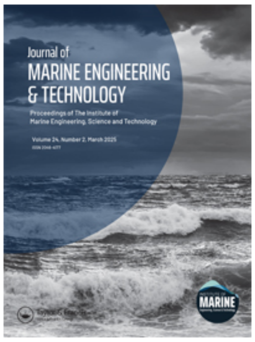

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Multi-factor influence-based ship trajectory prediction analysis via deep learning

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ABSTRACT

The trajectory prediction research based on deep learning methods shows more substantial competitiveness than classical ones in the context of big data analysis methods. However, the relevant literature fails to explain the collective impact of multiple influential factors identified from Automatic Identification System (AIS) data, including latitude, longitude, Course Over Ground (COG), and Speed Over Ground (SOG). To fill in this research gap, six classical deep learning methods are newly employed to conduct ship trajectory prediction, taking into account multiple influential factors for the first time. Two real AIS datasets collected from water areas of high representation are chosen to test and analyse the performance of the six deep learning models against seven indexes. The experimental results reveal that both the traditional factors of longitude and latitude and the newly incorporated ones of SOG and COG play a key role in trajectory prediction. Moreover, the effect of SOG on the accuracy of prediction results is greater than that of COG. Furthermore, the advantages and disadvantages of the six trajectory prediction models revealed by the experimental results provide useful insights into the best-fit method under different circumstances of traffic management involving Maritime Autonomous Surface Ships (MASS).

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1. Introduction

Seaborn trade accounts for approximately 90% of international transportation volume and has become one of the most significant modes of international trade and transport (Hu and Zhu 2009). Meantime, the escalating disruptions in the traffic environment caused by climate change and sea traffic complexities, which encompass significant alterations within specific time frames and water conditions, pose new and unbearable challenges to maritime traffic safety. The associated maritime traffic accidents will undoubtedly bring significant, often intolerable, economic losses, environmental damages, and potential safety hazards (Qin et al. 2022). With the growth and maturity of digitalisation technologies (Xu et al. 2022a), shipping 4.0 (Aiello et al. 2020), and communication technology (Babanli and Ortaç Kabaoğlu 2022), nearly real-time communication based on radar radio equipment has become a reality and is rapidly popularised. Simultaneously, unmanned ships are being fast developed, coming into reality and becoming possible future transportation modes across seas (Du et al. 2022; H. Li and Yang 2023). It brings a crucial research issue to deal with mixed maritime traffic of manned and unmanned ships to ensure ship navigation safety in the maritime field (Cheraghchi et al. 2018; Xin et al. 2023a) given that the current classical ship traffic prediction methods are almost certain not to be infeasible any more. Compared with traditional manipulation experience and human intuition, massive AIS data-driven mining can help provide intelligent decision-making for ships (Li et al. 2020, 2022a), ensuring the safe navigation of manned ships and assisting Maritime Autonomous Surface Ships (MASS) in navigating autonomously (Ali et al. 2015). Among them, ship trajectory prediction is an important method to realise the early warning of risks and prevent ship collision accidents (Perera et al. 2015; Polvara et al. 2018). Therefore, it is necessary to conduct more precise trajectory prediction than ever to assist ship situation awareness and navigation safety (Bai et al. 2021; Li et al. 2023b; Li et al. 2022b; Yang et al. 2021).

The International Maritime Organisation (IMO) stipulates that ships should be equipped with Automatic Identification System (AIS) equipment (Capobianco et al. 2021) to continuously broadcast multiple real-time information, combined with Vessel Traffic Service (VTS) and radar data to realise real-time information exchange. The AIS system can transmit data frequently (every 3–10 s), providing a solid foundation for maritime traffic monitoring (Volkova et al. 2021; Xin et al. 2023b). It has three categories in AIS data: static ship information (e.g. ship name, Maritime Mobile Service Identify (MMSI) number, call sign, IMO number, ship width, ship type, and captain), dynamic ship information (e.g. latitude, longitude, heading, trajectories speed, and direction), and ship voyage information (e.g. ship status, draft, and destination) (Zhang et al. 2018). Among them, dynamic ship information is essential to support all prediction models to locate a ship's future movement.

To tackle the complexity of dynamic ship information, although witnessing the applications of deep learning methods to ship trajectory prediction (Statheros et al. 2008; Huang et al. 2020), the current research still reveals some research challenges that have theoretical

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implications yet to be well-addressed and want new solutions to be found, including:

(1) What types of dynamic information should be included to enhance the accuracy of prediction results?
(2) How to choose the best-fit deep learning models for vessel trajectory prediction under different circumstances in terms of both data size and prediction performance?
(3) How to evaluate the effect of different influential factors individually and collectively in ship trajectory prediction?

Compared to vehicle trajectory prediction, it is more challenging to predict ship trajectories as they are inherently involved with a high level of freedom and uncertainty without any constraint by predefined lanes and are affected by multiple factors. It is even worrisome given the fast development of ship autonomy in recent years. The prediction effectiveness of various deep learning techniques in shipping concerning various influential factors becomes necessary and beneficial for manned ships, autonomous ships and/or their combined traffic. This study delves into trajectory prediction utilising deep learning within the realm of big data analytics. AIS data encompasses various influential factors like longitude, latitude, Speed Over Course (SOG), and Course Over Ground (COG). While these components individually affect trajectory prediction, existing literature lacks clarity on their cumulative impact. By controlling variables, this study shed light on the significance of these factors within a deep learning-based prediction model.

To address the abovementioned issues, the influence of multiple dynamic factors (longitude, latitude, SOG, and COG) on trajectory prediction is explored through a full test of six deep learning methods and their experimental comparison using two real case datasets. The six widely used deep learning prediction models are Long Short-Term Memory (LSTM), Gate Recurrent Unit (GRU), Bi-directional Long Short-Term Memory (Bi-LSTM), Bi-directional Gate Recurrent Unit (Bi-GRU), Sequence to Sequence (Seq2seq), and Transformer. Furthermore, a control variable method is newly proposed to conduct the experiments to quantitatively analyse and explore the impact of different factors on the prediction accuracy of ship trajectories. As a result, the experimental results and findings provide a theoretical foundation and valuable reference to strike a new research dimension of ship trajectory prediction. Historical AIS data from two real water areas are used to compare the influence of multiple factors, verify the performance of different models, and illustrate the viability of the research findings. Finally, this paper uses seven indicators to evaluate the prediction performance of each deep learning method in different cases.

This paper pioneers a holistic approach to ship trajectory prediction by incorporating multiple AIS data factors such as longitude, latitude, SOG, and COG. To gauge the efficacy of the aforementioned six models, two AIS datasets from representative maritime areas were chosen. Seven metrics were employed to examine the models' performance. The findings underscore the pivotal roles of both traditional elements like longitude and latitude and newer variables like SOG and COG in trajectory prediction. The advantages and limitations of the six models are also elucidated, offering valuable perspectives for selecting the optimal technique across varied traffic management contexts, especially within MASS. The new contributions of this paper are presented as follows.

(1) New investigation of the combined effect of four dynamic influential factors (i.e. longitude, latitude, SOG, and COG) on ship trajectory prediction.
(2) Comparative analysis of the six deep learning methods and their performance for ship trajectories under different circumstances.
(3) Comprehensive evaluation of the overall prediction performance across four cases using seven indexes.
(4) Investigation of the generality of the findings using two real case water areas of representative traffic systems.

The structure of this paper is described as follows. Section 2 reviews the research status of ship trajectory prediction. The selected six deep learning prediction methods are described in Section 3 with a focus on their characteristics when being applied for trajectory prediction. Section 4 presents the methodology of this paper, while Section 5 provides the experimental results on real datasets and elaborates on the evaluated impact of different factors on trajectory prediction. Finally, section 6 summarises this work with its limitations and future research directions.

2. Literature review

2.1. A bibliometric analysis

The Web of Science (WoS) database is used to retrieve ship trajectory prediction publications between January 2001 and March 2025 (Li et al. 2021). The following search strategy is set:

Topic 1: 'Ship∗ and trajectory prediction', or.
Topic 2: 'Vessel∗ and trajectory prediction', or.
Topic 3: 'Ship∗ and route prediction', or.
Topic 4: 'Vessel∗ and route prediction', or.

In total, there are 1171 papers found from the initial search using the above strategy. To ensure the high quality and relevance of the results, any book chapters, reports, and case studies are excluded from the search. 641 papers are reserved after the first round of screening. Any articles on vehicles, pedestrians, and aircraft trajectory prediction are also removed to ensure that the focus of papers is restricted to ships. The title, keywords, and abstract are further checked to ensure that the results remain highly relevant to the research issue. Only journal articles related to ship trajectory prediction in the shipping industry are collected and included in our database. The total number of papers is reduced to 281 after the above screening procedures. The introduction, content, method, and conclusion are further reviewed and screened and consequently, 154 papers are finally kept to support the bibliometric analysis (i.e. keywords and topics).

This paper presents a systematic review of 85 carefully selected publications that apply deep learning methods to ship trajectory prediction. A co-occurrence analysis of keywords extracted from these 85 results was conducted using the CiteSpace software, with the results visualised in Figure 1. The figure illustrates the clustering of keywords into six distinct thematic categories, each reflecting a specific research focus within the field of ship trajectory prediction.

Cluster #5 represents the core theme of vessel trajectory prediction, emphasising the application of advanced deep learning models such as LSTM, GRU, and Graph Neural Networks (GNN) to capture complex spatiotemporal patterns in maritime traffic. Cluster #0 highlights the critical role of AIS data in trajectory prediction, particularly the importance of dynamic information such as ship behaviour and AIS trajectories in enhancing prediction accuracy and reliability.

Cluster #2 explores the potential of Deep Reinforcement Learning (DRL) in optimising trajectory prediction, showcasing its adaptability in complex maritime environments through anticipatory collision avoidance and dynamic decision-making. Cluster #3 emphasises practical applications of trajectory prediction in ensuring maritime safety, integrating aspects such as collision risk assessment, collision avoidance strategies, and anticollision technologies.

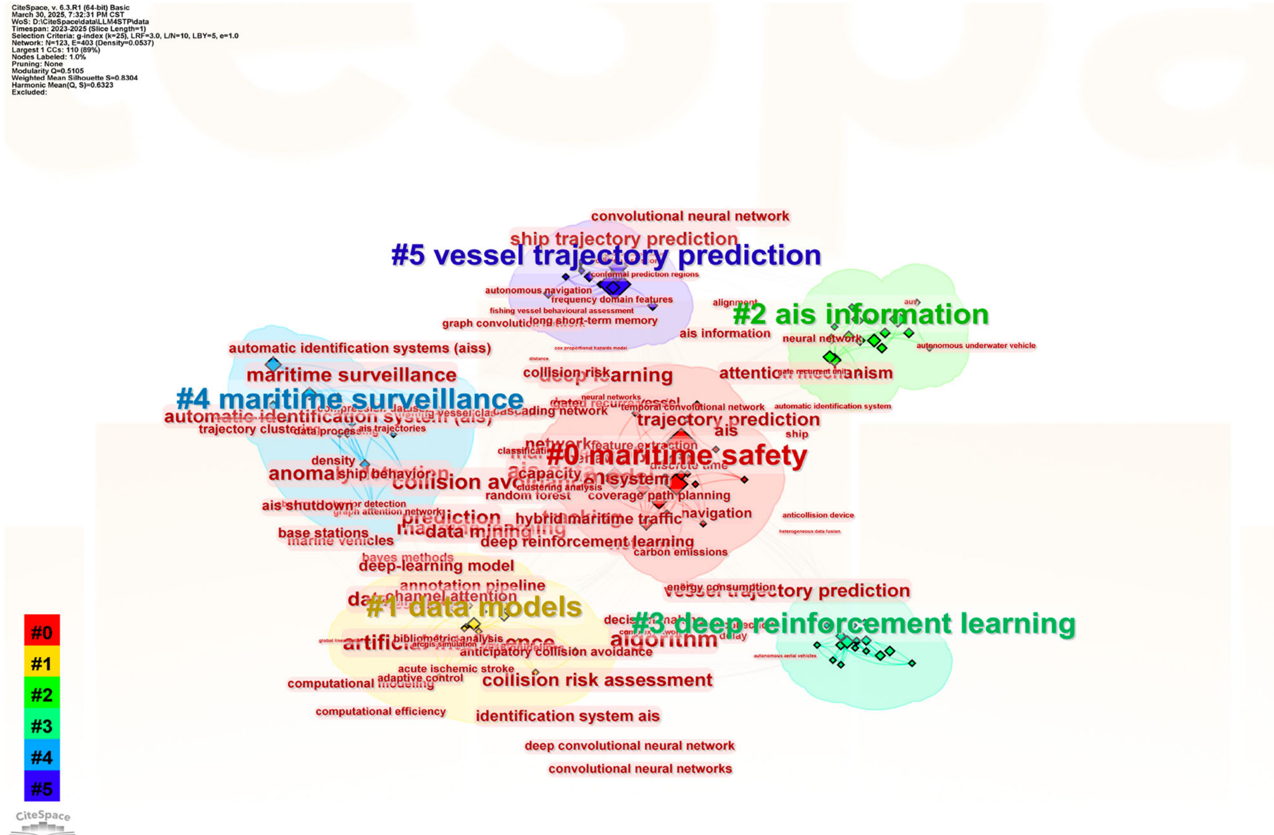


Figure 1. Co-occurrence analysis of keywords in the screened publications from 2021 to 2025.

Cluster #1 highlights the importance of robust data preprocessing and model optimisation, with keywords such as data models, annotation pipelines, and computational modelling reflecting the need for efficient and scalable frameworks to support high-performance prediction. Finally, Cluster #4 connects trajectory prediction to broader maritime surveillance applications, demonstrating its relevance for real-time vessel monitoring and decision-making support for maritime authorities through vessel behaviour analysis and collision risk assessment.

Overall, the analysis reveals a well-structured research landscape that integrates dynamic AIS data, advanced deep learning techniques, and safety-critical applications. It provides valuable insights into both the current state and emerging directions of deep learning-based ship trajectory prediction research.

2.2. In-depth critical review

This section critically reviews the existing main research methods on ship trajectory prediction in the literature. Currently, the research techniques for predicting ship trajectories are mostly separated into two types: methods based on ship physical characteristics and based on feature learning models, respectively.

2.2.1. The trajectory prediction based on physical models

Physical feature-based trajectory prediction methods establish corresponding motion functions based on specific physical models to predict the future trajectory of ships, including but not limited to transverse models (Last et al. 2019) and curve models (Wang et al. 2015). The prediction function is established based on the mathematical equation and all factors that may affect the ship's navigation, such as the ship's mass, the centre of mass, inertia, and size. Such models are often highly interpretable because they take into account a large amount of information and influencing factors. However, the establishment of physical models often heavily relies on the ideal environment and state assumptions. Therefore, they are argued to be of certain limitations on their applications, in which the uncertainty and randomness of ship navigation data are kept at a reasonably low level.

2.2.2. The trajectory prediction based on feature learning methods

The feature learning-based trajectory prediction methods analyse the ships' historical and real-time trajectory data by establishing models, mining the operating characteristics, and inferring the motion rules for predicting future motion trends. In essence, the trajectory prediction based on feature learning is a regression problem. Because of its powerful learning ability and fitting ability, deep learning has become the most popular trajectory prediction method in the field.

Within this context, most studies currently only engage longitude and latitude information as the model's input to predict the ship's position information. For instance, Zhong et al. (2019) developed an efficient prediction model by combining Bi-LSTM with an RNN model for ship trajectory repair, ensuring the integrity and reliability of AIS data. Chen et al. (2020) combined Bi-LSTM and the Mixed Density Network (MDN) to build a Bi-directional Circular Mixed Density Network (BiRMDN) model to realise trajectory prediction for developing an intelligent transportation system. Ma et al. (2021) proposed an Accumulated Long Short-Term Memory (ALSTM) model, which addressed the limitations of the traditional LSTM model by using adaptive memory modules and jump connections. The ALSTM model can accurately predict the uncertainty of ship motion to identify the ship's navigation intention. Hu et al.

(2021) put forward a novel type of a two-channel long short-term memory model, which can realise drift prediction and residual correction, thus correcting the random errors caused by microelectronic interference and electrostatic paranoia in the prediction process. Capobianco et al. (2021) used a Seq2seq model to realise trajectory prediction and aided ship autonomous navigation. Wang and He (2021) used a generated countermeasure network and an attention mechanism to forecast the future trajectory to achieve ship intention identification and collision avoidance.

Although showing much attractiveness, the above studies overlooked other influential factors such as SOG and COG, which affects their validity when traffic complications involving, for example, MASS cannot be comprised in reality. More specifically, predictions based on latitude and longitude data are inadequate for forecasting when the demand for high accuracy (e.g. collision avoidance in port waters) in the prediction is presented. To achieve high-precision prediction, researchers explored the effects of other influential factors in the model's training and tried to integrate different information to obtain better results. Among them, such dynamic ship information as SOG and COG, along with the input of the longitude and latitude, are incorporated into new models for training and prediction. Karataş et al. (2021) input the dynamic information of longitude and latitude and SOG into an LSTM model for training prediction. Hammedi et al. (2023) proposed a Federated Deep Learning Approach called ConvLSTM and used four kinds of information (i.e. longitude, latitude, SOG, and COG) to predict ship future trajectories. Yang et al. (2022) used a Bi-LSTM model to predict the location and realise ship collision avoidance based on the above four factors. Ma et al. (2020) combined the attention mechanism with Bi-LSTM to improve prediction accuracy. Liu et al. (2021a) fused the four modules of Bi-LSTM, attention mechanism, convolution, and dense layers to construct a new prediction model, which better integrated the space–time characteristics of the trajectory and achieved more accurate prediction results. Gao et al. (2021) applied a Trajectory Proposal Network (TPNet) model, commonly used in vehicle trajectory prediction, and LSTM for ship trajectory prediction. The endpoint prediction in TPNet is a classification problem and is hence not suitable for maritime traffic prediction without adaptation, while the prediction in LSTM is a regression problem. Their combination can achieve more accurate prediction results. Wang et al. (2025) introduced a switching input mechanism based on LSTM (SI-LSTM) and constructed a ship trajectory prediction model based on the SI-LSTM model. Billah et al. (2022) utilised a transformer model to realise ship trajectory prediction based on an Encoder and a Decoder model, including multi-layer and Multi-head Attention Mechanisms (MHA). Li et al. (2024b) used a model that combines data encoding representation, attribute correlation attention module, and long short-term memory network (ACoAtt-LSTM) model in conjunction with AIS data for ship trajectory prediction. Their approach integrates data encoding representations, an attribute-related attention module, and LSTM units. Specially, position coding is used to capture essential sequential information, thereby enhancing the model's decoding performance. Similarly, Zhao et al. (2024) proposed a dual attention end-to-end neural network that integrates LSTM units with attention mechanisms to generate trajectory data. Liu et al. (2024) integrated CNN, attention mechanism, and GRU for trajectory prediction. This combination not only improves the prediction accuracy but also provides a more interpretable decision-making process, enabling researchers to gain deeper insights into the operational mechanisms behind ship trajectory prediction models. Huang et al. (2022) designed a convolution module to extract the multi-scale features of AIS trajectory data and meteorological data, and fused the extracted features into a transformer model for prediction. The increase of input information will aid the model to learn more complex trajectory features; however, it will also slow down the speed of training the model and further affect the real-time prediction.

To address this concern, many scholars began to consider preprocessing the original trajectory so that the processed data can reveal self-explanatory feature information to enable a model to capture the features contained in massive AIS data quickly. Suo et al. (2020) applied a Density-Based Spatial Clustering of Applications with Noise algorithm (DBSCAN) to cluster trajectories, extract main trajectories, eliminate redundant data, and then input the processed data into a GRU model for training. This method significantly improved the efficiency of model calculation. Park et al. (2021) utilised a spectral clustering method and a Bi-LSTM model to predict the ship's location. Xu et al. (2022b) first deleted the anchor points in the original trajectory, repaired the abnormal trajectories based on a statistical algorithm, and then proposed a two-stage clustering algorithm (DBSCAN-K-means) to cluster the processed trajectories. The prediction accuracy is further improved by stacking Bi-GRU models. You et al. (2020) encoded the Spatio-temporal trajectory sequence data as context vectors and input them into a Seq2seq model. This model alleviated the gradient decline problem of LSTM and GRU models. Murray and Perera (2021) combined the Variational Recurrent Autoencoder (VRAE) and the hierarchical DBSCAN algorithm to cluster trajectories. This work improved the training speed and the prediction accuracy of the model. Mehri et al. (2021) proposed a new trajectory compression method and combined it with LSTM to construct a Context-aware LSTM (C-LSTM) prediction model. C-LSTM embedded the influence of geographic information in the process of trajectory compression and took into account more factors to make the prediction more reliable. Ma et al. (2022) used a hierarchical clustering algorithm to compress trajectories with different lengths into the same size and then input them into an LSTM model for training to realise simultaneous prediction of multiple trajectories. Alizadeh et al. (2021) first calculated the trajectories' similarity between the target and the surrounding ships, and then utilised the distance information between the input sequence and the sequence with the highest similarity as the input of a LSTM model to predict the divergence and convergence trend of the trajectory more accurately. Venskus et al. (2021) predicted the range of the future trajectory by training two LSTM automatic encoders to assess the abnormal behaviour of their investigated ships.

In addition, due to its large number of parameters, deep learning is much more difficult to train than other prediction methods. Another method to improve the model's convergence speed is to use an intelligent optimisation algorithm to find the optimal parameters of the network quickly. Qian et al. (2022) applied a Genetic Algorithm (GA) to optimise the parameters of an LSTM network and obtain a more accurate prediction result with a faster convergence speed. Bao et al. (2022) introduced MHA to calculate the correlation between AIS data features and assigned different weights to the results according to the correlation. MHA extracted more critical information from the long-term ship trajectory sequence, improving the prediction accuracy of a Bi-GRU model.

The factors used in the current literature on prediction research based on deep learning methods are summarised in Table 1 to show the state of the art in this field. According to the review mentioned above, 40 papers (74%) take into account position, SOG, and COG in the training of a prediction model, 12 papers (22%) use location information, and 2 papers (4%) utilise location information and SOG. No paper uses location information and COG for prediction.

2.3. Research gaps

The literature review identifies four key research gaps in the current studies on ship trajectory prediction. First, existing research has applied specific deep learning methods in a fragmented manner,

Table 1. Factors influencing ship trajectory prediction in the literature.

Factor	Literature	Sum
Position	(Chen et al. 2020; Capobianco et al. 2021; Han et al. 2024; Hu et al. 2021; Jurkus et al. 2023; H. Li et al. 2023a; Ma et al. 2021; Wang et al. 2023; Wang and He 2021; Wu et al. 2023; Zhong et al. 2019; Zhao et al. 2023)	12
Position and SOG	(Karataş et al. 2021; Zhang et al. 2023c)	2
Position and COG	None	0
Position, SOG, and COG	(Alizadeh et al. 2021; Gao et al. 2021; Bao et al. 2022; Billah et al. 2022; Guo et al. 2023; Hammedi et al. 2023; Huang et al. 2022; Jia et al. 2023a; Jia and Ma 2023; Jia et al. 2023; Jiang et al. 2023; Jiang and Zuo 2023; Li et al. 2024a; Lin et al. 2023; Li et al. 2024b; Liu et al. 2021a; Liu et al. 2023; Liu et al. 2024; Ma et al. 2022; Ma et al. 2020; Suo et al. 2020; Mehri et al. 2021; Murray and Perera 2021; Park et al. 2021; Venskus et al. 2021; Qian et al. 2022; Tian and Suo 2023; Wang et al. 2025; Wang and Xiao 2023; Xi et al. 2023; Xu et al. 2022b; Yang et al. 2022; You et al. 2020; Yang et al. 2023; Zhang et al. 2023a; Zhang et al. 2023b; Zhang et al. 2023d; Zhang et al. 2023e; Zheng et al. 2023; Zhao et al. 2024)	40

lacking a systematic comparison of model performance. Second, critical dynamic factors such as SOG and COG are often overlooked, and their combined impact on prediction accuracy remains insufficiently explored. Third, many studies rely on simplified or unrepresentative datasets, which do not adequately reflect the complexity and variability of real-world maritime traffic scenarios. Fourth, there is a notable lack of comprehensive evaluation metrics, making it difficult to assess the effectiveness of different models or to select the most appropriate method for specific operational scenarios.

By filling these gaps, the study advances the field of ship trajectory prediction and contributes practical value to intelligent maritime traffic management and autonomous navigation. To the best of our knowledge, this work represents the first systematic effort to analyse the influence of dynamic factors, compare state-of-the-art deep learning approaches, and evaluate their performance using complex real-world maritime data. The findings provide actionable insights for both academic research and the development of intelligent navigation systems.

3. Preliminary

3.1. Definitions

Definition 3.1: Trajectory. A trajectory of a ship i in trajectory prediction task is defined as a sequence of 4D dynamic coordinates $Traj_i^T = \{(lat_i^t, lon_i^t, sog_i^t, cog_i^t) | t \in [1, T]\}$, where T is the timestep of the trajectory.

Definition 3.2: Trajectory Prediction. The goal of ship trajectory prediction is to train a model $f(Traj_i^T)$ to predict the trajectory of one or more-time steps in the future $Y_i^K = \{(lat_i^t, lon_i^t, sog_i^t, cog_i^t) | t \in [1, K]\}$ by inputting the historical trajectory sequence $Traj_i^T$, where K is the timestep of the forecast.

Definition 3.3: The inputted AIS data. The model takes in a time-synchronised AIS data sequence where trajectory points are spaced at 5-second intervals. Given an input of trajectory points across 5 time steps, the model predicts the coordinate points for the subsequent time step.

3.2. Research questions

Question 1: Enhancing prediction accuracy through the integration of dynamic information.

To improve the accuracy of prediction, the paper begins by identifying a set of dynamic variables closely linked to the prediction accuracy. By regulating input factors and analysing the prediction results of the model, it is possible to determine the varying levels of influence that different factors have on trajectory prediction. Following this, deep learning models that incorporate dynamic information are compared. The models are specifically designed to effectively leverage the benefits of dynamic variables, aiming to refine the accuracy of predicting ship trajectories. As a result, they offer a more dependable predictive tool for both research and practical applications within the domain of autonomous ships.

Question 2: Optimal selection of deep learning models for ship trajectory prediction.

To determine the most effective configuration within a deep learning framework, the process is initiated by introducing a performance metric $f(v, p)$, where v represents the volume of data and p represents the prediction performance. By exploring the parameter space, the optimal combination of model architecture and hyperparameters is determined to maximise the performance function. A selection criterion is established to efficiently select the most suitable model for various scenarios, rooted in the performance function's outcomes, providing an objective evaluation framework. This streamlined approach ensures the selection of optimal deep learning model configurations for different data sizes and prediction accuracy requirements, enhancing ship trajectory prediction performance.

Question 3: Evaluating influential factors in ship trajectory prediction.

The four influential factors include longitude, latitude, SOG, and COG. These factors generate four distinct cases, as outlined below:

Case 1: longitude and latitude.
Case 2: longitude, latitude, and COG.
Case 3: longitude, latitude, and SOG.
Case 4: longitude, latitude, SOG, and COG.

By utilising the control variable method and conducting comparative experiments, the influence of each case on trajectory prediction is independently assessed. Subsequently, an integrated evaluation metric is devised to measure the cumulative impact of these factors on enhancing the accuracy of ship trajectory prediction.

3.3. Evaluation indices

Seven evaluation indicators are employed to quantify the trajectory prediction performance of six deep learning models and measure the prediction performance, including Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Final Displacement Error (FDE), Symmetric Mean Absolute Percentage Error (SMAPE), Fréchet Distance (FD), and Average Euclidean distance (AED). Traditional indexes, MAE, MSE, RMSE, and SMAPE, are commonly used in the performance evaluation of prediction methods. The AED, FED, and FD methods can help measure the prediction accuracy of the final point and the whole trajectory. Therefore, all these seven indexes can ensure that the assessment is objective, reasonable, and comprehensive.

Each metric offers unique insights into model performance, making them valuable for different aspects of ship trajectory prediction. MSE, RMSE, and MAE quantify average position errors and are critical for minimising prediction deviations in scenarios like collision avoidance. FDE evaluates the accuracy of the final predicted position, which is essential for navigation planning. SMAPE allows for cross-scale performance comparison, aiding benchmarking studies. FD measures trajectory similarity, highlighting path consistency in traffic flow analysis and anomaly detection. AED provides an average error across all trajectory points, ensuring consistent performance in real-time monitoring.

In ship trajectory prediction, FDE and FD are particularly relevant due to their focus on endpoint accuracy and overall path similarity, which are critical for navigation safety and efficiency. However, the choice of metrics should align with specific maritime requirements and stakeholder priorities. For instance, FD may be emphasised in regulatory compliance scenarios, while MAE and RMSE are more pertinent in dynamic environments with rapid trajectory changes.

By understanding the significance and applicability of each metric, researchers and practitioners can better interpret results, select appropriate models, and enhance the study's credibility in real-world maritime applications. The smaller the result of the evaluation metrics, the better the prediction performance of the model. The specific calculation process is presented in Equations (1)–(7).

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(pre_i - real_i)^2, \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(pre_i - real_i)^2}{n}}, \tag{2}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|pre_i - real_i|, \tag{3}$$

$$\mathrm{SMAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|pre_i - real_i|}{(|pre_i| + |real_i|)/2}, \tag{4}$$

$$\mathrm{FDE} = \sqrt{(pre_n - real_n)^2}, \tag{5}$$

$$\mathrm{FD} = \min_{\pi\in\prod n}\max_{i=1}^{n}\sqrt{\begin{array}{c}(pre_i(lat) - real_i(lat))^2\\ +(pre_i(lon) - real_i(lon))^2\end{array}}, \tag{6}$$

$$\mathrm{AED} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{\begin{array}{c}(pre_i(lat) - real_i(lat))^2\\ +(pre_i(lon) - real_i(lon))^2\end{array}}, \tag{7}$$

where pre_i and $real_i$ is the prediction and real result of the ith point, respectively. $pre_i(lon)$ and $pre_i(lat)$ are respectively the longitude and latitude of the ith prediction point. $real_i(lon)$ and $real_i(lat)$ are the corresponding longitude and latitude of the ith real sample trajectory point. n is the number of coordination points in the test trajectories.

4. Methodology

To offer a benchmark and reference for future trajectory prediction in maritime transportation, a comprehensive comparative experiment is implemented by the listed six methods based on the four factors influencing ship trajectories and the seven indicators evaluating prediction accuracy. The flowchart of the methodology is shown in Figure 2, which includes five parts.

Firstly, this study utilises AIS data to capture real-time vessel movements and trajectories. AIS data is collected from two highly representative water areas: the CSJ and ZS. These regions were selected due to their high traffic density and complex navigational conditions, providing a realistic and challenging environment for trajectory prediction. AIS data offers dynamic variables such as longitude, latitude, SOG, and COG, which are essential for understanding vessel behaviour and trajectory patterns.

Secondly, data preprocessing is applied to the raw AIS data to ensure high data quality for model training (Li et al. 2022a; Zhang et al. 2022). This includes denoising, completing missing entries, removing abnormal values, and normalising the data. To address the issues of noise, missing data, and spatiotemporal inconsistency, a multi-dimensional threshold detection method based on ship kinematics is adopted. Abnormal longitude and latitude points are detected using the 3σ rule (e.g. positions outside port boundaries or on land), while physically implausible velocities (e.g. exceeding 50 knots) are filtered using domain-specific thresholds (Xi et al. 2023). Additionally, only active navigation statuses, specifically 'Under way using engine' and 'Under way sailing', are retained, while static states such as anchored or moored are excluded.

For handling missing data, trajectories with more than 20% missing values or time gaps exceeding 5 min are discarded as low quality. The remaining data is interpolated using cubic spline interpolation to correct temporal discontinuities caused by inconsistent AIS broadcast frequencies. After interpolation, all trajectories are resampled at 10-second intervals to ensure uniform time alignment.

Thirdly, experiments are conducted to evaluate the impact of four key dynamic factors, namely longitude, latitude, SOG, and COG, on trajectory prediction performance when used together. These factors are selected based on their strong relevance to vessel navigation behaviour. Six advanced deep learning models, including LSTM, GRU, Transformer, and others, are employed due to their demonstrated capabilities in time-series forecasting and their effectiveness in capturing complex temporal dependencies.

Fourthly, the preprocessed trajectory dataset is split into training, validation, and test sets using stratified random sampling: 60% for training, 20% for validation, and 20% for testing. Each model and corresponding setup is described in detail in Section 3.

Finally, to comprehensively evaluate the prediction performance, seven widely recognised metrics are employed: MSE, MAE, RMSE, MAPE, ADE, FD and FDE. These metrics provide a multi-faceted assessment of prediction accuracy, reliability, and robustness (Sun et al. 2022). The theoretical basis for these metrics lies in their ability to quantify different aspects of prediction error, making them suitable for comparing model performance across diverse scenarios.

5. Experimental results and analysis

5.1. Dataset description and experimental setting

5.1.1. Dataset description

This paper selects two real historical ship AIS datasets from the ZS and the CSJ water areas for experimental comparison. The CSJ water area is the only way for ships to enter and exit Bohai Bay, with a large traffic flow and high density. At the same time, it is also a famous fishing ground, forming the complicated interactions between cargo fleets and fishing ships. Due to intersecting waterways and fishing ships' activities, which are not foreseeable as commercial ships entering in and out of the port, the traffic situation in the water is complicated, leading to the occurrence of maritime accidents occurring more frequently than the norm. The ship traffic flow in the eastern and north-eastern water areas of the original routing system in the water area has been significantly regulated through an existing ship routing/traffic control system. Therefore, ship trajectory prediction in this typical water area has significant application

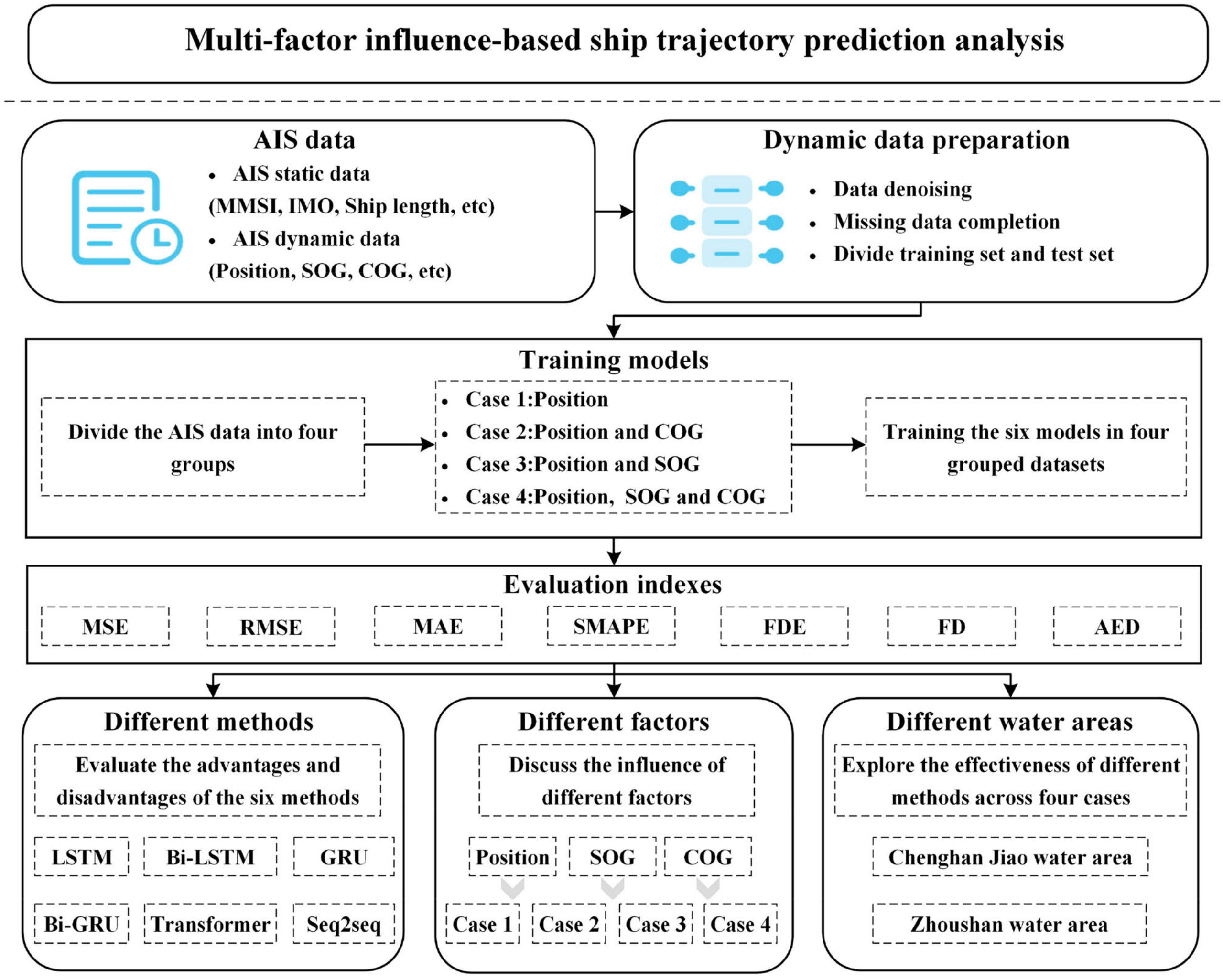


Figure 2. The flowchart of the experiment.

scenarios. Comparatively, the ZS water area has more complicated hydrology and traffic due to its connection with the world's largest and busiest port. It is the intersection of the north–south sea channels and the east–west Yangtze River transportation channel, with high traffic complexity and density. In summary, the CSJ water is chosen to present the area of traffic control and a relatively small-to-medium size dataset, while the ZS water is selected to demonstrate the complicated traffic with a large dataset.

Eventually, 2000 ships with 1495208 trajectory coordinate points are retained from the initial dataset of the CSJ water area. The trajectories in the whole area are classified based on its designated ship route system. The visualisation results of the experimental dataset are shown in Figure 3. It is clear that ship trajectory categorisation characteristics exist in the CSJ water, so nine typical ship trajectories are chosen from various clusters to compare the accuracy of future predictions.

The ship routing system provides different channels for navigation. Meantime, the typical navigational patterns can be extracted from historical AIS data (Li et al. 2022a). According to the Traffic Separation Schemes (TSS) and the pattern extraction results, it is therefore selected the nine ship trajectories with different characteristics and routes to have comprehensive experimental analysis and evaluation. The MMSI of the nine chosen

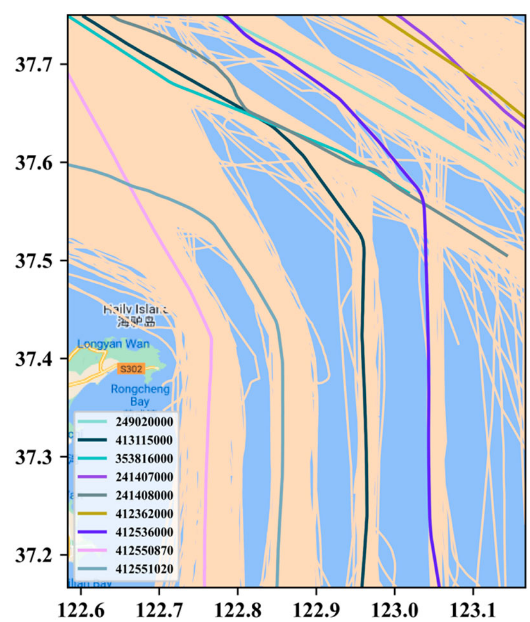


Figure 3. Visualisation of ship trajectory dataset in the CSJ water area.

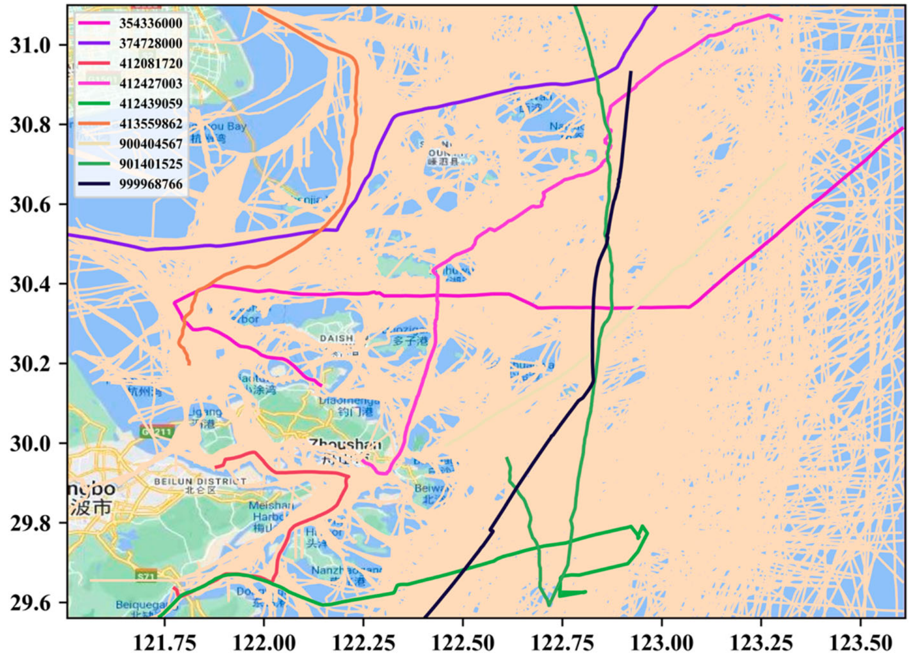


Figure 4. Visualisation of ship trajectory dataset in the ZS water area.

ship trajectories is 24902000, 241407000, 241408000, 413115000, 353816000, 412362000, 412536000, 41250870 and 412551020, respectively. Moreover, the nine selected trajectories are expressed in different colours in Figure 3 to show their difference.

To further verify the influence degree of different factors, the prediction performance of these six methods, as well as the generalisation of the findings, this paper also selects another real AIS data of the ZS water area. 4116922 coordinate points contained in 4840 ships are included in the dataset after data preparation, as shown in Figure 4. Similar to the selection methods in the CSJ water, nine trajectories with different characteristics under different routes are chosen. Their MMSIs are 354336000, 374728000, 412081720, 412427003, 412439059, 413559862, 900404567, 901401525 and 999968766, which are shown in coloured lines in Figure 4.

5.1.2. Experimental setting

To ensure the comparability of experimental results, the parameters of the six prediction models are normalised. The Rectified Adaptive Momentum Estimation algorithm (RAdam) optimiser is used to update and optimise model parameters. When the optimiser does not have enough data to make accurate adaptive momentum decisions, the model will perform exceptionally severely at the initial stage of training. RAdam is deemed the best choice for the optimiser to start training. RAdam uses an active rectifier to adjust Adam's adaptive momentum according to variance and effectively provides an automatic warm-up mechanism. This process can be customised according to the current dataset, ensuring that the training takes the first step smoothly on a solid basis (Liu et al. 2021b). The initial learning rate settings of the six models are 0.0001. The attenuation is 0.9, which indicates the learning rate attenuation after the parameter update. The models also include an early stop mechanism. It is demonstrated that the model has converged when the learning rate falls to less than 10^{-6}, or the testing effect of the model after ten consecutive iterations does not improve. At that point, the training will automatically end. The maximum number of model iterations (epoch) is set to 200. In addition, the experiment used a discard mechanism to prevent overfitting, and the values of the six models were developed to 0.5. Given the extensive size of the experimental dataset, the batch size is set to 256, the hidden layer size to 128, and the number of layers in the basic unit stack to 2.

Table 2. Hardware and software environment.

Hardware	Model	Software	Version
CPU	i9-11900U Intel Core	PyCharm	2021.1.2
Host Memory	32 GB DDR5	CUDA	11.3
GPU	GTX 1080Ti	Pytorch	1.9
Global Memory	11GB GDDR6	Python	3.9

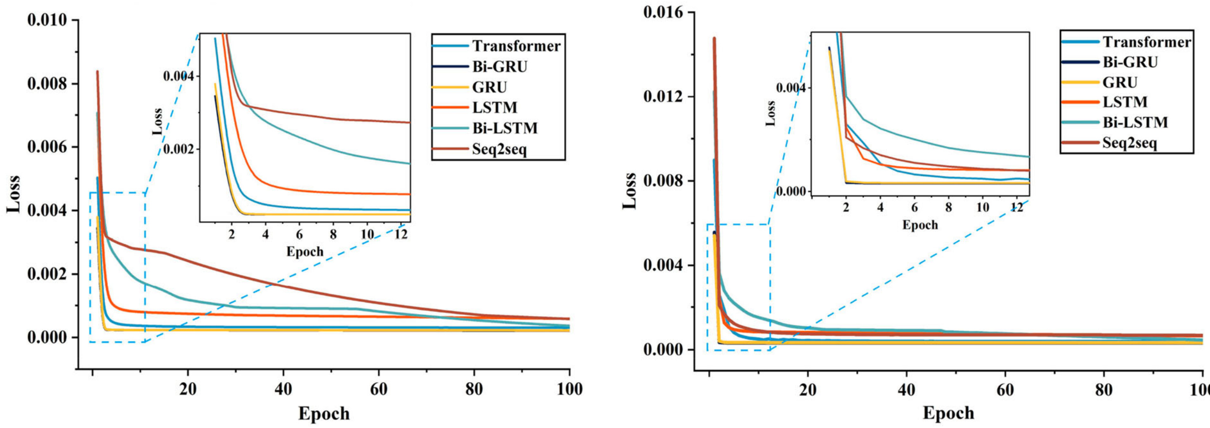
The hardware and software environment of the trial is shown in Table 2. All algorithms are implemented based on the Pytorch framework.

5.2. Model validation

This section will visually display the training performance of six deep learning methods on two real water areas. Each model is trained under four distinct experimental cases to comprehensively evaluate their effectiveness in vessel trajectory prediction. To ensure consistency and mitigate the effects of outliers, To ensure the robustness and reproducibility of results, each training experiment is repeated five times. The average loss across these runs is reported as the final outcome to reduce the impact of random outliers and ensure statistical reliability.

Figure 5 illustrates the loss value variation curves for the Transformer, GRU, Bi-GRU, LSTM, Bi-LSTM, and Seq2Seq models across training epochs. Figure 5(a) shows the results in the CJP water area, while Figure 5(b) corresponds to the ZS region. The loss values decrease rapidly in the initial epochs and gradually level off, indicating that all models successfully converge within the 100-epoch training window.

The zoomed-in insets in both plots highlight the early-stage convergence behaviour, where differences among model performances are more discernible. Notably, models such as the Bi-LSTM and Transformer demonstrate a faster convergence rate and lower overall loss, suggesting their superior capacity to capture complex spatiotemporal vessel dynamics. In contrast, Seq2Seq exhibits a relatively higher loss and slower convergence, implying less effectiveness



(a) Loss values curve in the CJP water area.

(b) Loss values curve in the ZS water area.

Figure 5. Loss value variation curves of six models trained on two water areas. (a) Loss values curve in the CJP water area. (b) Loss values curve in the ZS water area.

in modelling real-time trajectory patterns in high-density maritime environments.

Across both water regions, the loss curves reflect a consistent pattern: models that incorporate bidirectional mechanisms or attention-based architectures tend to outperform their simpler counterparts. This reinforces the importance of advanced temporal modelling strategies in AIS-based vessel trajectory prediction tasks.

5.3. Visualisation results

5.3.1. Visualisation of prediction results in the CSJ promontory water area

The prediction effects of the chosen six deep learning models against four different cases in the CSJ water area are shown in Figure 6. The six rows from top to bottom correspond to the results of Bi-LSTM, Bi-GRU, GRU, LSTM, Seq2seq and Transformer, respectively. The four columns from left to right are the prediction results of cases 1–4 (the combination of different influential factors, see Section 4), respectively. Horizontally, the prediction performance of the six methods is apparent, and the prediction results of the Bi-GRU and Transformer models are superior to the other four models. Meantime, the predicted trajectory of the Seq2seq model has the worst fitting degree compared to the real trajectory. Vertically, the predicted results of Transformer, Bi-GRU, and GRU models are more closely matched to the real trajectory in case 1, while LSTM and Seq2seq have poor prediction effects. In case 2, with the addition of COG, the performance of Bi-LSTM, LSTM, and Seq2seq models declines slightly compared with that of case 1, while Bi-GRU and GRU models still maintain high accuracy. In case 3, the addition of SOG makes the performance of the six models on most test trajectories slightly improved compared with the results of case 1.

In Case 4, when considering the combined effects of longitude, latitude, SOG, and COG, the performance of the Bi-GRU and GRU models neither showed significant improvement nor decline in comparison to the results from the other three experimental groups. Moreover, the performance of the LSTM, Bi-LSTM, and Seq2seq models is slightly worse than that of case 3 and case 1, but better than that of case 2.

5.3.2. Visualisation of prediction results in the ZS water area

Similarly, the prediction results of the six deep learning models on four cases in the ZS water area are displayed in Figure 7. The orange, blue, yellow, and green trajectories correspond to cases 1–4, respectively. Horizontally, it can be seen that the training and prediction results in complex water areas (i.e. the ZS) are similar to those in simple water areas (i.e. the CSJ). The performance of Bi-LSTM is notably superior to that of LSTM. Meanwhile, the Bi-GRU model delivers the best results, whereas Seq2seq performed the worst. Vertically, similar to the experimental results in the CSJ water area, the addition of SOG can improve the accuracy of trajectory prediction (cases 3 and 4). However, compared with case 1, the addition of the COG information (case 2) will affect the fitting accuracy of the predicted trajectory to some extent.

5.4. Discussion of four kinds of case studies

This section takes the meanvalue of seven index results in all nine test trajectories as each method's final test result in each case. The visualisation results of different evaluation indexes in the CSJ and the ZS water areas are displayed in Figures 8 and 9, respectively. Based on the prediction results of the two water areas, the following findings are revealed.

(1) The Seq2seq, LSTM and Bi-LSTM models are less robust than GRU, Transformer, and Bi-GRU models in ship trajectory prediction. Specifically, there are significant differences in the prediction results of the two models with LSTM as the basic unit when being applied in the four cases. Meantime, the prediction performance has little difference when using two models with LSTM and the Seq2seq in different cases.
(2) The limitation of trajectory prediction based on longitude and latitude information is significantly revealed from the results of the comparative experiments in practical application. It can be seen from the average value of seven indexes that some models (e.g. Bi-LSTM, GRU, and Bi-GRU) can achieve relatively good prediction results when only longitude and latitude training is used (case 1). However, ship navigation is also closely related to SOG and COG due to the influence of ship routing systems, ship encounters and other factors in actual navigation. Therefore, it is not recommended to only use latitude and longitude data as the prediction basis in trajectory prediction.
(3) SOG plays a more important role than COG in trajectory prediction. In the results of comparison experiments, the prediction accuracy of the experimental groups with SOG (i.e. cases 2 and 4) is higher than that of case 3 with COG. It is consistent with reality. In the prediction of equal time intervals, the speed

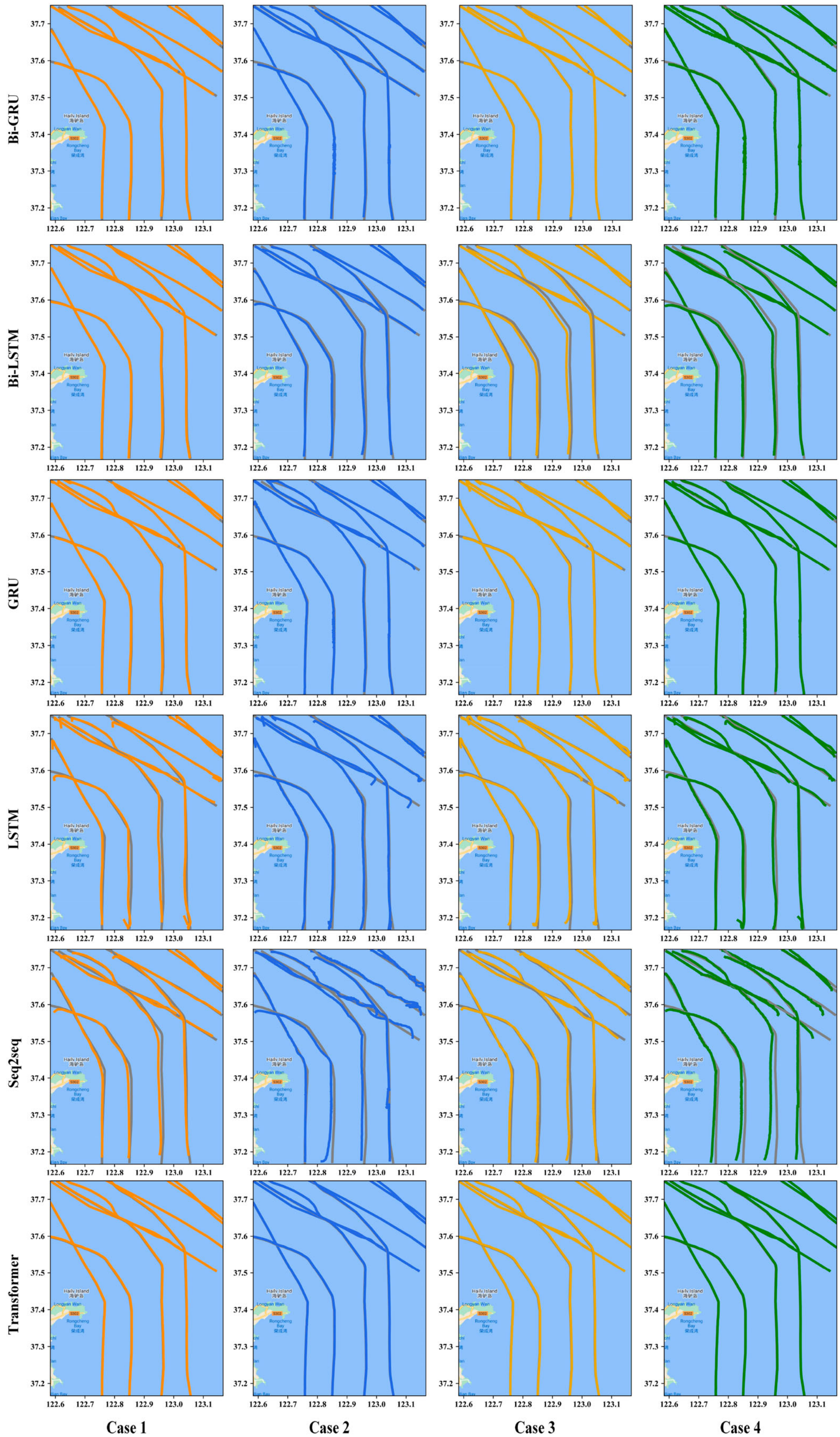


Figure 6. Visualisation of prediction effects of nine trajectories in different cases based on six methods in the CSJ water area.

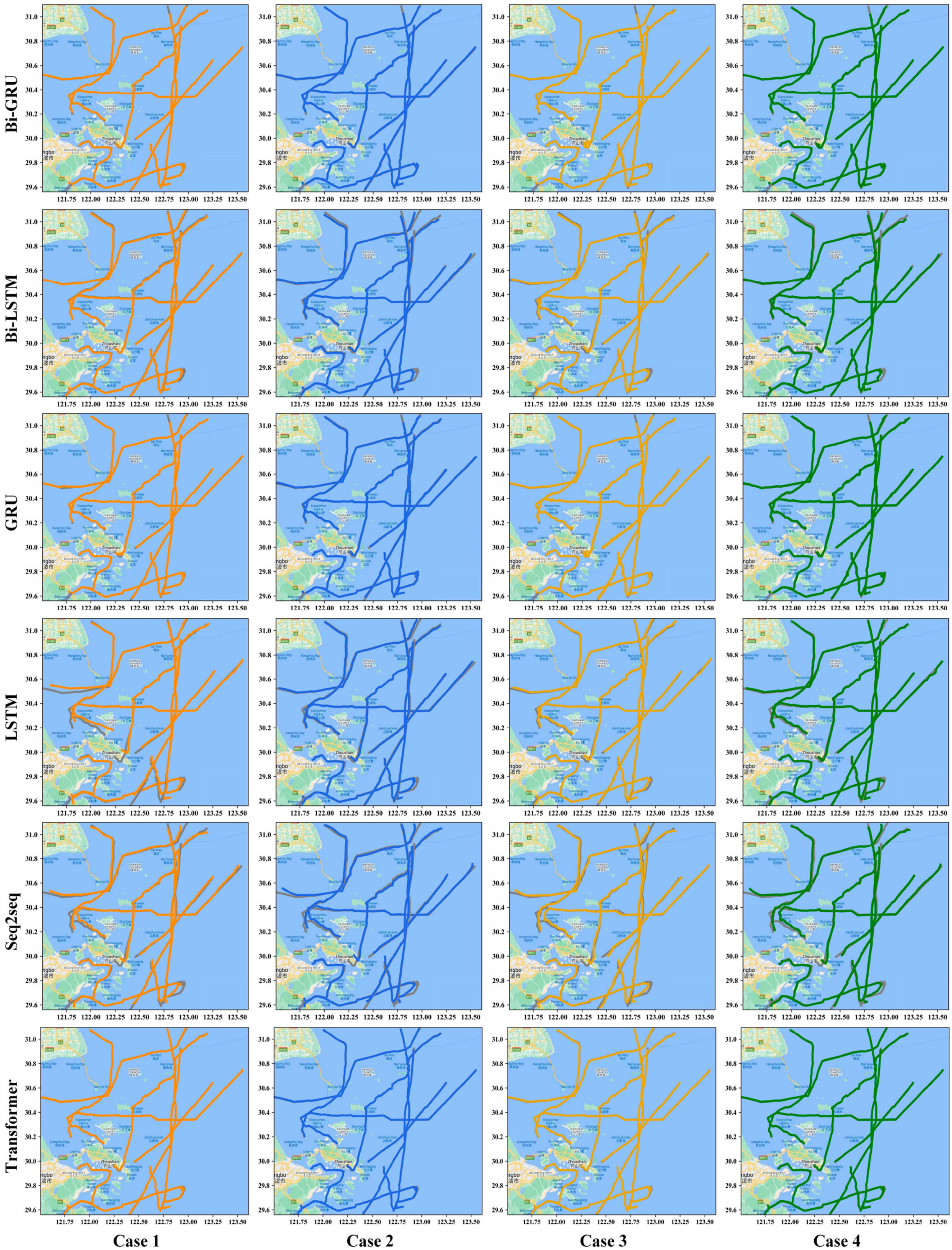


Figure 7. Visualisation of prediction effects of nine trajectories in the ZS water area.

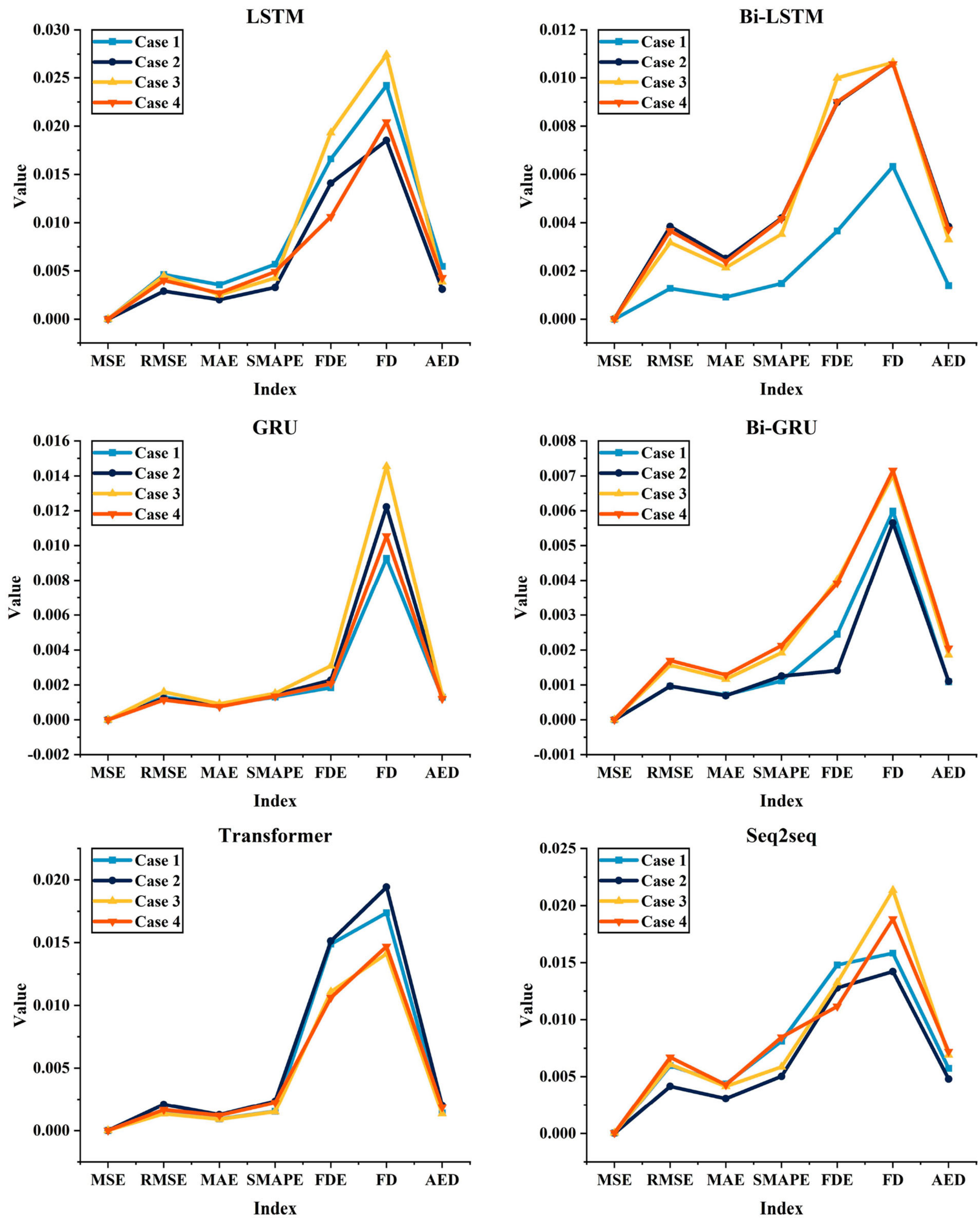


Figure 8. Different factors' effects against seven evaluation metrics in the CSJ water area.

information will largely determine the ship's position at the next time. The turning process of a ship is notably more gradual than that of other vehicles like cars or aircraft. Sharp and swift turns in maritime navigation are rare unless prompted by emergencies. Therefore, COG has less influence on trajectory prediction than SOG.

(4) To compare the metrics effects more clearly, the results of FD and FDE in the CSJ water area are shown in Figure 10. The combination of the two indicators can comprehensively measure the similarity of trajectories. It can be seen that the trajectory similarity predicted by the model with SOG training is closer to the real trajectory.

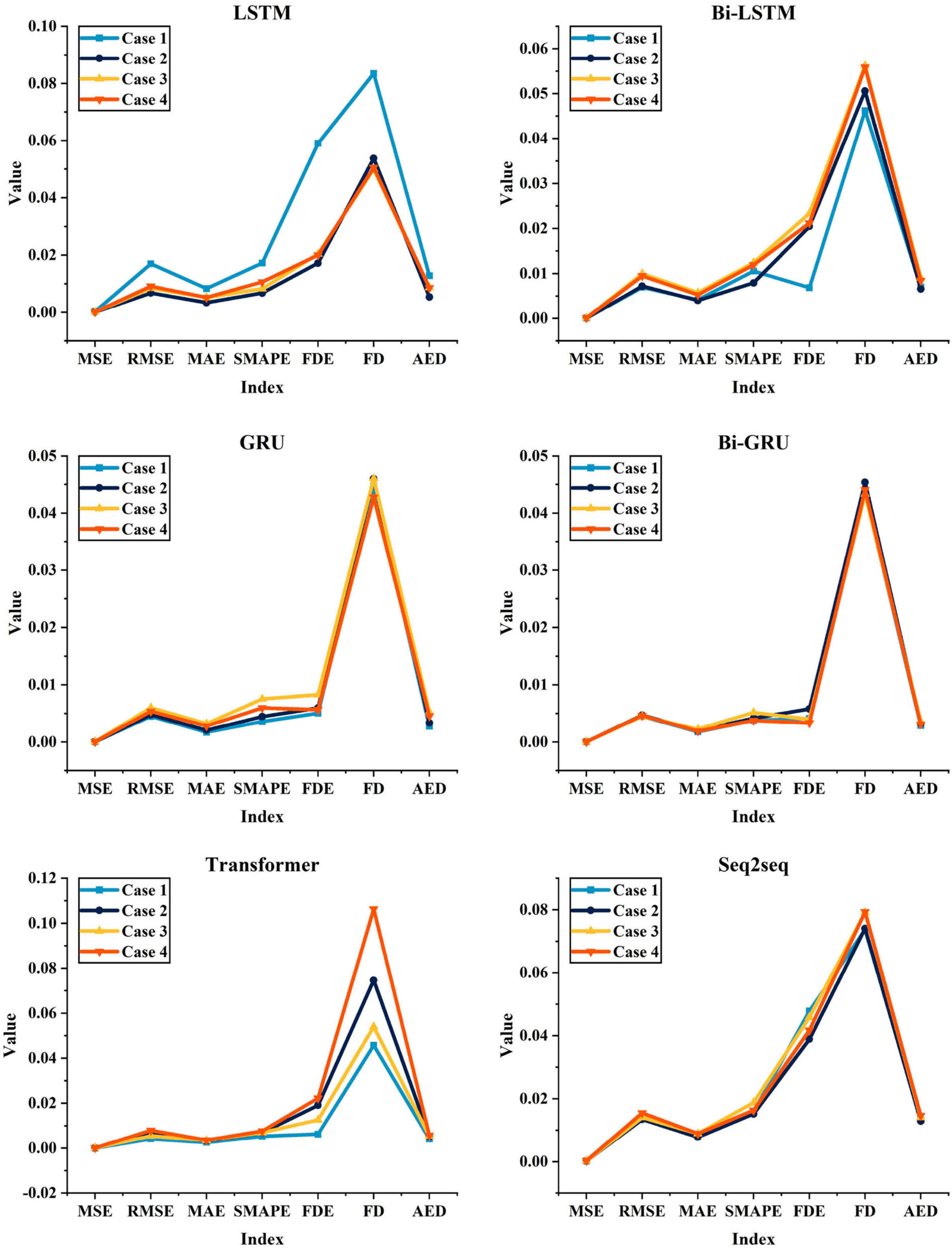


Figure 9. Different factors' effects against seven evaluation metrics in the ZS water area.

5.5. Discussion of different methods

The prediction performance of the sixmethods in two water areas is displayed in Figures 11 and 12, respectively. It can be seen that each set of four subgraphs corresponds to the four cases, namely cases 1 through 4. Within each subgraph, six polylines represent the outcomes of the six prediction methods. The following findings are drawn from the two sets of line charts:

(1) The prediction accuracy of bidirectional networks is higher than unidirectional networks. The prediction performance of two

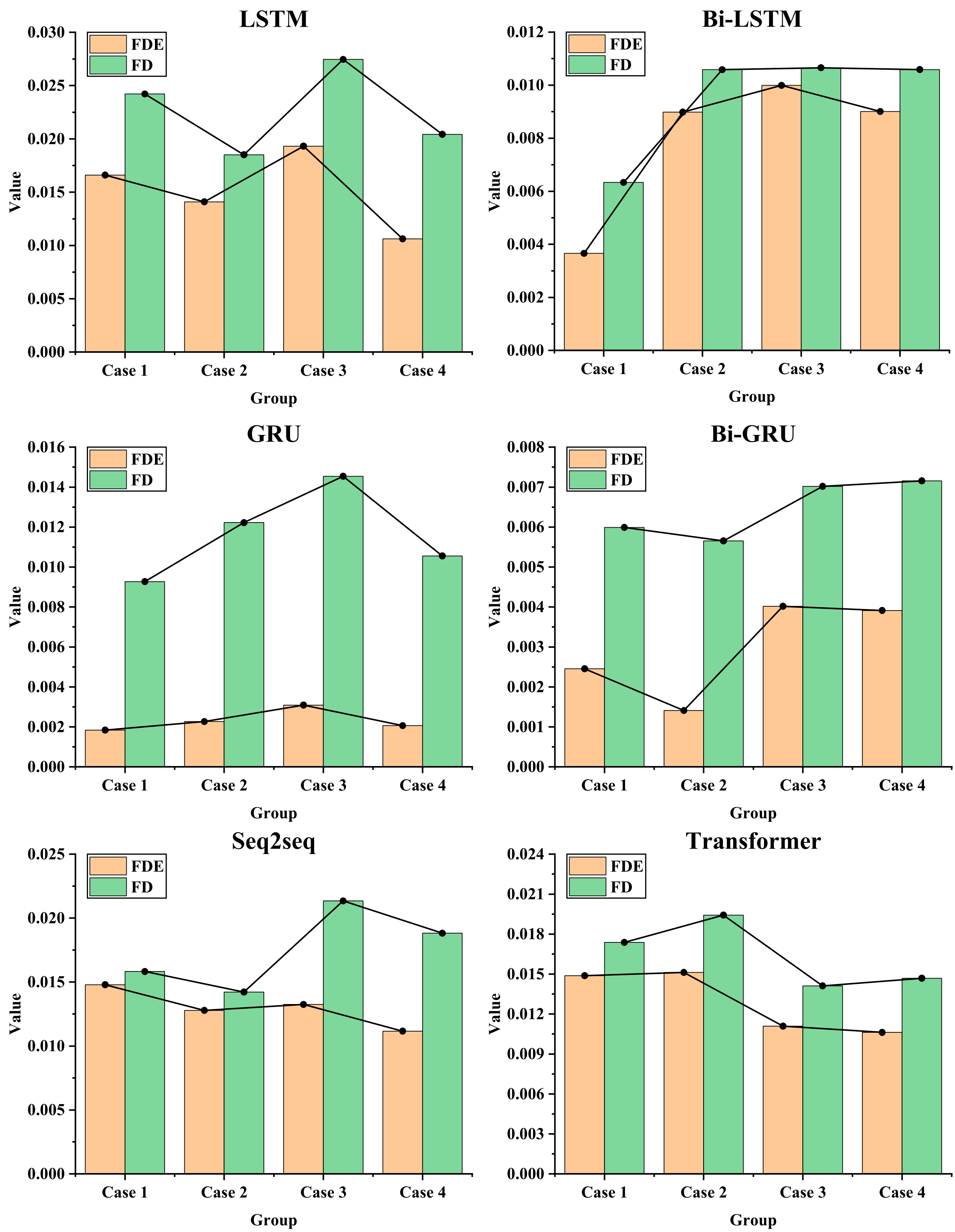


Figure 10. The result of FD and FDE in the CSJ water area.

kinds of bidirectional networks is better than their corresponding unidirectional networks. The result verifies and demonstrates the theory that bi-directional networks can capture context information of sequences more effectively.

(2) The performance of the GRU model is superior to the Bi-LSTM and LSTM models. Compared with LSTM, GRU reduces the number of gates, making the model parameters less and the convergence speed faster. The experiments in this paper are based on the same training data and experimental settings. Under the same conditions, the prediction accuracy of the two models based on the GRU unit is significantly higher than that of the two models based on the LSTM unit.

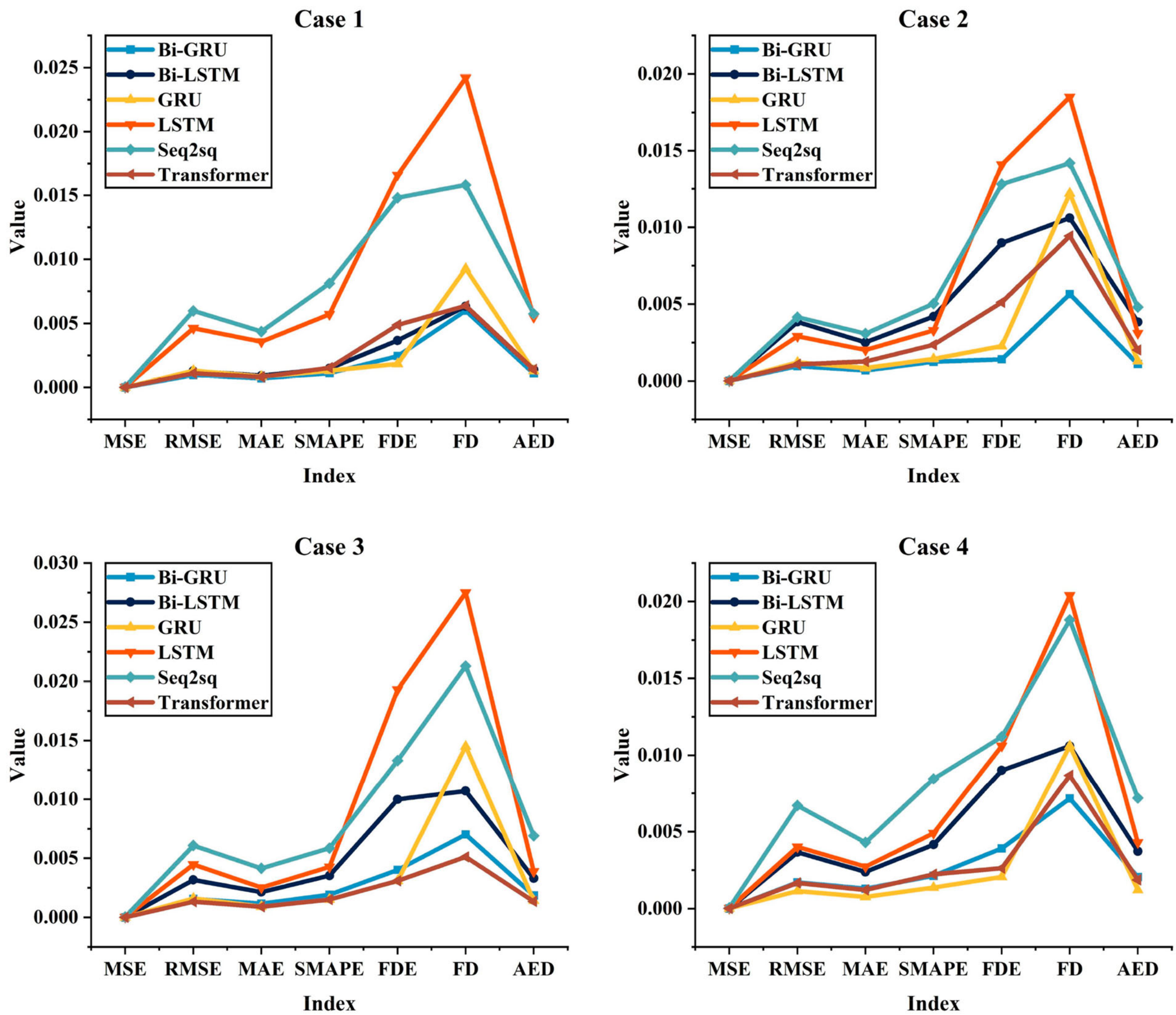


Figure 11. The results of different methods under seven evaluation metrics in the CSJ water area.

(3) The performance of the six deep learning prediction models from high to low is Bi-GRU > Transformer > GRU > Bi-LSTM > LSTM > Seq2seq. Among them, the Seq2seq model is less effective because it is composed of an encoder and a decoder. The model has involved more parameters, complex optimisation, and challenging training.

(4) FD can help measure the similarity of the whole trajectory and can judge the stability of the model from the perspective of similarity and ensure the comprehensiveness of the evaluation. The larger the FD value, the smaller the similarity of the entire trajectory. It can be seen that the FD value is the largest of the seven index values from Figures 11 and 12. Among the seven evaluation metrics, MSE, RMSE, MAE, and FDE are commonly used to evaluate the results of trajectory prediction. Based on the results of the two water areas, the six models are ranked as Bi-GRU > Transformer > GRU > Bi-LSTM > LSTM > Seq2seq, which also verifies the results in (3).

The superior performance of the Bi-GRU model can be attributed to several key factors. Firstly, its bidirectional structure enables the model to capture both past and future contextual information, which is crucial for accurately predicting ship trajectories. This capability is particularly valuable in maritime scenarios where ship movements may be influenced by anticipated conditions or navigational decisions.

Secondly, the GRU architecture's simplicity and computational efficiency contribute significantly to its effectiveness. Compared to more complex architectures, GRU has fewer parameters and converges faster, allowing it to learn meaningful patterns quickly while reducing the risk of overfitting – a common issue in models with high parameter complexity.

In terms of parameter optimisation, the performance of the Bi-GRU model is further enhanced through careful tuning of critical hyperparameters such as learning rate, batch size, and the number of layers. These hyperparameters significantly influence the model's ability to learn efficiently and generalise to unseen data. For instance, an appropriately chosen learning rate can accelerate convergence and prevent the model from becoming trapped in local minima. Similarly, batch size plays a key role in the stability of the training process and the quality of the gradient updates.

Another notable advantage of Bi-GRU lies in its computational efficiency. Its streamlined structure and reduced parameter count translate into lower resource demands, making it particularly well-suited for real-time applications, including onboard vessel trajectory prediction systems where computational capacity may be limited.

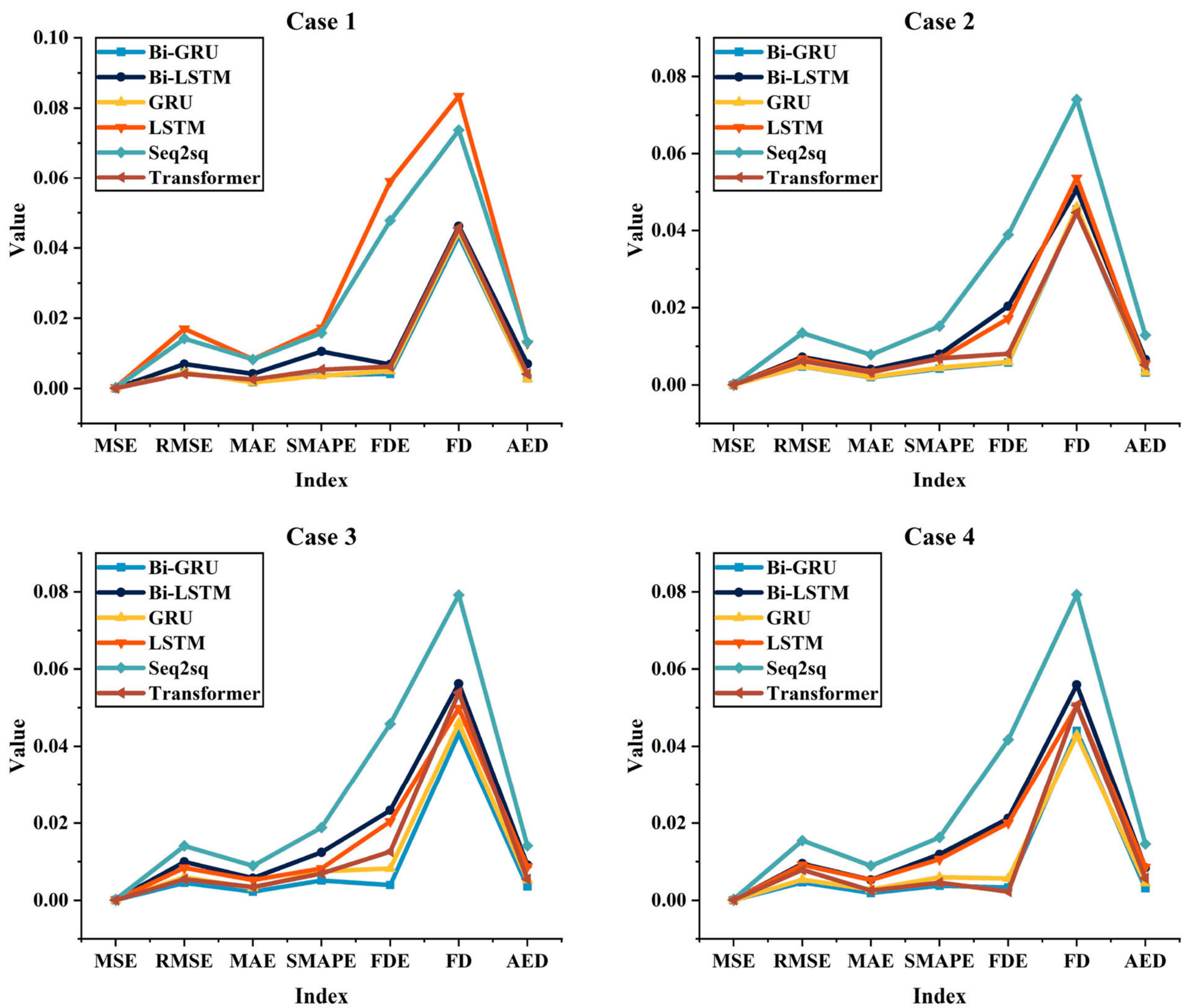


Figure 12. The results of different methods under seven evaluation metrics in the ZS water area.

Nonetheless, it is important to acknowledge that each model has its own strengths and limitations. While Bi-GRU demonstrates strong performance in many scenarios, it may encounter challenges when dealing with very long sequences that require modelling extended temporal dependencies. In such cases, Transformer models – despite their higher computational overhead – may offer superior performance due to their self-attention mechanisms. Moreover, the Seq2Seq model, although less competitive in certain configurations, can still be effective for tasks requiring precise Seq2Seq mapping when properly regularised and optimised.

5.6. Discussion on the best-fit method under different scenarios

Table 3 presents the predictive performance of the six models across various cases, along with their respective advantages and disadvantages. Rankings from 1 to 6 indicate the performance order of the six models in four cases. Figure 13 shows the predictive performance of the model in different cases and the relative size of the model parameters. The results highlight a comparable performance among the six deep learning techniques across the cases. Notably, Bi-GRU, Transformer, and GRU outperform the other three methods, namely Bi-LSTM, LSTM, and Seq2seq. Bi-GRU achieves the best predictive performance with a relatively small number of parameters. It can be further seen from Figure 13 and Table 3 that the prediction accuracy becomes higher after incorporating SOG information (i.e. case 1) compared with the other three cases without it. The comprehensive experiments validate the efficacy of the six deep learning methods in four cases and clarify their advantages and disadvantages.

5.7. Implications

This paper applies the six most widely used deep learning models and explores the influence of dynamic ship information (i.e. longitude, dimension, SOG, and COG) on trajectory prediction accuracy through multiple comparison experiments. The performance of different prediction methods and the effect of multiple influential factors are compared and analysed to generate valuable findings. The findings and implications of such a prediction comparison could include the following:

(1) Model efficacy: A clear understanding of which deep learning model(s) outperform others when predicting ship trajectories using dynamic ship information. This could help streamline research and operational efforts toward the most effective models.

Table 3. Advantages and disadvantages of the six methods and their performance under different cases.

Methods	Case 1	Case 2	Case 3	Case 4	Advantages and disadvantages of the methods
LSTM	6	4	5	5	Poor robustness, many parameters, and slow training speed.
GRU	3	3	3	2	Fewer model parameters, faster convergence speed, and better performance.
Seq2seq	5	6	6	6	More model parameters and lower training efficiency.
Bi-LSTM	4	5	4	4	Bi-directional information, but not good at long sequence calculations.
Bi-GRU	1	1	1	1	Bi-directional information, long-term dependencies, but can not be computed in parallel.
Transformer	2	2	2	3	Long-term sequence modelling, global dependencies, parallel computing

Note: The numbers 1–6 mean the performance ranking of six methods in different cases. Case 1 indicates longitude and latitude; Case 2 denotes longitude, latitude, and COG; Case 3 is longitude, latitude, and SOG; Case 4 expresses longitude, latitude, SOG, and COG.

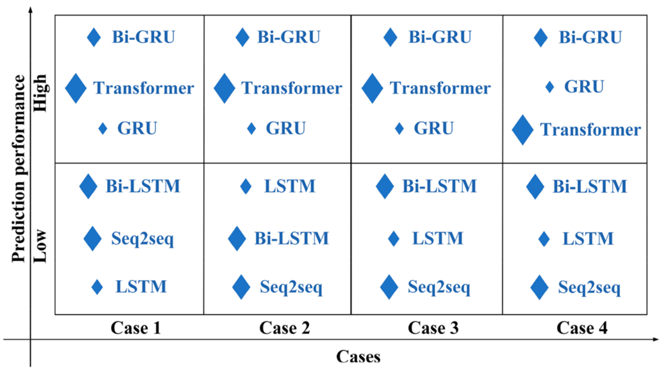


Figure 13. Prediction performance and parameter count of six models across different cases. Note: The size of the diamond-shaped markers indicates the number of model parameters – larger shapes represent more parameters.

(2) Variable importance: Insights into how individual dynamic ship information variables (like longitude, dimension, SOG, and COG) influence prediction accuracy. This could guide data collection and preprocessing efforts.
(3) Optimised techniques: Identification of potential hybrid models or techniques that combine the strengths of individual models, offering improved prediction capabilities.
(4) Operational efficiency: Accurate trajectory predictions can lead to safer and more efficient maritime operations, especially in congested or high-risk areas.
(5) Strategic planning for MASS: The findings could provide MASS with data-driven strategies to enhance their autonomous navigation capabilities, reduce risks, and improve overall operational efficiency.
(6) Potential for further research: Highlight areas where additional research could lead to even more accurate trajectory predictions, possibly considering other influential factors or fine-tuning of models.
(7) Real-world applications: The comparison might reveal specific scenarios or conditions under which certain models or dynamic ship information is especially crucial, guiding real-world applications and operational strategies.

In essence, by comparing the prediction methods and influential factors, researchers and maritime professionals can gain a more nuanced, evidence-based understanding of ship trajectory prediction, ultimately driving safer, more efficient maritime operations.

6. Conclusion

It is essential to accurately predict ship trajectory to ensure maritime traffic safety, especially within the framework of MASS. This paper applies the six most widely used deep learning models and explores the influence of dynamic ship information (i.e. longitude, dimension, SOG and COG) on trajectory prediction accuracy through multiple comparison experiments. The performance of different prediction methods and the effect of multiple influential factors are compared and analysed to generate valuable findings. For example, (1) shipowners/operators can use the findings to better plan their ship routing; (2) maritime administration/authority can better guide the ships passing the waters of their justice safely; and (3) MASS manufacturers can use the findings to detect ship collision risks and design an early risk warning systems. Furthermore, the experimental results show that SOG is more important than COG in prediction, and the performance of the six deep learning models is also verified. This paper pioneers a new perspective for the study of maritime traffic prediction and provides scientific theoretical support and a practical basis for the rational use of AIS data and selecting prediction methods.

Building on the theoretical foundation established in this study, future work will focus on validating the model through real-time case studies. These studies will examine important aspects such as data latency, processing efficiency, and hardware constraints to assess the model's feasibility and robustness in practical MASS operations.

Additional research will explore the inclusion of contextual factors such as weather conditions, marine environments, and the movement of nearby vessels to improve prediction accuracy. The development of lightweight and efficient models will also be considered to support real-time onboard deployment and enhance the practical application of trajectory prediction in autonomous maritime systems.

Disclosure statement

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Data availability statement

Data will be made available on request. The source code is publicly available at: https://github.com/Maritime-Autonomy/Multi-factor-influence-based-ship-trajectory-prediction-analysis-via-deep-learning.

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