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Ship Service Speed Estimation Based on the Backpropagation Neural Network

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Abstract

To enhance the accuracy of ship service speed estimation, a model based on a Backpropagation (BP) Neural Network was developed. This model was trained using data from 53 bulk carriers built over the past 30 years, and the corresponding model parameters were derived. A reference regression formula was then generated by re-fitting the training data to evaluate the BP Neural Network's estimation performance. Comparative analysis of the results demonstrates that both the BP Neural Network model and the reference regression formula significantly outperform the original regression formula in terms of estimation accuracy. Furthermore, residual analysis indicates that the BP Neural Network model offers greater estimation stability than the reference regression approach, making it well-suited for practical applications in ship service speed prediction.

Keywords

Service Speed; Estimation; Regression formula; BP Neural Network.

1. INTRODUCTION

The ship's service speed plays a critical role in determining both the operational efficiency and economic performance of maritime transport. As the primary speed used during regular navigation, accurately estimating service speed is of great practical importance. Earlier researchers have made valuable contributions to ship parameter estimation, and their findings have been widely applied across various related fields. Katsoulis collected operational data from various dry cargo ships and bulk carriers and proposed a regression formula for estimating the service speed of dry bulk carriers [1]. Jiang analyzed the key parameters of large transport vessels and compared them with existing empirical formulas [2]. Pan estimated the block coefficient of container ships and developed a corresponding regression formula, which could be converted into an empirical formula for service speed estimation [3]. Cheng applied regression analysis to derive an empirical formula for the service speed of large container ships [4]. Bao examined data from nearly one hundred small- and medium-sized container ships to propose an estimation formula for the block coefficient [5]. Wu used regression methods on data from a similar number of large container ships to generate empirical formulas for their principal parameters [6]. Song employed statistical analysis to derive empirical formulas for specific container ship parameters [7].

These studies provided valuable insights, including ship parameter benchmarks and empirical formulas for service speed estimation across different vessel types. However, most were based on earlier ship data, which may no longer reflect current vessel designs and performance. Given ongoing advancements in shipbuilding and improvements in vessel

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efficiency, many of these early empirical models now exhibit limited accuracy. As a result, there is a pressing need to develop updated empirical formulas and estimation methods based on modern ship data to support contemporary research and engineering applications.

The Back Propagation (BP) Neural Network is a multi-layer feedforward network trained using the error backpropagation algorithm. As one of the most widely used neural network models, it has found applications across a broad range of research domains. In the maritime field, BP neural networks have demonstrated strong performance in ship design and navigation. Liu developed an improved BP neural network algorithm to assess ship collision risks [8]. Cui applied BP neural networks to enhance the remote monitoring systems of ocean-going vessels, enabling accurate fault trend analysis and early warnings [9]. Zeng combined BP neural networks with genetic algorithms to optimize propeller design based on the traditional atlas design method [10]. Zhang investigated the application of BP neural networks to address two practical problems in ship and marine engineering, focusing on numerical prediction and key considerations for implementation [11]. Hu introduced a radar target correlation algorithm incorporating artificial intelligence and BP neural networks [12], while Zhu proposed an intelligent model for recognizing ship signal lights using a reverse error propagation neural network [13].

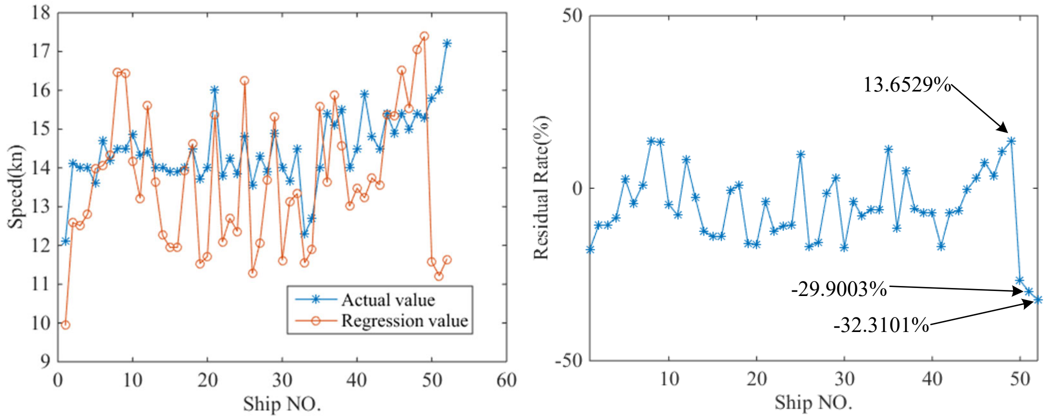
These studies collectively demonstrate the effectiveness of BP neural networks in maritime applications, particularly in prediction and computation tasks, and their reliability has been validated by multiple scholars. Building on this foundation, the present study applies a BP neural network to estimate ship service speed, aiming to develop a model that improves estimation accuracy through data-driven learning.

2. MULTIPLE REGRESSION FORMULA

The service speed of a ship is closely influenced by its type and key design parameters. Katsoulis [1] collected empirical data from various dry cargo ships and bulk carriers, and proposed a regression formula—commonly referred to as the Katsoulis formula—presented in Equation (1).

$$V_s = 0.7261 C_b^{-1.63} L^{0.6846} B^{-0.5007} d^{0.2805} \tag{1}$$

In this formula, V_s represents the service speed, C_b is the block coefficient, L is the ship's length, B is the beam (width), and d is the draft. To evaluate the validity of the Katsoulis formula, data from 53 bulk carriers constructed over the past 30 years were used for calculation based on Equation (1). The results are presented in Fig.1.



(a) Comparison of the real value and the estimated value (b) Estimated residual rate

Figure 1. Calculations result and residual error of Katsoulis Formula

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As shown in Figure 1, the service speeds estimated using the Katsoulis formula exhibit significant deviation from the actual values. Statistical analysis of the residuals indicates a mean error of 9.8472%, with substantial discrepancies observed, particularly in Figure 1(b). These results suggest that the Katsoulis formula is no longer suitable for accurately estimating the service speed of modern bulk carriers. Proposed in 1975, the formula was derived from ship data that are now outdated. Advances in ship design and technology over the past decades have led to considerable changes in ship performance characteristics. Consequently, the limited applicability of the Katsoulis formula to contemporary vessels is understandable.

To address this, a revised regression model based on the structure of the Katsoulis formula (as shown in Equation (2), where aiai denotes the regression coefficients) can be developed using up-to-date data from modern bulk carriers. Additionally, regression analyses can be conducted on collected datasets for oil tankers and container ships to derive corresponding empirical formulas for estimating their service speeds.

$$V_S = a_1 C_b^{a_2} L^{a_3} B^{a_4} d^{a_5} \tag{2}$$

Data from 53 bulk carriers, 51 container ships, and 98 oil tankers constructed over the past 30 years were used to perform regression analysis on Equation (2). The resulting regression formulas are presented in Equation (3).

$$\begin{cases} V_S = 3.7682 C_b^{-0.3236} L^{0.3566} B^{-0.0455} d^{-0.1866} & \textit{Bulk carrier} \\ V_S = 0.9804 C_b^{-0.9809} L^{0.7416} B^{-0.3742} d^{-0.025} & \textit{Container ship} \\ V_S = 1.633 C_b^{-0.3280} L^{0.7256} B^{-0.5122} d^{-0.0214} & \textit{Oil tanker} \end{cases} \tag{3}$$

3. ESTIMATION MODEL BASED ON BP NEURAL NETWORK

The Back Propagation (BP) neural network is a widely used model across various fields due to its strong nonlinear mapping capabilities. By training the BP neural network with relevant ship parameters, it is possible to accurately estimate the ship's service speed. The structure of the model is illustrated in Fig.2.

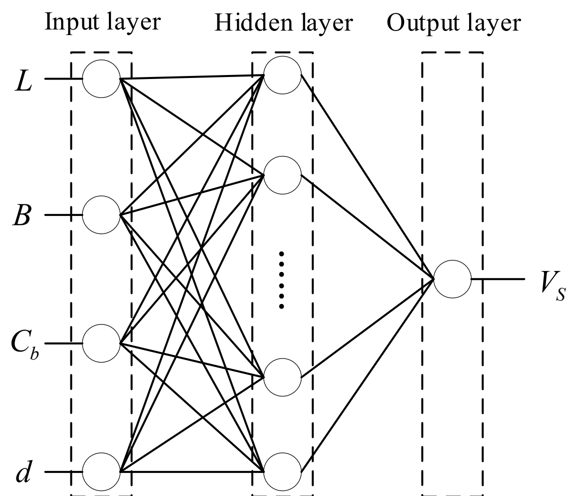

Figure 2. Schematic diagram of BP neural network structure

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Based on the regression formula, the input layer of the BP neural network includes four neurons corresponding to the parameters L, B, C_b, and d. The output layer consists of a single neuron representing the estimated service speed V_s. Following the approach described in reference [14], the hidden layer is configured with nine neurons. The activation function used is the Sigmoid function, as defined in Equation (4).

$$f(x) = \frac{1}{1+e^{-x}} \tag{4}$$

The training parameters are normalized according to Equation (5), where x_{bottom} and x_{top} represent the minimum and maximum values, respectively, determined based on the actual conditions of ship development. These values are listed in Table 1.

$$x' = \frac{x-x_{bottom}}{x_{top}-x_{bottom}} \tag{5}$$

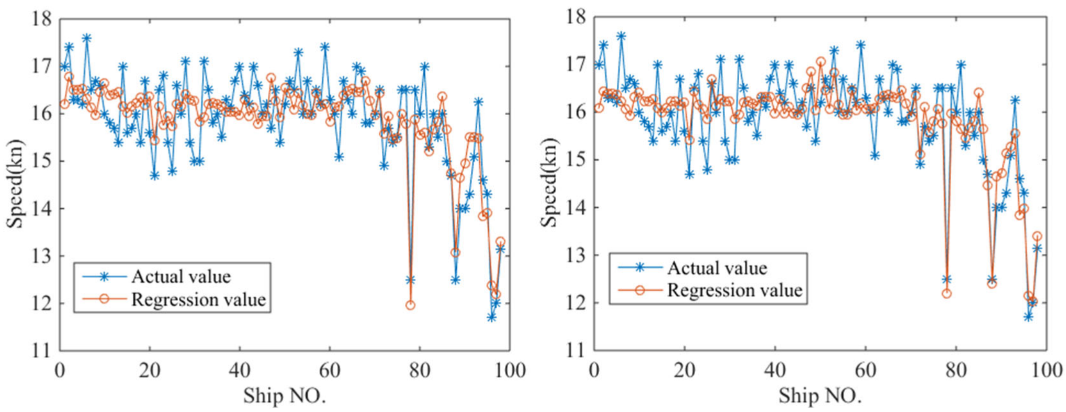
Table 1. Normalized range of training parameters

Parameters	x_{bottom}	x_{top}
L (m)	20	500
B (m)	5	80
C_b	0.4	1.0
d (m)	2	40
V_s(kn)	2	40

4. EXPERIMENTAL ANALYSIS

4.1. Experimental result

The regression equations derived from multiple nonlinear regression were compared with the predictions of the developed BP neural network model. Calculations were performed using data from 53 bulk carriers, 51 container ships, and 98 oil tankers. The results are presented in Figures 3 to 5.



(a) Calculation result of the regression formula (b) Calculation results of BP neural network model

Figure 3. Comparisons of calculation results of service speed of oil tankers

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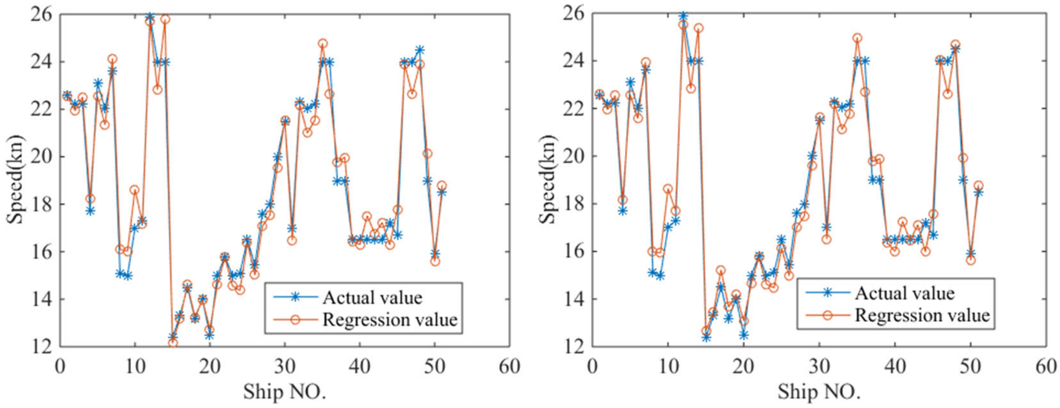
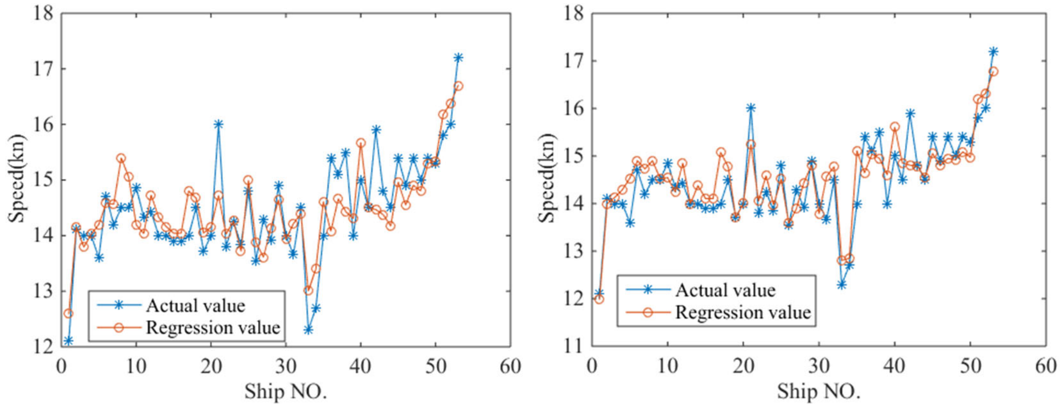


(a) Calculation result of the regression formula (b) Calculation results of BP neural network model

Figure 4. Comparisons of calculation results of service speed of container ships

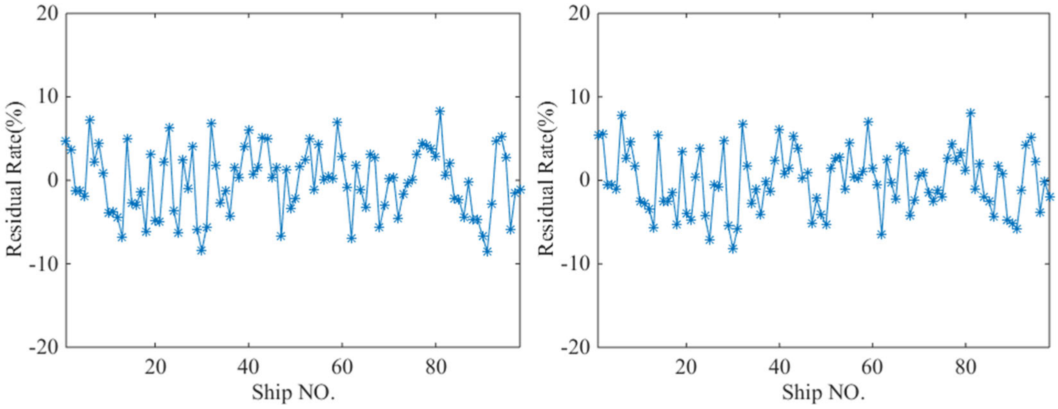


(a) Calculation result of the regression formula (b) Calculation results of BP neural network model

Figure 5. Comparisons of calculation results of service speed of bulk carriers

4.2. Analysis of Experimental Results

The results indicate that both the multiple nonlinear regression formula and the BP neural network model effectively estimate the service speeds of the three ship types. To further evaluate their respective strengths and weaknesses, a comparison of their estimation accuracy is necessary. The residuals for each ship type are illustrated in Figures 6 to 8.



(a) Residual rate of the regression formula (b) Residual rate of the BP neural network model

Figure 6. Comparisons of residuals of service speed of oil tankers

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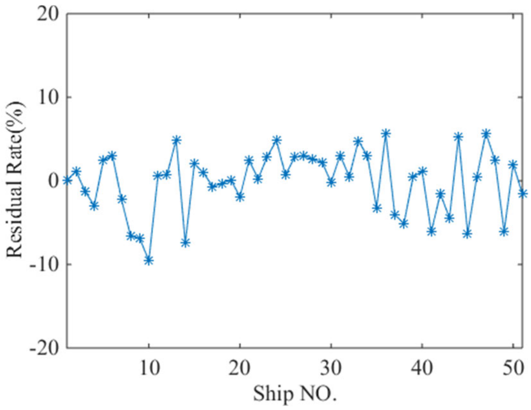
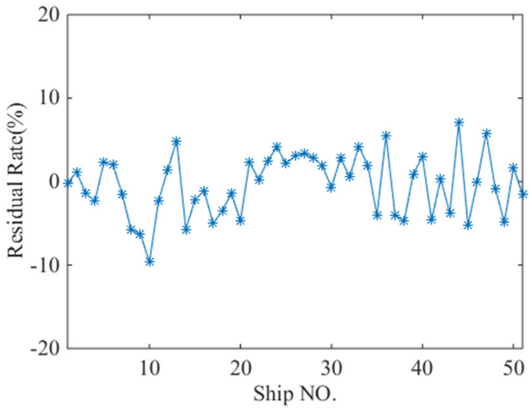
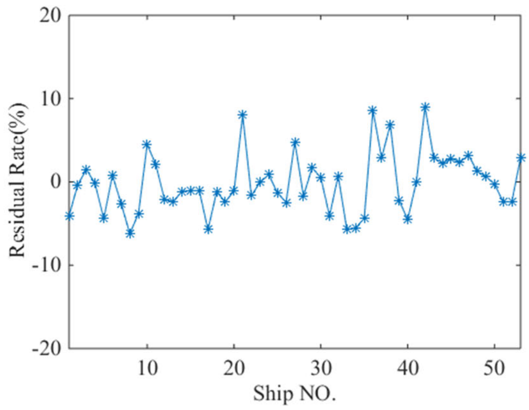
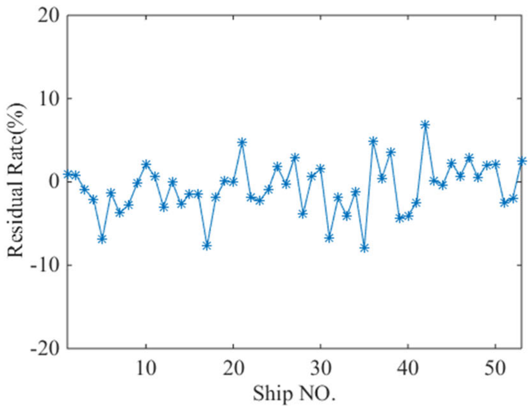




(a) Residual rate of the regression formula (b) Residual rate of the BP neural network model

Figure 7. Comparisons of residuals of service speed of container ships





(a) Residual rate of the regression formula (b) Residual rate of the BP neural network model

Figure 8. Comparisons of residuals of service speed of bulk carriers

The residuals were statistically analyzed, and the results are summarized in Table 2.

Table 2. Comparison of Statistical Remainder Values

Type	Average value (%)		Variance		Maximum value (%)	
	RF	BP	RF	BP	RF	BP
Oil tankers	3.3435	3.0398	4.7285	4.2758	8.5079	8.2098
Container ships	2.9579	3.1458	5.2448	4.1911	9.5595	9.0925
Bulk carriers	2.8228	2.4144	4.8923	4.0750	8.9916	7.9333

RF: Regression formula

BP: BP neural network

As shown in Table 2, the average residuals for both estimation methods using the neural network model trained on actual ship data are below 5%, outperforming the regression formula results. This demonstrates that the BP neural network is an effective approach for estimating ship service speed. To further compare the performance of the two methods, the relative differences in residual statistics between the BP neural network model and the regression equation were calculated, with the results presented in Table 3.

Table 3. The advantage of BP Neural Network computing model compared with regression formula

Type	Average value reduction (%)	Variance value reduction (%)	Maximum value reduction (%)
Oil tankers	-9.0833	-9.5739	-3.5038
Container ships	+6.3525	-20.0904	-4.8852
Bulk carriers	-14.4679	-16.7058	-11.7699

Based on the results presented in Tables 2 and 3, the regression formula and the BP neural network estimation model can be evaluated as follows:

(1) In terms of mean residual values, the BP neural network model provides more accurate estimates for oil tankers and bulk carriers. For container ships, although the regression formula achieves slightly lower estimation errors, the difference between the two methods is negligible. Overall, the BP neural network demonstrates superior estimation accuracy.

(2) Regarding estimation stability, the residuals from the BP neural network model exhibit greater consistency compared to those from the regression formula.

(3) Considering both mean and maximum residual values, the BP neural network model not only achieves higher accuracy but also offers a more stable estimation performance, with a higher likelihood of producing lower maximum residuals than the regression formula.

(4) While the regression formula performs slightly less effectively than the BP neural network model, its residual analysis confirms that it remains a valid and effective method for estimating ship service speed in the absence of a neural network approach.

5. CONCLUSION

The verification of the Katsoulis formula revealed that the ship data used for its regression was outdated, resulting in calculation accuracy that no longer meets current research requirements. To address this, a substantial dataset of modern ship data was collected, and a widely used BP neural network was employed to develop a new ship service speed estimation model. To evaluate this model, regression formulas for the three ship types were re-derived using the same data in the form of the Katsoulis formula.

Comparison of the results indicates that the BP neural network model achieves slightly higher accuracy and greater estimation stability than the regression formulas. Consequently, the proposed BP neural network model provides more precise service speed estimates and offers robust support for related ship transportation calculations.

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