Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 3713268, 9 pages
https://doi.org/10.1155/2022/3713268

Research Article

Exploration on the Construction of Cross-Border E-Commerce Logistics System Using Deep Learning

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Received 18 April 2022; Accepted 13 May 2022; Published 16 June 2022

Academic Editor: Xiantao Jiang

The intention of this article is to solve the disadvantages of the current logistics model and promote the healthy development of modern cross-border e-commerce (CBEC) Logistics. First, this paper expounds on and compares the traditional and CBEC logistics models. Then, the CBEC logistics system is constructed and adjusted according to system construction requirements. Further, two key subsystems are designed: the logistics object distribution subsystem and risk detection subsystem, based on the deep learning backpropagation neural network (BPNN) algorithm. The relevant parameters of the object distribution subsystem are calculated and sent to the risk detection subsystem model and tested. It is concluded that the sorting completion rate before 18:00 can reach 95.2%, indicating that the proposed CBEC logistic system can meet the needs of CBEC logistics enterprises. Logistics risk detection's expected and actual outputs can fit 99%, indicating a tiny deviation. The research has certain reference significance for clarifying the logistics system and service mode of CBEC.

1. Introduction

The global economy, science, and technology are advancing rapidly, among which the fastest are Internet technology, information technology, and mobile Internet economy. Cross border E-commerce (CBEC) has seen outbursts since the Corona Virus Disease 2019 (COVID-19) outbreak. Due to the ongoing pandemic, international consumption has depressed. Under such less optimistic situations, the world begins to look for a breakthrough, which becomes the best opportunity for CBEC development. Globally, the CBEC has shown a trend of centralization and rapid growth. Therefore, higher standards have been put forward for the quality and speed of cross-border logistics: more data, information, and intelligence must be incorporated. The latest report analysis shows that in 2020, due to the continuous impact of the epidemic, the scale of online consumption will expand rapidly. In particular, from 2019 to 2020, the total retail sales of e-commerce in major countries in Europe, America, and the Asia Pacific region increased by more than 15%, realizing rapid growth. The step-up of global CBEC is inseparable from efficient and reliable cross-border logistics. Therefore, cross-border logistics has become a prerequisite for CBEC development.

Before the concept of e-commerce logistics, previous studies have analyzed military, enterprise, and e-commerce logistics in the supply chain (SC) using the simulation method [1]. The impact of order segmentation has been examined on the total logistics cost [2]. Major Western nations, such as the United States, Britain, Germany, France, and Spain, rely on the mature market environment. Their e-commerce ecology has taken shape. The penetration rate and the growth rate of e-commerce users, and the per capita GDP are at the world's highest level [3]. Some developed countries and international organizations have done many works and made some progress in establishing a unified information system through advanced communication technologies and perfect social sharing systems [4]. Now, the uncertainty distribution of the logistics system has been effectively controlled, and the subsystem design that can minimize risk is being carried out. Such a proposal is to treat the logistics distribution problem under uncertainty from a macro perspective [5]. However, the microdetailed system design is still vacant.

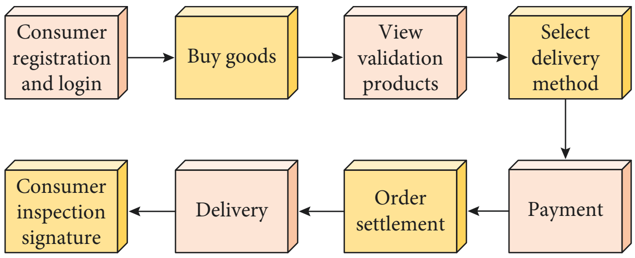

Figure 1: Traditional E-commerce logistics transportation process.

Nowadays, CBEC has also become a new economic development point. With the continuous increase in consumer demands, the e-commerce logistics model is also innovating. As a result, the following problems complicate the emerging disadvantages of the original model. The customs clearance and bonded system are not perfect, the after-sales service experience is poor, and the SC logistics system is not mature [6]. The nature of CBEC belongs to cross-border trade, which involves changes in the national policy environment. These problems hinder the stable development of modern CBCE logistics while providing an opportunity for optimization and improvement. So far, many relevant theoretical studies can be found. However, the CBEC logistics system research is very few, and the establishment of the CBEC logistics system is imminent. Aiming at the construction objectives and principles of the CBEC logistics system, this paper determines the two-level subsystem and three-level constituent elements of the CBEC logistics system. Specifically, it constructs the CBEC logistics distribution subsystem, the CBEC logistics-oriented evaluation index system (EIS), and the risk detection subsystem based on the deep learning backpropagation (BP) neural network (NN) algorithm. The conclusion reads as follows: the proposed system can meet the needs of the CBEC logistics enterprise. The CBEC logistics distribution system has fewer faults and errors. The innovation is to study CBEC logistics from a systematic perspective and enrich the research system of CBEC logistics. Two CBEC logistics subsystems are constructed: Logistics distribution and risk detection subsystems. This study studies and optimizes the logistics distribution efficiency and distribution risk of CBEC, which has a certain reference significance for clarifying the Logistics system and service mode of CBEC. The findings provide a reference for developing Logistics enterprises.

2. Construction and Parameter Calculation of CBEC Logistics System

2.1. Comparative Analysis of Traditional Mode and Cross-Border Mode of E-Commerce Logistics. A traditional logistics system is a set of coherent logistics transportation schemes, more commonly known as the enterprise resource planning (ERP) system, completed through electronic information technology (EIT). The traditional ERP has been relatively mature and extended multiple functions based on simple household delivery. However, it has some deficiencies and relies heavily on human labor and material resources, making it unsuitable for the emerging CBEC logistics [7].

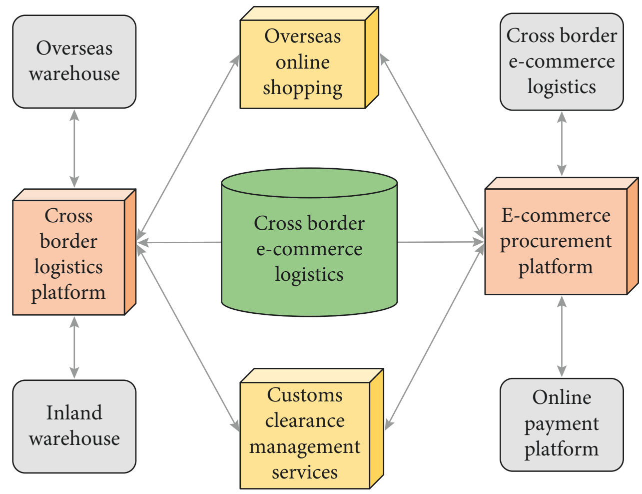

Figure 2: CBEC logistics and transportation process.

Figure 1 gives the traditional e-commerce logistics transportation process.

From Figure 1, the e-commerce enterprise (ECE) presents the commodity information online, where the buyer visits and selects the goods and then fills in the order [8]. The ECE confirms and informs the buyer of the charging amount and payment method upon order. At the same time, the ECE has the supply of the goods prepared. The buyer makes settlement and capital delivery, and the information is notified to the buyer and the seller. Then, the ECE delivers the goods and waits for the buyer's confirmation. E-commerce represents the future consumption and service mode as a new digital trade mode. Therefore, to improve the overall consumption environment, there is a need to break through the traditional system of inherent industry and develop a comprehensive manner characterized by commodity agency and distribution [9]. This is a complete system that links Logistics, business flow, and information flow into a whole. The specific process gradually reflects a series of new characteristics of the logistics model: informatization, automation, and networking. The CBEC logistics and transportation process is shown in Figure 2.

CBEC involves multiple nodes in the SC. The operation of each node is drawn in Figure 2: the seller contacts the company to place an order, pick up the goods on-site, transport them to the port or airport, have the documents signed by relevant departments, and transport the goods to the transportation system for customs clearance, transfer, or storage at the destination. CBEC logistics can integrate resources and industries to provide standardized customer service, order management, unified business, and other services. It is an essential link connecting production and trade [10]. Meanwhile, CBEC logistics are classified according to customized customer needs to provide efficient logistics services such as warehousing, distribution, and transportation.

2.2. Research on CBEC Logistics Operation. With booming CBEC, CBEC Logistics enterprises must improve the level of logistics information technology and continuously enhance

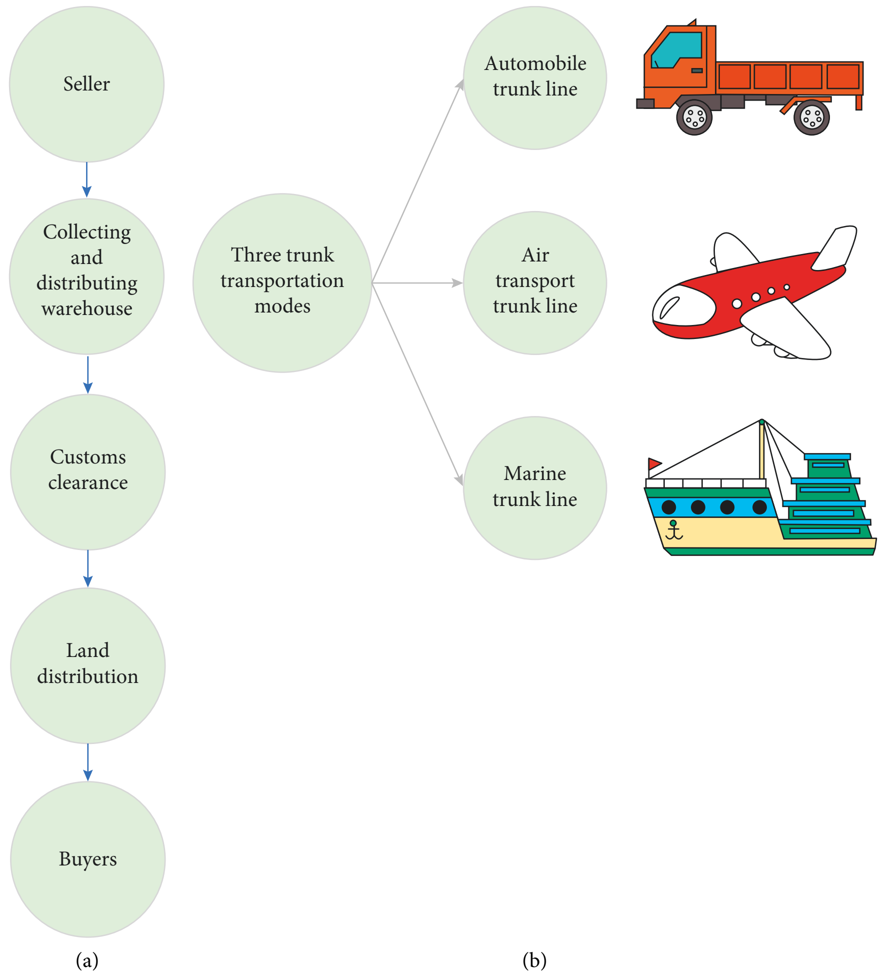

FIGURE 3: International special line logistics operation rules (a) special line operation framework and (b) transportation mode options.

the corresponding ability of the cross-border logistics supply chain (CBL-SC). At the same time, there is a need to reduce the cost of CBEC Logistics and management and improve service satisfaction to raise revenue [11]. There are mainly three logistics operation modes in CBEC: Postal Small Parcel, Four International Express, and International Special line.

International express mainly refers to the four major commercial express giants: Dalsey, Hillblom, Lynn (DHL), Thomas National Transport (TNT), Federal Express (FedEx), and United Parcel Service of America (UPS). These international couriers bring excellent Logistics experience to online shoppers through their own global network, powerful information technology (IT) system, and localized services worldwide. International Special Line Logistics is generally transported overseas by air charter and then send packages to the destination country through cooperative companies [12]. The advantage of special line logistics is that it can concentrate large quantities of goods to a specific country or region while reducing costs through the scale effect. Therefore, its price is generally lower than commercial express [13]. In terms of timeliness, special line logistics is slightly slower than commercial express but much faster than postal parcels. The operation flow of International special line logistics is drawn in Figure 3.

As in Figure 3, special line logistics can choose three special transportation lines: shipping, land transportation, and sea transportation, served by professional logistics personnel. The advantage of special line logistics is that it can concentrate batch goods to a country to reduce costs. Therefore, its price is generally lower than other express delivery. The most common special line logistics products in the market are the American special line, special European line, Australian special line, and Russian special line. Many logistics enterprises have also launched the Middle East special line, South America special line, and South Africa special line [14]. However, the special line logistics sees some delays compared with other commercial expresses, but it is still much faster than postal parcels. The common operation feature of the four international express is multiobjective, as given in Figure 4.

Figure 4 describes the CBEC logistics modes. Apparently, CBEC Logistics mode establishment should focus on seeking the most efficient way to interconnect time, space, materials, equipment, handling, warehousing, personnel, communication, and other elements of the overall Logistics

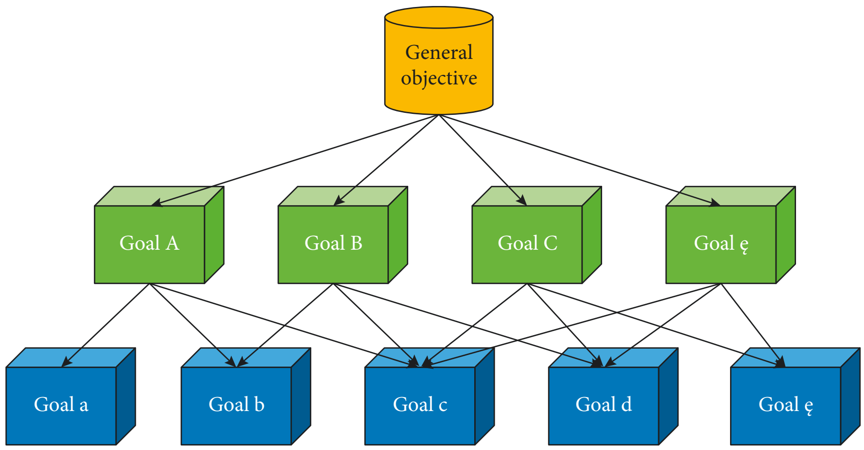

Figure 4: Multiobjective mode of goods of four international express.

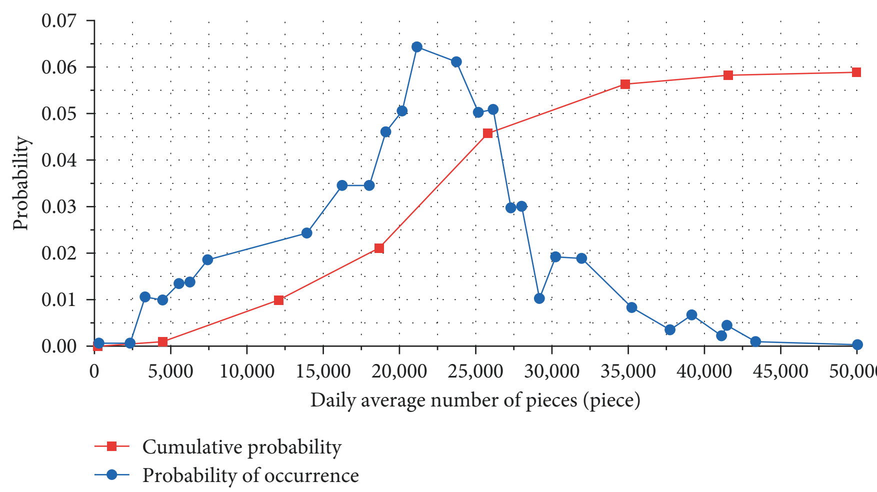

Figure 5: Demand sampling and density function of the average daily processing capacity of a CBEC logistics enterprise.

diagram. The system is more than just a multi-link-spliced unity. It also aims to maximize the overall system benefit over the sum of the benefits of each link [15]. The logistics system should factor in the external environment and development conditions. The construction of the CBEC logistics system must focus on the overall system goal. In the meantime, the system should consider the rational distribution of resources to maximize the overall timeliness and benefits.

2.3. Establishment of the CBEC Logistics Sorting System and Risk Detection Subsystem Model. First, the sampling density function is tested according to the sampling data of a logistics enterprise. According to the demand analysis, the enterprise's average daily processing volume presents a deterministic probability of V distribution [16]. The mean daily processing volume is 19,325, with a standard deviation of 7,387. The demand sampling and density function curve of the average daily processing volume is outlined in Figure 5.

From Figure 5, China has put forward higher standards for the quality and speed of CBEC logistics: more data, information, and intelligence accommodation are needed. Further, V in probability events can generate a random variable Vd according to the Monte Carlo simulation method. Its distribution follows the above density function distribution [2]. Suppose the number of pieces arriving at different time windows Tn should be ITn. In that case, the probability can be determined for pieces reaching ITn in different time windows in a day combined with the actual pick-up plan of the sampled enterprise and the operation time plan of the transfer center. The whole process of the sorting center is divided into seven basic links: unloading, inbound scanning, security inspection, label changing, customs clearance scanning, sorting, and loading air containers. According to the fieldwork data collection, its service capacity has relatively stable variation. It fluctuates from the mean value within a certain standard deviation range [17]. Additionally, postwork is physical activity, so the service capacity also changes according to the increase in working time t. The simulation flowchart of the CBEC Logistics sorting system mainly solves two problems: the sorting completion time $Z(Tc)$ and the appropriate capacity $Z(Snt)$ of the platform in each link after the input of random variable VD.

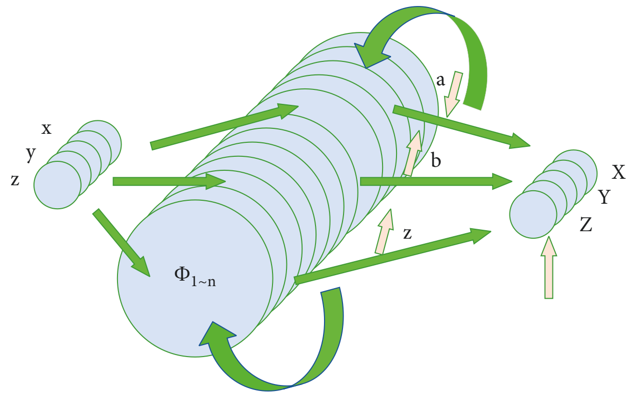

Figure 6: BPNN internal structure.

The objective function of the sorting system can be established as in (1):

$$Z(Tc) = T\text{start} + \sum_{t=1}^{\infty} \text{Max}\left(\frac{ITn}{C_1} \times \frac{1}{60}, \frac{ITn}{c_2} \times \frac{1}{60}, \frac{ITn}{C_s} \times \frac{1}{60}, \ldots\ldots, \frac{ITn}{c_n} \times \frac{1}{60}\right). \quad (1)$$

In equation (1), T is the labor time and $Z(Tc)$ represents the sorting completion time after input. Tstart denotes the operation start time, usually a constant. After the target price function of the sorting system is obtained, the potential risk factors must be determined in the overall CBEC logistics system. Then, the results are analyzed to obtain a scientific and reasonable risk detection subsystem. Based on BPNN and genetic algorithm (GA), this paper designs the proposed CBEC logistics system's risk detection subsystem model. The model tests the reliability of the logistics distribution subsystem, thus forming a complete system [18].

Each attribute of the BPNN model is determined by its internal properties. BPNN has the functions of association and memory, classification and recognition, distributed storage and memory, and processing, so it is more convenient than the traditional method. Generally, BPNN includes three levels: input, output, and hidden layers. During model learning, network parameters are constantly updated, studied, and modified to establish a model with minimum error. Its basic unit is the neuron, roughly the same as an animal neuron [19]. The function used in the process of sample data acting on BPNN neurons denotes only $I = \sum_{j=1}^{n} w_{ij}x_j - \theta_j$ and $y_i = f(I_i)$. x_j signifies the neuron input from the outside or other neurons. w_{ij} is the connection weight between neurons. θ_j is the output threshold of neurons. y_i means the output signal of the neuron. $f(I_i)$ refers to an excitation function used to limit the output of neurons. The internal structure of BPNN is unfolded in Figure 6.

As in Figure 6, the middle of BPNN has a multilayer feedforward NN. Then, the BPNN is trained using the input and output sample sets. The internal weights and thresholds are studied and adjusted repeatedly to approach the linear or nonlinear relationship between the input and output samples. The internal law underlying data samples can be learned. The learning process of BPNN is portrayed in Figure 7.

From Figure 7(a), the BPNN propagates forward and unidirectionally. The samples are transmitted from the neurons in the input layer and finally transmitted to the neurons in the output layer through calculations. When the network training results do not conform to the preset error, the error signal will propagate in the opposite direction of the error function. Then, multiple iterations and calculations are performed through the calculation process in Figure 7(b) to adjust the weight and threshold between neurons in each layer to reduce the output error [20]. When the output reaches the expected error accuracy, it will automatically stop running and output the final data.

The operation process of the specific risk detection subsystem is displayed in Figure 8.

According to Figure 8, the NN is used to address the nonlinear relationship of the data. Through learning and training, the weight of the data sample can be determined, and then the GA is introduced to solve the maximum value of the event. There are two methods in selecting coding and detection functions, which are combined to complement each other to obtain a more comprehensive output [21]. The steps of constructing the risk detection factor set and sample training, as well as the equations involved in calculating the values, are as follows:

$$U = \{U_1, U_2, \ldots\ldots, U_n\}, \quad (2)$$

$$M = \{m_1, m_2, \ldots\ldots, m_n\}, \quad (3)$$

$$s = \sqrt{M + N} + y. \quad (4)$$

In order to build a CBEC logistics risk detection subsystem, the values of M and N must be counted [22]. In equations (2)–(4), M, N, and y are the neuron sample set, output result, and a constant. s and m are the numbers of neurons in the hidden layer and input layer, respectively.

$$1 = m * n + (s + 1) * n, \quad (5)$$

$$W = \left|w_{jr}\right|_{n*s}. \quad (6)$$

In equations (5) and (6), n is the number of neurons in the output layer [23]. W refers to the weight matrix from the input layer to the hidden layer. Based on the neuron sample set and output results, the model proceeds to the next step:

$$V = \left|v_{kr}\right|_{s*m}, \quad (7)$$

$$B = \left|b_1, b_2, \ldots\ldots, b_s\right|, \quad (8)$$

$$C = \left|C_1, C_2, \ldots\ldots, C_m\right|, \quad (9)$$

$$E_{\min}(k)\frac{1}{2}\sum_{k-1}^{p}\left(d_k^p - O_k^p\right)^2. \quad (10)$$

The number of neurons in the output layer and the weight from the input layer to the hidden layer are obtained. Equation (7) calculates the weight matrix from the hidden layer to the output layer. In equations (7)–(9), V denotes the

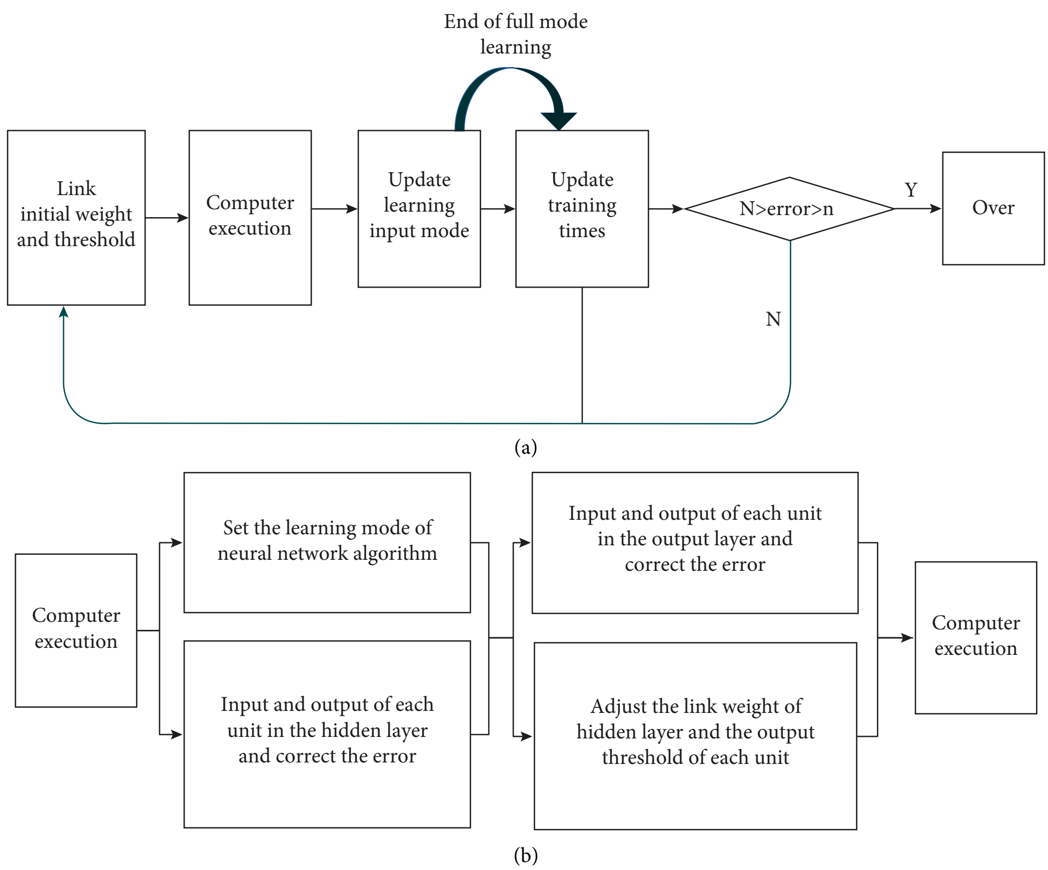

Figure 7: Internal learning process of BPNN: (a) overall learning process; (b) computer execution process.

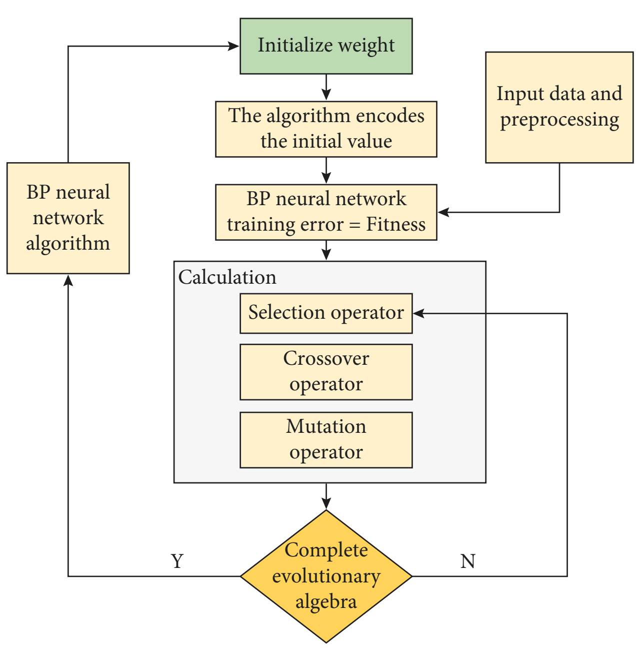

Figure 8: Process framework of the risk detection subsystem.

weight matrix from the hidden layer to the output layer. B is the threshold of neurons in the hidden layer. C stands for the threshold of neurons in the output layer. p signifies the training sample. After the weight matrix from the hidden layer to the output layer and the threshold of the hidden layer, neurons are determined for the risk detection subsystem, the training output error is calculated as follows:

$$F = \frac{1}{E}, \tag{11}$$

$$f\left(E_{\min}(k)\right)\frac{1}{E_{\min}(k)}. \tag{12}$$

Equation (11) is its functional equation. In equation (12), $E_{\min}(k)$ represents the output error of sample training [24]. The number of neurons can be determined based on the model output:

$$n_H = \sqrt{n+m} + a, \tag{13}$$

$$n_H = \sqrt{n * m}, \tag{14}$$

$$n_H = \frac{n+m}{2}. \tag{15}$$

Equations (13)–(15), n_H is the number of neurons in the hidden layer. a denotes a constant between [1, 10, 25]. $n_H = \sqrt{n+m} + a$ is most commonly used to calculate the number of neurons in the hidden layer.

After data collection, analysis, and preliminary modeling preparation, the sorting time window and basic resource distribution are determined by extracting the historical capacity data of the sorting center. The business department provides volume forecast data according to customer demand. Then, the site layout is designed according to the processing flow to determine the form and rules of the sorting queuing model. According to the cargo operation time window, cargo arrival time, queuing rules, and other situations, the parcel processing model of the sorting center is established. Multiple simulation experiments are carried out by continuously varying cargo flow and adjusting resource distribution. Based on the model results, the resource will be distributed, and the cost difference under the optimal resources distribution is obtained by comparing the daily ordinary express sorting processing cost. At the same time, the maximum capacity limit of the sorting center is obtained. Finally, the numerical result is sent to the risk detection subsystem. The target samples are optimized and trained through the NN. As such, the risk detection results are outputted to determine the risk level of the CBEC Logistics system. The specific risk level standard is detailed in Figure 9.

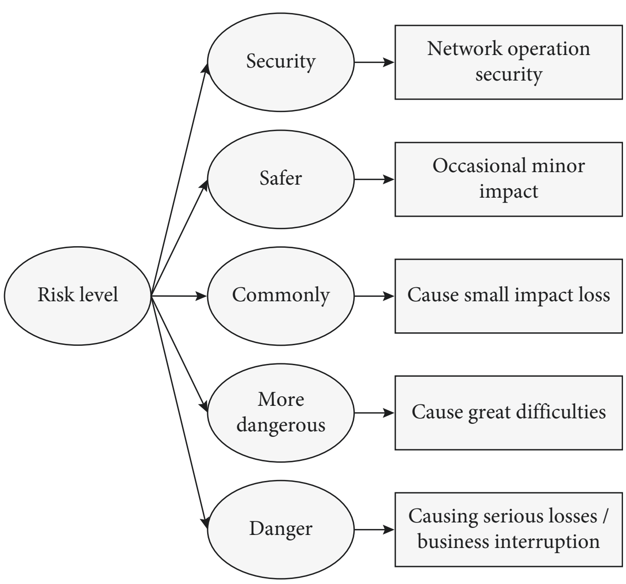

Figure 9: Risk level standards of the CBEC logistics system.

Figure 9 is the risk analysis and SC-level risk classification of the CBEC logistics system, including five levels. They are safe (corresponds to risk range of (0, 0.2)), safer ((0.2, 0.5)), general ((0.5, 0.67)), relatively dangerous ((0.67, 0.85)), and dangerous ((0.85, 1)) levels [26]. Then, training data are imported into MATLAB. 7.0 and are trained by the toolbox for simulation.

3. System Model Test and Result Analysis

3.1. Analysis of Experimental Results of the CBEC Logistics Distribution Subsystem Model. In MATLAB 7.0, inputs are used to represent and import information data, and simulation experiments are carried out. The object distribution time and accumulated pieces of the CBEC logistics distribution subsystem are counted in Figure 10.

According to the simulation results of the resource input in Figure 10, the sorting completion rate before 18:00 can reach 95.2% so that the resource configuration can meet the business needs. After 1,000 times of operation, the sorting center obtains the queue form of each operation link. At the same time, it restricts the backlog of packages in the time window and the specified time unit. By adjusting the station configuration, the standard processing efficiency has increased from 480 pieces/station/hour to 900 pieces/station/hour. Thus, the object distribution subsystem model can effectively optimize the efficiency of object distribution and processing efficiency in the CBEC logistics system.

3.2. Analysis of Experimental Results of the Risk Monitoring Subsystem Model. Here, the risk detection subsystem tests the CBEC logistics object distribution subsystem to detect its reliability. First, the number of hidden layer nodes is determined. Then, it is calculated that when the number of hidden layer nodes is 8 and 11, the model is the most reasonable. Therefore, the model will be further trained with 8 and 11 hidden layer nodes to get the relationship between the number of iterations and the Mean Square Error (MSE). The specific MSE distribution is drawn in Figure 11.

As in Figure 11, the samples with the best fitness are searched according to the optimal conditions. The optimal

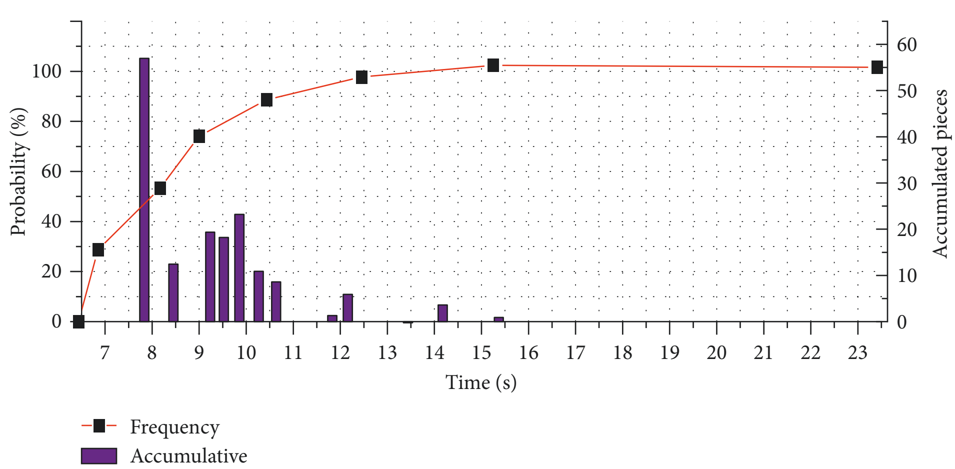

Figure 10: Distribution of simulated sorting completion time and accumulated piece probability of CBEC logistics distribution subsystem.

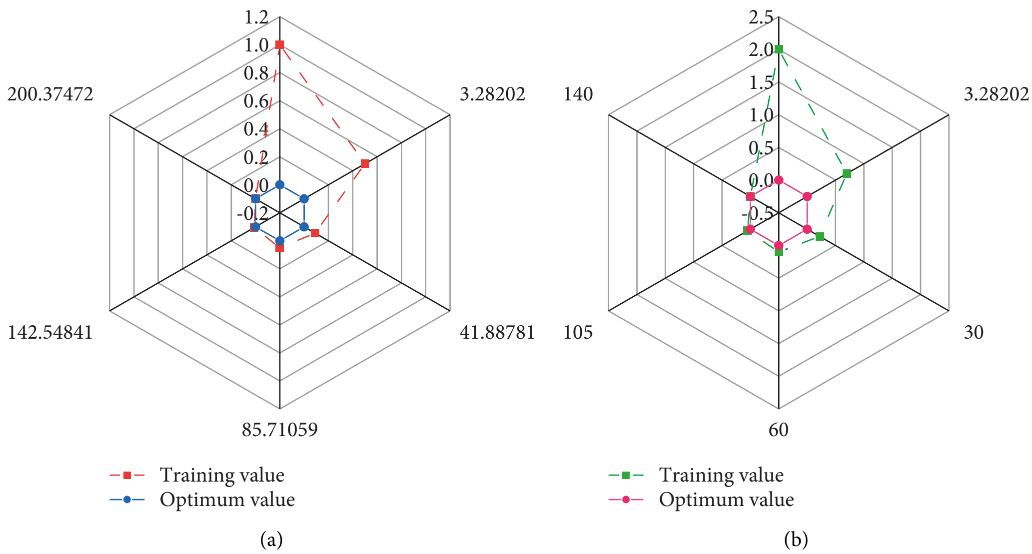

Figure 11: Distribution of the relationship between iteration times and MSE: (a) hidden layer nodes = 8; (b) hidden layer nodes = 11.

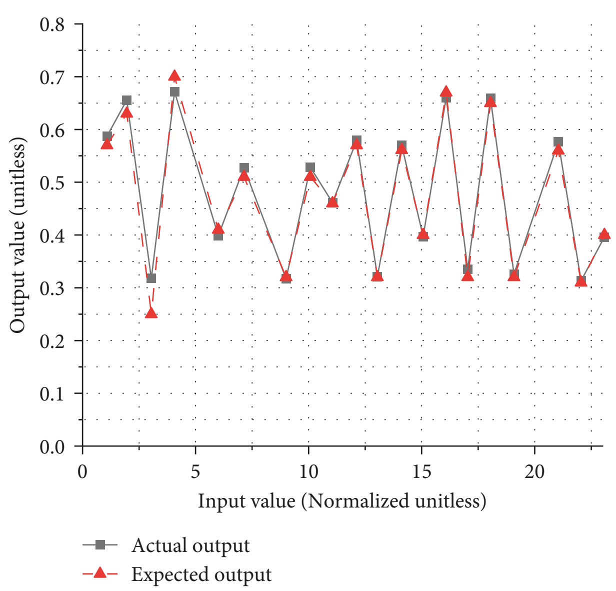

Figure 12: Fitness between expected output and actual output.

decoding value is obtained and applied to the established NN structure as the initial weight and threshold to train the NN model further. Suppose the MSE of the risk detection of the logistics system is 0.0001. In that case, the system needs fewer learning and training iterations to reach the target value when hidden layer nodes are 11. Accordingly, the number of hidden layer nodes is set as 11 optimal and is substituted into the CBEC logistics system to conduct the fitting experiment. Afterward, the obtained weights and thresholds are fine-tuned to obtain the best fitting results further. The specific fitting results are manifested in Figure 12.

From Figure 12, the actual output and the expected output of the training sample fit perfectly with only a minor deviation. The fitness is close to 99%. Thus, the system can learn by itself and gets an output closer to the input to improve the accuracy of internal system calculation. At the same time, the model learns by itself and further adjusts the NN parameters. Hence, the model has an excellent learning ability for nonlinear relations. It is proved that the CBEC logistics distribution subsystem is reliable and meets the expected standards. Additionally, the accuracy of the logistics risk detection subsystem also meets the standard. Overall, the complete CBEC logistics system can be widely used in CBEC trade.

4. Conclusion

In recent years, global CBEC has shown a trend of centralized and rapid growth. Therefore, higher standards have been put forward for the quality and speed of CBEC logistics. In the process of incremental innovation of the logistics model, the attendant problems have become more complex, and the disadvantages of the original model have gradually appeared. There are many relevant theoretical studies, but the research on the CBEC Logistics system is rare, so establishing the CBEC logistics system is imminent. First, this paper delves into and compares the traditional and CBEC logistics models, and the CBEC logistics system is constructed and adjusted according to the system construction principle. Further, it designs two key subsystems: object distribution system and distribution risk detection subsystem, based on the deep learning NN algorithm. Then, the relevant parameters are calculated and tested. Finally, experiments are designed to test the two subsystems. In summary, the proposed CBEC logistics system can meet the needs of the CBEC Logistics enterprise. The failure and error of the proposed system are small. Still, due to time constraints, there is a vast space for further research and practice, such as the processing flow optimization of packages of different packaging types.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research study was sponsored by Xuzhou Industrial Vocational and Technical College Doctoral Program, project number: XGY2021EB01; Xuzhou Industrial Vocational and Technical College Service Industry Development Research Institute Industrial R&D Project: "Research on the Evaluation System of Smart Logistics Distribution from the Perspective of Customers"; and project by funded by Jiangsu Province 2019 "Qing Lan Project" Excellent Teaching Team Project "Practical Teaching Team of Business Professional Group."

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