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Real-time Optimization of Ship Energy Efficiency Based on GWO

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Abstract

With the rapid increase in energy consumption and the gradual exhaustion of non-renewable resources, the high energy consumption and serious environmental pollution caused by maritime transportation have received more and more attention, and the research on ship energy saving and emission reduction technology Without delay. This paper uses actual ship navigation data and establishes a ship fuel consumption model based on BP neural network. On this basis, combined with the definition of EEOI, an optimization goal is established. Then the Grey Wolf Optimizer is used to solve the problem, and the optimized speed is obtained to achieve the purpose of energy efficiency optimization.

Keywords

BP neural network; EEOI; Grey Wolf Optimizer.

1. Introduction

As the most economical mode of transportation under the background of current trade globalization, marine transportation plays a vital role in global trade. More than 90% of global trade is completed by marine transportation[1]. At the same time, the high energy consumption and serious environmental pollution caused by maritime transportation have also received more and more attention. According to research conducted by the International Maritime Organization (IMO), the annual carbon dioxide emissions of the international shipping industry are not optimistic. If strict measures are not taken to control them, the CO_2 emissions of the international shipping industry will reach the total emissions of 2012 (about 938 million tons) 1.5-2.5 times[2]. In fact, as early as the 59th MEPC meeting in 2009, IMO passed the "Guidelines for Voluntary Use of Ship Energy Efficiency Operation Index (EEOI)", which introduced the Ship Energy Efficiency Operation Index (EEOI) is used to evaluate the carbon dioxide emission performance of ships, which can be regarded as a benchmark tool for monitoring the energy efficiency performance of ships. In recent years, with the increasing emphasis on energy conservation and emission reduction, exploring ways to effectively improve energy efficiency based on the combination of EEOI has gradually become a research focus.

At this stage, the main ways to improve the energy efficiency of ships are as follows: ship speed optimization, weather route optimization, ship trim optimization, and monitoring and optimization of main engines [3]. Among them, the optimization of ship speed is a very effective way to improve energy efficiency for ships that have been put into operation. Chen Qiankun used the measured data of inland ships to establish the relationship model between main engine fuel consumption and speed. On this basis, considering the influence of water velocity on the speed, the ship EEOI and main engine speed models were established and optimized to achieve speed optimization[4]. Ma Laihao et al. established ship operating benefit estimation model and ship energy efficiency index estimation model with ship speed as the independent variable and maximum voyage return and minimum EEOI as optimization goals. The genetic algorithm is used to solve the models separately, and the optimal speed of the ship in different

situations is obtained[5]. Hou introduced uncertainty analysis and optimization theory when considering important random factors such as ice load. Taking the speed of the ship's main engine in the ice area as the design variable, an optimization model with minimum EEOI as the goal is established, and the ASA algorithm is used to solve the model, and the speed optimization result with both robustness and reliability is obtained[6].

At present, steady-state optimization is more common in ship energy efficiency optimization. However, in the real-time navigation of a ship, the changes in sea conditions will have a great impact on the resistance of the ship, which directly affects the energy efficiency of the ship. For this purpose, this article first takes the "Yuming" ship as an example to establish a real-time fuel consumption model based on BP neural network that can dynamically respond to the ship's sailing status. Based on this, a real-time optimization model of ship energy efficiency is established with the goal of predicting the front and back EEOI relationship. The gray wolf algorithm (GWO) is used to solve the model.

2. Ship Fuel Consumption Prediction Model

The current research on ship fuel consumption models can be divided into two categories: white box model and black box model according to different technical routes. The white box model, the mechanism model, is a model based on known physical relationships. In practical applications, it is difficult to accurately describe the relationship between the various factors that affect fuel consumption, so a large number of empirical parameters are involved, so the general adaptability of the white box model is poor, and it can only be applied to specific ships on specific routes. . At the same time, because of the complex structure of the white box model and the long calculation time, it will be subject to certain restrictions in real-time fuel consumption prediction of ships.

With the popularization of technologies such as big data and neural networks, the black box model of fuel consumption prediction based on neural networks has been widely concerned and applied because it does not need to clarify the physical relationship between various factors, but only needs to consider the characteristics of the input-output relationship. Chen Weinan used principal component analysis to preprocess real-time ship operating data, combined with BP neural network to establish a ship navigation state recognition model and a main engine fuel consumption model, and regarded the predicted fuel consumption as the ideal value and the real-time measured fuel consumption. For comparison, take the difference between the two as a reference for evaluating ship energy efficiency[7]. Ye Rui established a ship fuel consumption prediction model based on the multilayer perceptron artificial neural network combined with the principal component analysis method, which provides a reference for the navigation optimization of ships in operation, and plays a certain guiding role in improving the ship energy efficiency operation index EEOI[8]. Based on artificial neural network and multiple regression method, Farag established a highly accurate model that can predict the power and fuel consumption of ships in various marine environments in real time. This model provides support for the development of decision support systems. Can guide the crew to adjust the ship's navigation status[9].

This article uses Matlab neural network toolbox, back propagation (BP) neural network, and uses ship navigation data and sea state data to train the neural network model to obtain the ship fuel consumption prediction model. Since the change of the main engine speed can be directly reflected in the ship speed, the design variable of the fuel consumption model selects the main engine speed. Therefore, the ship fuel consumption prediction model based on neural network should take the main engine speed and sea state data as input, and take the speed and fuel consumption as output. The specific modeling process can be found in literature [10].

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2.1. Data Preprocessing

During the actual voyage of the ship, the positioning, communication and monitoring equipment installed on the ship will continuously collect and record the operation information of the ship's equipment, the ship's navigation information, the navigational sea conditions and the data related to energy consumption. The increase is constantly growing and updating. This makes it feasible to improve ship energy efficiency in real time, and has laid a solid data foundation for it. The output of the fuel consumption model established in this paper is speed and fuel consumption, which are related to many factors, the main influencing factors include speed, range, speed, fuel consumption, wind speed and wave height. Some of these factors directly affect the state of navigation, while others are indirect, and there is a certain correlation between different factors. In order to improve the predictive ability of the established fuel consumption model, it is necessary to preprocess the collected data.

Preprocessing includes data pruning, data synchronization, dimensionality reduction processing and normalization. Data pruning is to remove the data that is part of the stationary state of the ship when it is docked or at anchor. Data synchronization is to eliminate the non-overlapping part of the data of various factors, and obtain the overlapping part of each dimension data in a certain time series. The dimensionality reduction process is to dig out the main factors among many influencing factors and extract the key features. Normalization is to eliminate the dimensional difference of each historical data. When performing dimensionality reduction processing, first of all, suppose that the fuel temperature is controlled within a stable range and the density does not change much, and the cargo capacity of the ship during the voyage can also be regarded as a fixed value, and the draft does not change the ballast. The following can also be regarded as fixed, so the data of 4 influencing factors are first excluded. Subsequently, the data of the remaining influencing factors of each dimension is used to perform dimensionality reduction using correlation analysis, and redundant feature information is deleted. Finally, there is a very strong positive correlation between the main engine power, main engine revolution, car clock command and other factors. Therefore, it is combined into one influencing factor, namely the "main engine speed". The wind speed, wind angle and other factors have a high degree of correlation with the output. Therefore, all the influencing factors of the input network are finally reduced to 5 dimensions, namely: main engine revolution, wind speed, wind direction, wave height, and water flow, and the network output parameters are two-dimensional, namely: ship speed and fuel consumption rate.

2.2. Forecast Model

According to the results of the above data preprocessing, the Matlab neural network toolbox is used and the BP neural network is used to establish a ship fuel consumption prediction model. The number of input layer nodes of the model is 5, the number of hidden layer nodes is 12, and the number of output layer nodes is 2. The neural network framework diagram is shown in Figure 1.

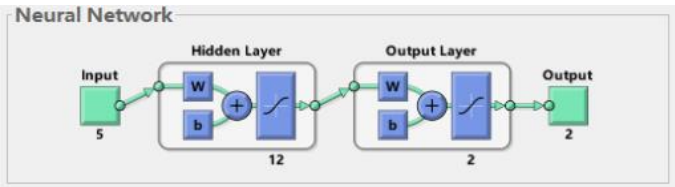

Figure 1: BP neural network framework

The hidden layer of the model uses the Sigmoid function as the activation function between nodes, the output layer uses the linear function as the activation function of each node, and the Levenberg-Marquardt algorithm is used for the training data. Divide the preprocessed data into 70% as the training set, 15% as the validation set, and 15% as the test set. The training process of this network is shown in Figure 2.

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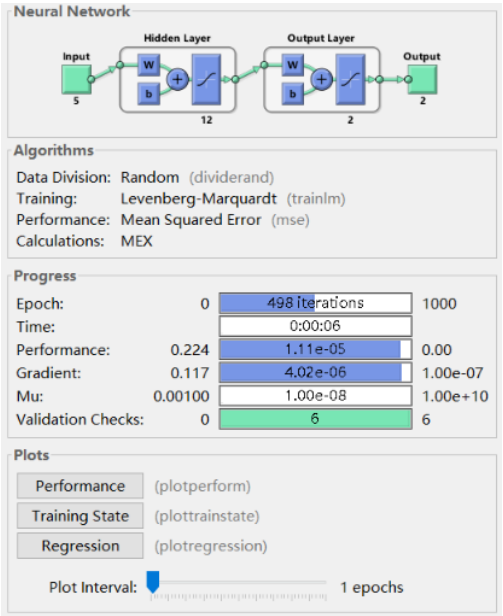

Figure 2: BP neural network training process

Figure 3 shows the mean square error change curve of the network. It can be seen from the figure that the error has met the requirements at the 492th iteration. In combination with Figure 2, it can be seen that when the number of iterations reaches 498, the mean square error Achieved, and the convergence rate is very fast.

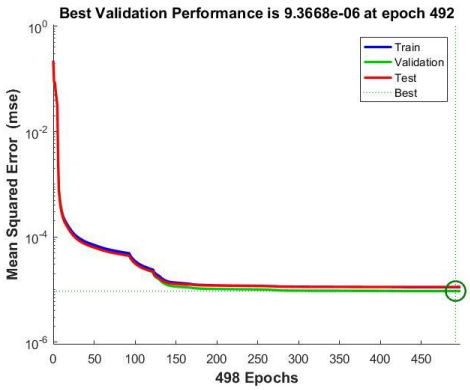

Figure 3: Mean square error change curve

Figure 4 shows the regression analysis results of the network. It can be seen from the figure that the model can achieve a higher fitting result. Therefore, the model is suitable for the optimization model to be established in this article.

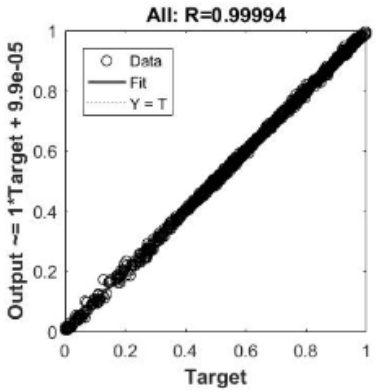

Figure 4: Neural network regression analysis results

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3. Establish Optimization Goal

For ships that have been put into operation, slowing down is the most effective way to reduce energy consumption [11]. This section aims to establish an appropriate optimization target and provide a reference basis for the crew to make dynamic adjustments to the ship's navigation status based on actual operational needs.

3.1. Real-time EEOI

Before establishing a comprehensive optimization goal, we first need an indicator that can reflect the energy efficiency of ships in real time. This article uses EEOI recommended by IMO as the indicator. In the MEPC.1/Circ.684 "Guidelines for Voluntary Use of Ship Energy Efficiency Operation Index (EEOI)" issued by IMO in 2009, the calculation formula of EEOI is [13]:

$$EEOI = \frac{M_{CO_2}}{Q} \tag{1}$$

Where:

M_{CO_2} : CO_2 Emissions, the unit is t;

Q : Traffic volume, the unit is t.

It can be seen from the above formula that the EEOI index reflects the emissions of ship transportation operations, so the formula for a single voyage can be rewritten as:

$$EEOI = \frac{\sum_j FC_j \times C_{Fj}}{m_{cargo} \times D} \tag{2}$$

Where:

j : Fuel type;

FC_j : The consumption of fuel j in a single voyage, the unit is t;

C_{Fj} : CO_2 Conversion factor, that is, the amount of CO produced by consuming unit j of fuel;

m_{cargo} : Cargo capacity, the unit is t;

D : Corresponding to the transport distance of the cargo capacity, the unit is nm.

In view of the above formula, the guidelines suggest that the rolling average value can be calculated by selecting an appropriate period (one year or 6-10 voyages closest to the end of the voyage). Therefore, the formula cannot reflect the energy efficiency level of the ship in real time. Make some adjustments to meet real-time performance. It can generally be considered that in a single voyage, the cargo capacity of a ship is fixed, while parameters such as fuel consumption, speed and range change in real time. Therefore, real-time EEOI can integrate the real-time values of the variables involved in the formula in a short time. As long as the integration time is short enough, it is equivalent to real-time relative to the entire flight time.

3.2. Objective Function

After obtaining the real-time EEOI formula, this section uses the host speed as the design variable to optimize the real-time optimization of EEOI, because the purpose of this article is to obtain the optimal EEOI, so the larger the difference before and after the EEOI optimization, the better the optimization effect. Take the maximum EEOI difference before and after optimization as the optimization goal, as shown below:

$$O = \max\left(EEOI - EEOI'\right) \tag{3}$$

Where:

$EEOI'$: The real-time value of EEOI calculated according to the prediction of the fuel consumption prediction model.

4. Optimized solution based on GWO

Traditional genetic algorithm (GA) has many applications in ship energy optimization due to its high efficiency and stability, but it also has the disadvantage of premature convergence leading to unsatisfactory results. The Gray Wolf Algorithm (GWO) was first proposed by Mirijili et al. in 2014 [13]. It is a relatively new meta-heuristic algorithm inspired by the gray wolf's social hierarchy and hunting behavior. Compared with GA, GWO has more memory ability, and because of its features such as fewer adjustable parameters, simple structure, and strong convergence, it has been successfully applied in many fields.

4.1. Optimization process

After obtaining the trained ship fuel consumption model and establishing the optimization target, the monitoring data at the current speed is obtained, and the main engine speed and the required sea state data are input into the ship fuel consumption model to obtain the predicted value of the speed and fuel consumption rate at the corresponding speed. Subsequently, the predicted value of ship speed and fuel consumption rate is brought into formula to calculate real-time EEOI, and the engine speed is used as a design variable. Under the limit of its boundary conditions, the maximum EEOI difference before and after optimization is used as the objective function to establish an energy efficiency optimization model. After optimizing the model and obtaining the optimal host speed, the corresponding optimized real-time EEOI is obtained.

The energy efficiency optimization model established in this paper is based on neural networks as a whole, and the online learning capabilities of neural networks can continuously adapt to changes in sea conditions through the increase and update of navigation data, forming a continuously improved optimization system, so as to better post In accordance with the actual navigation environment, the model achieves higher accuracy as the number of voyages increases.

4.2. Results After Optimization

The gray wolf algorithm used in the optimization process has a number of search individuals of 60 and a maximum number of iterations of 100. When the main engine speed is optimized, the optimization range is controlled at 80-130 r/min, and the main engine is running in the high efficiency range. In this section, five sets of sea states are selected to verify the feasibility of the algorithm. The optimized performance is shown in Table 1:

Table 1: Comparison of Results Before and After Optimization

Navigation Information				Before		After	
Wind speed (m/s)	Wind direction (°)	Wave high (m)	Water flow (m/s)	ne (rpm)	EEOI	ne (rpm)	EEOI
0	3.14	1.5	-2	128	7.47	119	6.67
5	0	1.86	0	128	7.72	120	6.99
8	3.14	2.45	0	128	7.36	122	6.51
10	3.14	3	-1	128	7.24	121	6.59
12	0	3.65	2	128	7.26	120	6.61

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5. Conclusion

It can be seen from the optimization results that the optimized host speed has indeed decreased, and EEOI has also decreased. It shows that the model proposed in this paper can adjust the speed of the main engine in real time according to the changes of the current navigation environment of the ship, so as to optimize the speed and reduce EEOI. At the same time, this optimization model solves the previous steady-state optimization problem of EEOI of ships with a single route as a unit, and is more realistic. The fuel consumption model established by the neural network can be continuously updated with the increase of voyages and voyage data to better fit the actual sailing conditions. The model has a certain general applicability and can be adjusted according to the data collected by different ships.

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