Design of Efficient Logistics Management System Based on Cloud Database

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Abstract: This paper studies a logistics management system based on cloud database, which aims to solve the problems of inventory forecasting and low transportation efficiency in logistics management of manufacturing enterprises. In the research process, based on the design of data collection, storage, analysis and decision support subsystem, a variety of machine learning algorithms are integrated and applied in practical scenarios. After the implementation of the system, the experimental data showed that the inventory turnover rate of the study subjects increased by 83.3%, the transportation cost decreased by 26.9%, and the order delay rate decreased by 60%. The results show that the system significantly improves the logistics management efficiency of the enterprise, reduces the operating cost, and the application effect is very significant. It can be seen that the design is very successful and effective, and can be invested in practical applications to better demonstrate the application effect of cloud database-related technologies in it.

1 INTRODUCTION

The logistics management system is a key part of enterprise supply chain management, and its core problems are inaccurate inventory management and low transportation efficiency. Many researchers have suggested that such problems could be better addressed by optimizing transportation routes and improving the accuracy of their inventory forecasts. However, these methods generally ignore the dynamic changes of real-time data, which makes the optimization effect limited. Some researchers also propose to use static data analysis to optimize the system, but it cannot effectively cope with the fluctuation of demand during peak periods, and it is easy to cause inventory shortages and backlogs. It has been proposed to use a simple linear operating mechanism for forecasting, but the prediction effect is not satisfactory because it ignores the complexity in the supply chain. In order to solve these problems, this paper adopts the method of intelligent algorithm combined with the real-time data processing capability of cloud database, and dynamically adjusts the decision-making strategy based on the seamless connection of multiple operating mechanisms, so as to improve the adaptability and efficiency of the system, with the aim of optimizing inventory management and transportation scheduling based on intelligent means. This round focuses on the analysis of the importance of logistics management in enterprise supply chain management, and analyzes the problems therein, and at the same time, analyzes the shortcomings of the commonly used logistics management methods, and proposes a logistics management method based on cloud database.

2 RELATED WORKS

2.1 Cloud Data Development

With the continuous development of cloud computing technology, cloud data storage and processing technology has become a key to modern information technology. Cloud databases have many characteristics (Adeleke, 2022), such as high efficiency, elasticity, and scalability. As a result, this allows enterprises to process massive amounts of data and store and compute in real time without increasing hardware investment. In logistics and logistics management, the application of cloud database can significantly improve the efficiency of data access (Bhargava, Bhargava et al. 2022), especially when dealing with complex supply chain management

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systems, it can quickly respond to business changes, and then achieve real-time data processing and decision support (Cherchata, Popovychenko et al. 2022). With the advent of the era of big data, cloud data has become an important technical foundation in an efficient logistics management system, providing an efficient data support environment for various intelligent algorithms (Gomes, de Lima 2023).

2.2 Efficient Logistics Management Covers Inventory Management, Transportation Scheduling and Other Parts

An efficient logistics management system relies on accurate inventory management and transportation scheduling, and theoretically covers supply chain optimization, inventory control theory and transportation management theory. In inventory management, the classic economic order quantity (EOQ) operation mechanism and material requirement planning (MRP) operation mechanism have been widely used (Kozhamkulova, Kuntunova et al. 2024), but these traditional operation mechanisms will basically show shortcomings when dealing with complex demand fluctuations and multi-dimensional inventory problems. Therefore, modern efficient logistics management theory has begun to introduce intelligent technologies, such as machine learning and big data analysis, to enhance prediction and scheduling capabilities. Transportation management theories rely more on route optimization and vehicle scheduling operation mechanisms, such as the use of linear programming and integer programming algorithms to optimize transportation costs and time (Kundu, Sheu et al. 2022). However, these theories rely on static data in traditional applications, while modern enterprises need real-time dynamic scheduling capabilities, which provides a new development direction for the combination of cloud computing and intelligent algorithms (Verbivska, Zhygalkevych et al. 2023).

2.3 Advantages of Combining Random Forest Algorithms with Cloud Data

As a seamless connection learning method, random forest algorithm is based on the seamless connection of multiple decision trees to improve the accuracy and stability of prediction, which is especially suitable for processing complex nonlinear data. When random forests are combined with cloud data (Wang, 2023), they can be of great advantage. Cloud databases provide random forests with powerful data storage and processing capabilities, can quickly process large-scale datasets, and supports parallelized computing, which will effectively improve the efficiency of training and prediction (Wang, Luo et al. 2024). In addition, the real-time nature of the cloud database also allows the random forest operation mechanism to be continuously updated and dynamically adjusted based on the latest inventory and transportation data, which is especially critical in peak periods and complex supply chain environments. Based on the elastic scalability of cloud computing, enterprises can adjust computing resources according to their needs, and then achieve rapid response and optimized decision-making (Zhai, Han et al. 2022). This combination greatly improves the forecasting accuracy of the logistics management system, effectively reducing the risk of inventory backlog and transportation delays.

3 METHODS

3.1 Functions of Each Part of an efficient Logistics Management System Based on a Cloud Database

In this system, it mainly includes 6 major subsystems. Specifically, the function of the data acquisition subsystem is to collect warehousing data, transportation status, order information based on sensors, RFID, GPS and other devices, and then upload it to the cloud database in real time. The system ensures timely aggregation of data from different sources and supports the flow of data in large-scale logistics networks. The function of the data storage subsystem is to provide distributed storage, support scalable and efficient data access, and ensure the security management of historical data and real-time data. The task of the data analysis and operation mechanism subsystem is to intelligently predict inventory and transportation based on a variety of machine learning algorithms, such as random forests and time series operation mechanisms. Seamlessly connect with automated reporting to generate inventory and logistics trend analysis. The decision support subsystem will be responsible for providing managers with inventory replenishment recommendations, transportation scheduling optimization, and manual and automated decision-making processes based on the analysis results. The user interface subsystem needs to provide a graphical monitoring panel that allows the user to view real-time data, forecast results, and make necessary adjustments to the settings of the logistics system. The system security and monitoring subsystem ensures the security of the system, based on user rights management, data encryption, and real-time monitoring of system resources and running status.

3.2 Design of Various Subsystems of an Efficient Logistics Management System

In terms of design, the data acquisition subsystem provides a standardized API interface to ensure that all kinds of equipment can be connected to the system, and the data is unified based on the preprocessing process and ensures the accuracy of the data. The data storage subsystem uses partitioning and index optimization to improve the query speed of its data, and implements a backup and recovery mechanism to prevent data loss. The data analysis and operation mechanism subsystem is based on the parallel processing of cloud computing to further accelerate the operation speed of the operation mechanism, and automatically optimize the operation mechanism parameters to ensure the accuracy of prediction. The subsystem also automates the report generator, which provides users with detailed periodic summaries based on real-time data and analysis results. The decision support subsystem dynamically adjusts the decision parameters based on the built-in rule engine, and users can manually modify the rules and let the system automatically adjust. In addition, the user interface subsystem is designed as an intuitive dashboard, which allows for real-time display of key indicators such as inventory levels, shipping status, and support for custom queries and data exports. The system security and monitoring subsystem is designed to integrate permission management, logging functions, and use encryption technology to ensure data security and real-time monitoring of system resource usage. In addition, the system needs to respond to potential threats based on an alarm mechanism.

3.3 Efficient Logistics Management Mechanism Based on Cloud Database

In order to select an optimal logistics management system in the cloud database, it is necessary to select the optimal solution, for which the random forest algorithm operation mechanism is selected. This is because the operating mechanism can handle complex data relationships, especially in logistical scenarios such as fluctuations in inventory demand and optimization of transportation routes. Random forests are based on seamlessly connecting multiple decision trees to predict nonlinear data, which can show its ability when processing large-scale datasets. See Eq. (1) for details.

Provides strong predictive capabilities and excels when working with large-scale data sets.

$$M_{\text{rf}} = argmin_{M_i} \mathcal{L}(M_i, X_{\text{train}}, y_{\text{train}}, n_{\text{trees}}, \text{depth}, \text{compute}_{c_{\text{ost}}}) \quad (1)$$

In this formula, $M_{\text{rf}}$is the random forest operation mechanism is represented and used to handle tasks such as inventory demand forecasting and transit time estimation in logistics management. $\mathcal{L}(M_i, X_{\text{train}}, y_{\text{train}}, n_{\text{trees}}, \text{depth}, \text{compute}_{c_{\text{ost}}})$ is a function that evaluates the operating mechanism, and its main purpose is to calculate the cost by combining the operating mechanism error. X_{train}Characteristics that represent the training dataset, such as inventory records as well as shipping routes and order processing times. y_{train}Represents target variables, such as future inventory requirements, optimal time for transportation routes. n_{trees} represents the number of decision trees, which affects the complexity and prediction ability of the operating mechanism, and improves the robustness of the operating mechanism. depthRepresents the maximum depth of the tree, controls the complexity of each tree, and ensures that the operating mechanism does not overfit to a specific transportation and inventory pattern. $\text{compute}_{c_{\text{ost}}}$Represents the computing cost, which measures the resource consumption of the running mechanism in the cloud database.

Each tree in a random forest can run in parallel in a cloud database, and the advantage of cloud computing is the ability to support efficient parallel computing and quickly process large-scale datasets. In the logistics scenario of large data sets, such as warehousing and transportation data, parallel computing will be used to significantly reduce the training time of the operating mechanism and improve the response speed of the system. See Eq. (2) for details.

$$T_{\text{parallel}} = \frac{T_{\text{sequential}}}{n_{\text{nodes}}} \quad (2)$$

In this formula, T_{parallel}represents the parallel running time, and the training speed of the running mechanism is improved based on parallelized computing. $T_{\text{sequential}}$Represents the sequential run time, that is, the training time when parallel is not used. n_{nodes}Represents the number of nodes for parallel computing, i.e., distributed cloud computing resources, which can be used to increase the computing power of the system.

Once the runtime is in place, it will be deployed in the cloud and used to process new data in logistics in real time. When real-time inventory information and transportation data are constantly updated, the operating mechanism can automatically make forecast adjustments based on its new inputs, which in turn provides important support for logistics decisions. See Eq. (3) for details.

$$\hat{y}_{\text{real-time}} = M\text{rf}(X_{\text{real-time}}) \tag{3}$$

In this formula, $\hat{y}_{\text{real-time}}$is the result of real-time forecasting, such as real-time inventory demand and transit time estimation, is represented. M_{rf} represents the trained random forest operation mechanism, which is executed in real time in the cloud. $X_{\text{real-time}}$Represents the logistics data obtained by the cloud database in real time, such as the latest warehouse inventory and transportation status.

3.4 Further Operation and Optimization of the Operating Mechanism

After the operation mechanism is selected and the data is prepared, the operation mechanism is trained based on cloud computing resources. The large-scale storage and parallel computing capabilities of the cloud database enable the random forest operation mechanism to quickly process massive logistics data, such as warehouse inventory records and daily transportation route information. The operation process uses distributed computing, and the parameters of the operation mechanism are optimized to improve the accuracy and generalization ability of prediction. After the training is completed, the operating mechanism can accurately predict future inventory demand and transit time.

In order to improve the prediction performance of the operating mechanism, it is necessary to optimize the features based on the importance of logistics data based on the automatic feature selection method. For example, based on the feature importance assessment of random forests, the most influential variables for inventory forecasting and transit time, such as inventory turnover rate and weather impact, are selected. For this, see Eq. (4).

$$\text{Features}_{\text{opt}} = \text{SelectTopK}(\phi(X_{\text{train}}), K) \tag{4}$$

In this formula, $\text{Features}_{\text{opt}}$refers to an optimized set of features that select the features that contribute the most to logistics forecasting. $\text{SelectTopK}(\phi(X_{\text{train}}), K)$ refers to the feature selection function, which automatically screens out the most important K features, such as inventory change rate, transportation timeliness, etc. $\phi(X_{\text{train}})$ refers to the characteristics of all operating sets, covering various dimensions of inventory, transportation, and equipment. $K$is the number of features retained after optimization is mainly used to ensure that the operating mechanism can focus on the most critical prediction indicators.

To accommodate the scale of different logistical tasks, the system dynamically adjusts the architecture of the random forest based on real-time workloads. For example, when processing a large number of orders, increase the number of decision trees; At low loads, you need to reduce the number of trees to optimize resource usage. See Eq. (5) for this.

$$n_{\text{trees adjusted}} = f(\text{order}_{v_{\text{olume}}}, \text{response}_{t_{\text{ime}}}) \tag{5}$$

In this formula, the $n_{\text{trees adjusted}}$is number of decision trees adjusted according to the real-time order volume is used to ensure the efficiency of the operating mechanism under different loads. $\text{order}_{v_{\text{olume}}}$Refers to the current order volume, which determines the calculation requirements of the system. $\text{response}_{t_{\text{ime}}}$Refers to:

Response time requirements to ensure fast response during peak hours.

In order to improve the forecasting accuracy of its logistics management system, it is necessary to seamlessly connect the methods of multiple operating mechanisms. For example, the random forest is combined with the time series operation mechanism and the linear regression operation mechanism, and the advantages of different operation mechanisms are used to make comprehensive predictions to improve the overall performance of the system. See Eq. (6) for details.

$$\hat{y}_{\text{ensemble}} = w_1 \cdot M\text{rf}(X) + w_2 \cdot M_{\text{ts}}(X) + w_3 \cdot M_{\text{lr}}(X) \tag{6}$$

In this formula, the $\hat{y}_{\text{ensemble}}$is final prediction result of the seamlessly connected operating mechanism is depresented, and the prediction based on the different operating mechanisms can be weighted averaged. M_{rf} refers to the prediction results of the random forest operation mechanism, which deals with nonlinear complex data. M_{ts} refers to the prediction results of the time series operation mechanism, which is suitable for the prediction of short-term data fluctuations. M_{lr}Refers to the prediction results of the linear regression operating mechanism, which can be used to deal with long-term linear trends. w_1, w_2, w_3Refers to the weight of each operating mechanism. Adjusted based on its historical performance, seamless connectivity results will be optimized.

3.5 Seamless Connection of Efficient Logistics Management System Design

The purpose of the seamless connection of the system is to effectively integrate data acquisition and storage, analysis, decision support, and user interface subsystems to form an efficient logistics management system. Among them, the data acquisition subsystem is responsible for docking with the warehouse system, transportation management system, and various sensing devices based on standardized API interfaces, obtaining inventory, order, and transportation data in real time, and uploading them to the cloud database. The data storage subsystem is responsible for using the distributed storage of cloud databases to ensure fast access and elastic expansion of data, and support real-time access and backup of large-scale data. The data analysis subsystem is responsible for seamlessly connecting multiple machine learning algorithms, such as random forests and time series operation mechanisms, to intelligently predict key indicators such as inventory demand and transit time. The decision support subsystem is responsible for dynamically providing inventory replenishment suggestions, transportation route optimization, and vehicle scheduling strategies based on the analysis results, and automatically adjusting parameters based on the rule engine to improve the adaptability and response speed of the system. The user interface subsystem is responsible for displaying inventory levels, shipping status, and order progress in real time based on interactive dashboards, and supporting users' custom queries and operations. The system security and monitoring subsystem is responsible for comprehensive data encryption, user authentication, and permission management, real-time monitoring of system operation status and capturing abnormal behaviors, and timely generation of alarms to ensure the stability and security of the system. Based on the deep and seamless connection of the above subsystems, the system can provide efficient and accurate intelligent services in large-scale and changeable logistics management scenarios.

4 RESULTS AND DISCUSSION

4.1 Background of the Case

Company C is a large-scale manufacturing enterprise, mainly engaged in the production and sales of household appliances. The company has multiple factories and distributed warehouses, and its products are transported to the major points of sale based on a complex supply chain network,The introduction of the data situation of the school logistics management system is shown in Table 1..

Table1: Logistical management issues prior to the implementation of the system by company

Project	Data
Inventory turnover	6 times/year
Average delivery time	70 hours
Demand forecast accuracy	60%
Shipping costs	13 million yuan/year
Inventory overstock rate	35%
Peak order delay rate	25%

Table 1 shows the logistical management issues of Company C prior to the implementation of the system. The inventory turnover rate is only 6 times/year, the inventory backlog rate is as high as 35%, the average delivery time is 70 hours, the demand forecast accuracy is 60%, and the transportation cost and order delay problems are more serious.

4.2 The Overall Structural Changes of the Logistics Management System

In recent years, because the order volume of Company C has increased year by year, the company's logistics management system has exposed many problems, such as low inventory management efficiency, unoptimized transportation routes, and inaccurate demand forecasts, resulting in inventory backlogs and shortages, and high warehousing and transportation costs. Especially during the promotional season, the number of orders surges, because of inaccurate forecasts, resulting in untimely inventory scheduling, delayed deliveries, and decreased customer satisfaction, which in turn leads to rising operating costs.

Table 2: Logistics management improvements following the implementation of the system

Project	Data
Inventory turnover	11 times/year
Average delivery time	45 hours
Demand forecast accuracy	85%
Shipping costs	9.5 million yuan/year
Inventory overstock rate	18%
Peak order delay rate	10%

Table 2 shows the improvements made after the implementation of the system. Company C's inventory turnover rate in terms of logistics management. Specifically, its inventory turnover rate has increased from 6 times per year to 11 times per year, the inventory backlog rate has decreased significantly, the transportation cost has been significantly reduced, the demand forecast accuracy has been greatly improved, and the order delay rate has been significantly reduced. The process of data changes in the management system is shown in Figure 1.

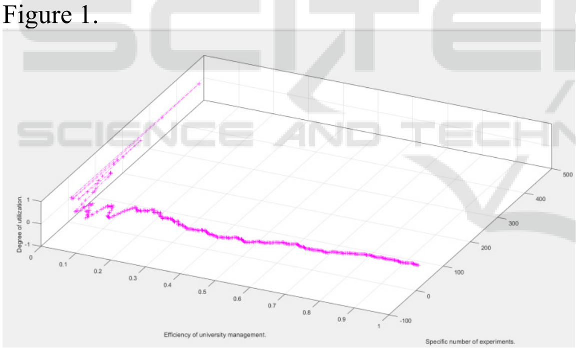

Figure 1: Changes in system data

The specific data shows that before the introduction of the system, Company C's inventory turnover rate was 6 times per year, the average delivery time reached 70 hours, and the accuracy of demand forecasting was only 60%. In addition, the company's transportation cost is as high as 13 million yuan/year, and the inventory backlog rate is 35%. During peak order periods, 25% of orders are delayed, which seriously affects customer satisfaction and operational efficiency. To this end, Company C decided to introduce an efficient logistics management system based on cloud database to improve management efficiency and optimize various operational indicators.

4.3 The Management Results of the Logistics Efficient Management System

From the tabular data, it can be seen that Company C has significantly improved all indicators of its logistics management after the implementation of the system. The inventory turnover rate has increased from 6 times per year to 11 times per year, indicating that the inventory management efficiency has been improved, the inventory backlog rate has also been greatly reduced from 35% to 18%, and the inventory scheduling is more reasonable. In terms of transportation efficiency, the average delivery time has been shortened from 70 hours to 45 hours, the transportation cost has been reduced by 26.9%, and the system has optimized transportation routes and scheduling, The overall design result of the logistics system is shown in table.3.

Table 3: Analysis of the combined benefits of the system after implementation

Project	Before optimization	After optimization	Degree of improvement
Inventory turnover	6 times/year	11 times/year	83.3% higher
Average delivery time	70 hours	45 hours	35.7% reduction
Demand forecasting accuracy	60%	85%	Increase it by 25%
Shipping costs	13 million yuan/year	9.5 million yuan/year	26.9% reduction
Inventory overstock rate	35%	18%	48.6% reduction
Peak order delay rate	25%	10%	60% reduction

Table III summarizes the changes in the key data in the logistics management of Company C after the application of the system. Among them, its inventory turnover rate has been greatly improved, the inventory backlog rate has been basically halved, the transportation cost has been significantly reduced, the average delivery time has been significantly shortened, the accuracy of demand forecasting has been significantly improved, and the order delay rate during peak periods has also been greatly improved. Better conduct systematic analysis of management and continuously monitor its processes, as shown in Table 2.

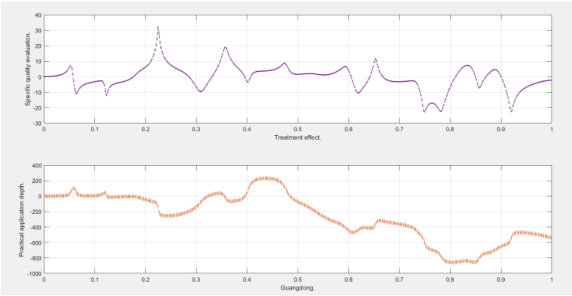

Figure 2: Results of data and demand changes

Thus, it can be seen that the process of changes in the logistics management system presents a dramatic change, and the content is relatively ideal, which can meet the practical analysis needs.The accuracy rate of demand forecasting has been increased from 60% to 85%, significantly reducing the risk of inventory shortages and surpluses. The order delay rate has been reduced from 25% to 10%, and customer satisfaction has been greatly improved. It can be seen that after applying the system built this time, Company C has significantly improved the accuracy of inventory management and transportation optimization and demand forecasting, effectively reducing operating costs and improving the efficiency of its overall logistics management. The system has been successfully designed and the application effect is remarkable.

5 CONCLUSIONS

The efficient logistics management system based on the cloud database proposed in this study has shown that it can successfully solve the problems of inventory management and transportation efficiency of manufacturing enterprises. Based on the function of the application cloud database and combined with the random forest algorithm, the efficient logistics management system significantly improves the accuracy of inventory forecasting, the efficiency of transportation scheduling, and effectively reduces the risk of operating costs and supply chain uncertainty. The experimental results show that the system plays a key role in optimizing the logistics management process and improving the overall operational efficiency of the enterprise. It can be verified that the efficient post-management system design based on cloud database has practical application value. At the same time, the system can flexibly respond to demand fluctuations and peak pressures, significantly improving its enterprise resource scheduling capabilities. In short, the system built this time has a relatively broad application prospect, and then provides a reliable solution for the modernization of logistics management. Although this paper has some achievements in many aspects, there are inevitably errors and omissions in the paper, and I hope that this can be further optimized in the future.

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