Hindawi

Retraction

Retracted: Intelligent Prediction Algorithm of Cross-Border E-Commerce Logistics Cost Based on Cloud Computing

Scientific Programming

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] W. Gao, "Intelligent Prediction Algorithm of Cross-Border E-Commerce Logistics Cost Based on Cloud Computing," *Scientific Programming*, vol. 2021, Article ID 7038294, 10 pages, 2021.

Research Article

Intelligent Prediction Algorithm of Cross-Border E-Commerce Logistics Cost Based on Cloud Computing

Wanli Gao [ID]

Economics and Management School, Jilin Agricultural Science and Technology University, Jilin 132101, China

Correspondence should be addressed to Wanli Gao; gaowanli@jlnku.edu.cn

Cross-border e-commerce logistics cost prediction algorithm does not consider logistics distribution scheduling, and logistics information interchange is not enough, which leads to confusion of logistics cost parameters and large deviation. Therefore, an intelligent prediction algorithm of cross-border e-commerce logistics cost based on cloud computing is designed. Introduce cloud computing platforms, optimize the scheduling of cross-border e-commerce logistics distribution tasks, and select the targets for the scheduling of cross-border e-commerce logistics distribution tasks from the aspects such as the shortest waiting time required by customers, the degree of resource load balance, and the costs consumed in completing cross-border e-commerce logistics distribution tasks, and design logistics scheduling process. On this basis, the logistics distribution data are classified, the association rules between the data are mined, and the monitoring of abnormal values in the cost forecasting process is completed. In order to eliminate the interference caused by the difference of different cost management interval, the function value is calculated by weighted Euclidean distance. Design feedback forecast mechanism to realize intelligent forecast algorithm of cross-border e-commerce logistics cost. Experimental results show that the proposed algorithm has better accuracy of cross-border e-commerce logistics cost prediction and higher completion rate of logistics tasks.

1. Introduction

The development of cross-border e-commerce and that of cross-border logistics complement each other. The development of cross-border logistics greatly promotes the development of cross-border e-commerce, and the rapid development of cross-border e-commerce also provides greater development space and more development opportunities for cross-border logistics [1]. Cross-border e-commerce has developed rapidly, but cross-border logistics has not yet adapted to its development, and the two cannot achieve coordinated development. Cross-border logistics network systems lack synergies, specifically manifested in the lack of synergies in warehousing, transportation, customs, distribution, and other logistics functions, the lack of synergies in the connection between China's logistics, international logistics, and the logistics in the destination country, and the lack of synergies between cross-border logistics and the logistics environment such as

language, customs, technologies, and policies [2]. At present, the main modes of cross-border logistics include international postal parcels, international express delivery, overseas warehouses, international logistics lanes, border warehouses, bonded zones and free trade zones, cargo logistics, third-party logistics, and fourth-party logistics. For the future development of cross-border e-commerce logistics, it is necessary to promote the coordinated development of cross-border e-commerce and cross-border logistics and the coordination of cross-border logistics networks, promote the upgrading of the logistics outsourcing mode represented by the fourth-party logistics by adopting multiple cross-border logistics modes, realize the localized operation of cross-border logistics, and strengthen the cooperation with local logistics companies [3].

In order to optimize the research on cross-border e-commerce logistics costs, some good results have been achieved. Reference [4] takes four main factors such as distribution vehicle transportation, cold chain energy

consumption, cargo loss, and time window punishment as the research object, constructs the cost model of each factor, and determines the objective optimization function of cost optimization in the process of cold chain logistics distribution. The ant colony algorithm is used to solve the example of cost optimal objective function in the process of cold chain logistics distribution, and the optimization roadmap of cold chain logistics distribution path network is obtained. As mentioned in [5], in order to effectively reduce logistics cost, it is necessary to study the logistics cost problem under multicustomer random demand factors. When studying the logistics cost of an enterprise, assuming that the demand of the demander obeys the Poisson distribution, the ordering cost, goods cost, inventory occupancy cost, and transportation cost of the enterprise are calculated, respectively. These four variables are sorted out and solved by genetic algorithm to achieve the global optimization. Big data has become an important direction in the development of modern information technology. PERSONA is the mathematical modeling of users in the real world. It is the concrete application of big data in economic life. By representing user information through different things and statistics, they can be well correlated and matched. Based on PERSONA, integrated EOQ system, derived sales forecasting system, and inventory control system. Reference [6] builds a perfect dynamic architecture. From the initial B2B model to the network retail model and then to the eye-catching C2B model, people are concerned about the status, problems, and suggestions of e-commerce model, but there is a lack of corresponding theoretical research among e-commerce models. Reference [7] studies the path, theoretical mechanism, and future development direction of cross-border e-commerce mode.

However, the above two methods ignore the consideration of logistics distribution scheduling, and the amount of logistics information interaction is not enough, resulting in confusion of logistics cost parameters and large errors in cost prediction. Therefore, an intelligent prediction algorithm of cross-border e-commerce logistics cost based on cloud computing is designed.

Our contribution is threefold:

(1) We designed an intelligent prediction algorithm of cross-border e-commerce logistics cost based on cloud computing.

(2) Through the introduction of cloud computing platform, we optimize the scheduling of cross-border e-commerce logistics and distribution tasks and design the logistics scheduling process from the minimum waiting time required by customers, the load balancing degree of resources, and the cost consumed in completing cross-border e-commerce logistics and distribution tasks.

(3) Clustering logistics distribution data, mining association rules between amounts of data, complete the monitoring of outlier points in the process of cost forecasting. In order to eliminate the interference caused by the difference between different cost management intervals, weighted Euclidean distance is used to calculate the function value.

The remainder of this paper is organized as follows. Section 2 introduces cloud computing cross-border e-commerce logistics distribution task scheduling. Section 3 discusses the logistics distribution cost prediction method based on cloud data mining technology. Logistics distribution cost prediction method based on cloud data mining technology. Section 4 discusses simulation experiment analysis. Section 5 presents the conclusions of the study.

2. Cloud Computing Cross-Border E-Commerce Logistics Distribution Task Scheduling

Cloud computing is a business computing model that provides resources for a fee as a service. The resource services provided by it fall into three categories: platform as a service, software as a service, and infrastructure as a service [8, 9]. They provide different services and focus on different types of applications, but they all have resource problems and scheduling problems for cross-border e-commerce logistics distribution tasks. Cross-border e-commerce logistics dispatching in cloud computing is related to the stability of cloud services, the utilization of resources, operating costs, and the quality of service. Therefore, cloud computing cross-border e-commerce logistics distribution task scheduling problem is of great theoretical and practical significance. In the cloud computing environment, there are many dynamic and uncertain factors in the resource and its load. When dispatching and optimizing cross-border e-commerce logistics distribution tasks of cloud computing, the objectives of dispatching cross-border e-commerce logistics distribution tasks of cloud computing shall be selected from the aspects such as the shortest waiting time needed for customers, the degree of resource load balance, and the costs consumed in completing cross-border e-commerce logistics distribution tasks [10].

(1) Minimum waiting time required by the customer:

The minimum amount of waiting time needed for the customer is

$$T_{\min} = \max_{j=1} \sum_{i=1}^{\text{sum}(V_j)} t(i), \qquad (1)$$

where $t(i)$ represents the execution time of cloud computing cross-border e-commerce logistics distribution tasks on the virtual machine and $\text{sum}(V_j)$ represents the total number of cross-border e-commerce logistics distribution tasks allocated on the virtual machine. The time spent in processing the cross-border e-commerce logistics distribution task is the ratio of the command length A_i of the cross-border e-commerce logistics distribution task to the execution speed v of the virtual machine [11], expressed as

$$t' = \frac{A_i}{v}. \qquad (2)$$

(2) Resource load balancing degree:

The calculation formula of resource load balancing degree on virtual machine is

$$\gamma = \sqrt{\frac{\sum_{j=1}^{m}\left(\text{sum}(t_j) - \overline{\text{sum}(t_j)}\right)^2}{m}}, \qquad (3)$$

where $\text{sum}(t_j)$ represents the total time for the multiobjective logistics distribution task to be executed on the virtual machine, $\overline{\text{sum}(t_j)}$ represents the average time consumed by the virtual machine to execute the multiobjective logistics distribution task, and m represents the resource load balancing probability on the virtual machine.

(3) Cost for completing multiobjective logistics distribution tasks:

The formula for calculating the cost for completing the multiobjective logistics distribution task is as follows:

$$M = \sum_{j=1}^{m} \text{sum}(V_j) \times T_{\min} \times \gamma. \qquad (4)$$

Formula (4) fully reflects the cost of cloud computing cross-border e-commerce logistics and distribution tasks handled on virtual machines, and the cost of completing cross-border e-commerce logistics and distribution tasks is closely related to the central processor [12], bandwidth performance [13], and memory of the virtual machines.

Based on the shortest waiting time, the resource load balance, and the cost of completing the multiobjective logistics distribution task, this paper measures the scheduling effect of the multiobjective logistics distribution task and establishes the following mathematical models.

$$\begin{cases} \min t', \quad \min M, \\ \text{s.t.} \quad \sum_{j=1}^{m} a_{ij} = 1 \quad a_{ij} \in [0,1]\, i = 1, 2, \ldots, n. \end{cases} \qquad (5)$$

Using the shortest waiting time target needed for the customer, the time spent in processing the cross-border e-commerce logistics distribution task is calculated, and the calculation of resource load balance degree and the cost for completing the multiobjective logistics distribution task is combined to establish a mathematical model to measure the scheduling effect of the multiobjective logistics distribution task, and the target of the scheduling of multiobjective logistics distribution task in cloud computing is selected [14].

In cloud computing, there are some constraints among the optimization objectives of multiobjective logistics distribution task scheduling. Therefore, we can determine the optimal multiobjective function of multiobjective logistics distribution task scheduling based on the understanding of the impact of each step on the scheduling process.

Assuming that, in the cloud computing multiobjective logistics distribution task set, N_{first} represents the first processing multiobjective logistics distribution task and N_{last} represents the last processing multiobjective logistics

distribution task, then the processing time of the cloud computing multiobjective logistics distribution task set can be calculated by using the following formula:

$$t_{\text{sum}} = t_e(N_{\text{last}}) - t_s(N_{\text{first}}). \qquad (6)$$

Define that the number of multiobjective logistics distribution tasks in the cross-border e-commerce logistics distribution task set of cloud computing is N, and the calculation formula is

$$N = N_{\text{last}} - N_{\text{first}}. \qquad (7)$$

For the operation cost c_{total} required by the cloud computing multiobjective logistics distribution task set in the processing process, assuming that the cost required by the multiobjective logistics distribution task T_i on the virtual machine per unit time is c_i, then c_{total} can be expressed as

$$c_{\text{total}} = \sum_{i=1}^{p} c_i \cdot (t_e(T_i) - t_s(T_i)). \qquad (8)$$

If the computing performance of multiobjective logistics distribution task on virtual machine is good enough, the value of c_i in formula (8) will be greater.

Load balancing for cloud computing multiobjective logistics distribution tasks on virtual machines is not the same as the more the cross-border e-commerce logistics distribution tasks assigned on virtual machines, the better the load balancing effect [15]. Define the estimated execution time of all cross-border e-commerce logistics distribution tasks on a virtual machine as T'', expressed as

$$T'' = \sum_{i=0}^{u-1} \left(\frac{\text{amount}(T_i)}{N} \right), \qquad (9)$$

where u represents the number of multiobjective logistics distribution tasks assigned to the virtual machine [16]. Define that the average expected execution time of all multiobjective logistics distribution tasks on virtual machines is $\overline{T}$, and the calculation formula is

$$\overline{T} = \frac{1}{P} \cdot \sum_{j=0}^{N-1} t_{\text{sum}}(N), \qquad (10)$$

where w represents the number of multiobjective logistics distribution tasks assigned to the virtual machine and p represents the number of multiobjective logistics distribution tasks in the set of multiobjective logistics distribution tasks.

Define that the load balance variance of cross-border e-commerce logistics distribution task scheduling is E, which is expressed as

$$E = \frac{\sqrt{\left(\left(\sum_{j=0}^{N-1} t_{\text{sum}}(N)/u\right) - \overline{T}\right)}}{w}. \qquad (11)$$

The smaller the value of E, the better the load balance of multiobjective logistics distribution tasks in the data center

in the process of cloud computing multiobjective logistics distribution task scheduling [17].

For cloud computing users, they must spend the lowest cost in the shortest time. Therefore, the minimum values of t_{sum} and c_{sum} are taken. Considering that cloud computing belongs to a commercial service mode, when designing Pareto dominance relationship, the time and cost related to user interests are higher in priority than load balancing. Therefore, the objective function of cloud computing multiobjective logistics distribution task scheduling is constructed, as shown in the following formula:

$$\begin{cases} t_{sum} = \min\left(t_e\left(T_{last}\right) - t_s\left(T_{first}\right)\right), \\ c_{sum} = \min\left(t_e\left(T_i\right) - t_s\left(T_i\right)\right), \\ E = \min\left(\sqrt{\left(\left(t_{sum}/u\right) - \overline{VL}\right)/w}\right). \end{cases} \quad (12)$$

By calculating the processing time of cloud computing cross-border e-commerce logistics distribution task set, the number of multiobjective logistics distribution tasks in the cross-border e-commerce logistics distribution task set is defined, and the load balance variance of multiobjective logistics distribution task scheduling is calculated according to the expected execution time of all multiobjective logistics distribution tasks on the virtual machine. The objective function of cloud computing multiobjective logistics distribution task scheduling is constructed.

The basic flow of cloud computing multiobjective logistics distribution task scheduling optimization algorithm is shown in Figure 1.

To sum up, from three aspects: the shortest waiting time, the resource load balance degree, and the cost of completing the multiobjective logistics distribution task, this paper selects the target of multiobjective logistics distribution task scheduling of cloud computing, designs the optimization algorithm of multiobjective logistics distribution task scheduling of cloud computing, and realizes the scheduling of multiobjective logistics distribution task.

3. Logistics Distribution Cost Prediction Method Based on Cloud Data Mining Technology

Data mining technology [18, 19] aims to process large amounts of data with complex information types and diverse structural forms. The cross-border e-commerce logistics and distribution industry is developing rapidly, and some companies regard cross-border e-commerce logistics and distribution as an extension of their development. Therefore, the financial sector has higher requirements for estimating the cost of cross-border e-commerce logistics and distribution. Traditional cost forecasting methods, less consideration of the impact of factors, for the division of relevant data are not careful, which makes managers query related data and database smaller; forecasted cost value will affect the development of enterprises. So, a new cost forecasting method is studied. This method uses cluster analysis, classification analysis, anomaly analysis, cluster analysis, and
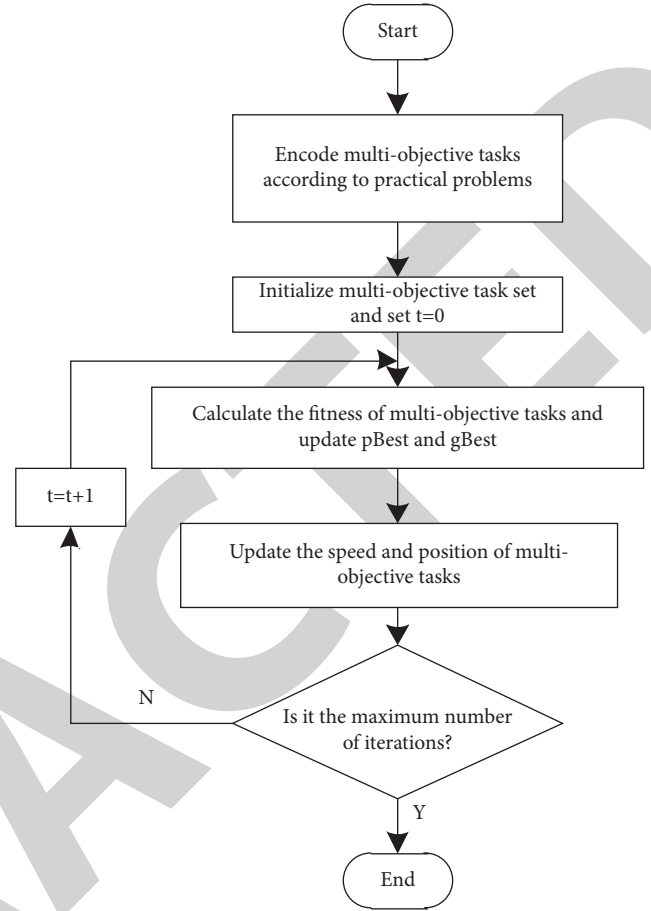

FIGURE 1: Cloud computing cross-border e-commerce logistics scheduling process.

correlation analysis to improve the accuracy of cost prediction by finding the hidden rules.

3.1. Clustering Logistics Distribution Data. Cloud data mining technology is related to computer science. Through data collection, regression analysis, data clustering, association rules, and neural network methods, hidden data information with special association attributes can be grabbed from massive data to predict or forecast the relevant data.

Cross-border e-commerce logistics and distribution costs are mainly generated in the distribution process and distribution links, mainly including sorting costs, circulation and processing costs, assembly costs, and transportation costs. At present, there is a method that uses fuzzy self-defense algorithm to optimize multiobjective task scheduling. This method has a good convergence effect [20]. Sorting expenses shall include sorting manual expenses and sorting equipment expenses; circulation and processing expenses shall include the sum of expenses such as circulation and processing equipment, processing materials and wages and bonuses of management personnel, workers, and the relevant personnel engaging in processing activities in the course of circulation and processing; assembly expenses shall include assembly materials, labor, and the relevant

auxiliary expenses; transportation expenses shall include vehicle expenses and other operating overhead expenses. Therefore, after the distribution cost is refined, there are many types of expenses and the second-level items are more cumbersome. Therefore, the data clustering means in cloud data mining technology [21] shall be used to organize the data information into several different classes or clusters according to the approximation of the data related to the distribution cost, so as to ensure that there are certain attributes among amounts of data of the same class or cluster and certain differences among different classes or clusters. Therefore, the calculation formula for the data relating to the distribution costs of cluster cross-border e-commerce logistics is

$$C = \sum_{i=1,i\neq j}^{m} \sum_{j=1}^{m} \left(a^j - b^i \right)^2, \tag{13}$$

where m represents the number of clusters after clustering, i and j, respectively, represent the clusters with one characteristic attribute, n_j represents the number of items in the data cluster, j represents a data item in the data cluster j, and b_i represents a data item in the initial central node in the data cluster i.

3.2. Mining Association Rules between Amounts of Data.
According to the cost data cluster after clustering, find out the internal relationship between different pieces of information in the same characteristic data. Each structure is usually used to enumerate the possible data class clusters, generally including y data class clusters of different phases; there may be multiple frequent data class clusters, and there will be K rules [22]. Therefore, in these complex and cumbersome data sets, find all frequent data clusters that meet the minimum support threshold and then mine association rules with high confidence from these clusters. The possible rules between frequent data clusters can be expressed by the following formula:

$$G = \sum_{g=1} \left[C \binom{y}{g} \cdot \sum_{d=1}^{y-g} \binom{y-g}{d} \right], \tag{14}$$

where G is the possible association rules analyzed according to the clustering data cluster of formula (14), g represents the number of candidate clusters, and d represents the support count of each candidate cluster. According to these possible association rules, the degree of interest between these rules is measured. Let $A = \{\mu_1, \mu_2, \ldots, \mu_n\}$ represent the set of all items. If $X \subseteq A$, it means that X is a pattern. When there are f amounts of data information in this pattern, X is called the f item set. Suppose that data D is a set of distribution costs, where each expense data F is a set of items, and each data type is represented by H, E, and $I Q$. U and V are two cluster-like item sets; there are $U \subseteq A$ and $V \subseteq A$ and $U \cap V = \delta$, and the cost data F contains U; if and only if $U \subseteq F$, the association rule is $U \Longrightarrow V [u, v]$. Support is the probability that both U and V exist in database D; that is, when confidence appears, U and V also appear, which represents the strength of association rules. At this time, the support is expressed in

$\text{support}(U \Longrightarrow V) = P(U \cup V)$. The cost data support after mining is shown in Table 1.

According to the frequent data cluster items in Table 1, the support between all amounts data is calculated to obtain the association degree of each relationship between the amounts of data and find out the association rules between different costs.

3.3. Outlier Detection of Cost.
Most of the existing cost forecasts focus on the total cost after cost management accounting and do not consider the current cost deviation. Therefore, this paper proposes an outlier detection method, which can control the quality and quantity of input parameters under the condition of multidimensional cost management data environment, use the optimal distance function to make different cost management dimensions having the same importance, then find out the cost dimension beyond cost management, and clarify the direction of cost management.

The concept of outlier detection: firstly, calculate the distance between two objects in the cost management data set X, accumulate the distance between different objects and other objects, and formulate z to represent the total amount of expected outliers; then the z objects with the largest sum of distances are outliers.

If x_i and x_j are proposed to represent two cost management sample objects in X, and d_{ij} represents the distance between x_i and x_j, then the distance matrix H of G can be formulated as

$$\psi = \begin{pmatrix} d_{11} & d_{12} & \ldots & d_{1n} \\ d_{21} & d_{22} & \ldots & d_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ d_{n1} & d_{n2} & \ldots & d_{nn} \end{pmatrix}. \tag{15}$$

The deviation degree δ_i of x_i is proposed as the sum of row i in distance matrix ψ:

$$\delta_i = \sum_{j=1}^{n} d_{ij}. \tag{16}$$

3.4. Distance Function Determination.
In the concept of isolated point, the key point of cost management data analysis is to calculate the distance between one-to-one amounts of corresponding data. In the data set, all data objects are represented by many kinds of dimensions, such as classification dimension, continuous dimension, and time dimension. Different dimension data have different measurement algorithms. Outlier detection discusses the distance measure of continuous data types, and the most common distance is Euclidean distance. In the cost management data set, in order to eliminate the interference caused by the differences of different cost management intervals, the value of the function is calculated by weighted Euclidean distance. The formula is as follows:

Table 1: Frequent cluster support of cost data.

Distribution area	Type of goods delivered	Frequent class cluster (%)
N1	H	69
N2	E	88
N3	I	90
N4	Q	54

$$\left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{N} \frac{\left(x_{ik} - x_{jk} \right)^2}{\sigma^2}}, \tag{17}$$

wherein σ represents variance. It can be seen from the above definition that the greater the deviation degree δ_i, the farther the distance between object i and the remaining objects, and the greater the possibility that it is an isolated point. In fact, after calculating all δ_i, you can arbitrarily specify the z value to view the isolation degree of different cost management data objects, and you can also rely on the proposed isolation points to realize automatic detection, so as to obtain the approximate value distribution exceeding cost management in the cost management data set, so as to provide a strong basis for subsequent cost management prediction [23].

3.5. Design of Cost Forecasting Algorithm.

Based on the data association rules, a feedback forecasting mechanism and a cost forecasting algorithm are designed to predict the total cost of cross-border e-commerce logistics distribution. After the cost data mining is completed, a large amount of cost information is obtained, which is taken as the feedback information for forecasting. Before the control, the deviation threshold for forecasting the cross-border e-commerce logistics costs is set. When the cross-border e-commerce logistics costs exceed the range of deviation thresholds, the cost feedback information is collected to forecast the cross-border e-commerce logistics costs. The specific control mechanism is shown in Figure 2.

From the feedback control in Figure 2, in the intelligent forecast of cross-border e-commerce logistics, the expected cost and the actual cost are used to calculate the cost deviation, and then the cost deviation rate is obtained. In the phase of logistics distribution, if the deviation rate of cost is less than the set deviation threshold, the project construction needs to be satisfied and no feedback control is required. If the deviation of cost is greater than the set deviation threshold, the trigger control mechanism can obtain the project cost information through the cost data mining technology in real time and adjust the overall project cost according to the cost information.

In general, the distribution cost is mainly related to the labor cost and the transportation vehicle and equipment cost. So, in the process of forecast, the direct labor cost and transportation cost are calculated according to the dispatch of the managers, stevedores, and transportation personnel in the two processes of distribution and transportation. Based on the regression difference moving average method, the distribution cost is predicted according to the linear time
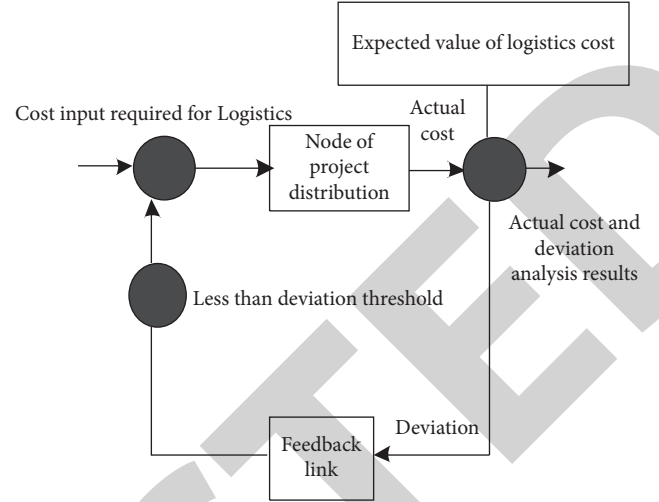

Figure 2: Feedback forecast of cross-border e-commerce logistics cost.

series. The time series of dynamic changes can be transformed into a stationary one by several time difference calculations. Set a parameter as ω, treat it as the difference degree, use ω, χ, and q to build prediction model, model the transformed stationary sequence, and then replace it with the original sequence. The prediction algorithm based on parameters ω, χ, and q is as follows:

$$Q = \sum_{\chi=q}^{m} \varphi_m \left[\varepsilon_\chi + \gamma_q - \varepsilon_q \right], \tag{18}$$

where Q represents the predicted cost of cross-border e-commerce logistics distribution and φ_m represents the m rules between expense amounts of data. ε_p represents the model under characteristic parameter p, and γ_q represents the model under characteristic parameter q; ε_q represents the random error under the characteristic parameter q.

In the process of calculation, the stability of time series should be ensured. When the data series has the characteristic of volatility, it should be treated by difference. At this point, cloud data mining technology is used to predict the cross-border e-commerce logistics distribution costs at this stage.

4. Simulation Experiment Analysis

In the simulation platform, the cloud computing cross-border e-commerce logistics cost prediction algorithm is added to the category of data center broker, and the ant colony algorithm-based logistics distribution cost prediction algorithm proposed in [4] and the logistics cost prediction algorithm under multicustomer random demand proposed in [5] are used as the experimental control group. Quantitatively analyze the intelligent prediction results of cloud computing cross-border e-commerce logistics cost from three aspects: deadline violation rate, virtual machine, and resource utilization.

This experiment uses the data recorded by the financial management department of a large cross-border

e-commerce logistics enterprise to forecast the transportation costs for the current year by year based on the 450 GB distribution costs recorded from 2010 to 2020 through the establishment of the Hadoop experimental cloud platform. The simulation environment is composed of simulation computer, special server, real-time changing LCD screen, and network stable routing. This experiment selects two computers with the same model and same configuration. The CPU of the computer is 3.4 GHz, 8 GB memory, and 500 GB hard disk space; high speed computing network and gigabit storage network are selected, and the wireless route-connected computer is opened. The operating system of the computer is Ubuntu 18.04, and the Java execution environment is jdk-7u21-linux-i586. It logs into the simulation software MAT-LAB 2016a and tests the software program. The software runs smoothly and runs on the Hadoop platform. The platform can work normally in single machine mode, pseudodistributed mode, and complete distributed mode. Set up a data cluster, a total of 26 nodes, including 2 management nodes, 1 IO node, and 23 compute nodes; specify node01-node23, when management node finds variable cost data; timely modify the path set to 192.168.0.201. After the preparation, according to the selected subjects, the experiment began.

4.1. Experimental Analysis of Outlier Detection in Cost Prediction.
In the above set prediction index samples, an index is randomly selected as the experimental standard, and the isolated points between attributes in the index are detected by the proposed method. The results are shown in Figure 3.

It can be seen from the experiment of extraction project indicators for the service lanes in Figure 3 that cost management serving driveway data exist in the two data concentrations, the two dots; that is, the target cost management of the normal price and the other three separate data points are detected by the method of isolated points; these isolated points represent. In the distribution of cost management data, a phenomenon of premium appears, but the degree of premium is low.

4.2. Comparison of Logistics Time Consumption under Different Algorithms.
By setting different quantities of cloud computing cross-border e-commerce logistics delivery tasks, the maximum completion time of the three methods is compared, and the results are shown in Figure 4.

As can be seen from the results in Figure 4, the maximum completion time of the three methods is also getting longer with the increase of the number of cloud computing cross-border e-commerce logistics distribution tasks. The logistics cost prediction algorithm proposed in [5] under the random demands of multiple customers not only improves the advantages and disadvantages of the traditional method, but also takes into account the multiobjective property. Compared with the ant colony algorithm-based logistics distribution cost prediction algorithm proposed in [4], it has a shorter maximum completion time. The ant colony algorithm-based logistics distribution cost prediction algorithm proposed in [4] has the problem of slow convergence,
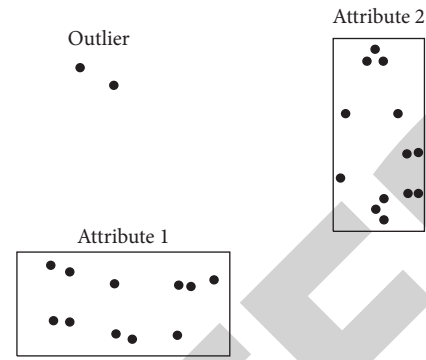

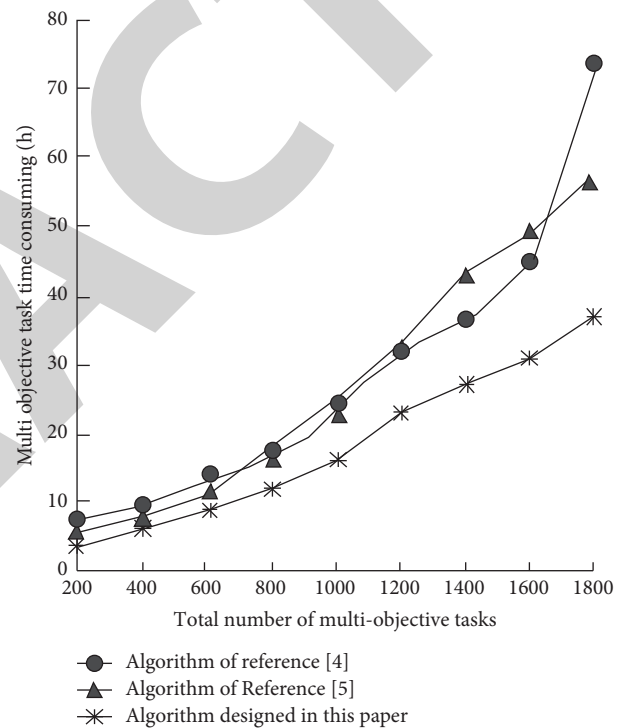Figure 3: Outlier detection results of the proposed method.

Figure 4: Comparison results of maximum completion time of cloud computing cross-border e-commerce logistics task scheduling.

resulting in a long completion time. The cloud computing cross-border e-commerce logistics cost method plans the three objectives of the shortest waiting time of customers, the load balancing degree of resources, and the cost of completing the cross-border e-commerce logistics distribution task as a single objective evaluation function and takes them as the scheduling target, achieving good scheduling effect.

4.3. Comparison of Logistics Task Completion Rate under Different Algorithms.
By setting different quantities of cloud computing cross-border e-commerce logistics delivery tasks, the three methods are compared for the failure rate of deadline, as shown in Figure 5.
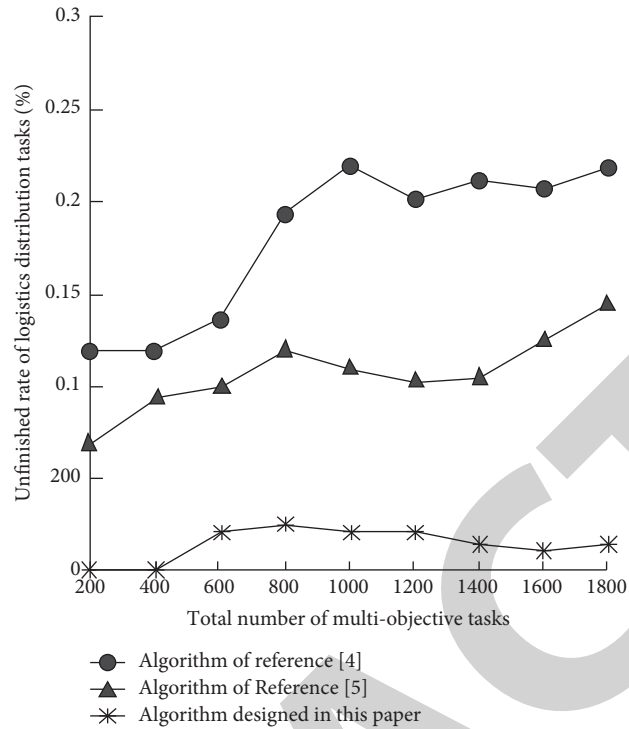
Figure 5: Test results of unfinished rate of deadline of cross-border e-commerce logistics task scheduling.

Table 2: Cost prediction deviation comparison of different algorithms (unit: ten thousand yuan).

Logistics cycle	This paper designs the algorithm	Reference [4] algorithm	Reference [5] algorithm	Actual cost
1	2.42	2.44	2.35	2.48
2	2.75	2.69	2.56	2.78
3	2.95	2.28	2.37	2.92
4	2.82	2.05	2.45	2.71
5	2.88	2.72	2.68	2.82
6	2.94	3.11	3.20	2.92
7	3.36	3.73	3.18	3.39
8	3.69	3.12	3.58	3.66
9	2.76	3.24	3.43	2.74
10	3.01	3.60	3.18	3.01
11	3.64	4.03	4.10	3.64
12	3.99	4.60	4.28	3.99
13	4.88	4.22	4.56	4.80
14	4.52	5.40	4.35	4.51
15	4.85	5.88	5.12	4.83
16	4.23	5.46	5.35	4.22
17	4.15	5.56	5.64	4.15
18	4.95	5.21	5.83	4.90
19	5.02	5.37	5.97	5.02
20	5.58	6.09	6.37	5.58

The increased amount of cross-border electricity distribution tasks can be seen from the results of Figure 5, with cloud computing, based on the fuzzy self-defense cross-border electricity distribution algorithm of cloud computing task scheduling optimization method, and authors in [5] proposed many customers under the random demand of the logistics cost prediction algorithm which is maintained in a lower cutoff time not completed. However, the deadline completion rate of cloud computing distribution task scheduling optimization method based on fuzzy self-defense algorithm is relatively low, about 5%. The ant colony algorithm-based logistics distribution cost prediction algorithm proposed in [4] takes the cutoff time as a constraint condition, and the optimization of the distribution task scheduling algorithm is not in place, which affects the final scheduling effect.

4.4. Comparison of Logistics Cost Forecasting Errors under Different Algorithms. Table 2 shows the statistical results of actual cost control in 20 logistics cycles of three test groups with different algorithms.

According to Table 2, the total cost of the logistics project of the experimental group is also basically consistent with the expected cost, and the error is very small. However, the logistics project cost of [4] algorithm and [5] algorithm is quite different from the expected cost. The test results of the above three stages verify that the proposed cost intelligent prediction method is more effective than the two traditional prediction algorithms. As can be seen from the experimental results, the prediction results obtained by our method are closer to actual cost. This shows the effectiveness of the proposed method.

5. Conclusion

In recent years, cross-border e-commerce logistics and transport industry have developed rapidly. In order to better predict logistics costs, this study designed a cross-border e-commerce logistics cost intelligent prediction algorithm based on cloud computing. Introduce cloud computing platforms to optimize the scheduling of cross-border e-commerce logistics distribution tasks. On the basis of selecting the target of cloud computing cross-border e-commerce logistics distribution task scheduling, by constructing the target function of cloud computing cross-border e-commerce logistics distribution task scheduling, this paper realizes the scheduling of cloud computing cross-border e-commerce logistics distribution task and optimizes the effect of intelligent prediction of cross-border e-commerce logistics cost. Experimental results also show that the proposed algorithm has higher accuracy and higher completion rate of logistics tasks and has significant advantages over the existing algorithms.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

Acknowledgments

References

[1] J. Anson, M. Boffa, and M. Helble, "Consumer arbitrage in cross-border e-commerce," *Review of International Economics*, vol. 27, no. 4, pp. 1234–1251, 2019.

[2] M. Labouré, "Pensions: the impact of migrations and cross-border workers in a small open economy," *Journal of Pension Economics and Finance*, vol. 18, no. 2, pp. 247–270, 2019.

[3] D. Pamucar, K. Chatterjee, and E. K. Zavadskas, "Assessment of third-party logistics provider using multi-criteria decision-making approach based on interval rough numbers," *Computers & Industrial Engineering*, vol. 127, pp. 383–407, 2019.

[4] Z. X. Zeng, C. D. Zou, J. F. Wei, H. Lu, E. Lv, and Q. Ruan, "Optimization of distribution cost model of cold chain logistics for litchi based on ant colony algorithm," *Packaging Engineering*, vol. 40, no. 11, pp. 58–65, 2019.

[5] J. D. Han, X. F. Yang, and Q. Tian, "Logistics cost control under stochastic demand of multiple customers," *Price:Theory & Practice*, vol. 417, no. 3, pp. 157–160, 2019.

[6] I. Czarnowski and P. Jędrzejowicz, "Data reduction and stacking for imbalanced data classification," *Journal of Intelligent and Fuzzy Systems*, vol. 37, no. 6, pp. 7239–7249, 2019.

[7] L. Jia, "Research on the cost control of cross-border e-commerce overseas warehouse from the perspective of big data technology and storage theory model," in *Proceedings of the 2020 Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC)*, pp. 423–427, IEEE, Dalian, China, April 2020.

[8] J. Wang and C. Xing, "Factors affecting the evolution of advanced manufacturing innovation networks based on cloud computing and multiagent simulation," *Mathematical Problems in Engineering*, vol. 2021, no. 1, Article ID 5557606, 12 page, 2021.

[9] G. J. Mirobi and L. Arockiam, "DAVmS: distance aware virtual machine scheduling approach for reducing the response time in cloud computing," *The Journal of Supercomputing*, vol. 77, no. 6, pp. 1–12, 2021.

[10] J. Lian, "An optimization model of cross-docking scheduling of cold chain logistics based on fuzzy time window," *Journal of Intelligent and Fuzzy Systems*, vol. 41, no. 2, pp. 1–15, 2021.

[11] A. K. Mishra, D. K. Yadav, Y. Kumar, and N. Jain, "Improving reliability and reducing cost of task execution on preemptible VM instances using machine learning approach," *The Journal of Supercomputing*, vol. 75, no. 4, pp. 2149–2180, 2019.

[12] D. Dhanya and D. Arivudainambi, "Dolphin partner optimization based secure and qualified virtual machine for resource allocation with streamline security analysis[J]," *Peer-to-Peer Networking and Applications*, vol. 12, no. 18, Article ID 1276, 2019.

[13] M. Kaynia, C. Buratti, and R. Verdone, "On the performance of wireless ad hoc networks using bandwidth partitioning," *Wireless Networks*, vol. 25, no. 7, pp. 4215–4229, 2019.

[14] H. Chen, Y. Jin, and B. Huo, "Understanding logistics and distribution innovations in China," *International Journal of Physical Distribution & Logistics Management*, vol. 50, no. 3, pp. 313–322, 2020.

[15] S. Sotiriadis, N. Bessis, C. Amza, and R. Buyya, "Elastic load balancing for dynamic virtual machine reconfiguration based on vertical and horizontal scaling," *IEEE Transactions on Services Computing*, vol. 12, no. 2, pp. 319–334, 2019.

[16] A. Curioni, C. Vesper, G. Knoblich, and N. Sebanz, "Reciprocal information flow and role distribution support joint action coordination," *Cognition*, vol. 187, pp. 21–31, 2019.

[17] F. Lu, L. Wang, H. Bi, Z. Du, and S. Wang, "An improved revenue distribution model for logistics service supply chain considering fairness preference," *Sustainability*, vol. 13, no. 12, Article ID 6711, 2021.

[18] Z. Zhen and Y. Yanqing, "Lean production and technological innovation in manufacturing industry based on SVM

algorithms and data mining technology," *Journal of Intelligent and Fuzzy Systems*, vol. 37, no. 5, pp. 6377–6388, 2019.

[19] X. Guan, Y. Fan, Q. Qin, D. Kea, and G. Yang, "Construction of science and technology achievement transfer and transformation platform based on deep learning and data mining technology," *Journal of Intelligent and Fuzzy Systems*, vol. 39, no. 1, pp. 1–12, 2020.

[20] X. Guo, "Multi-objective task scheduling optimization in cloud computing based on fuzzy self-defense algorithm," *Alexandria Engineering Journal*, vol. 60, no. 6, pp. 5603–5609, ISSN 1110-0168, 2021.

[21] B. N. Yang, "Simulation of sorting and searching encrypted cloud data based on K-mean clustering algorithm," *Computer Simulation*, vol. 37, no. 9, pp. 451–455, 2020.

[22] F. H. Kuwil, F. Shaar, A. E. Top cu, and F. Murtagh, "A new data clustering algorithm based on critical distance methodology," *Expert Systems with Applications*, vol. 129, pp. 296–310, 2019.

[23] H. Yuanyuan, "The cross-border C2B development study based on the information cost theory," in *Proceedings of the 2020 IEEE International Conference on Power, Intelligent Computing and Systems (ICPICS)*, pp. 542–545, IEEE, Shenyang, China, July 2020.