**Prediction of Main Engine Speed and Fuel Consumption of Inland Ships Based on Deep Learning**

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**Abstract.** The accurate fuel consumption forecasting system is for shipping companies to carry out fuel management more effectively in order to improve economic benefits. This article aims to use deep learning algorithms to improve the accuracy of ship engine speed and fuel consumption prediction. First, the main factors affecting the engine speed and fuel consumption of inland watercrafts are analyzed, and the input parameters of the neural network model are determined. Secondly, based on the dynamic time series characteristics of inland water vessels, the LSTM (Long short-term memory) algorithm with “time parameters” was selected to establish a neural network prediction model. Finally, the difference between the LSTM deep neural network model and the traditional machine learning model is compared, and the obtained prediction data is compared with the actual data. The experimental results show the superiority of deep learning in the prediction of main engine speed and fuel consumption of inland watercraft.

**Keywords.** Deep learning; LSTM; fuel consumption prediction.

1. **Introduction**

At present, many studies have been carried out on the prediction of fuel consumption and engine speed of aircraft and vehicles [1-2]. However, research on ships in this area is still in its infancy. The reason is that the overall system of ships is too large, especially ocean-going ships, which are more like a “sea city” compared to transportation tools such as airplanes and vehicles, and their fuel consumption and main engine speed change daily are not large. So more research is focused on energy efficiency optimization. However, research has found that inland watercrafts are similar to aircraft and vehicles to a certain extent. First, the road conditions in the inland river basin are relatively complicated, especially the “nine bends and eighteen bends” in the Yangtze River basin, which require higher ship maneuvering accuracy, so there is a certain demand for speed prediction; second, the travel time of inland river ships is much lower each time. For ocean-going ships, most of them are concentrated between 3-10 days, and the route is relatively fixed, carrying too much fuel to increase the transportation burden, so there is a certain demand for fuel consumption forecast. Good predictions are easier to apply and test. At the same time, good prediction is not only the basis of energy efficiency optimization, but also has a good auxiliary role for shipping company management and captain decision-making. It is a research work that should not be ignored.

Scholars at home and abroad have been using different methods to conduct research. Liu [3] took an inland water diesel dual-fuel container ship as the research object. On the basis of calculating the static water resistance of the ship and the additional resistance of the navigable environment, he established a Simulink-based energy efficiency model of the ship’s main engine based on the principle
of ship-machine-propeller matching. This research method is called the "white box model". Due to the high requirements for simulation and the lack of actual test data, it is quite different from the actual ship data. Leifsson [4] used the gray box method to simulate ocean ships. The research combines the traditional analysis model (white box model) based on physical principles with the feedforward neural network (black box model). The results show that, compared with the white box model, both the serial and parallel gray box modeling methods can significantly improve the prediction of ship fuel consumption. BalBes [5] used ANN (Artificial Neural Network) to predict ship fuel consumption. The study concluded that the artificial neural network can accurately understand the relationship between input variables and ship fuel consumption. Rudzki [6] developed a decision-making system to support the operator of a controllable pitch propeller ship to select the best command output (command engine speed and pitch ratio). They merged two ANN functional models in the multi-objective optimization model to estimate fuel consumption and speed. Yuan [7] developed the GP (Gaussian Processes) meta-model, which can simply predict the fuel consumption of a ship, thereby assessing the impact of operating variables and weather variables on the energy efficiency of the ship. Coraddu [8] used the data measured by the shipboard automation system to study the problem of predicting fuel consumption in actual operations and providing the best value for the trim of the ship. Three alternative modeling strategies are compared: white box model, black box model and gray box model. The study also concluded that the superiority of the black box model based on a series of historical observations surpasses the latest numerical model or white box model that uses system physics knowledge in work tasks.

This article uses deep learning technology to obtain a total of 30,000 real-time data (fuel consumption, load, ship speed, rotation speed, water depth, water flow speed, wind speed, etc.) of the “Juhang 777” in the Shituo-Zhenjiang basin of the Yangtze River in Chongqing for 5 months. In the process, the characteristic parameters of the ship's operating conditions that have an impact on the fuel consumption and the engine speed are extracted, and a data-driven forecast model of the ship's engine speed and fuel consumption is established based on the characteristic parameters.

2. Data Acquisition and Preprocessing

2.1. Real-Time Operating Status Data Collection

In terms of data collection, the relevant parameters for installing sensors on the ship to record the operating status of the ship in real time include operating time T, main engine speed N, stern shaft speed Ni, deadweight W, fuel tank level LI, wind speed Va, wind direction Da, and river velocity Vr, river depth h, GPS information (longitude LONG, latitude LAT), etc. The original data is recorded every 10 seconds, and the amount of data is too large, and it is converted into an average value per minute and stored, a total of 190,000 records. The data format is shown in table 1.

2.2. Data Preprocessing

In the data preprocessing stage, the GPS, time, and liquid level information are substituted into the calculation program written in Python to obtain the displacement S, speed V and fuel consumption F corresponding to the time. Since only running time data is needed, data that is not running time and data that does not meet the actual situation are eliminated, and the data quality is improved to prepare for subsequent modeling. Due to the fluctuation of the differential pressure level gauge, the data is finally integrated in units of half an hour to reduce the error. At the same time, bad data such as refueling, parking, and excessive liquid level fluctuations are eliminated. The data format is shown in table 2.

For neural networks, if the input dimension of the system is too large, there will be a gradient explosion phenomenon; if the input dimension is too small, the model will be prone to overfitting. Therefore, it is necessary to select parameters with high correlation and appropriate input dimensions [9]. We can use the Spearman Rank Correlation method to correlate higher parameters with ship speed and fuel consumption. The final parameters are deadweight W, River velocity Vr, River depth h, Tail
shaft speed $N_i$, Ship speed $V$, when predicting fuel consumption (Fuel consumption) When $F$, the engine speed $N$ is added as input, and when the engine speed $N$ is predicted, fuel consumption $F$ is added as input.

Table 1. Format of collected data.

| Number | $T$ (s) | $N$ (r/min) | $n_i$ (r/min) | $W$ (t) | Li1 | Li2 | gps_long | gps_lat | $V_a$ (m/s) | $D_a$ (°) | $V_r$ (m/s) | $h$ (m) |
|--------|---------|-------------|---------------|---------|-----|-----|----------|---------|-------------|---------|------------|-------|
| 1      | 2020-06-01 00:00:00 | 0 | 0 | 0 | 220 | 951.3333 | 117.107165 | 30.49336433 | 2.97 | 131.1220.833125 |
| 2      | 2020-06-01 00:01:00 | 0 | 0 | 0 | 219.6667 | 951.3333 | 117.10717 | 30.49336867 | 2.6433 | 138.2610.833125 |
| ...    | 2020-10-12 23:59:00 | 355.6 | 100 | 5829479.6667 | 665.6667 | 108.1222357 | 30.30288933 | 4.05667 | 726256.245.3670.8 | 4.5 |

Table 2. Format of pre-processed data.

| Number | $T$ (s) | $N$ (r/min) | $W$ (t) | $V$ (km/h) | $F$ (kg/o.5h) | $S$ (km) | $R$ (m) | $V_a$ (m/s) | $D_a$ (°) | $V_r$ (m/s) | $h$ (m) |
|--------|---------|-------------|---------|------------|--------------|---------|--------|-------------|---------|------------|-------|
| 1      | 2020/06/09 02:00:00 | 550.82 | 5867 | 8.18 | 44.71 | 4.14 | 1050 | 2.32417 | 131.1220.833125 |
| 2      | 2020/06/09 02:30:00 | 550.65 | 5867 | 9.81 | 40.64 | 4.91 | 1050 | 2.4865 | 138.2610.833125 |
| ...    | 2020/10/08 15:30:00 | 452.95 | 5829 | 6.75 | 39.48 | 3.37 | 1000 | 7.26256 | 245.3670.8 | 4.5 |

3. Establishment of Neural Network Model

3.1. Establishment of LSTM Neural Network Model

Since the navigation time and route of the inland watercraft are relatively fixed, the data shows a certain law in the time series. After searching in the deep neural network model, the LSTM neural network is selected to build the model. LSTM is a variant of RNN (Recurrent Neural Network). Because the gradient of the RNN structure is continuously multiplied during the direction propagation process, the value is either getting larger or smaller, so that the gradient disappears or the gradient explodes during the training process, so RNN is often used to train the data. The long model does not get the expected effect [10].

Compared with RNN, LSTM neurons are still calculated based on the input and the output of the upper hidden layer, the external structure has not changed, and the internal structure has added input gate $i$, forget gate $f$, output gate $o$ and internal memory Unit $c$.

- Input gate $i$: Control the extent to which the input $X$ and the current calculated state are updated to the memory unit;
- Forgetting gate $f$: Controls the degree to which the input $X$ and the output $h$ of the upper hidden layer are forgotten;
- Output gate $o$: The control input $X$ and the current output depend on the degree of the current memory unit.

And when there is no useful information in the input sequence, the value of the forget gate $f$ will be close to 1, and the value of the input gate $i$ will be close to 0, so that the useful information in the past will be saved. When there is important information in the input sequence, the value of the forgetting gate $f$ will be close to 0, and the value of the input gate $i$ will be close to 1 [11]. At this time, the LSTM model forgets past memories and records important memories. This solves the problem that RNN cannot learn too long sequences when the data is too large.
This article uses Python code and the deep learning framework Tensorflow to build an LSTM neural network (figure 1), learns the preprocessed data, and determines the neural network parameters and weights, choosing minibatch Size = 27 for dividing the training data evenly, and reducing the amount of minibatch Size filling, input Size=7, numHiddenUnits = 100, Learning rate = 0.01. 80% of the data is used as the training set for training the deep neural network, and 20% of the data is used as the test set for testing the prediction accuracy of the model.

3.2. Establishment of BP Neural Network Model
BP (Back Propagation) neural network neural network adopts the learning rules of the steepest descent method, and continuously adjusts the weights and thresholds of the network through back propagation, so that the error square of the network is minimized. This article uses Matlab to model the BP neural network, Transfer function is sigmoid, input Size=7, Hide Layer=6, Using 70% of the data as the training set, 15% as the validation set, and 15% as the test set.

4. Comparison of Forecast Results
300 sets of data are selected from the test set to compare the results of the shallow neuron network and the deep neuron network. The comparison chart of the host speed prediction results is as follows:

![Figure 2. Comparison of main engine speed prediction results (a) LSTM model, (b) BP model.](image)

The comparison chart of fuel consumption forecast and engine speed forecast is as follows:
Figure 3. Comparison of fuel consumption prediction results: (a) LSTM model, (b) BP model.

Table 3. Comparison of algorithm relative error.

|                        | Average relative error (%) | LSTM   | BP    |
|------------------------|-----------------------------|--------|-------|
| fuel consumption forecast | 3.1805                      | 7.5380 |       |
| Prediction of main engine speed | 1.2779                      | 3.8858 |       |

From figures 2, 3 and table 3, it can be seen that LSTM is stronger than BP in fuel consumption prediction and engine speed prediction, and the average relative error of fuel consumption prediction and speed prediction is reduced by 57.8% and 67.1%, respectively, which is a significant improvement. The above results show that, for inland water vessels, the LSTM deep neural network is more suitable for prediction of fuel consumption and engine speed.

5. Conclusion
This article analyzes the application of deep learning in airplanes and automobiles, finds the potential of inland watercraft in the LSTM deep neuron network, and analyzes the importance of predicting fuel consumption and engine speed. At the same time, through correlation analysis, it finds the relationship between fuel consumption and engine speed. The five factors that have the greatest impact on the speed. Finally, a deep neuron network model is established through the LSTM algorithm. The predicted value is compared with the actual value, and compared with the prediction effect obtained by the BP algorithm. It is found that the LSTM algorithm has better and high-precision effects. The black box model established in this paper based on the deep learning method can be used to predict fuel consumption and main engine speed, which can provide a reference for ship operators, formulate reasonable operating plans, and improve shipping energy efficiency.

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