Waterway Cargo Transportation

Subjects: Operations Research & Management Science

Contributor: Guangying Jin , Wei Feng , Qingpu Meng

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.

water transport cargo volume | MTS | BP neural network

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][6][7][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][10][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][13][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][16][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.

2. Waterway Cargo Transportation

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][19][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 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].

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