

Article

Prediction of Waterway Cargo Transportation Volume to Support Maritime Transportation Systems Based on GA-BP Neural Network Optimization

Guangying Jin , Wei Feng and Qingpu Meng

School of Maritime Economics and Management, Dalian Maritime University, Dalian 116026, China

* Correspondence: guangying.jin@dlmu.edu.cn; Tel.: +86-188-4084-7405

Abstract: Water transportation is an important part of comprehensive transportation and plays a critical role in a country's economic development. The world's cargo transportation is dominated by waterway transportation, and maritime transportation Systems (MTS) are the main part of the waterway transportation system. The flow of goods plays a key role in the economic development of the ports along the route. The sustainable development of maritime transportation, the maritime transportation economy and the environment have great practical significance. In this paper, the principle of the BP (back propagation) neural network is used to predict the freight transportation volume of China's waterways, and the genetic algorithm (GA) is used to optimize the BP neural network, so as to construct the GA-BPNN (back propagation neural network) prediction model. By collecting and processing the data of China's water cargo transport volume, the experimental results show that prediction accuracy is significantly improved, which proves the reliability of the method. The experimental methods and results can provide certain reference information for the optimization, upgrade, and more scientific management of sustainable MTS in China and internationally, provide key information for port cargo handling plans, help optimize port layout, and improve transportation capacity and efficiency.

Keywords: water transport cargo volume; MTS; BP neural network; GA algorithm; GA-BPNN model



Citation: Jin, G.; Feng, W.; Meng, Q. Prediction of Waterway Cargo Transportation Volume to Support Maritime Transportation Systems Based on GA-BP Neural Network Optimization. *Sustainability* **2022**, *14*, 13872. <https://doi.org/10.3390/su142113872>

Academic Editor: Luca D'Acierno

Received: 6 September 2022

Accepted: 21 October 2022

Published: 25 October 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Water transportation of goods is one of the main modes of modern transportation, and the MTS plays a key role in the water transportation system [1,2]. Waterway cargo transportation can be divided into inland waterway transportation and sea transportation according to the navigation area of ships, which is the basic transportation form of waterway transportation. Waterway cargo transportation refers to the behavior in which the carrier collects freight between domestic coastal ports, coastal and inland river ports, and inland river ports and is responsible for transporting the goods consigned by the shipper from one port to another port by water. An important form of transportation is a way of using ships to move goods between ports in different countries and regions through sea lanes.

Compared with railway and road transportation, waterway transportation uses natural rivers and oceans as transportation channels, so the energy and resources consumed per unit project are small. Waterway transportation also causes much less damage to natural resources and the environment, and waterway transportation produces less harmful gases or other wastes, which is a relatively environmentally friendly mode of transportation. Especially in recent years, the low-carbon economy has been steadily and further developed, and under the control of the national carbon peaking and carbon neutrality goals, the energy consumption of water transportation is relatively low, and the pollution to the environment is also very small. Water transportation has large capacity and low energy consumption, less pollution, is the best choice for "green shipping", and can be expected in the future.

Water transport has several advantages, including (1) large single shipment volume; (2) low transportation cost per unit of mileage; (3) small unit mileage investment of the route and saved land resources; (4) high labor productivity; (5) ease international trade; and (6) long average transport distance.

The MTS is an important part of waterway transportation, which plays an important role in the country's economic development [3,4]. Maritime transport is very important to the global economy as it accounts for approximately 80% of global trade [5–8]. JS Park et al. believe that the regional economy is closely related to the throughput of the port; the cargo port's purpose is, only in the case of sufficient throughput for the regional economic growth, to promote the role. When the inhibition effect is insufficient, the economic development of the port can provide employment opportunities for the nearby area, reduce the unemployment rate in the region, and promote the development of the regional economy, while the impact of the maritime transport system on the world economy is greater than that of air and land transport [9–11]. At present, the world economy is being hit by COVID-19, which has had a great impact on water transport, such as the general increase in freight rates and impact on oil prices [12–14]. Ocean freight is one of the most important transports in the global network of transportation systems. The composition of the maritime transport system includes waterways, ports and landside connections. The maritime transport system consists of 7241 nautical miles of routes. MTS relies on the existence of sea lanes for maritime services. MTS helps to ensure fair competition in trade and commerce. There are multiple intermodal connections at MTS, such as airport-ferry connections and ferry-to-train connections. There are many kinds of goods transported by water, among which the transportation of bulk cargoes such as coal, petroleum and its products, mineral building materials, metallic ores and nonmetallic ores occupies the main position. There is a close relationship between water transportation and land transportation. It is necessary to predict it, and it has an important reference role for land transportation. The forecast of water transportation is based on the needs of national economic and social development for transportation. The tasks that need to be undertaken are to seek the goals and ways to develop transportation capacity, to study the reasonable distribution of transportation volume among various transportation modes and the construction of comprehensive transportation network to form the basis for a reasonable transportation industry structure, such as the combination of waterway and railway transportation, making accurate forecasts can rationalize the network and quantity of shipments.

Most of the world's freight transport is based on the waterway to transport goods, so waterway transport port cargo flow research has great practical significance. At present, highways, railways, and other transportation modes are developing rapidly, water transportation is facing fierce market competition, some shipping markets are in a state of stagnation for a long time, and prospects are not optimistic. Some shipping lines have excess capacity, shipping enterprises generally have low profits, and some even suffer serious losses. According to statistics from relevant departments in China, in 2020, China invested 4933 km in new railway lines. At the end of 2021, China's ports had 20,867 berths for production terminals, a year-on-year decrease of 1275; China carried 125,900 water transport vessels in 2021, down 0.7 percent year-on-year. According to the United Nations Conference on Trade and Development (UNCTAD) [8], global seaborne trade shrank by 3.8% in 2020. Due to the continuous impact of the COVID-19 pandemic and the development of the situation in Russia and Ukraine, there is still some uncertainty in the market and volatility will increase. Many ports have the advantages of accommodating large ships, good geographical location and high route accessibility, and port service capacity has high port service capacity under these advantages, providing a strong business basis for the maritime transport system. However, some ports are far away from the main routes and have less direct connection with the main routes, so the business capacity of such ports is low. According to the relevant literature and data analysis, a considerable number of ports have excessive service capacity, especially under the impact of COVID-19. The phenomenon of oversupply is becoming increasingly obvious, and the risk of port congestion

is increasing, leading to the low utilization rate of some routes and ports. However, the service capacity of some ports cannot meet the transportation needs, the port capacity is low, and ship congestion often occurs [15–17]. At the same time, due to the slow freight speed, the freight transportation is divided into road transportation and railway transportation. Compared with railway transportation and road transportation, the quality of shipping services by waterway transportation is not high. At the same time, the delivery period is prolonged, and the punctuality rate is low, which leads to the decline of customer satisfaction, thus losing a stable source of customers and reducing the competitiveness of enterprises. Therefore, improving the vitality of shipping enterprises and promoting the healthy development of waterway transportation is a key problem that needs to be solved at present. It is necessary to forecast the volume of freight transported by waterways. This is conducive to optimizing port and route planning and distribution in the MTS, and helps managers provide information on optimizing the system, helping the government and shipping companies plan the transportation of goods and avoid transportation risks. It is of great significance to forecast the volume of waterway cargo transportation to ensure that the transportation industry adapts to the development of the economy.

The meaning mainly includes three contents: (1) it can be used as a powerful reference for government departments to adjust the waterway transport capacity structure and formulate waterway transport plans and corresponding macro shipping policies; (2) it provides guidance and a theoretical basis for shipping enterprises to choose business scale and market investment direction; and (3) the forecast data provides important reference information and a decision-making basis for the sustainable MTS.

2. Literature Review

In terms of conventional forecasting methods, some scholars use the economic indicators of the forecast object as variable input to find the relationship between variables and forecast sequences analysis, principal component analysis, multivariate adaptive regression splines, etc. [18–20]. Niu Z et al. applied the grey model GM (1,1) to the short-term forecasting of railway passenger traffic, and the experiments proved that GM (1,1) is not a single forecasting model; it can reduce the forecasting error by using a combined model [21]. The main research object of academic authors such as MiChaelw is to collect the amount of grain transported on the railway as the original data. Due to the large volatility of the data, regression modeling is difficult to achieve. Therefore, a time series model is proposed to conduct experiments for the purpose of predicting the data [22].

A variety of forecasting methods to the original time series, such as establishing forecasting models based on analyzing factors such as outliers and situational changes can be applied, optimizing traditional forecasting methods, or using integrated forecasting models [23]. For example, SARIMA refers to a method of forecasting based on time series. When Farhan J used this model to predict the container throughput of international container ports, the experiment proved the validity of the SARIMA model [24]. Awah P C et al. provided a practical method for predicting the actual handling capacity and attracted maximum container throughput of ports based on time series through random forest (RF) and multilayer perceptron (MLP) models [25].

Many scholars use neural network methods to make predictions, and they mainly use the asymmetric principle of BP neural network to make predictions. These methods are mainly combined with machine learning to make predictions. To improve the operational efficiency and energy efficiency of shipping, Zhi Yung Tay et al. analyzed the application of big data analysis and machine learning in port ships, using supervised and unsupervised machine learning systems to analyze and preprocess shipping-related data. The study shows that machine learning methods can handle complex data, while giving the advantages and disadvantages of supervised and unsupervised machine learning in operational efficiency and energy efficiency, which can provide reference for mitigating the adverse effects of climate change [26]. Pocajt V et al. used the selected sustainability indicators to predict the municipal waste generation (MWG) of countries with different development

levels through a neural network prediction method. The experimental results show that the model is suitable for national MWG prediction [27]. Rahman et al. used different data-driven models of the ANN method to forecast renewable energy; these models can be applied to renewable energy and forecasts in the future, and these models have important significance and impact [28]. Niedbała G. et al. used a neural network prediction model to predict rapeseed yield. The experimental results are reliable, and the yield can be improved by reducing the dosage of mineral fertilizers [29]. Barrera J M et al. used the prediction method of a neural network to predict the energy output of solar panels. The experimental results show that the model is suitable for predicting the energy output of target solar panels, and the experimental results are reliable [30]. Using BP neural network algorithm and MATLAB toolbox, W Jiang et al. proposed a new product reliability prediction model and used reliability prediction to predict the reliability parameters of the example, and the prediction effect was more perfect [31]. Taking the Baishuihe landslide in the Three Gorges Reservoir as an example, HT Long et al. used the BP neural network to predict the landslide deformation. The results show that the prediction value of the BP neural network prediction model is highly accurate [32]. Lúcia Moreira et al. used the data on ship-related routes to train a neural network to predict ship speed and fuel consumption. The experimental results show that the neural network prediction model has good adaptability and good accuracy in predicting ship speed and fuel consumption [33]. Tamara A. Volkova et al. used an artificial neural network to correct the position coordinates of the ship when it is close to the water building, and then helped the trajectory prediction of the navigation section during the ship maneuvering process [34]. Michalis Chondros et al. developed an artificial neural network model suitable for flood risk prediction in coastal areas, which is helpful to the development and utilization of ships and routes in MTS [35].

However, most scholars use other methods combined with the BP neural network algorithm to make predictions before using BP neural network to make predictions, indicating that a single asymmetric neural network has certain shortcomings, and it needs to be optimized by combining other algorithms. For example, the container throughput prediction method based on the ARIMA-BP neural network by Zhang Y et al. can improve the accuracy of container throughput [36]. Zhang L et al. proposed a constrained optimization method based on the BP neural network in another study. By combining the fitting and optimization of the BP network, the application of the BP neural network was expanded. The optimization method is effective [37]. Arsad has established a performance prediction system based on neural network and linear regression with the students of Universiti Teknologi MARA as the research object [38]. Zhang Q et al. predicted traffic flow based on a wavelet neural network and IFOA's hybrid frame model (IFOA-WNN), which provided sufficient information for the formation of symmetric traffic flow. The experimental results showed that the model has higher prediction accuracy and stability [39]. Lee C Y et al. established a feature selection process composed of MIV to extract features as a feature database and used the PSO-BPNN model for fault diagnosis. The results show that the model is effective [40]. Juan Fang et al. constructed a deep neural network fusion-based collaborative filtering recommendation algorithm (CF-DNNF) to improve the recommendation performance of the collaborative filtering algorithm, and the experimental results show that the accuracy of the CF-DNNF model is significantly improved [41]. Zhao Y et al. combined the gray prediction model with the BP neural network model to improve the prediction accuracy of water traffic accidents, and the experiment proved that the Gray-BP model has less error, higher prediction accuracy and better stability [42]. Cheng W et al. used particle swarm optimization to optimize the BP network. The experiments of this study show that the PSO-BP algorithm can improve the prediction accuracy of network traffic and accelerate the convergence speed of the BP network [43]. Ma S et al. established a prediction model by combining the factor analysis method and neural network method, to improve the feasibility and accuracy of the prediction model of blasting vibration velocity. The research experiment proves that the improved BP neural network prediction model has better prediction accuracy [44]. Shi L et al. combined particle swarm optimization (PSO)

and principal component analysis (PCA) to compensate for the shortcomings of the BP neural network. In this model algorithm, PCA is mainly used to process the original data. The experimental results show that the BPNN optimized by PSO has higher accuracy than the single BPNN [45]. Ding, HW et al. proved through simulation experiments that using KPCA method to reduce the data dimension and modify the initial value and loss function of the BP neural network can improve the learning ability of the BP neural network, and the learning accuracy is improved [46]. Muhammad Nasir Amin et al. used a neural network and ANFIS to predict the compressive strength of VAM by the sixfold symmetry of concrete failure [47]. Based on the algorithm model of prediction and neural network (ST-BPN), Haiming Liu et al. established an improved M-CNN (Convolutional Neural Network) model to search and track underwater targets. The experimental results show that the recognition accuracy of the M-CNN is higher than 99% [48]. Youngmin Park et al. used deep neural networks and convolutional neural networks to predict maritime storm surges in the Korea Strait based on global forecast system data, providing key weather prediction results for the MTS, and the validation showed that the model is suitable for South Korea Marine storm surge weather forecasts for the strait [49]. Panayiotis Theodoropoulos et al. used feedforward neural network (FFNN) and recurrent neural network (RNN) to predict the propulsion power of ships and compared the prediction results. At the same time, they studied and analyzed the relevant parameters that play a decisive role in the experimental results [50]. Yumin Su et al. used the long short-term memory (LSTM) of the recurrent neural network to perform a real-time prediction algorithm for the vertical acceleration of the ship and used Python to predict the data. The results show that the recurrent neural network prediction model is effective [51].

Genetic Algorithms can search for optimal solutions during evolution. The general iterative operation makes the neural network algorithm fall into the local minimum and loop phenomenon, and then the neural network algorithm cannot run, and GA is a global optimization algorithm, which can overcome this phenomenon [52]. In order to improve the inventory bonus, Xiaoning Li et al. used GA to eliminate relatively redundant features in the optimal solution of the model, and further explained the superiority of GA [53]. Dunjing Yu et al. used GA to optimize the nonlinear predictive controller of the ship trajectory tracking model. The experiments showed that GA improved the efficiency and accuracy of the controller [54].

Through the analysis of the above literature, it can be seen that a single BPNN has advantages and disadvantages. The advantage is that it has a strong nonlinear ability, and this advantage makes it outstanding in solving problems with complex internal mechanisms. At the same time, the self-learning and adaptive ability of BP neural network is very strong. The learning results are stored as the weights of the network. These advantages can improve the prediction accuracy. However, its shortcomings will affect the prediction results, that is, as the training ability of the BP neural network algorithm improves, the prediction ability will decrease, that is, so-called “overfitting” occurs, which is easily falls into local extreme values, resulting in network training failure and convergence slowly.

3. Materials and Methods

3.1. BP Neural Network

A neural network is a machine learning model. The algorithm of this model is inspired by the principle of neuron information processing in the human brain. It is a neural network model built on the basis of many neurons. Each neuron in the model can be regarded as an independent unit of study. These neurons take certain features as input and obtain output according to their own models. The neural network has an input layer, a hidden layer, and an output layer. The input layer is the input sample value. The hidden layer and the output layer are calculated by an activation function, and the layers are connected by a weight matrix. The hidden layer of the neural network is invisible; there can be multiple, such as a black box, and the output layer is the classification or regression result we want.

Figure 1 shows a neural network with a 3-layer structure. It can be seen that the neural network structure is very symmetrical, and the so-called symmetry relative to a hidden layer, no matter how many layers, are symmetrical.

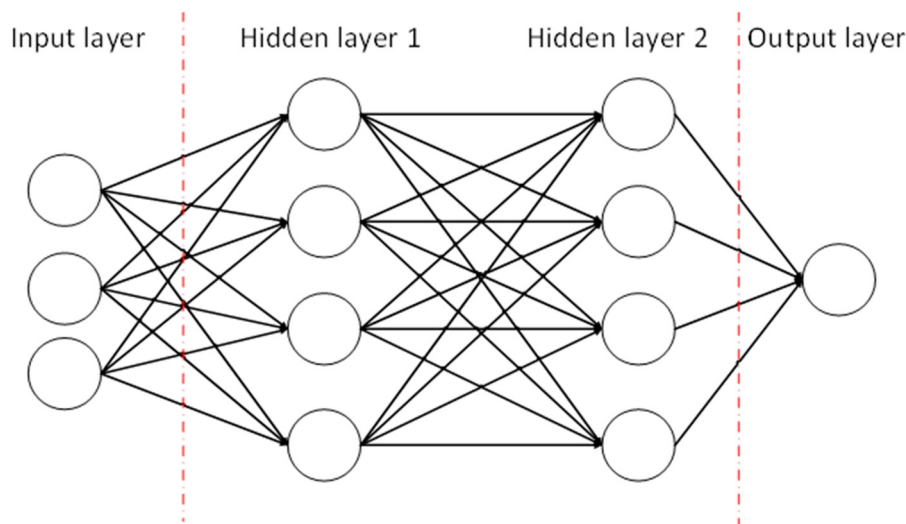


Figure 1. Neural network with three-layer structure.

If all parameters are set to 0, the weight on each edge above is 0, which means that the parameters of neurons on each column of the hidden layer are the same, and the updates obtained by each neuron are consistent. Additionally the weights of the updated neurons are still the same, which causes the network to enter a symmetric state. The consequence of this is that the forward propagation and back propagation algorithms of all neurons are the same, so the symmetry cannot be broken (fail to break symmetry), and the neural network cannot learn more features and ends up being a linear neural network. Therefore, all parameters cannot be initialized to 0, nor can they be initialized to any of the same values, because we have to “break the symmetry”. Since the residual connection breaks the symmetry or symmetric state of the network, the representation ability of the network is improved. As the depth of the network increases, the weight matrix degenerates and the network degenerates.

Cong Fang [55] proposed an analytical model of “stripping” between layers of neural networks and gave a new idea for the symmetric structure of deep neural networks, as well as generalization performance and robustness. Cong Fang [56] discovered a brand-new phenomenon from theoretical analysis, Minority Collapse, which pointed out that when the number of some classes in the training sample is large, and the number of others is small, the neural network of the highly symmetric simple equiangularly compact frame structure is broken in the collapse, and the class with a larger number of samples dominates the loss function.

The network connection of the BP neural network is connected by residuals, which breaks the symmetry/symmetry state of the network but improves its representation ability. Therefore, the optimized BP neural network is used in this paper to predict China’s waterway cargo transportation volume.

The BP neural network is an asymmetric network. The learning process of the BP neural network includes signal forward propagation and signal back propagation. Forward propagation inputs the sample from the input layer, and the signal passes through the hidden layer and then outputs the signal from the output layer. When the output value does not match the expected value, the error will be backpropagated. The error is input to the input layer by layer through the hidden layer, and at the same time, the error is distributed to all units of each layer, and then the basis for the weights of each unit is corrected. The BP neural structure diagram is shown in Figure 2. The number of nodes in the input layer is M and the number of output layers is L . The input and output values are $O_1, O_2, O_3, \dots, O_L$ and

$x_1, x_2, x_3, \dots, x_M$. ω_{ij} is the connection weight between the input layer node and the hidden layer node, and ω_{ki} is the connection weight between the hidden layer and the output layer. Figure 2 shows that the input value and output value of the BP network can be regarded as independent variables and dependent variables of the nonlinear function, respectively, and the BP neural network represents the functional relationship from M independent variables to L dependent variables.

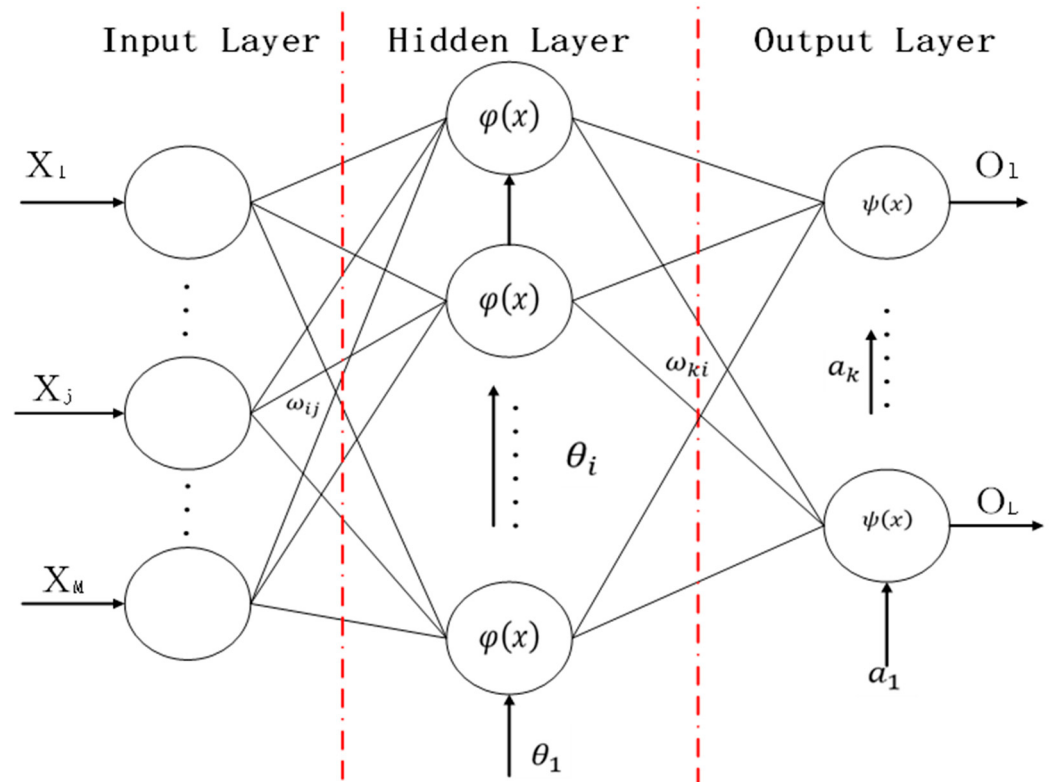


Figure 2. Neural network structure diagram.

3.1.1. Process of Signal forward Propagation

The input net_i of the i th hidden layer node.

$$net_i = \sum_{j=1}^n \omega_{ij} x_j - \theta_i \quad (1)$$

The output y_i of the i th hidden layer node.

$$y_i = \varphi(net_i) = \varphi\left(\sum_{j=1}^n \omega_{ij} x_j - \theta_i\right) \quad (2)$$

The input net_k of the k th node of the output layer.

$$net_k = \sum_{j=1}^q \omega_{ki} y_i - a_k \quad (3)$$

The input O_k of the k th node of the output layer.

$$O_k = \psi(net_k) = \psi\left(\sum_{j=1}^q \omega_{ki} y_i - a_k\right) \quad (4)$$

3.1.2. Error Backpropagation Process

The reverse input of the error is to first calculate the output error of the neurons in each layer, then use the gradient descent method to modify the weights and thresholds of each layer, and finally make the output value closer to the expected value I need.

The quadratic error criterion function for each sample p is E_p :

$$E_p = \frac{1}{2} \sum_{k=1}^L (T_k - O_k)^2 \quad (5)$$

The overall error criterion function of the system for p training samples is E :

$$E = \frac{1}{2} \sum_{p=1}^P \sum_{k=1}^L (T_k^p - O_k^p)^2 \quad (6)$$

The sequential correction process of the error gradient descent method is as follows.

$$\Delta\omega_{ki} = \eta \sum_{p=1}^P \sum_{L=1}^L (T_k^p - O_k^p) \cdot \psi'(net_i) \cdot y_i \quad (7)$$

$$\Delta a_k = \eta \sum_{p=1}^P \sum_{L=1}^L (T_k^p - O_k^p) \cdot \psi'(net_i) \quad (8)$$

$$\Delta\theta_i = \eta \sum_{p=1}^P \sum_{L=1}^L (T_k^p - O_k^p) \cdot \psi'(net_i) \cdot \omega_{ki} \cdot \varphi'(net_i) \quad (9)$$

$$\Delta\omega_{ki} = \eta \sum_{p=1}^P \sum_{L=1}^L (T_k^p - O_k^p) \cdot \psi'(net_i) \cdot \omega_{ki} \cdot \varphi'(net_i) \cdot x_j \quad (10)$$

where $\Delta\omega_{ki}$ is the correction of the output layer weight; Δa_k is the correction of the output layer threshold; $\Delta\omega_{ij}$ is the correction of the hidden layer weight; and $\Delta\theta_i$ is the correction of the hidden layer threshold.

3.1.3. Disadvantages of the BP Algorithm

The BP algorithm is a common method for training feedforward neural networks, it has the following two disadvantages:

1. The initial solution value randomly generated by the BP algorithm has a great impact on the performance of the algorithm, so the algorithm has unstable factors.
2. The gradient descent method is used in the BP algorithm, and this algorithm is prone to the situation that the convergence speed is too slow, and even falls into a local minimum and cannot converge.

3.1.4. Increase the Momentum Term in the BP Algorithm to Accelerate Learning Speed

In this paper, the momentum term (11) commonly used in the BP neural network algorithm is modified to (12), which is conducive to accelerating the convergence of the zone.

Original formula:

$$\Delta w_{ji}(n) = \eta \delta_j(n) y_i(n) \quad (11)$$

changes into:

$$\Delta w_{ji}(n) = \alpha \Delta w_{ji}(n-1) + \eta \delta_j(n) y_i(n) \quad (12)$$

Here α is the momentum constant, and $0 \leq \alpha < 1$.

The momentum term $\alpha \Delta w_{ji}(n-1)$ is the adjustment experience accumulated before the algorithm. The error gradient falls into the local minimum, although $w_{ji} \rightarrow 0$, $\Delta w_{ji}(n-1) \neq 0$ makes the algorithm eliminate the phenomenon of local minima, thereby speeding up the algorithm iteration convergence speed.

3.2. Genetic Algorithm (GA)

The GA was proposed by John Holland in the 1970s. The basic principle is to draw lessons from the natural selection and genetic mechanism of biological evolution. The essence of the algorithm is to search for the optimal solution in the evolutionary process.

Figure 3 shows the main flowchart of the genetic algorithm. It mainly includes six parts.

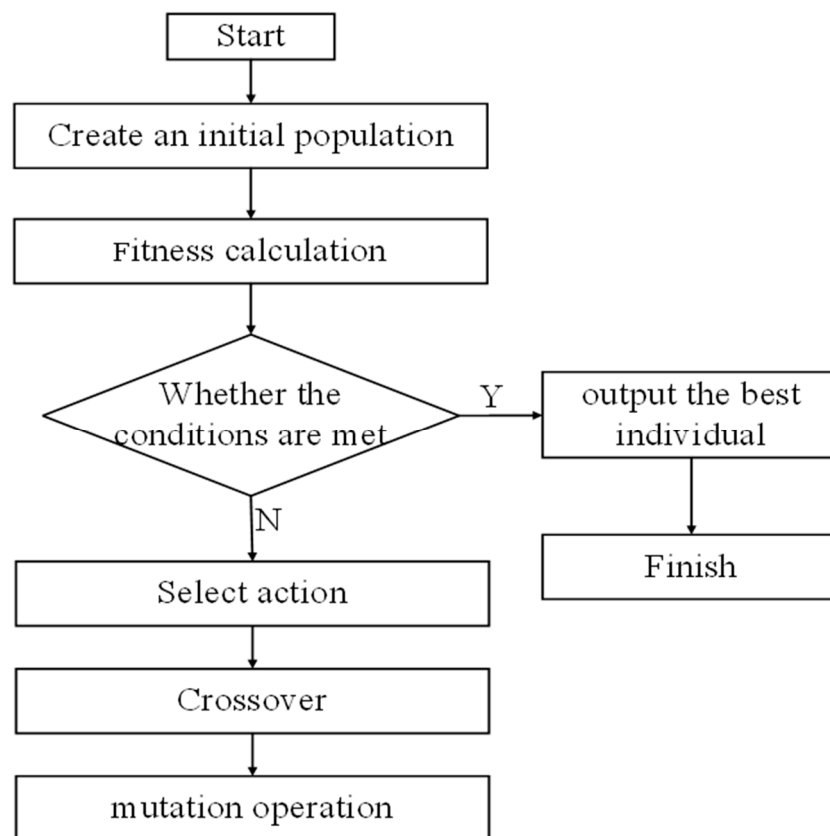


Figure 3. Genetic algorithm structure.

The initialization is mainly to set the relevant parameters, the evolutionary algebra counter g is set to 0, the maximum evolutionary algebra is set to G , and NP individuals are randomly generated by the algorithm, and they are used as the initial group $P(0)$. To Choosing an operation: The selection operator is applied to the group, and according to the fitness of the individual, excellent individuals are selected to be inherited into the next generation group. The mutation operation applies the mutation operator to the population, and for the selected individual, some gene values are changed to other alleles with a certain probability. Population $P(t)$ obtains the next generation population $P(t + 1)$ after evolution. Its fitness is sorted according to the fitness value and prepared for the next genetic operation. Algorithm termination condition: when $g > G$, the calculated individual with the maximum fitness is output as the optimal solution, then the algorithm terminates; when $g \leq G$, then $g = g + 1$, and the algorithm re-evaluates the individual to calculate its fitness value.

The genetic algorithm has strong adaptability: it does not need to use gradient and other problem information in the iterative process, there is no problem of flat areas, and the selection operator can be used to eliminate models that fall into local minima. The genetic algorithm has excellent global search performance: there are multiple individuals in a population, and they perform global search in parallel to ensure that the optimal a model can be found in the end. The genetic algorithm can make the BP neural network eliminate the phenomenon of falling into the local minimum, thus improving the accuracy of the algorithm model.

The advantages of using GA to optimize BP lie in the following three points:

- (1) Genetic algorithms do not easily fall into local optima when searching in space and can easily obtain the global optimum solution.
- (2) The genetic algorithm is particularly suitable for dealing with complex nonlinear problems, because the conventional algorithm adopts gradient descent, the search direction is fixed, and the genetic algorithm adopts the overall search strategy.
- (3) The genetic algorithm adopts a parallel search mechanism, which has a small amount of calculation and more processing modes.

3.3. Construction of the GA-BP Neural Network Model

In the process of BP neural network training, the algorithm is used to update the weight threshold through forward propagation of data and error backpropagation. On the one hand, in this process, the weights and thresholds of the first forward propagation process, that is, the weights and thresholds are initialized. The method of deep learning is to use the randomization method to obtain the initial weight and threshold parameters. After the initial parameters are selected, the gradient descent algorithm uses the initial parameter values as the starting point to optimize and update the parameters. The weight training process of BPNN is essentially an optimization problem of a complex function. The normal method of obtaining weights is to use certain definite rules and gradually adjust them during the training process.

In the development of optimization algorithms, there are two categories: deterministic algorithms and heuristic algorithms. A deterministic algorithm refers to the use of mathematical methods to find the optimal problem, and the result found is related to the initial point of the derivation, which is generally a definite value. The heuristic algorithm is inspired by the laws of biological evolution in nature. The main idea is to iteratively approach the optimum, and the result of the optimization is a variable value that meets the requirements of engineering accuracy (infinitely close to the theoretical optimum).

In the above process, as a deterministic algorithm, the convergence of the gradient descent algorithm has been proven, but the convergence value is not necessarily the global optimum, which is related to the initial parameter value (the starting point of the gradient descent algorithm). Since random initial parameters may not be the optimal starting point (meaning both accurate training and reliable prediction), the reliability and stability of the trained model are greatly affected by the initial random parameters. As a heuristic algorithm, the genetic algorithm GA has a very good global search ability, and GA is introduced to solve this problem.

The main steps are as follows:

- (1) Use floating-point numbers to encode the weight threshold of the neural network.
- (2) In the coding space, an initial population is randomly generated.
- (3) Calculate the group fitness value as a training sample according to Formula (13).

$$f(i) = \frac{1}{\sum_{j=1}^m (y_{ij} - \tilde{y}_{ij})} \quad (13)$$

where m is the number of training samples, $f(i)$ is the fitness value of the i th genetic individual, y_{ij} is the expected output of the j th training sample, and $\tilde{y}_{ij}$ is the actual output of the j th training sample.

- (4) Genetic manipulation of populations.

In this paper, the competitive selection method is used in the selection, that is, randomly selecting a certain number of individuals from the population, then selecting the best individual as the parent, and repeating this operation to complete the selection of the individual. The arithmetic intersection method (linear intersection) is used in the intersection, that is:

$$child1 = \alpha \times parent1 + (1 - \alpha) \times parent2 \quad (14)$$

$$child2 = \alpha \times parent2 + (1 - \alpha) \times parent1 \quad (15)$$

where α is a random number between [0,1], *parent1* and *parent2* are a certain component of the parent individual, and *child1* and *child2* are the corresponding components of the child individual.

- (5) Generate a new generation of groups.
- (6) Repeat steps (3) to (5), and when the evolution reaches N generations, the individuals with the best fitness will be retained. After the algorithm is over, the optimal individual in the final group can be decoded to obtain the weight threshold of the optimized BP neural network.

4. Experimental Section and Results

4.1. Data Processing

The empirical analysis data come from the statistical database of the Ministry of Transport of China [57]. The scope of data in this paper mainly includes the value of each month of waterway freight transportation in the whole of China. This paper selects the monthly data of waterway freight volume from January 2015 to December 2021, and forecasts based on these data. Taking the throughput of the first three adjacent months as the sample input value, and the throughput of the fourth month as the output value, we cyclically arranged 81 sets of statistical data. In this paper, the first 66 groups are used as the training set, and the last 15 groups of samples are used as the test set. Table 1 shows the data processing results.

Table 1. Data processing.

Number of Groups	First Three Months of Shipments (10,000 Tons)			Fourth Month as Forecast (10,000 Tons)
1	49,119	42,051	46,316	48,898
2	42,051	46,316	48,898	52,116
3	46,316	48,898	52,116	53,649
4	48,898	52,116	53,649	53,590
5	52,116	53,649	53,590	54,164
●	●	●	●	●
●	●	●	●	●
●	●	●	●	●
80	69,633	69,431	71,266	76,480
81	69,431	71,266	76,480	75,392

Note: The data from 2015 to 2021 are processed, and the first three months are used as the basis to predict the fourth month. The values of March and April are used to predict the value of May 2015. This cycle forms 81 sets of experimental data. The first 66 groups are training sets for neural network learning, and the next 15 groups are test sets for testing.

4.2. Setting of Experimental Parameters

1. Group size NP

The value of the swarm size affects the efficiency of the algorithm. If the NP is too small, the optimization performance of the GA will be reduced. If the NP is too large, the calculation of the algorithm will be complicated. Therefore, the optimal range of NP is 10–200.

2. Crossover probability P_c

P_c controls how often the crossover operation is used. Too large or too small P_c will make the algorithm unstable; P_c is generally taken as 0.25 to 1.00.

3. Mutation probability P_m

In general, a lower P_m can reduce the possibility of loss of important genes in the population, so P_m usually takes a value of 0.001 to 0.1.

4. Evolutionary algebra G

Terminating evolutionary algebra G is the condition for the end of genetic algorithm operation. The value of G depends on the specific problem, and the value of G can be between 100 and 1000.

In this experiment, the optimization training is carried out using MATLAB according to the process shown in Figure 4. We compiled the GA-BP neural network code for training. The largest feature of the genetic algorithm is its speed. The initial population can be 50–200. The initial population should not be too large, otherwise it will affect the operation speed. Therefore, the initial population of the GA algorithm is set to 50. The BP neural network adopts the most primitive three-layer structure. To determine the number of hidden layer nodes, the empirical Formula (16) is used. The activation function uses the S (Sigmoid abbreviation) type function. Compared with the linear function, its biggest advantage is nonlinearity. This means that when multiple neurons use a sigmoid function as the activation function, the output is also nonlinear. The training method uses trainlm, which has the fastest convergence speed for medium-scale BP neural networks, and is the default algorithm of the system, which reduces the amount of calculation in training.

$$\text{hiddennum} = (m + n)^2 + a \quad (16)$$

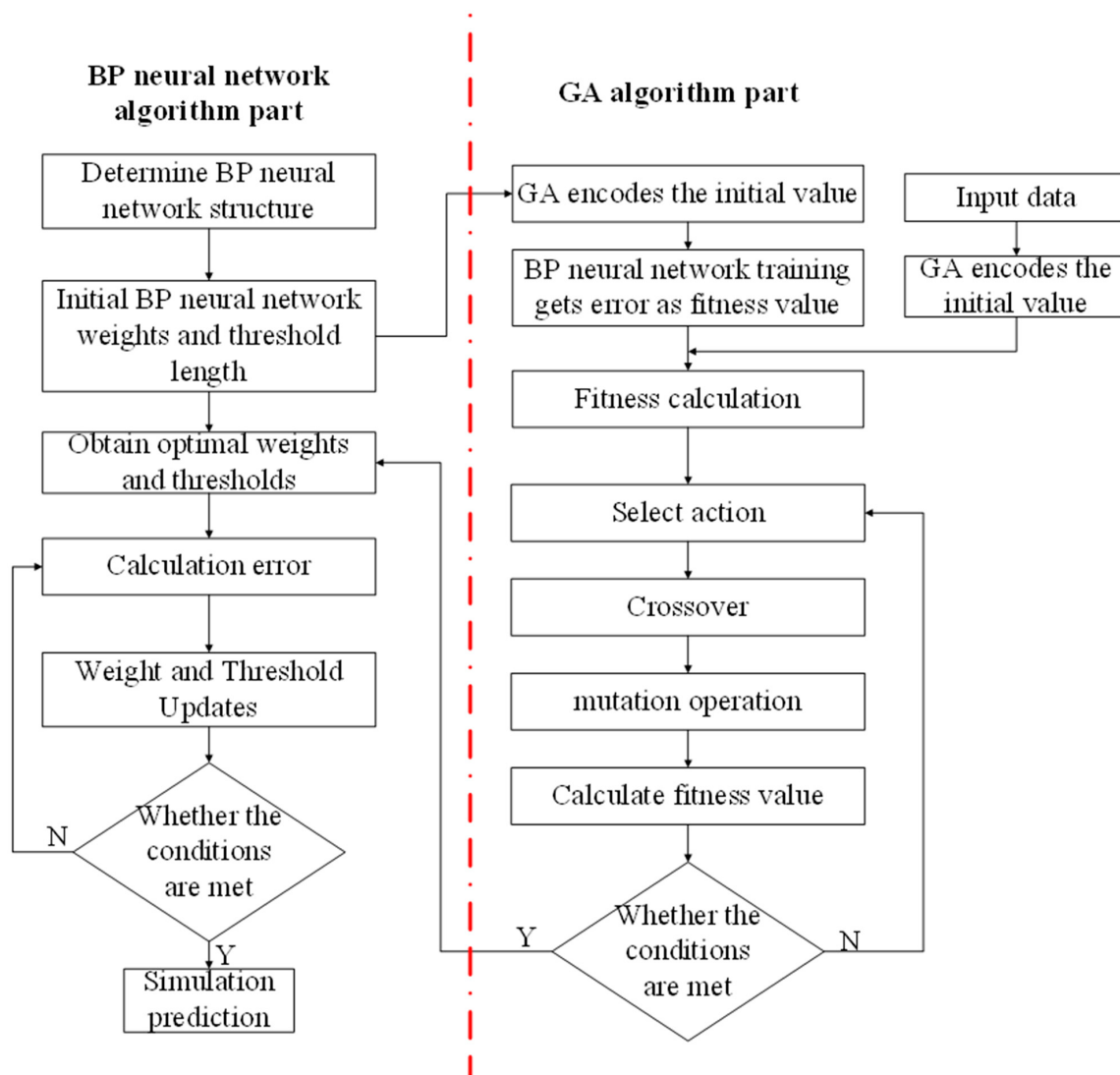


Figure 4. GA-BP neural network algorithm model.

4.3. Experimental Results

Figure 5 shows the neural network training interface. In this experiment, the numbers of input layers, hidden layers and output layers are three, eleven, and one, respectively. From the analysis of Figure 5 and Table 1, it can be seen that the optimal number of hidden layer nodes is 11, the training effect is better, and the corresponding mean square error is 0.041436. Table 2 shows the determination process of the hidden layer nodes.

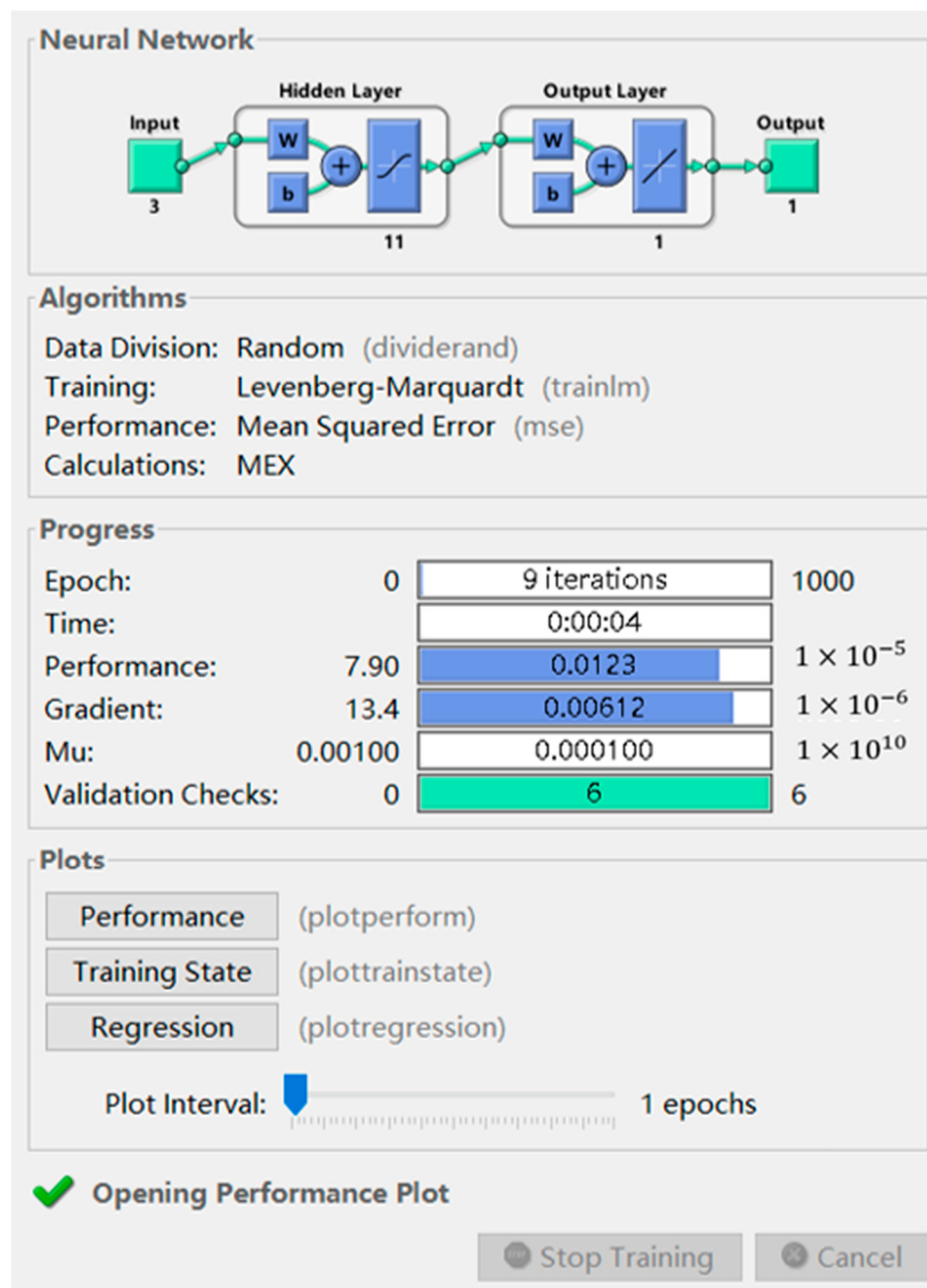


Figure 5. GA-BP neural network algorithm training interface.

Table 2. The determination process of hidden layer nodes.

Number of Hidden Layer Nodes	Corresponding Mean Squared Error
3	0.051892
4	0.049354
5	0.056236
6	0.084958
7	0.063768
8	0.046552
9	0.057265
10	0.042412
11	0.041436

As shown in Figure 6, the goodness of fit of the training samples is 89.675%, the goodness of fit of the test set is 80.74%, and the overall goodness of fit is 87.554%. This fitting verifies that the network training effect is excellent, and the model can fully predict China's waterway cargo transportation volume.

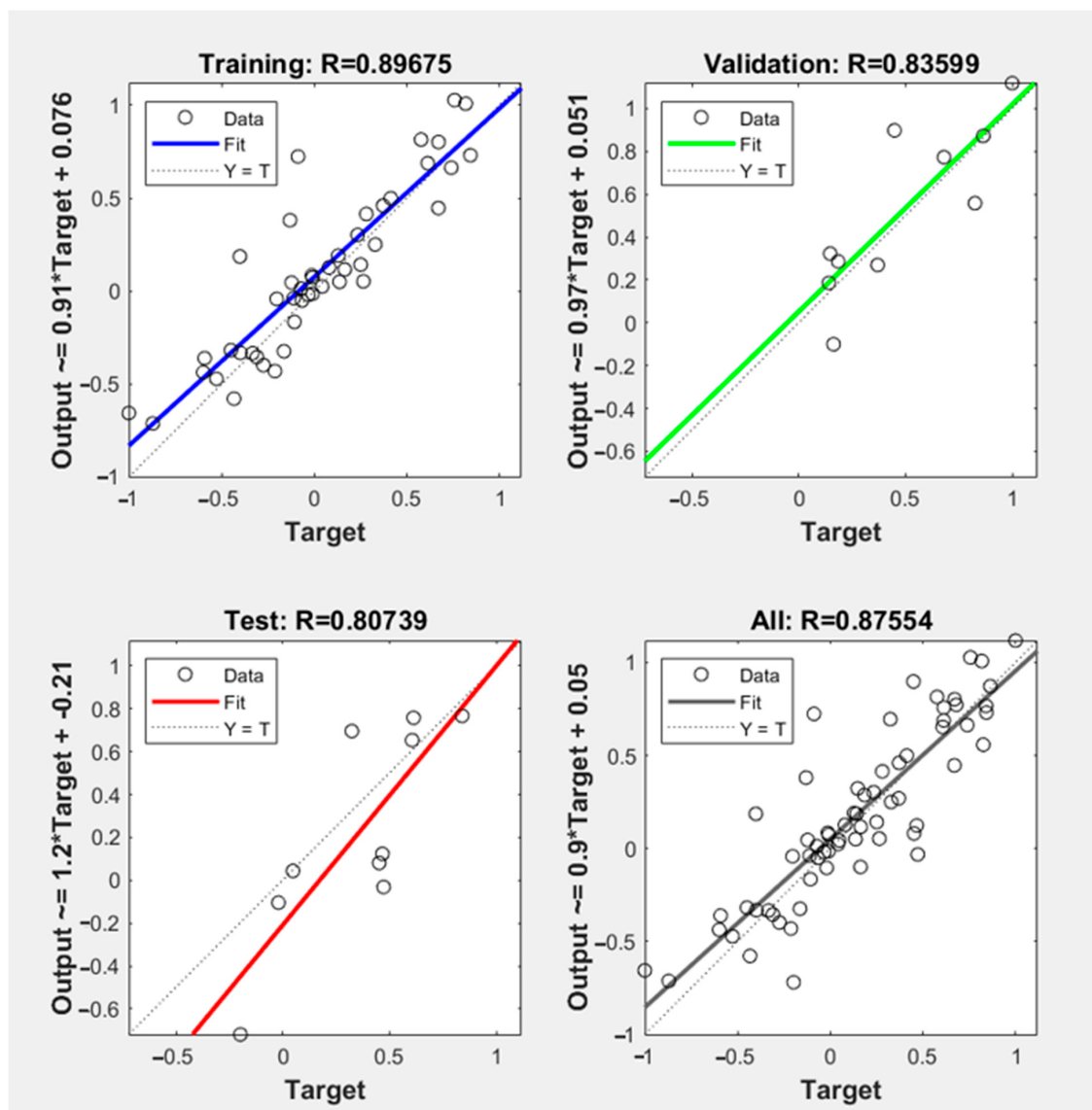
**Figure 6.** GA-BP neural network algorithm correlation analysis.

Figure 7 shows that the predicted value of the BP neural network algorithm improved by the GA is more accurate than the predicted value of the BP neural network without improvement, and the error of the GA-BP model algorithm is smaller than that of the BP algorithm. This shows that the GA plays a significant role in the optimization of the BP neural network.

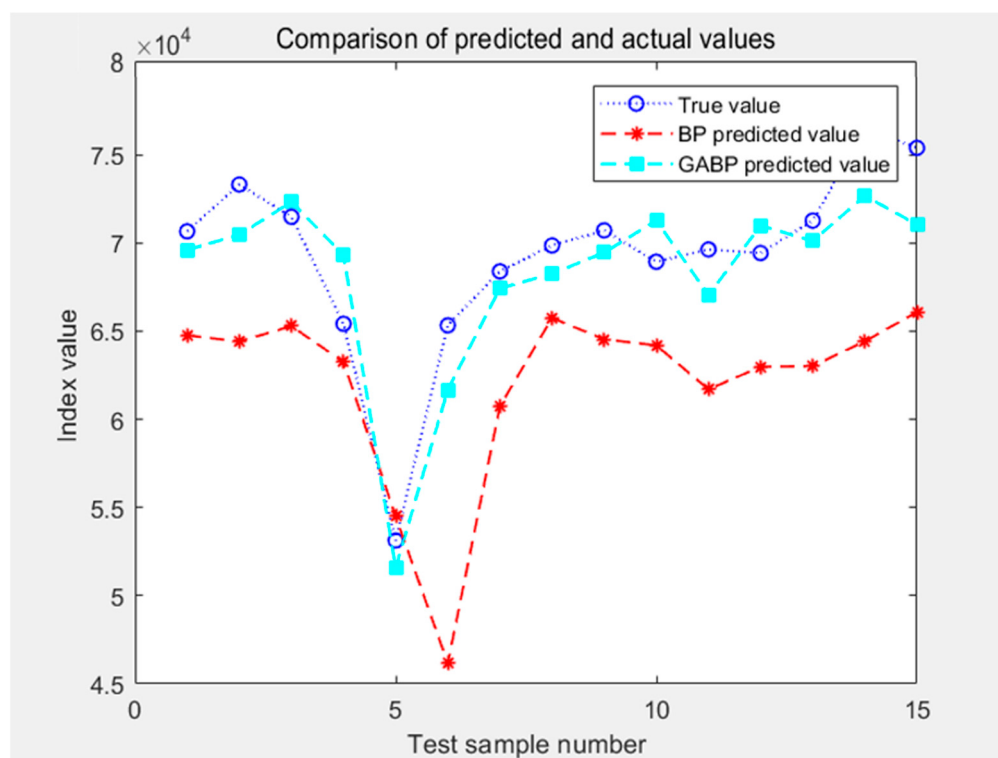


Figure 7. Comparison of predicted values before and after optimization with true values.

Table 3 is the comparison table between the prediction error of the BP neural network and the prediction error of the GA-BP neural network. The error of the BP neural network optimized by the GA is smaller than that of the BP neural network, which proves the feasibility of optimization. The mean absolute error percentage of the optimized BP neural network is 7.281% higher than that of the unoptimized neural network.

Table 3. Prediction error of the BP neural network and the prediction error of the GA-BP neural network.

	The Mean Absolute Error MAE	Mean Square Error MSE	Root Mean Square Error RMSE	Mean Absolute Percentage Error MAPE
BP	7358.3795	71,125,714.7667	8433.6063	10.4958%
GA-BP	2231.0894	6,353,182.3153	2520.552	3.2148%

Table 4 shows the prediction results of 15 test samples. In the table, the GA-improved neural network and the unimproved neural network are compared. The experiment shows that the BP neural network optimized by the GA is more accurate.

Table 4. Experimental results and error table.

Sample No.	Measured Value	BP Predicted Value	GA-BP Value	BP Error	GA-BP Error	
1	7.0659	6.4759	6.9597	−0.5900	−0.1062	$1 \times 10^4 *$
2	7.3313	6.4412	7.0472	−0.8901	−0.2841	$1 \times 10^4 *$
3	7.1487	6.5285	7.2324	−0.6202	0.0837	$1 \times 10^4 *$
4	6.5414	6.3248	6.9319	−0.2166	0.3905	$1 \times 10^4 *$
5	5.3129	5.4497	5.1590	0.1368	−0.1539	$1 \times 10^4 *$
6	6.5329	4.6166	6.1679	−1.9163	−0.3650	$1 \times 10^4 *$
7	6.8389	6.0750	6.7424	−0.7639	−0.0965	$1 \times 10^4 *$
8	6.9858	6.5746	6.8256	−0.4112	−0.1602	$1 \times 10^4 *$
9	7.0717	6.4535	6.9454	−0.6182	−0.1263	$1 \times 10^4 *$
10	6.8934	6.4193	7.1275	−0.4741	0.2341	$1 \times 10^4 *$
11	6.9633	6.1698	6.7041	−0.7935	−0.2592	$1 \times 10^4 *$
12	6.9431	6.2977	7.0987	−0.6454	0.1556	$1 \times 10^4 *$
13	7.1266	6.3018	7.0109	−0.8248	−0.1157	$1 \times 10^4 *$
14	7.6480	6.4426	7.2671	−1.2054	−0.3809	$1 \times 10^4 *$
15	7.5392	6.6081	7.1045	−0.9311	−0.4347	$1 \times 10^4 *$

Note: The * means that the data in this row is multiplied by 1×10^4 .

Table 5 uses the GA-BPNN prediction model proposed in this paper to predict the 12-month waterway cargo transportation volume in China in 2022.

Table 5. Full year forecast for 2022.

Month	GA-BP Forecast (10,000 Tons)
1	69,580
2	56,950
3	67,130
4	72,240
5	72,530
6	74,210
7	65,890
8	68,760
9	71,300
10	68,920
11	72,470
12	76,150

Figure 8 shows the GA-BPNN prediction model to forecast the trend of China's 12-month waterway cargo transportation in 2022. It can be seen that there is an upward trend throughout the year. Since the Chinese Spring Festival is mostly in February each year, the model can also identify the impact of the Chinese Spring Festival holiday. The lowest predicted value for February is 56,950, which is also in line with the actual situation in China. The model has a strong learning ability, which shows that the model reliability.

In summary, Tables 3 and 4, Figures 5–8 all show that the prediction accuracy of the GA-BP neural network is generally higher than that of the BP neural network.

Figure 9 shows the growth rate of China's 12-month forecast in 2022 compared to the same period in 2021. It can be seen that four months in 2022 will increase compared to the same period in 2021, and the whole year will show a growth trend, so it can be used for MTS to provide relevant decision-making and forecast information, make relevant preparations in advance for the growth of the same period, clear the shipping lanes in advance, reduce the phenomenon of port congestion, reduce the probability of overcapacity in ports and shipping routes, and improve the overall efficiency of the MTS, improving water transportation efficiency.

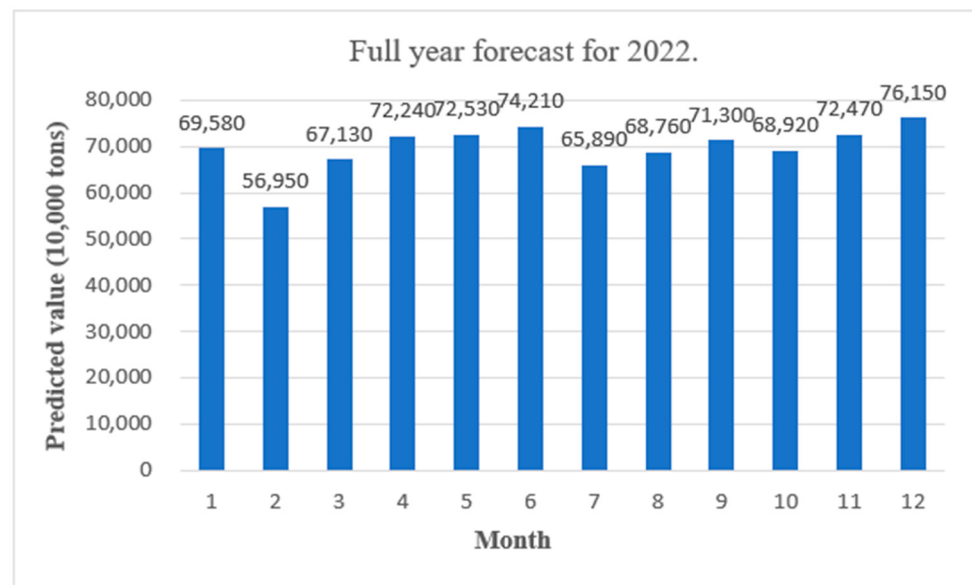


Figure 8. Full year forecast for 2022.

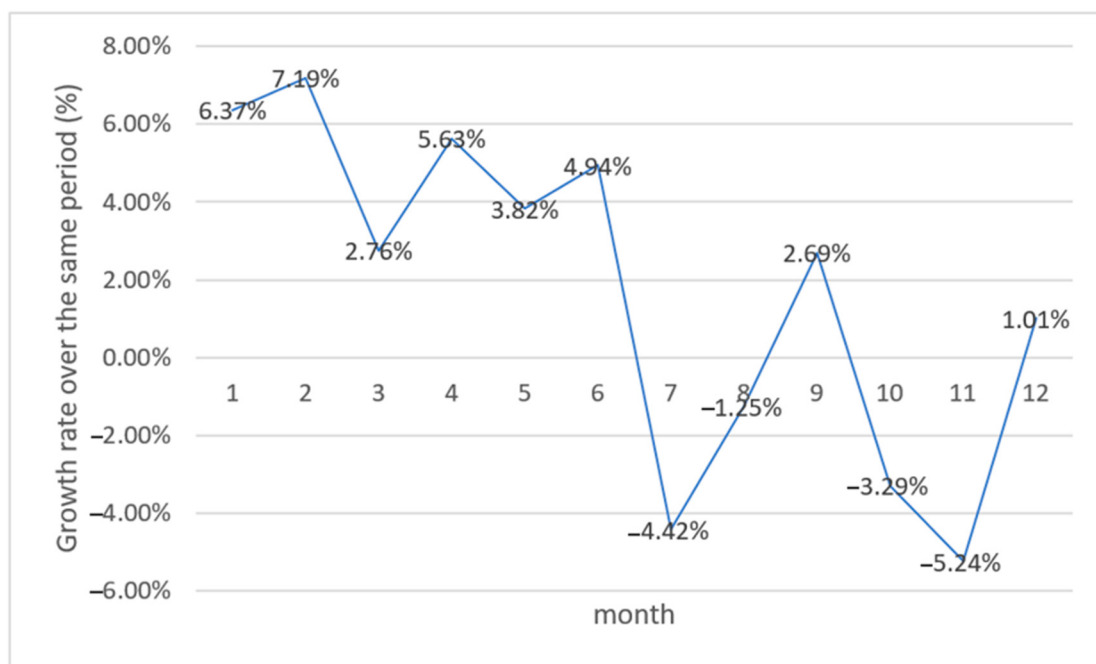


Figure 9. Annual gross growth rate.

Figure 10 shows China's 2015–2021 full-year total value and 2022 full-year forecast and annual growth rate. It can be seen that there is an increasing trend in 2015 and 2022, and the predicted value of the model in this paper is also in line with this trend, which further illustrates the adaptability and reliability of the model. The growth rate in 2020 was 2.1%, which was a decrease compared to the same period, mainly due to the impact of the global spread of COVID-19, which led to a downturn in the maritime transport market, increased port congestion, and reduced shipping capacity. Although the growth rate has increased in 2021, COVID-19 is still raging around the world, so the growth rate of the forecast model in this paper has been reduced. This actually provides important warning information to MTS managers and enterprises to prepare in advance for possible risks and reduce economic losses as much as possible.

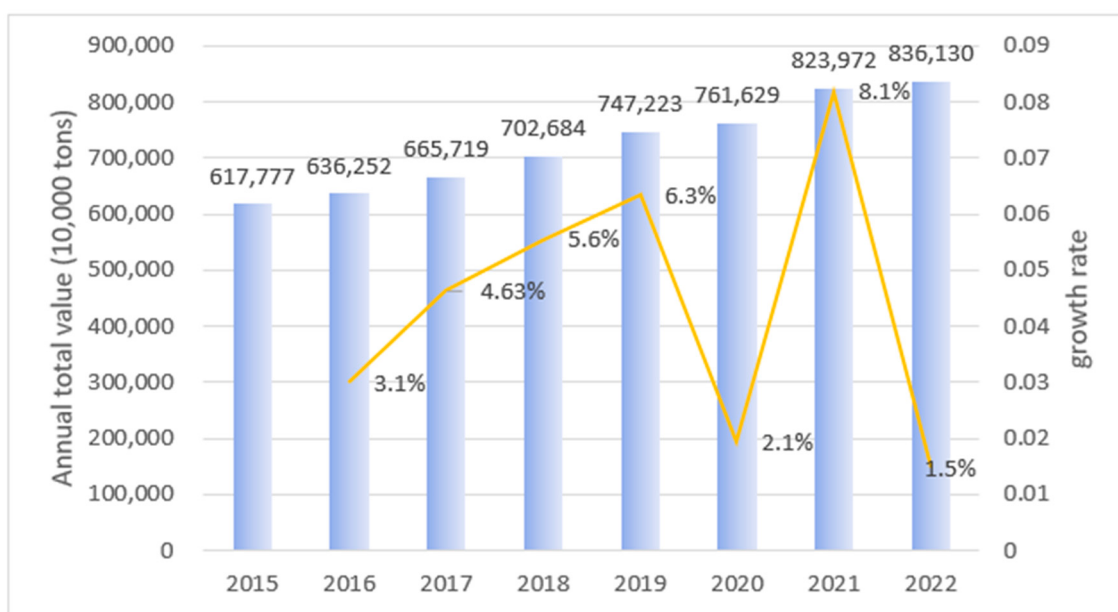
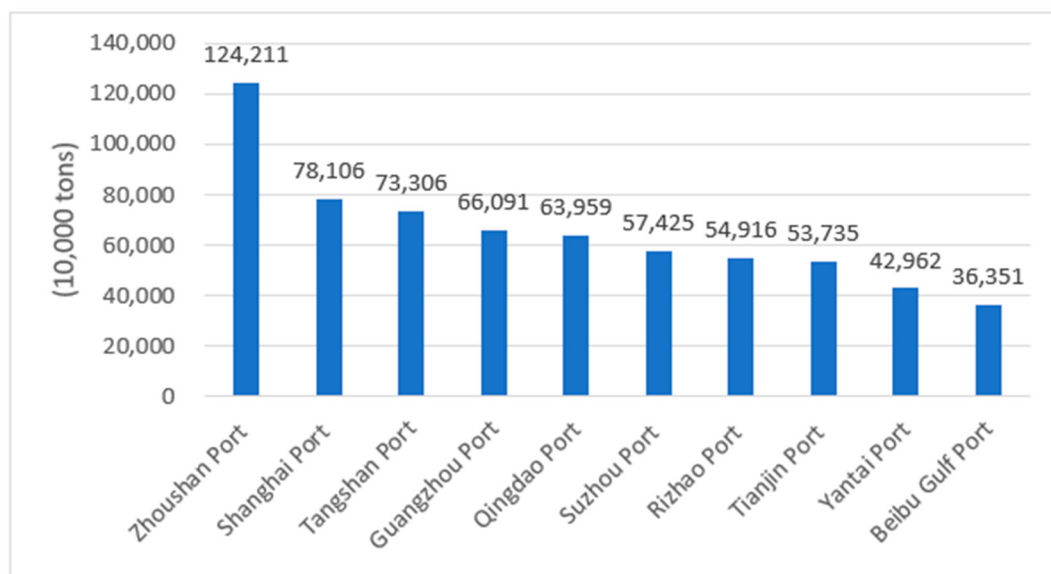


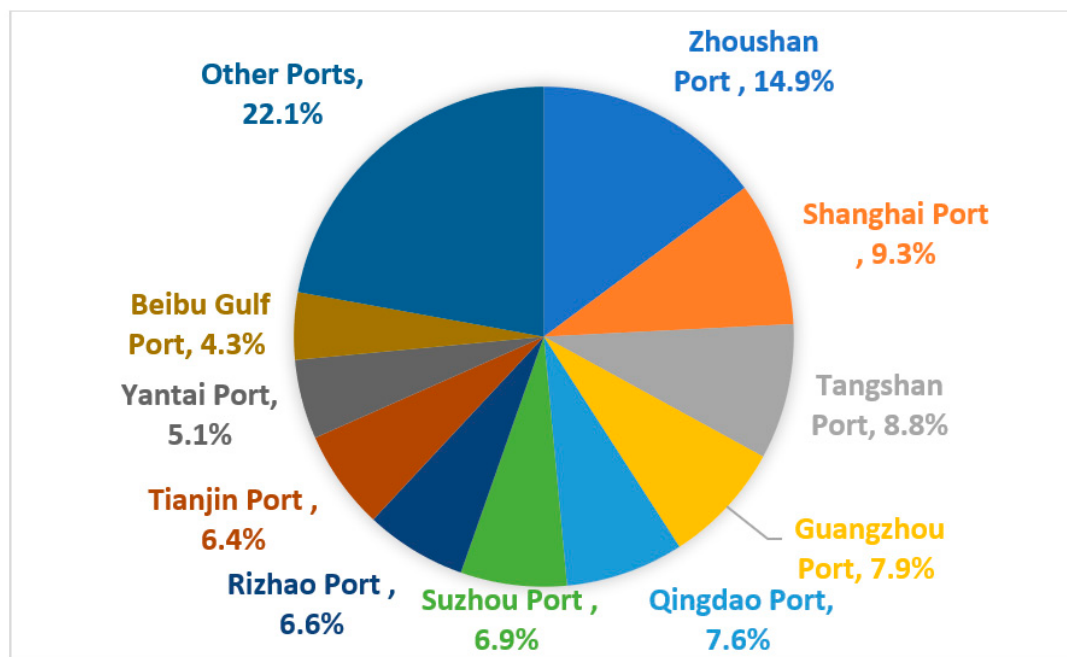
Figure 10. 2015–2022 total volume and growth rate of waterborne cargo transportation.

China's water cargo transportation occupies an important position in the world's MTS, and China is one of the world's important trading powers. According to the JOC released the 2019 global top ten container port throughput data ranking, China has seven ports in the top ten, which fully demonstrates that China's waterway cargo transportation has an important position in the world's waterway cargo transportation. According to statistics, the top 10 ports in China's coastal ports in terms of cargo throughput in 2021 are: Ningbo Zhoushan Port, Shanghai Port, Tangshan Port, Guangzhou Port, Qingdao Port, Suzhou Port, Rizhao Port, Tianjin Port, Yantai Port, and Beibu Gulf Port.

Figure 11a is the forecast result of the port cargo throughput of the top ten ports in China in 2021 for the whole year of 2022. The first port is Ningbo Zhoushan Port, whose predicted value is 124,211. Figure 11b is the proportion of the predicted cargo throughput of the top ten ports in the total waterway cargo transportation volume in 2022. The top ten ports accounted for the largest proportion of cargo throughput in Ningbo Zhoushan Port, and the total proportion of the top ten ports reached approximately 78%, the others accounting 22%. The distribution of these ports along the coast of China is shown in Figure 11c. The top ten ports are mostly in the eastern and northern coastal areas, and these areas are mostly connected to the sea routes in the MTS. These ports have an important position on the routes in the MTS. These ports have an important position in the MTS, so it is necessary to forecast their cargo throughput. The forecasts of these data can provide important information for the optimization and upgrading of the MTS to better cope with different emergencies and the downturn in the shipping economy caused by the still-spreading COVID-19 pandemic virus around the world.



(a)



(b)

Figure 11. Cont.



(c)

Figure 11. (a) The predicted value of the top ten port cargo throughputs. (b) Proportion of the predicted value of the top ten port cargo throughputs. (c) Distribution of the top ten ports by port cargo throughput.

5. Discussion and Conclusions

Studying the forecast of waterway cargo traffic has important implications for the study of sustainable MTS. Water transportation is the basic need and an important link of economic development, and water transportation has an irreplaceable position in transportation due to its advantages of wide coverage, small investment in waterways, strong transportation capacity, small footprint, and low cost. A good forecast in these aspects can better improve and upgrade the MTS. Doing these forecasts can better optimize the overall transportation system, while enabling seamless integration with rail, road, and air transportation systems, better protecting all MTS and maintaining higher levels of maritime traffic.

In the MTS, dry bulk transportation is an important component of the MTS and one of the main forms of water transportation. Therefore, it is of great significance to predict the volume of waterway cargo transportation. In 2021, the global dry bulk shipping volume will continue to grow, but the growth rate will slow down. According to the forecast of relevant institutions, the global dry bulk shipping trade volume in 2022 will be

5.46 million tons, a year-on-year increase of 1.6%. The predicted value of dry bulk shipping volume It accounted for 65.3% of the annual forecast value. Among them, the growth rate of iron ore, coal, and nickel ore remained relatively stable, and the growth rate of seaborne shipments of soybeans and bauxite continued to increase. All these provide important research information and ideas for the study of MTS.

Container transportation in the MTS is another important form of water transportation. The spillover effect of the container market running at a high level still exists, and the level of dry bulk freight is still in a cycle of recovery from the bottom. In 2022, the overall global container shipping demand will maintain a strong momentum. The World Trade Organization (WTO) predicts that the global merchandise trade volume will increase by 4.7% this year. A number of domestic and foreign institutions and shipping companies predict that the growth rate of international container shipping demand in 2022 will be 4–6%. Due to the spread of COVID-19 in many countries around the world, the congestion of some major ports in the world has not shown obvious signs of improvement, which will have a relatively long-term impact on the stability and smoothness of the international maritime logistics supply chain, which will directly affect the effective supply of shipping capacity and thus affect freight rates. Therefore, forecasting the of waterway cargo transportation volume is particularly critical, and the development of COVID-19 and port congestion will be the main factors determining the direction of the waterway cargo transportation market.

The forecast research of waterway cargo transportation volume can provide a powerful reference for the government departments of relevant countries to adjust the waterway transportation capacity structure, formulate waterway transportation planning and corresponding sustainable macro shipping policies, and serve as the basis for the planning and investment decision-making of shipping enterprises, which is conducive to helping shipping companies plan and formulate business strategies and sustainable development strategies. Therefore, the forecast of waterway cargo transportation will help reasonable planning of waterway transportation, MTS upgrade and optimization, and transportation enterprises to make correct sustainable management decisions. At the same time, it can provide a scientific decision-making reference for government departments in water transportation investment and other aspects. This paper chooses a more intelligent forecasting method among various forecasting methods, namely BP neural network forecasting. A BP neural network is a kind of asymmetric neural network. The fundamental reason is that the residual method introduced in the weight calculation breaks the symmetrical structure of the network, which is conducive to improving the representation ability of the network as the network increases. Improve its computing power and convergence speed. At the same time, the momentum term is added to accelerate the convergence speed of the algorithm, and the running speed of the algorithm is improved by modifying the formula of the commonly used momentum term.

Our research has explained the principle of neural networks and the significance of waterway cargo transportation from the beginning and introduced the commonly used BP neural network. Next, we introduce the main methods and their goals and problems for forecasting China's waterway freight volume. Then, considering the advantages and disadvantages of a single BP neural network and a genetic algorithm, for the slow convergence of the BP neural network prediction model and prone to local optima problems, the advantages of the genetic algorithm can make up for the shortcomings of the asymmetric neural network, namely that the GA algorithm has a fast convergence speed, which increases the possibility of getting rid of the local optimal phenomenon in the algorithm, which helps the algorithm find the global optimal solution. Finally, the genetic algorithm combined with the BP neural network is used to construct the prediction model, and the relevant data are collected to conduct experiments. The simulation experiments show that the use of the GA-BP prediction model, compared with the single traditional BP neural network prediction model, improves the convergence of the model. Speed and prediction accuracy reduce the possibility of the BP neural network prediction model falling into local minima. Shipping companies can use the forecast results of this method as a reference for related

work and management. This method can meet their adaptability requirements for forecast accuracy to the greatest extent. This method can be used to ensure that the forecasting process of waterway cargo transportation is more effective, more economical, and safer. Simulation experiments show that compared with the single traditional BP neural network prediction model, this method improves the model's convergence speed and prediction accuracy, and reduces the possibility of the BP neural network prediction model falling into local minima. The BP neural network waterway cargo transportation volume prediction model is optimized by the GA, and the prediction result is closer to the real waterway cargo transportation volume, which is suitable for the waterway cargo transportation volume prediction. In the experiment, the prediction accuracy is improved by 7.281%, and the average error is 3.2148%.

However, the method in this paper still has room for optimization, such as political factors, economic forms, weather, inventory and other external characteristics, which will also have a certain degree of impact on waterway transportation—though these factors are difficult to quantify and rationalize—and can be used in future research on orientation and direction for subsequent model tuning.

Author Contributions: Conceptualization, W.F. and G.J.; methodology, W.F.; writing—original draft preparation, W.F.; writing—review and editing, G.J. and Q.M.; supervision, G.J.; funding acquisition, G.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Fundamental Research Funds for the Central Universities (China), grant number 3132022291. This research was also funded by the Talent Research Start-up Foundation of Dalian Maritime University, grant number 02502329.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

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

References

1. Berle, Ø.; Rice, J.B., Jr.; Asbjørnslett, B.E. Failure modes in the maritime transportation system: A functional approach to throughput vulnerability. *Marit. Policy Manag.* **2011**, *38*, 605–632. [CrossRef]
2. Kumar, P.; Gupta, G.P.; Tripathi, R.; Garg, S.; Hassan, M.M. DLTI: Deep learning-driven cyber threat intelligence modeling and identification framework in IoT-enabled maritime transportation systems. *IEEE Trans. Intell. Transp. Syst.* **2021**. [CrossRef]
3. Omer, M.; Mostashari, A.; Nilchiani, R.; Mansouri, M. A framework for assessing resiliency of maritime transportation systems. *Marit. Policy Manag.* **2012**, *39*, 685–703. [CrossRef]
4. Dui, H.; Zheng, X.; Wu, S. Resilience analysis of maritime transportation systems based on importance measures. *Reliab. Eng. Syst. Saf.* **2021**, *209*, 107461. [CrossRef]
5. Psaraftis, H.N. The Future of Maritime Transport. In *International Encyclopedia of Transportation*; Elsevier: Amsterdam, The Netherlands, 2021; pp. 535–539, ISBN 9780081026724.
6. Fratila, A.; Gavril, I.A.; Nita, S.C.; Hrebenciuc, A. The importance of maritime transport for economic growth in the European union: A panel data analysis. *Sustainability* **2021**, *13*, 7961. [CrossRef]
7. Kilian, L. Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *Am. Econ. Rev.* **2009**, *99*, 1053–1069. [CrossRef]
8. UNCTAD. Review of Maritime Transport. 2021. Available online: https://unctad.org/system/files/official-document/rmt2021_en_0.pdf (accessed on 1 August 2022).
9. Park, J.S.; Seo, Y.J. The impact of seaports on the regional economies in South Korea: Panel evidence from the augmented Solow model. *Transp. Res. Part E Logist. Transp. Rev.* **2016**, *85*, 107–119. [CrossRef]
10. Park, J.S.; Seo, Y.J.; Ha, M.H. The role of maritime, land, and air transportation in economic growth: Panel evidence from OECD and non-OECD countries. *Res. Transp. Econ.* **2019**, *78*, 100765. [CrossRef]
11. Seo, Y.J.; Park, J.S. The role of seaports in regional employment: Evidence from South Korea. *Reg. Stud.* **2018**, *52*, 80–92. [CrossRef]
12. Michail, N.A.; Melas, K.D. Shipping markets in turmoil: An analysis of the COVID-19 outbreak and its implications. *Transp. Res. Interdiscip. Perspect.* **2020**, *7*, 100178. [CrossRef]
13. March, D.; Metcalfe, K.; Tintoré, J.; Godley, B.J. Tracking the global reduction of marine traffic during the COVID-19 pandemic. *Nat. Commun.* **2021**, *12*, 1–12. [CrossRef]

14. Michail, N.A.; Melas, K.D.; Batzilis, D. Container shipping trade and real GDP growth: A panel vector autoregressive approach. *Econ. Bull.* **2021**, *41*, 304–315.
15. Gui, D.; Wang, H.; Yu, M. Risk Assessment of Port Congestion Risk during the COVID-19 Pandemic. *J. Mar. Sci. Eng.* **2022**, *10*, 150. [\[CrossRef\]](#)
16. Cullinane, K.; Haralambides, H. Global trends in maritime and port economics: The COVID-19 pandemic and beyond. *Marit. Econ. Logist.* **2021**, *23*, 369–380. [\[CrossRef\]](#)
17. Xu, L.; Yang, S.; Chen, J.; Shi, J. The effect of COVID-19 pandemic on port performance: Evidence from China. *Ocean. Coast. Manag.* **2021**, *209*, 105660. [\[CrossRef\]](#)
18. Tang, S.; Xu, S.; Gao, J. An optimal model based on multifactors for container throughput forecasting. *KSCE J. Civ. Eng.* **2019**, *23*, 4124–4131. [\[CrossRef\]](#)
19. Li, M.W.; Geng, J.; Hong, W.C.; Chen, Z.Y. A novel approach based on the Gauss-vSVR with a new hybrid evolutionary algorithm and input vector decision method for port throughput forecasting. *Neural Comput. Appl.* **2017**, *28*, 621–640. [\[CrossRef\]](#)
20. Geng, J.; Li, M.W.; Dong, Z.H.; & Liao, Y.S. Port throughput forecasting by MARS-RSVR with chaotic simulated annealing particle swarm optimization algorithm. *Neurocomputing* **2015**, *147*, 239–250. [\[CrossRef\]](#)
21. Niu, Z.; Sun, Q. Study of Railway Passenger Volume Forecast Based on Grey Forecasting Model. In Proceedings of the 2016 International Conference on Logistics, Informatics and Service Sciences (LISS), Sydney, Australia, 24–27 July 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 1–4.
22. Jomnonkwo, S.; Uttra, S.; Ratanavaraha, V. Forecasting road traffic deaths in Thailand: Applications of time-series, curve estimation, multiple linear regression, and path analysis models. *Sustainability* **2020**, *12*, 395. [\[CrossRef\]](#)
23. Huang, A.; Lai, K.; Li, Y.; Wang, S. Forecasting container throughput of Qingdao port with a hybrid model. *J. Syst. Sci. Complex.* **2015**, *28*, 105–121. [\[CrossRef\]](#)
24. Farhan, J.; Ong, G.P. Forecasting seasonal container throughput at international ports using SARIMA models. *Marit. Econ. Logist.* **2018**, *20*, 131–148. [\[CrossRef\]](#)
25. Awah, P.C.; Nam, H.; Kim, S. Short term forecast of container throughput: New variables application for the Port of Douala. *J. Mar. Sci. Eng.* **2021**, *9*, 720. [\[CrossRef\]](#)
26. Tay, Z.Y.; Hadi, J.; Chow, F.; Loh, D.J.; Konovessis, D. Big data analytics and machine learning of harbour craft vessels to achieve fuel efficiency: A review. *J. Mar. Sci. Eng.* **2021**, *9*, 1351. [\[CrossRef\]](#)
27. Antanasijević, D.; Pocajt, V.; Popović, I.; Redžić, N.; Ristic, M. The forecasting of municipal waste generation using artificial neural networks and sustainability indicators. *Sustain. Sci.* **2013**, *8*, 37–46. [\[CrossRef\]](#)
28. Rahman, M.M.; Shakeri, M.; Tiong, S.K.; Khatun, F.; Amin, N.; Pasupuleti, J.; Hasan, M.K. Prospective methodologies in hybrid renewable energy systems for energy prediction using artificial neural networks. *Sustainability* **2021**, *13*, 2393. [\[CrossRef\]](#)
29. Niedbala, G. Application of artificial neural networks for multi-criteria yield prediction of winter rapeseed. *Sustainability* **2019**, *11*, 533. [\[CrossRef\]](#)
30. Barrera, J.M.; Reina, A.; Maté, A.; Trujillo, J.C. Solar energy prediction model based on artificial neural networks and open data. *Sustainability* **2020**, *12*, 6915. [\[CrossRef\]](#)
31. Jiang, W.; Zhang, M.; Chen, Z.L.; Liu, Y.; Li, N. Application of BP Neural Network in the Reliability Prediction. In *Applied Mechanics and Materials*; Trans Tech Publications Ltd.: Bäch, Switzerland, 2012; Volume 121, pp. 3814–3818.
32. Long, H.T.; Zhang, G.D.; Cao, J.L. The use of BP neural network in the landslide prediction of three gorges reservoir. In *Advanced Materials Research*; Trans Tech Publications Ltd.: Bäch, Switzerland, 2014; Volume 838, pp. 2179–2184.
33. Moreira, L.; Vettor, R.; Soares, C. Neural network approach for predicting ship speed and fuel consumption. *J. Mar. Sci. Eng.* **2021**, *9*, 119. [\[CrossRef\]](#)
34. Volkova, T.A.; Balykina, Y.E.; Bepalov, A. Predicting ship trajectory based on neural networks using AIS data. *J. Mar. Sci. Eng.* **2021**, *9*, 254. [\[CrossRef\]](#)
35. Chondros, M.; Metallinos, A.; Papadimitriou, A.; Memos, C.; Tsoukala, V. A coastal flood early-warning system based on offshore sea state forecasts and artificial neural networks. *J. Mar. Sci. Eng.* **2021**, *9*, 1272. [\[CrossRef\]](#)
36. Zhang, Y.; Fu, Y.; Li, G. Research on container throughput forecast based on ARIMA-BP neural network. *J. Phys. Conf. Ser.* **2020**, *1634*, 012024. [\[CrossRef\]](#)
37. Zhang, L.; Wang, F.; Sun, T.; Xu, B. A constrained optimization method based on BP neural network. *Neural Comput. Appl.* **2018**, *29*, 413–421. [\[CrossRef\]](#)
38. Arsad, P.M.; Buniyamin, N. Prediction of Engineering Students' Academic Performance Using Artificial Neural Network and Linear Regression: A Comparison. In Proceedings of the 2013 IEEE 5th Conference on Engineering Education (ICEED), Kuala Lumpur, Malaysia; IEEE: Piscataway, NJ, USA, 4–5 December 2013; pp. 43–48.
39. Zhang, Q.; Li, C.; Yin, C.; Zhang, H.; Su, F. A Hybrid Framework Model Based on Wavelet Neural Network with Improved Fruit Fly Optimization Algorithm for Traffic Flow Prediction. *Symmetry* **2022**, *14*, 1333. [\[CrossRef\]](#)
40. Lee, C.Y.; Ou, H.Y. Induction motor multiclass fault diagnosis based on mean impact value and PSO-BPNN. *Symmetry* **2021**, *13*, 104. [\[CrossRef\]](#)
41. Fang, J.; Li, B.; Gao, M. Collaborative filtering recommendation algorithm based on deep neural network fusion. *Int. J. Sens. Netw.* **2020**, *34*, 71–80. [\[CrossRef\]](#)

42. Zhao, Y.; Fan, Z.; Zhao, C. Combined Forecasting Model of Water Traffic Accidents Based on Gray-BP Neural Network. In Proceedings of the 2019 4th International Conference on Intelligent Transportation Engineering (ICITE), Singapore; IEEE: Piscataway, NJ, USA, 8–9 September 2019; pp. 34–38.
43. Cheng, W.; Feng, P. Network Traffic Prediction Algorithm Research Based on PSO-BP Neural Network. In Proceedings of the 2015 International Conference on Intelligent Systems Research and Mechatronics Engineering, Zhengzhou, China, 11–13 April 2015; Atlantis Press: Paris, France, 2015; pp. 1239–1243.
44. Ma, S.; Shi, X.; Yu, C.; Ren, Y.; Ma, R.; Tian, X.; Wang, W. Research on Improved Prediction Model of Blasting Vibration Speed by BP Neural Network. In Proceedings of the 2020 IEEE 5th Information Technology and Mechatronics Engineering Conference (ITOEC), Chongqing, China; IEEE: Piscataway, NJ, USA, 15–17 September 2020; pp. 1149–1154.
45. Shi, L.; Yang, Y.L.; Lv, J.H. PCA-PSO-BP Neural Network Application in IDS. In Proceedings of the 2015 International Power, Electronics and Materials Engineering Conference, Dalian, China, 16–17 May 2015; Atlantis Press: Paris, France, 2015; pp. 145–150.
46. Hongwei, D.; Liang, W. Research on Intrusion Detection Based on KPCA-BP Neural Network. In Proceedings of the 2018 IEEE 18th International Conference on Communication Technology (ICCT), Chongqing, China, 8–11 November 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 911–915.
47. Amin, M.N.; Javed, M.F.; Khan, K.; Shalabi, F.I.; Qadir, M.G. Modeling Compressive Strength of Eco-Friendly Volcanic Ash Mortar using Artificial Neural Networking. *Symmetry* **2021**, *13*, 2009. [\[CrossRef\]](#)
48. Liu, H.; Xu, B.; Liu, B. An Automatic Search and Energy-Saving Continuous Tracking Algorithm for Underwater Targets Based on Prediction and Neural Network. *J. Mar. Sci. Eng.* **2022**, *10*, 283. [\[CrossRef\]](#)
49. Park, Y.; Kim, E.; Choi, Y.; Seo, G.; Kim, Y.; Kim, H. Storm Surge Forecasting along Korea Strait Using Artificial Neural Network. *J. Mar. Sci. Eng.* **2022**, *10*, 535. [\[CrossRef\]](#)
50. Theodoropoulos, P.; Spandonidis, C.C.; Themelis, N.; Giordamli, C.; Fassois, S. Evaluation of different deep-learning models for the prediction of a ship's propulsion power. *J. Mar. Sci. Eng.* **2021**, *9*, 116. [\[CrossRef\]](#)
51. Su, Y.; Lin, J.; Zhao, D.; Guo, C.; Wang, C.; Guo, H. Real-time prediction of large-scale ship model vertical acceleration based on recurrent neural network. *J. Mar. Sci. Eng.* **2020**, *8*, 777. [\[CrossRef\]](#)
52. Al-Absi, M.A.; Lee, H.J. Introduce a Specific Process of Genetic Algorithm through an Example. In Proceedings of the 2019 International Conference on Information and Communication Technology Convergence (ICTC), Jeju Island, Korea, 16–18 October 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 422–425.
53. Li, X.; Yu, Q.; Tang, C.; Lu, Z.; Yang, Y. Application of Feature Selection Based on Multilayer GA in Stock Prediction. *Symmetry* **2022**, *14*, 1415. [\[CrossRef\]](#)
54. Yu, D.; Deng, F.; Wang, H.; Hou, X.; Yang, H.; Shan, T. Real-Time Weight Optimization of a Nonlinear Model Predictive Controller Using a Genetic Algorithm for Ship Trajectory Tracking. *J. Mar. Sci. Eng.* **2022**, *10*, 1110. [\[CrossRef\]](#)
55. Fang, C.; He, H.; Long, Q.; Su, W.J. Exploring deep neural networks via layer-peeled model: Minority collapse in imbalanced training. *Proc. Natl. Acad. Sci. USA* **2021**, *118*, e2103091118. [\[CrossRef\]](#) [\[PubMed\]](#)
56. Papayan, V.; Han, X.Y.; Donoho, D.L. Prevalence of neural collapse during the terminal phase of deep learning training. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 24652–24663. [\[CrossRef\]](#) [\[PubMed\]](#)
57. People's Republic of China's Port Cargo Throughput Statistics. Available online: <https://www.mot.gov.cn/tongjishuju/gangkouhuowulvkettil/> (accessed on 25 August 2022).