/jas.2020.1003243

Zhao, F. G., Sun, J. S., Zhang, L. W., & Ma, Z. S. (2010, Jul 09-11). Genetic Algorithm for the Multi-Echelon Inventory Problem of Weapon Equipment Repairable Spare Parts.*International Conference on Computer Science and Information Technology* [Iccsit 2010 - 3rd ieee international conference on computer science and information technology, vol 2]. 3rd IEEE International Conference on Computer Science and Information Technology (ICCSIT), Chengdu, PEOPLES R CHINA.