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Research on Short-Term Motion Prediction of Ore Transport Vessels Based on the LSTM Model

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ABSTRACT: *Environmental factors such as wind, waves, and currents create six degrees of freedom in vessel motion during marine operations, with wave-induced movements posing a challenge to safety and operational efficiency. This study proposes a short-term motion prediction technique for ore transport vessels using a Long Short-term Memory (LSTM)model, aimed at enhancing transfer safety in deep-sea mining operations. The model's performance was evaluated by analyzing the impact of vector order, neuron count, and optimizer type on prediction accuracy. Simulation results indicate that the optimal parameter configuration—balancing prediction accuracy and training costs—includes a vector order of 240, 128 neurons, and the Adam optimizer.*
KEYWORDS - *LSTM, neural network, Ore Transport Vessels，short-term motion prediction*

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I.INTRODUCTION

With the rapid growth of the global economy, demand for mineral resources has surged, intensifying resource extraction and depleting terrestrial supplies. Marine mineral resources now offer a critical foundation for sustainable development. Deep-sea polymetallic nodules contain metals such as manganese, copper, cobalt, and nickel, with reserves estimated to be 200, 40, 129, and 328 times greater, respectively, than terrestrial sources. These high-grade deposits are vital for industrial production and defense applications. Consequently, the abundant mineral resources on the deep-sea floor have garnered global attention as strategic assets with substantial commercial potential, making deep-sea mining technology a priority research focus worldwide.

Deep-sea mining operations rely on mining vessels and ore transport ships, with the latter frequently traveling between ports and the mining base vessel. Ensuring the stability and safety of these vessels is critical to mining success. Therefore, studying short-term motion prediction techniques for ore transport vessels is essential for understanding motion patterns and forecasting near-future movements. Such research supports improved operational decision-making, safety, and efficiency.

According to the differences in modeling methods, the time series prediction methods for ship motion can mainly be divided into traditional time series prediction methods and machine learning prediction methods. Among them, traditional time series prediction methods mainly model and predict the time series data of ship motion by using statistical and mathematical models, such as the Auto-regressive (AR) model[1,2], the Auto-regressive Moving Average (ARMA) model, etc[3]. The AR model has been widely applied in the field of ship motion prediction due to its simple algorithm and strong adaptability[4-6]. However, the ship's rolling motion response system in waves belongs to a typical nonlinear system. The construction of traditional time series prediction models often relies on linear theory. Therefore, when predicting the ship motion under medium and high sea conditions, there will be problems such as a short predictable time span and low prediction accuracy. As a data-driven method as well, the machine learning method can realize the fitting of a nonlinear system by adding nonlinear mapping units during the process of constructing a neural network model, and it has shown good application effects in the field of ship and ocean engineering[7,8].

The machine learning method mainly extracts data features through the training and learning of a large amount of data, and then constructs the mapping relationship between the historical time series and the future time series to achieve the prediction task. According to the complexity of the feature extraction model, it can be divided into shallow machine learning prediction methods and deep learning prediction methods. In the application of shallow machine learning methods, Li proposed a ship motion prediction method based on the

Support Vector Regression (SVR) model, and verified the prediction accuracy of the model by comparing the prediction results of the heaving motion under multiple wave directions[9]. Wang carried out a time series prediction study on the ship's rolling motion based on the internal regression neural network[10]. In addition, methods such as the Artificial Neural Network (ANN) and the Radial Basis Function (RBF) neural network have all been successfully applied to the extremely short-term prediction of ship motion[11,12]. However, the prediction effect of the initial shallow machine learning methods is often limited by the network structure, and it is unable to extract deep-level data features. Until 2006, Hition first proposed the concept of deep learning, marking the emergence of deep learning methods with more complex network structures and stronger nonlinear fitting capabilities, which gradually became the main research direction in the field of ship motion prediction[13]. In deep learning methods, a variety of neural network structures have been designed for sequence prediction tasks. Among them, the Recurrent Neural Network (RNN) enables the model to have a better prediction effect when conducting long-term predictions by introducing the concept of time memory, and it has a wide range of application scenarios. And it has gradually evolved to include the Long Short-term Memory (LSTM) neural network, the Gated Recurrent Unit (GRU) model, etc. In terms of the extremely short-term prediction of ship motion, many scholars have optimized the model structure to adapt to the time series characteristics of ship motion[14-16].

This study utilizes an LSTM model to conduct short-term motion prediction for ore transport vessels, analyzing the impact of vector order, neuron count, and optimizer type on prediction accuracy.

II.SHORT-TERM MOTION PREDICTION PRINCIPLE FOR ORE TRANSPORT VESSELS USING AN LSTM MODEL

Unlike traditional feedforward neural networks, the LSTM neural network is derived from the Recurrent Neural Network (RNN) model and is commonly used for processing sequential data. The primary feature of RNNs is their ability to incorporate the concept of time through neuron self-looping. Essentially, RNNs expand along the time axis to capture recurring patterns in sequential data, achieved by parameter sharing. Unlike feedforward networks, which treat each input as an independent feature, RNNs group inputs as features that connect sequentially along the time axis and compress them into a single neuron through repeated cycles. This unique structure gives RNNs a “memory” capability, allowing the output to be influenced by both current input and past states.

The iterative formula clearly demonstrates how data flows through recurrent neurons and how memory is retained within them, as shown in the following equation:

$$s^{(t)} = f(s^{(t-1)}; W) \quad (1)$$

In the equation, $s^{(t)}$ represents the system state. The state value s at time t depends on the previous state at t-1, which clearly shows that Equation (1) is recursive. For a finite number of steps a, repeating this equation a-1 times completes the process. Assuming a=3, the expanded form of the equation is as follows:

$$s^{(3)} = f(s^{(2)}; W) = f(f(s^{(1)}; W); W) \quad (2)$$

The following steps are typically required to build an LSTM model for time series prediction:

1. Data Preprocessing: Convert the time series data into a supervised learning dataset. This typically involves formatting the data for LSTM input, such as using a sliding window approach to create multiple input-output sequence pairs.

2. Model Construction: Define the structure of the LSTM model, including the input layer, hidden layers (LSTM layers), and output layer. Model parameters include input dimensions, the number of neurons in hidden layers, and the number of LSTM layers.

3. Model Training: Train the LSTM model using the training dataset. During training, the model learns the relationship between inputs and outputs, adjusting its weights to minimize prediction error.

4. Model Evaluation and Prediction: Evaluate the model's performance using the test dataset and perform future time-point predictions. During prediction, the model's output can be fed back as new input to generate continuous predictions for multiple future time points.

III.RESULTS AND ANALYSIS

3.1 Research Subjects and Environmental Parameters

The principal dimensions of the ore transport vessel are shown in Table 1.

Table 1. Principal dimensions of the Ore Transport Vessel

Item	Unit	Value
Overall Length L	m	216.40
Length between perpendiculars L_{BP}	m	212.8
Breadth B	m	39.20
Depth H	m	21.40
Design draft T_d	m	12.06
Transverse radius of gyration K_{xx}	m	13.26
Longitudinal radius of gyration K_{yy}	m	53.19
Vertical radius of gyration K_{zz}	m	55.32

The lines plan of the ore transport vessel are shown in Figure 1.

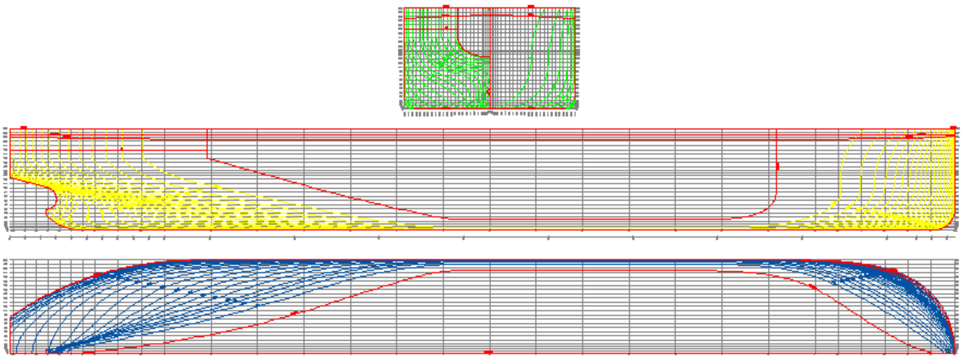

Fig.1. Lines Plan of the Ore Transport Vessel

During transfer operations, the ore transport vessel encounters sea conditions with a significant wave height of 4 m, a characteristic period of 8.3 s, head-oblique wave conditions with a wave angle of 135°, and a speed of 15 knots.

3.2 Analysis of Influencing Factors

3.2.1 Impact of Vector Order on Prediction Accuracy

The different input vector orders of LSTM neural networks can also affect the performance and training process of the model. Theoretically, the fitting effect will be better with the increase of the input vector order, but in practice, the increase of the input vector order will also increase the risk of model overfitting, especially when the training data is insufficient, the model may be too complex to generalize well to new data; the network usually needs to deal with a large number of high-power terms and cross terms, resulting in increased computational complexity of the network, and the network requires more computing resources and time for training and inference; the generalization ability of the model is reduced, especially when the training data volume is small or the data quality is poor. Excessive features may cause the model to be too sensitive to noise, thus affecting the performance of the model on new data.

This section explores the impact of different input vector orders on the prediction accuracy for ore transport vessel motion. The time step for input data is 0.5 seconds, so an input length of 120 corresponds to a 60-second input duration, with a forecast duration set to 10 seconds. The results for each degree of freedom are shown in Figures 2～4.

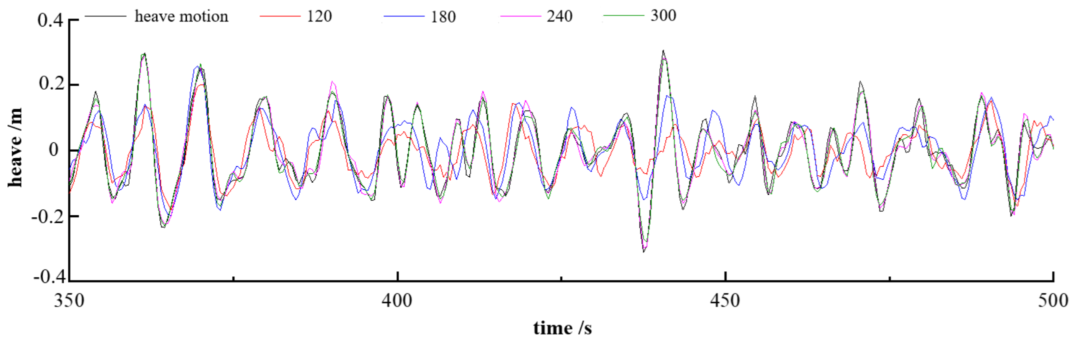

Fig.2. Comparison of Predicted Heave Motion of Ore Transport Vessel with Different Input Vector Orders

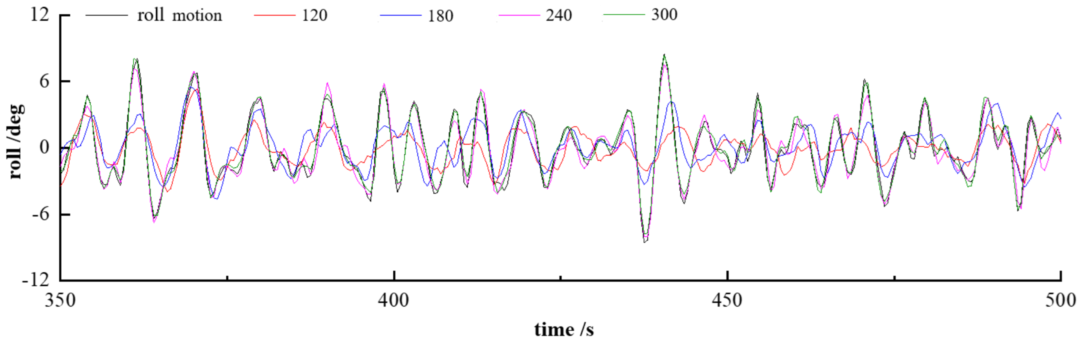

Fig.3. Comparison of Predicted Roll Motion of Ore Transport Vessel with Different Input Vector Orders

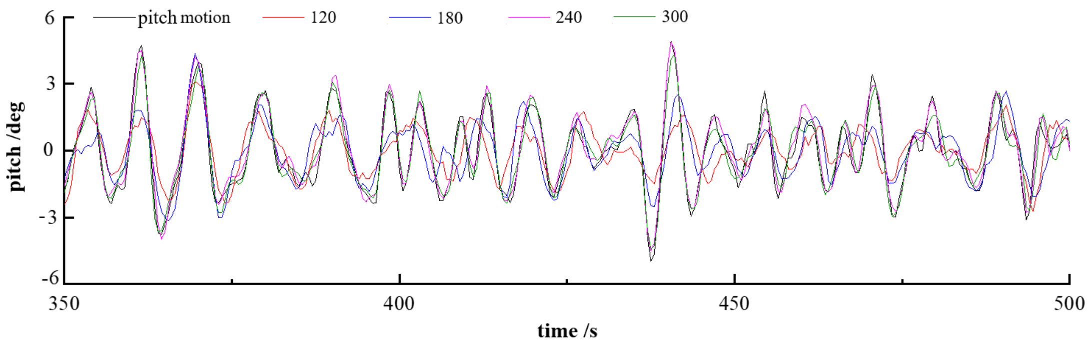

Fig.4. Comparison of Predicted Pitch Motion of Ore Transport Vessel with Different Input Vector Orders

Table 2. Impact of Different Input Vector Orders on Prediction Results (Root Mean Square Error, RMSE)

Input Vector Order	Heave	Roll	Pitch	Average
120	0.4142	1.3758	1.4410	1.0770
180	0.3929	1.2616	1.3226	0.9924
240	0.1637	0.5219	0.5608	0.4155
300	0.1559	0.3687	0.5834	0.3693

Table 3: Forecast Errors (Relative Errors) for Different Orders of Input Vectors

Input Vector Order	Heave	Roll	Pitch	Average
120	10.21%	12.05%	11.09%	11.12%
180	9.68%	11.05%	10.18%	10.31%
240	4.04%	4.57%	4.32%	4.31%
300	3.84%	3.23%	4.49%	3.85%

Tables 2 and 3 present the prediction errors for different input vector orders, showing a notable variation in how well predictions match the actual motion of the ore transport vessel. The general trend indicates that prediction error decreases as input vector order increases. When the input vector order is set to 120 or 180, prediction error remains relatively high, failing to accurately capture the motion trend. However, at an input vector order of 240, prediction error significantly decreases, reducing from around 10% (at 180) to approximately 4%. Further increasing the input vector order to 300 provides only marginal improvements in accuracy, while increasing the complexity and cost of model training, and even causing a slight decrease in prediction accuracy for pitch motion. Therefore, for efficient model training, an input vector order of 240 is recommended.

3.2.2 Impact of Neuron Count on Prediction Results

The neuron structure within an LSTM neural network is a key parameter affecting model training performance. Using too few neurons leads to underfitting, while an excessive number of neurons can cause overfitting, as the limited information in the training set may be insufficient to effectively train all neurons in the hidden layers. Even with ample training data, too many neurons in the hidden layers increase training time and may prevent the model from achieving optimal performance. Therefore, selecting an appropriate neuron count is crucial.

This section examines the impact of varying neuron counts on the prediction accuracy of ore transport vessel motion. The input duration is set to 120 seconds of historical data, with a forecast duration of 10 seconds. Results for each degree of freedom are shown in Figures 5–7.

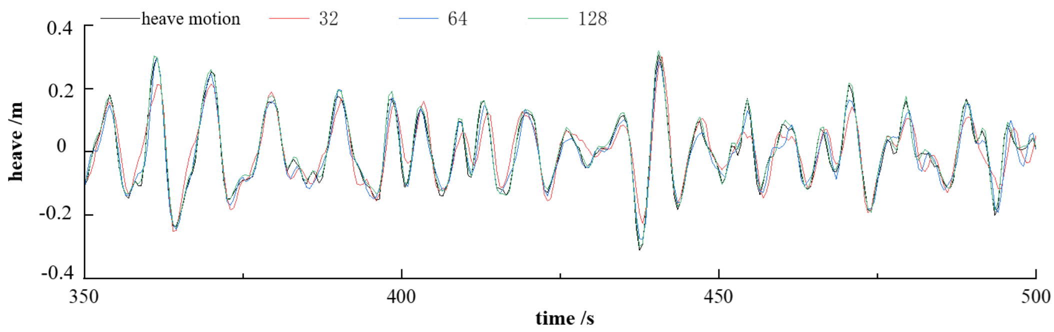

Fig.5. Comparison of Predicted Heave Motion of Ore Transport Vessel with Different Neuron Counts

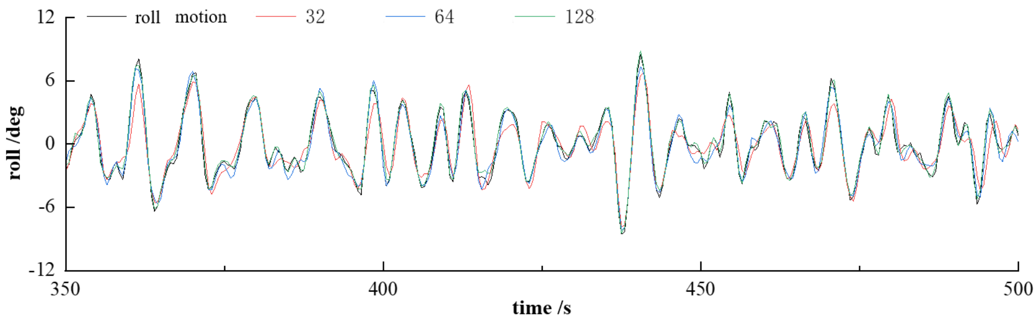

Fig.6. Comparison of Predicted Roll Motion of Ore Transport Vessel with Different Neuron Counts

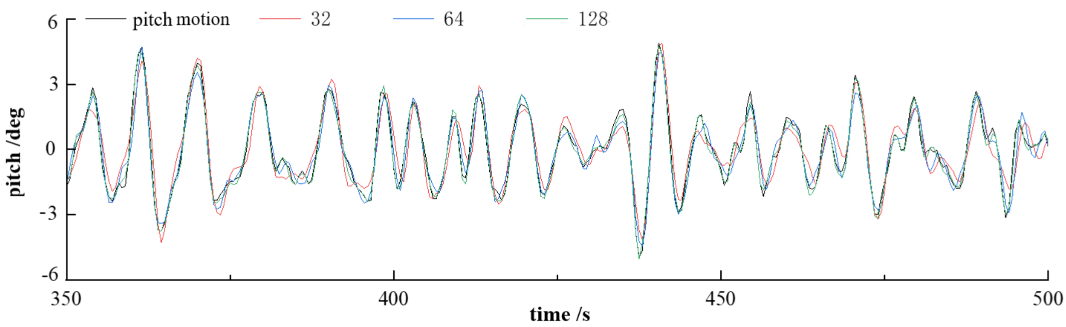

Fig.7. Comparison of Predicted Pitch Motion of Ore Transport Vessel with Different Neuron Counts

Table 4. Impact of Different Neuron Counts on Prediction Results (Root Mean Square Error, RMSE)

Neuron Count	Heave	Roll	Pitch	Average
32	0.2559	0.7136	0.8350	0.6015
64	0.1766	0.5333	0.6460	0.4520
128	0.1104	0.3936	0.4306	0.3115

Table 5. Prediction Errors with Different Neuron Counts (Relative Error)

Neuron Count	Heave	Roll	Pitch	Average
32	6.31%	6.25%	6.43%	6.33%
64	4.35%	4.67%	4.97%	4.66%
128	2.72%	3.45%	3.32%	3.16%

Based on the data in Tables 4 and 5, comparing models with 64 and 32 neurons shows an approximate 25% reduction in error. When the neuron count is increased to 128, the error reduction reaches around 33%. This indicates that model prediction performance improves significantly with a higher neuron count. Although the training cost with 128 neurons is higher than with 64 or 32, the improvement in prediction accuracy is substantial. Considering the characteristics of neural network models, setting the neuron count as a power of 2 enhances training efficiency. Additionally, the neuron count should not exceed the input length, making 128 neurons the optimal choice.

3.2.3Neural Network Optimizer

The basic principles of deep learning require the model to continuously update its weights during training to approximate the target. The choice of optimizer determines how the network updates its weights. Common optimizers include SGD, RMSprop, and Adam. SGD, or Stochastic Gradient Descent, is the most basic form of gradient descent, with its weight update method as follows:

$$w = w - \eta \cdot \nabla_w J\left(w; x^{(i)}; y^{(i)}\right) \tag{3}$$

In each epoch, SGD performs a gradient update for each sample, with the gradient direction opposite to the derivative of the loss function. Due to frequent updates, SGD can cause significant oscillations in the loss function. With a high learning rate, this oscillation might push the model out of a local minimum. However, when encountering a "ravine" on the loss surface (a direction much steeper than others), SGD tends to oscillate, making it difficult to converge to an optimal point. Additionally, using the same learning rate for all parameters hampers control over convergence and can lead the model to become trapped at saddle points.

RMSprop, an improved version of the Adagrad algorithm proposed by Geoff Hinton, incorporates momentum to prioritize adjustments to low-frequency parameters. This accelerates SGD and reduces oscillations, making it particularly effective for sparse data. The weight update method for RMSprop is as follows:

$$g_t = \nabla_w J(w; x^{(i)}; y^{(i)}) \tag{4}$$

$$E[g^2]_t = 0.9E[g^2]_{t-1} + 0.1g_t^2 \tag{5}$$

$$w_{t+1} = w_t - \eta \frac{g_t}{\sqrt{E[g^2]_t + \varepsilon}} \tag{6}$$

RMSprop incorporates an exponentially decaying average of the squared past gradients into its weight updates, allowing the optimizer to achieve an adaptive learning rate. This enables high-frequency and low-frequency parameters to be updated at different speeds during training.

Similar to RMSprop, Adam is an optimization method with an adaptive learning rate for each parameter. However, unlike RMSprop, Adam not only keeps an exponentially decaying average of the squared past gradients (vt) but also incorporates an exponentially decaying average of past gradients (mt), where:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\, g_t \tag{7}$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)\, g_t^2 \tag{8}$$

To prevent mt and vt from being initialized as zero vectors, bias correction is applied. The corrected values of mt and vt are as follows:

$$m_t = \frac{m_t}{1-\beta_1^t} \quad (9)$$

$$v_t = \frac{v_t}{1-\beta_2^t} \quad (10)$$

The gradient update rule for Adam is:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{v_t + \varepsilon}} \quad m_t \quad (11)$$

This section examines the impact of different optimizers on the prediction accuracy of ore transport vessel motion. Results for each degree of freedom are shown in Figures 8～10.

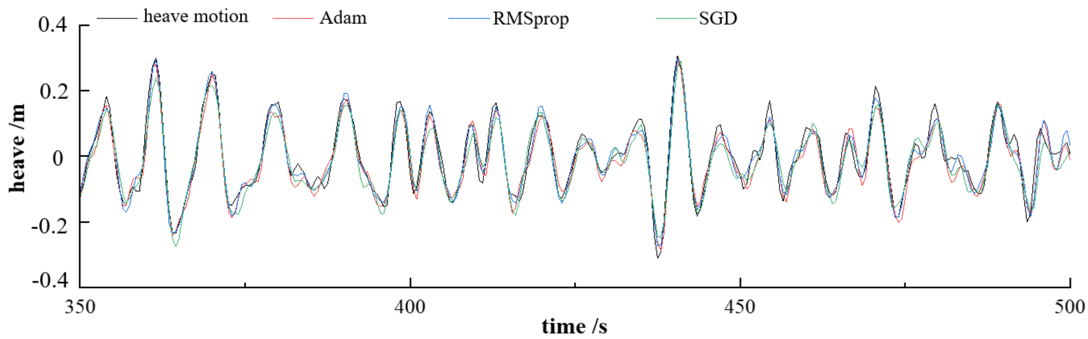

Fig. 8. Comparison of Predicted Heave Motion of Ore Transport Vessel with Different Optimizers

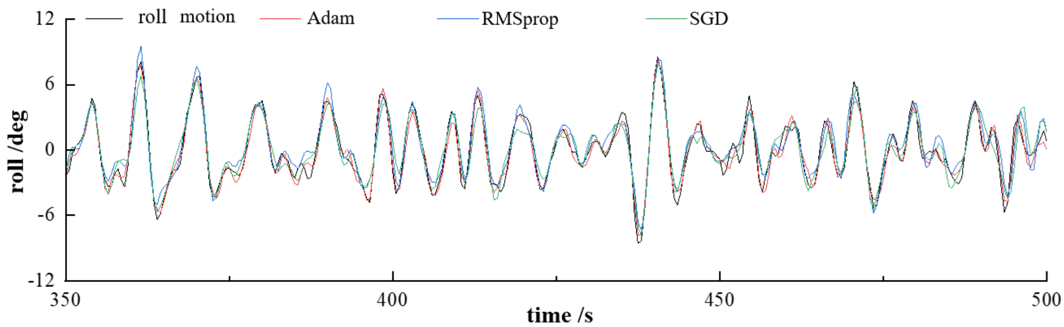

Fig.9. Comparison of Predicted Roll Motion of Ore Transport Vessel with Different Optimizers

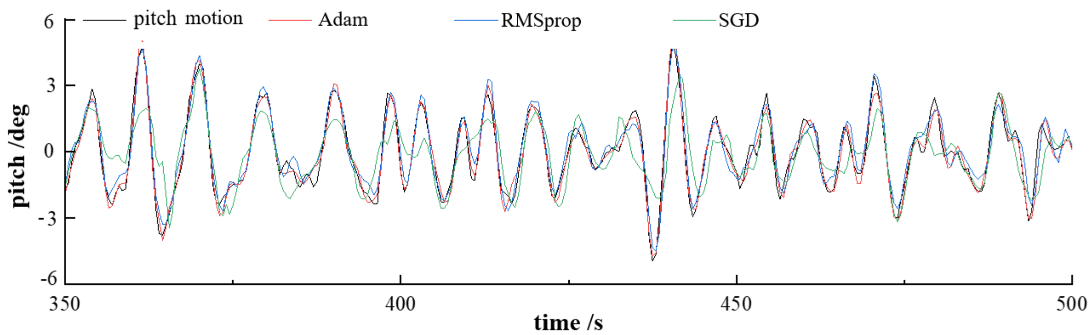

Fig.10. Comparison of Predicted Pitch Motion of Ore Transport Vessel with Different Optimizers

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Table 6. Impact of Different Optimizers on Prediction Results (Root Mean Square Error, RMSE)

Optimizer	Heave	Roll	Pitch	Average
Adam	0.2001	0.5554	0.5880	0.4478
RMSprop	0.1960	0.6938	0.7571	0.5490
SGD	0.2489	0.7708	1.2412	0.7536

Table 7. Prediction Errors with Different Optimizers (Relative Error)

Optimizer	Heave	Roll	Pitch	Average
Adam	4.93%	4.87%	4.53%	4.77%
RMSprop	4.83%	6.08%	5.83%	5.58%
SGD	6.13%	6.75%	9.56%	7.48%

Tables 6 and 7 present the prediction errors with different optimizers. Among the three degrees of freedom, each optimizer yields relatively good prediction results; however, Adam performs the best, SGD the worst, with RMSprop in between. This occurs because an LSTM model using SGD often converges at a saddle point. While RMSprop provides an adaptive learning rate through an exponentially decaying average of squared past gradients, it still does not outperform Adam. Therefore, Adam is recommended as the optimal optimizer.

IV.CONCLUSION

This paper developed a data-driven LSTM prediction model for the short-term motion forecasting of ore transport vessels. Using simulated data, the model was trained and optimized to achieve high-precision, rapid predictions of the vessel's heave, roll, and pitch motion during transfer operations. The study analyzed the influence of LSTM model parameters on prediction accuracy, leading to the following conclusions:

1.Comparative analysis of the three degrees of freedom prediction results under various LSTM model parameters indicates that, in terms of RMSE and relative error, input vector orders of 240 and 300 are significantly more accurate than 120 and 180. Considering training time costs, an input vector order of 240 is preferred as the optimal choice.

2.The impact of neuron structure and optimizer choice is relatively minor, and their effect on training costs is less significant than that of the input vector order.

3.Considering prediction accuracy and training costs across all three degrees of freedom, the optimal parameter configuration for the model includes an input vector order of 240, 128 neurons, and the Adam optimizer.

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