Research on Ship Speed Prediction Model Based on BP Neural Network

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Abstract. In order to predict the speed of ships, an prediction model is proposed according to the principal component analysis and BP neural network. Aimed at Changhang Yangshan ship 2, five main factors affecting speed are extracted through principal component analysis (PCA). Furthermore, the input and output of the BP neural network is designed by five main factors and predicted speed respectively. The initial parameters are selected to reduce the mean square error and the prediction error of the model. Finally, the prediction results show that the real speed is consistent with the predicted speed in trend, and the prediction accuracy is accurate. An effective way of speed prediction is provided by principal component analysis and BP neural network.

Keywords: Intelligent navigation · Ship speed prediction · Principal component analysis · BP neural network

1 Introduction

In recent years, due to the development of intelligent navigation optimization technology, ship intelligence has become the general trend of global shipping. Ship intelligence is inseparable from the support of economic speed. The forecast of economic speed can not only cut costs for the shipping industry, but also contribute to low-carbon and environmentally friendly construction [1].

The ocean is a relatively complex environment, which leads to the fact that the speed of ships sailing on the sea will be affected by many factors [2]. It is not accurate to predict the speed by simple linear regression, so an effective non-linear model is the key to solving the speed prediction. Due to the complexity of ship navigation, it is extremely complicated to establish a strict mathematical model. However, BP neural network can overcome this shortcoming and realize the prediction of ship speed based on data [3]. As for the input data to the neural network, it needs to be preprocessed, and the principal component analysis method can effectively reduce the dimensionality of the data factors and eliminate the correlation between the factors [4]. Therefore, this paper proposes a ship speed prediction model based on the combination of principal component

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analysis and BP neural network. The principal component analysis is used to select the main factors affecting the ship speed, then the ship speed is predicted by BP neural network. Finally, the network parameters are set to reduce the prediction error.

2 Dimensionality Reduction of Speed Influencing Factors Based on Principal Component Analysis

2.1 The Basic Idea of Principal Component Analysis

The basic idea of principal component analysis is to use the method of dimensionality reduction to convert multiple related input variables into several comprehensive input variables [5,6]. It mainly performs linear transformation on the data set, and projects the variance of the data sample into a new coordinate system. Then it calculates the variance of all input variables and arranges them in descending order.

The principal component analysis method ensures that the linearly transformed data contains the information of the original data to the greatest extent and achieves the purpose of reducing input variables at the same time [7,8]. This method selects the low-order components of the principal components and discards the high-order components, because in general, the low-order components of the principal components can well retain most of the information in the original data [9,10].

2.2 Dimensionality Reduction Analysis

The data used in this article is from the voyage data of Changhang Yangshan 2. The collected data is composed of environmental and ship's factors. Environmental factors include wind speed (m/s) and wind direction (°). Ship's own factors include course (°), speed (kn), rotation speed (rpm), torque (kNm), power (kW), fuel consumption (m^3). Since speed is the factor that we want to optimize and predict, we will use it as the dependent variable and the remaining 7 factors as independent variables. Our goal is to reduce repetitive effects and dimensionality reduction through PCA. Due to the large amount of data, Table 1 only lists part of sample data.

Table 1. Partial sample data table

Wind speed (m/s)	Wind direction (°)	Course (°)	Ship speed (kn)	Rotating speed (rpm)	Torque (kNm)	Power (kW)	Fuel consumption (m^3)
7.77	69.0	0.00	0.03	1.00	−4.71	24.44	0.000941
6.38	59.00	0.00	0.03	1.88	−4.72	24.60	0.030112
7.47	63.00	0.00	0.01	1.00	−4.68	24.77	0.030112
8.18	83.68	35.10	0.14	34.66	−12.91	−53.35	0.031053

Before the PCA process, the data needs to be preprocessed:

(1) Eliminating missing data.
(2) Taking the absolute value of the power data, and turning it into a positive number.
(3) Excluding the data of the ship in the stopped state, the standard of the ship in the stopped state is: the fuel consumption is 0, the speed is 0.

In this paper, the comprehensive indicators obtained by principal component analysis are used as the principal components of the sample data. They are not relative, and contain the main information of the original sample. The variance of the principal components is used to represent the coverage of the original sample information, and the index with the cumulative coverage exceeding 85% is used as the principal component of the sample data.

Table 2. Contribution rate of various factors

	Fuel consumption	Power	Torque	Rotating speed	Course	Wind speed	Wind direction
Coverage	0.4859	0.1763	0.1290	0.1129	0.0880	0.0069	0.0011
Cumulative coverage	0.4859	0.6622	0.7912	0.9041	0.9921	0.9990	1.0000

The contribution rate of each factor as shown in Table 2 is calculated by Matlab. The cumulative variance contribution rate of the first 4 components has reached 90%, exceeding the requirement of 85%. But we do not need to be limited to the 85% standard. In order to better cover the information of the original sample data, we have selected 5 components as the final principal components, which are the linear combination of 7 factors.

Table 3. Principal component coefficient table

	Component 1	Component 2	Component 3	Component 4	Component 5
Wind speed	0.2644	0.7185	0.3349	0.3846	−0.3920
Wind direction	−0.2017	−0.7784	0.3852	0.0895	−0.4437
Course	0.4541	−0.1460	−0.7723	0.2624	−0.3273
Rotation speed	0.9662	−0.0138	0.0569	−0.1952	−0.0079
Torque	−0.9705	0.0469	−0.1010	0.2014	0.0191
Power	0.9592	−0.0697	0.1173	−0.1879	−0.0253
Fuel consumption	0.5380	−0.2882	0.1382	0.6718	0.3963

The data in Table 3 represents the coefficients obtained after principal component analysis of each sample variable. Five input variables are finally selected as principal components, which not only contain most of the information of the original sample data, but also reduce the dimensionality of the input variables.

3 Prediction of Ship Speed Based on BP Neural Network

3.1 Construction of Neural Network for Ship Speed Prediction

Artificial neural network is composed of a large number of neurons which are connected to each other [11,12]. It is inspired by exploring the perception and processing of information by human brain nerves, so as to perform non-linear conversion of information and parallel processing of information [13,14].

BP neural network construction steps are as follows [15]:

(1) Initializing neural network.
(2) Selecting some training samples as the input of the neural network and training the network.
(3) Calculating the error between the actual output value of the neural network and the expected output value. If the error does not reach the preset accuracy, process backward propagation of errors.
(4) Through the back propagation of errors, iterative calculations are continuously carried out to correct the connection weight of the network. Step (3) is repeated until the preset error accuracy requirement is reached.

The above algorithm steps are represented as a flowchart as shown in Fig. 1:

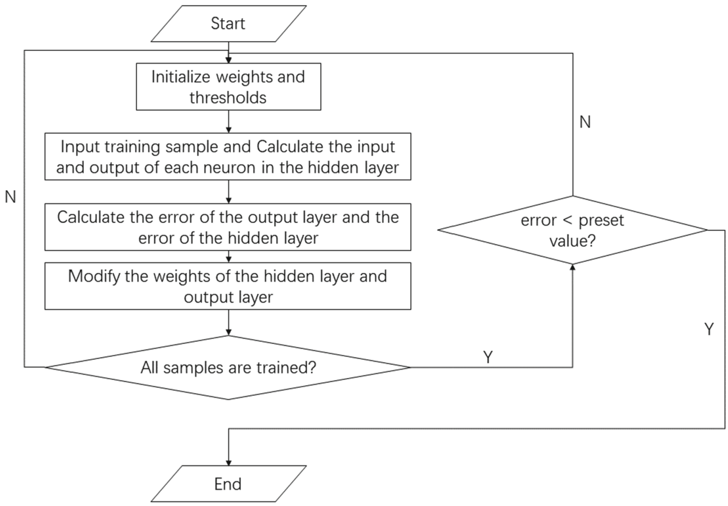

Fig. 1. Back propagation algorithm flow.

3.2 Predicting Results

The original sample data used in this article is taken from the voyage data of Changhang Yangshan 2 from May 5 to May 22. The initial parameters selected in this paper are represented as shown in Table 4. Neural network predicted value and expected value results as shown in Fig. 2. The green circle and the blue asterisk in Fig. 2 represents the expected value and the predicted results respectively. The test set error is shown in Fig. 3.

Table 4. The initial parameters in neural network

Layers	Learning rate	Hidden layer nodes	Input layer nodes	Output layer nodes
3	0.1	10	5	1

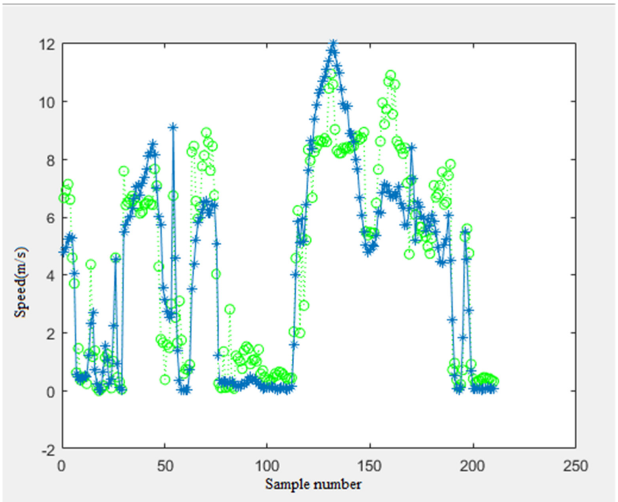

Fig. 2. Comparison between expected value and output value predicted by neural network.

In order to reduce the error of nerural network, the parameters of BP neural network need to be optimized. First, we need to select an appropriate activation function. The commonly used activation functions are sigmoid, tanh and relu.

Sigmoid function has been used widely, but in recent years, fewer and fewer people use it. This is mainly because when the input is very large or very small, the gradient of these neurons is close to 0, and the mean of output combined with sigmod is not 0.

Tanh is a deformation of sigmoid. The mean of output combined with tanh is 0. Therefore, tanh is better than sigmoid in practical application.

The convergence rate of SGD obtained by relu is much faster than sigmoid/tanh. Compared with sigmoid/tanh, relu only needs a threshold to get the activation value without a lot of complex operations. Therefore, we choose relu as our activation function.

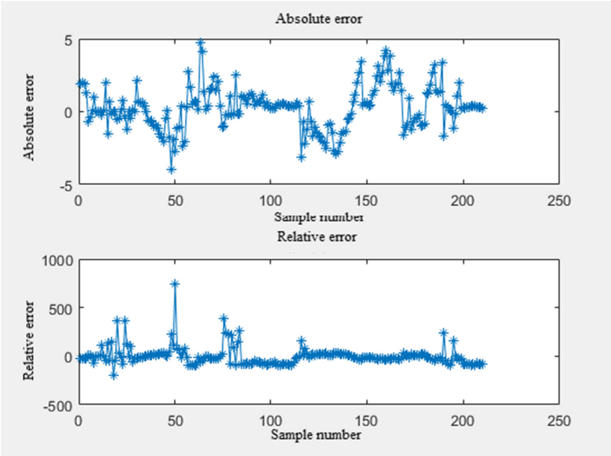

Fig. 3. Test set error.

Different optimization methods also have a great impact on the error results. There are three commonly used optimization methods: L-BFGS, SGD and ADAM. L-BFGS is the optimization of quasi Newton method family. The essential principle is Newton method, but a lot of optimization deformation has been carried out. SGD is a random gradient descent method, which will have the best performance (classification effect and iteration times) when the parameters are adjusted better. ADAM works well on relatively large data sets (thousands of samples or more). We choose SGD optimization method for parameter optimization.

Comparing the two BP neural networks in Python, it is found that the error after parameter optimization is smaller, and the results are shown in Table 5.

Table 5. Mean square error table

MSE	Train error (%)	Test error (%)
Before parameter optimization	2.4832	2.8975
After parameter optimization	1.4937	1.9718

4 Conclusion

In this paper, the principal component analysis method is incorporated to calculate the variance contribution rate of these factors and the top five factors with the most contribution are selected for dimensionality reduction. Then we establish a speed prediction optimization model based on BP neural network, which can better predict the speed at the next time. By introducing principal component analysis, BP neural network and parameter optimization into speed prediction can play a good guiding role in understanding the law of speed change, and correctly guide navigators to make navigation decisions. The BP neural network can been used as a redundant system in case of failure of a sensor providing the foreseen information for the controllers. Therefore, the BP neural network can help in anticipating some ship speed deviation from predefined target conditions, and optimizing the ship operation.

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