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RESEARCH ARTICLE

Collision Risk Prediction for Small Ships in South Korea Via Optimization of Wireless Communication Period

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Abstract

Since the emergence of COVID-19, there has been a global surge in demand for marine leisure activities. In Korea, the population using marine leisure has risen approximately 192% to 20,406 people, compared to 6,966 people in the year 2000, indicating a continuous growth over the past two decades. Maritime transportation has become increasingly intricate worldwide due to the development of increasingly autonomous, larger, and faster ships. To effectively address potential hazards in such complex traffic environments, it is imperative to anticipate future scenarios and respond rapidly. However, small vessels account for the highest proportion of marine accidents, exhibit movements that exceed the communication period, complicating their behavior prediction. This study aims to identify the appropriate communication interval and prediction methodology for estimating the navigational risk associated with small ships. To achieve this, prediction data were generated for Korean fishing boats using point-based and motion-based prediction methods and communication periods. The accuracy of these predictions was assessed by employing the root mean square error metric and a maritime traffic risk model based on existing data. The findings demonstrate that the point-based prediction method is more accurate in predicting the future risk of small ships by approximately three times compared to the motion-based prediction method. Among the communication intervals analyzed in this study, 5-s interval is recommended to ensure accurate navigational predictions. The significance of this study lies in its determination of the optimal prediction method and communication period for predicting the navigational risk of small ships, which has practical implications for enhancing maritime safety.

Keywords: Collision risk, Small ship, Prediction, Wireless communication

1. Introduction

Maritime transportation, accountable for over 80% of global trade volume [1], relies on ships to safely transport cargo. Ensuring the safety of both sea routes and ships is crucial. However, the maritime traffic environment has grown increasingly complex due to factors such as the recent rise in autonomous ship operations, high-speed navigation, the development of ultra-large ships, and a surge in demand for smaller leisure ships. Korean marine accident statistics from the past five years reveal a continuous increase in the number of marine accidents, with 85% of the total accidents involving fishing boats and leisure ships [2]. As a result, the risk posed by smaller ships is increasing in this ever-changing traffic landscape.

To address the navigational hazards associated with such ships, numerous studies have been actively conducted. In particular, research efforts have been

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concentrated on situational awareness and promoting risk avoidance strategies. Analyzing recent advancements in anti-collision systems for autonomous ships, Zhang et al. [3] categorized the methodologies used in previous studies into geometric approaches, optimization algorithms/bionics, virtual vector/field theories, and artificial methods. Johansen et al. [4] explored collision risk avoidance methods based on optimization and simulation, employing a model predictive control algorithm to optimize ship collision avoidance trajectories. Their work addresses risk avoidance and route optimization challenges in complex navigation scenarios involving multiple ships adhering to the Convention on the International Regulations for Preventing Collisions at Sea 1972(COLREGs) [5]. Similarly, Huang et al. [6] utilized the Velocity Obstacle (VO) algorithm, which corresponds to the virtual vector/field theory, to investigate intelligent obstacle avoidance for autonomous ships. They developed a comprehensive VO-Collision Avoidance System applicable to all ship types, visualizing the course and speed adjustments required to avoid collisions and validating the proposed system through simulations.

Woo and Kim [7] introduced a collision avoidance method based on Deep Reinforcement Learning (DRL), where they represented ship encounters using a grid map. They proposed a neural network architecture specifically tailored for constructing a DRL network and a semi-Markov decision process model for collision avoidance. Park et al. [8] employed a spectral clustering method to identify patterns in ship trajectories, leading to a ship trajectory prediction approach for sea collision avoidance. They developed a ship trajectory prediction model utilizing bidirectional Long Short-Term Memory (Bi-LSTM). In contrast, Hwang and Youn [9] aimed to incorporate the geographical environment into the collision avoidance problem of autonomous ships. They presented a novel anti-collision system that objectively classifies collision risk situations by applying Automatic Identification System (AIS) and Electronic Navigation Chart (ENC) data to a clustering algorithm.

To ensure the safety of ships at sea, it is crucial to comprehend the surrounding conditions, anticipate potential risks, and take appropriate actions [10]. Therefore, a fundamental requirement is to accurately determine the ship's precise position and navigational intentions. However, in the case of small ships expected to navigate autonomously in the future, AIS installation is not standard practice. Even if an AIS is installed, it often belongs to the Class B-type, which transmits and receives ship information for a maximum duration of 3 min depending on speed. This constraint complicates the real-time identification of risks [11,12]. Furthermore, the number of small ships is increasing worldwide and the navigation risk in the constantly evolving marine traffic environment is escalating. Therefore, this study aims to establish the optimal communication period capable of capturing behavioral changes, ensuring the safe navigation of small ships during their voyages. To achieve this, the trajectories of small ships operating along the coast of South Korea were extracted and predicted using various methods. Subsequently, the root mean square error (RMSE) calculations and maritime traffic risk analysis were conducted on the predicted and actual data to determine the optimal strategy.

2. Literature review and introduction of wireless communication

2.1. Literature review

Ibadurrahman et al. [13] conducted a comprehensive study on ship position prediction for navigation situation recognition, categorizing ship position prediction techniques into point-based, motion-based, and trajectory-based approaches. They investigated various studies employing each technique.

Duca et al. [14] focused on ship position prediction using a point-based method. They developed an algorithm based on the K-nearest neighbor classifier and tested it using AIS data from 841 ships in the vicinity of Malta. The authors demonstrated that the ship route prediction algorithm utilizing the K-nearest neighbor classifier achieved a high level of accuracy.

Czapiewska and Sadowski [15] predicted, compared, and analyzed AIS data collected in Gdansk Bay using linear, circular, and Kalman filtering algorithms to determine the optimal algorithm for ship motion prediction. Based on their analysis, the authors argued that the linear algorithm, being the simplest model for ship movement prediction, could operate efficiently while reducing the data storage requirements.

Perera et al. [16] conducted research on integrating vessel detection, tracking, state estimation, and navigational trajectory prediction functions into existing vessel traffic monitoring and information systems. They demonstrated the usability of their approach through computational simulation experiments. By utilizing a competitive neural network (CNN) to analyze the average position of each ship, they predicted the ship's condition and navigation trajectory. Additionally, they employed an extended Kalman filter algorithm to forecast the ship's trajectory.

Dalsnes et al. [17] predicted future ship tracks for a duration of 5−15 min to prevent ship collisions. They expanded the Neighbor Course Distribution Method (NCDM) using Gaussian Mixture Models (GMMs). The authors implemented NCDM with both the AIS data structure utilized in Hexeberg [18] and a newly proposed AIS data structure. They tested their approach using AIS data collected in Trondheimsfjorden, Norway, in 2015 and demonstrated its capability to provide probabilistic position predictions for ships.

On the other hand, examining prior research related to ship's wireless communication and communication periods, Lee et al. [19] emphasized that AIS, which has been instrumental for vessel safety at sea over the past decade, causes a continuous increase in traffic load on VDL (VHF Data Link). As this load escalates, AIS service quality may deteriorate. In response to this challenge, their study proposed a method for alleviating traffic load by automatically controlling VDL traffic within an AIS base station.

Similarly, Nguyen et al. [20] noted that in a densely populated coastal area, transmitter failure could occur, as the VTS station becomes overcrowded and is unable to process the AIS information of all ships according to the standard protocol. They asserted the need for an interpolation method to recover the missing AIS data, identifying linear interpolation, cubic Hermit interpolation, and an identification mechanism as the most suitable approaches.

Lázaro et al. [21] contended that the use of AIS has increased to the point that some systems in today's most congested waters are already overwhelmed. Recognizing the risk that this overload presents to AIS's primary function of collision avoidance, the International Association of Marine Aids to Navigation and Lighthouse Authorities (IALA) and several national maritime authorities initiated work on the VHF Data Exchange System (VDES). The authors provided an overview of VDES.

Min et al. [22] identified that the interval of vessel information reception time was the significant error factor in predicting future trajectories. Their study showed that the data collection interval of LTE-Maritime (Korea"s communication method of e-Navigation) was both dense and uniform compared to AIS, resulting in reduced track prediction error.

However, the majority of previous studies have predominantly relied on AIS data from cargo ships owing to their well-defined navigation patterns. In contrast, small ships, unrestricted by water depth, exhibit more erratic and unpredictable maneuvers characterized by abrupt changes in direction and speed, posing challenges for accurate prediction [23]. Moreover, small ships often lack reliable communication devices other than the AIS owing to economic constraints, making it impossible to precisely track their past trajectories [11]. Furthermore, previous location prediction studies focused on forecasting and validating future positions based on real-time AIS data. However, there has been a lack of research considering the accuracy of AIS data received over various time intervals. Hence, this study sets itself apart by specifically focusing on small ships for navigation risk prediction and thoroughly examining the accuracy of prediction data for each communication interval.

2.2. Introduction of wireless communication

2.2.1. Automatic Identification System

A common thread among prior studies that predicted ship positions using various methods is their reliance on past or real-time ship positions to forecast future positions. The past ship location information can be acquired through the utilization of an AIS.

The AIS was introduced by the IMO as part of the Convention on the Safety of Life at Sea (SOLAS) to enhance safety and security in maritime operations. AIS operates within the frequency range of 156.025−162.025 MHz, facilitating the real-time transmission and reception of a ship's navigation information between the ship and onshore base stations. Its key functions include collision prevention, ship location reporting, and monitoring during ship operations, as it provides vital situational awareness [24].

In July 2002, the IMO mandated the installation of AISs on passenger ships and new ships with a gross tonnage exceeding 300 tons [12]. However, safety concerns arose for non-SOLAS ships, leading to the development of a more cost-effective Class B AIS system specifically designed for small ships [24]. Notably, one significant operational distinction between Class A AIS and Class B AIS lies in the transmission frequency of dynamic information [12].

2.2.2. e-navigation (LTE-based maritime wireless communication)

E-navigation encompasses the integrated collection, exchange, analysis, presentation, and utilization of marine information using electronic means, aimed at enhancing navigation, safety, security, and environmental protection at sea [25]. Following the 81st Maritime Safety Committee (MSC) meeting in 2006, the IMO initiated the e-navigation project, collaborating with committee members, member countries, and international organizations to develop the e-navigation strategy [26]. Since 2016, South Korea has been actively involved in the “Korean e-Navigation construction project” [27]. The Korean initiative focuses on developing specialized equipment and services tailored to fishing boats and ships operating in coastal waters, which account for approximately 80% of all marine accidents [28].

LTE-based maritime wireless communication (LTE-M) is a high-speed data communication method that enables communication up to 100 km into the sea, and it serves as the backbone for Korean e-navigation services. It also plays a crucial role in establishing a maritime disaster network for search and rescue as well as ensuring a timely response in the event of a marine accident [29]. The Ministry of Oceans and Fisheries constructed LTE-M infrastructure, including base stations and network operation centers, along the country's coastlines in 2019. In 2020, LTE-M transceivers were installed on government ships, coast guard vessels, passenger ships, merchant ships, and fishing boats, followed by sea testing conducted along the coastlines. The world's first fully implemented sea navigation service utilizing LTE-M was launched in January 2021 [30,31].

2.2.3. Wireless access in vehicular environment (WAVE) communication

Wireless access in vehicular environments (WAVE) is a communication service that ensures road safety and vehicle security by supporting vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication through the integration of road traffic and IT technology [32]. The development of WAVE communication technology aimed to provide national-level traffic information and enhance vehicle safety services, with a primary focus on the US Department of Transportation [33]. Since WAVE communication, primarily utilized in road traffic, transmits object locations every 0.1 s, it offers the potential to promptly address collision risks for small ships through rapid inter-ship communication [11]. Table 1 provides a summary of the distinctive features of each wireless communication facility.

Since small ships primarily rely on AIS for communication at sea, there is a potential discrepancy in prediction performance between the AIS and WAVE, which has a communication period of 0.1 s, when it comes to accurately predicting and avoiding danger for small ships. Figure 1 illustrates that the WAVE system transmits and receives significantly more data than the AIS in the tracks of ships equipped with both the WAVE system and AIS. Furthermore, when using AIS data for prediction using a point-based method, the position accuracy is compromised due to the longer communication period compared to WAVE data.

Hence, this study aims to determine the optimal communication period required for precise position prediction and risk avoidance in small ships.

3. Position prediction

This section describes the various stages involved in predicting the future navigation risk of a vessel, including the pre-processing of vessel data and the methodology employed for position prediction, the execution of the prediction, and the verification of the prediction results. To ascertain the suitable communication period, data were classified into different communication periods as defined, and predictions were conducted accordingly. In the subsequent section, the similarity between the risk associated with each data set by communication period and the actual data is confirmed through the calculation of maritime traffic risk.

3.1. Introduction of ship operation data

WAVE data collected from fishing boats operating in the West Sea of Korea were utilized to evaluate the frequency with which a small ship should communicate to predict its future position and avoid

Table 1. Comparison of wireless communication devices [33].

Category	AIS	LTE-M	WAVE
Frequency	161.975 MHz 162.025 MHz	700 MHz	5.8 GHz
Communication Access type	SOTDMA, CSTDMA	OFDMA	OFDM, CSMA-CA
Power	2 W−12.5 W	200 mW	Less than 100 mW
Transmission Period	2 s−180 s	1 s	100 msec
Transmission Distance	Max. 50 miles	Max. 54 miles	Max. 5 miles
Security Method	−	EPS-AKA	IEEE 1609.2

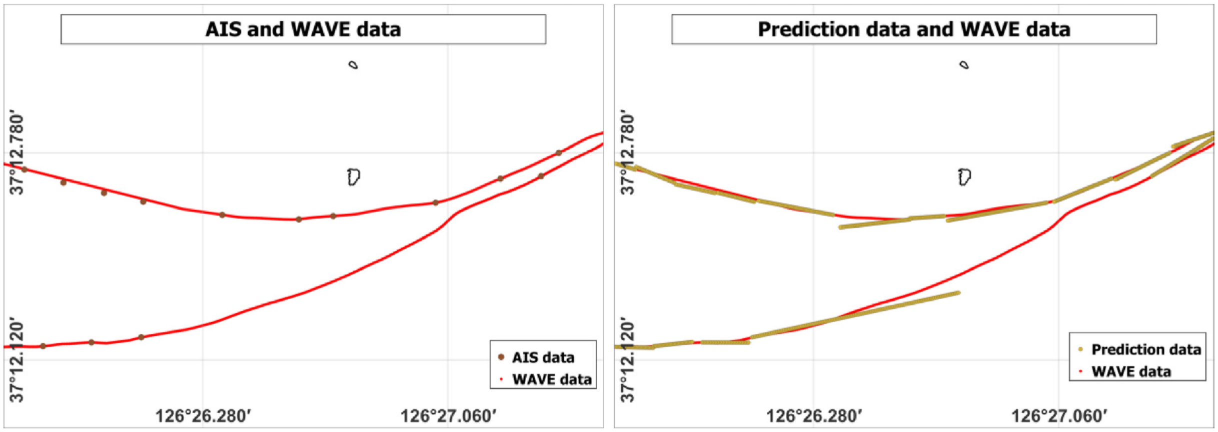

Fig. 1. Example of data by wireless communication equipment.

danger. The WAVE data were chosen as the ship's operational data for prediction due to the system's ability to generate data for each communication period, given the WAVE system's data transmission and reception interval of 0.1 s.

The West Sea of Korea experiences high fishing boat activity due to the concentration of population in the metropolitan area. Notably, the waters near Yeongheung Island in the West Sea have witnessed significant fishing boat traffic and navigation risks, exemplified by the collision incident involving the oil product carriers 15Myeongjin and fishing boat Seonchang1 on December 3, 2017, resulting in the loss of 15 lives [34]. Consequently, this study selected the waters near Yeongheung Island as the prediction area to assess the navigation risks of small ships. Figure 2 showcases the study area, depicting the sea area near Yeongheung Island in the northern part of the West Sea of Korea.

In the West Sea, the month of September consistently witnesses the highest abundance of fish species, resulting in a surge in tourism and a consequent increase in the number of ships sailing during this period. To capture the dynamics of ship positions, data were collected for a duration of 30 days in September 2022. The DBSCAN algorithm, a density-

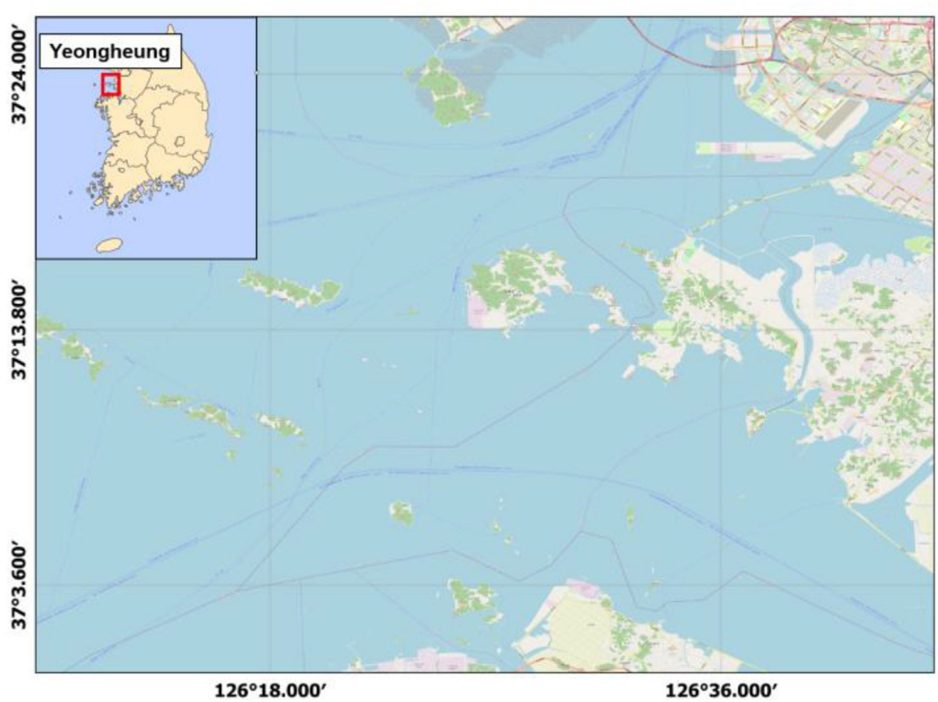

Fig. 2. Research area of the study.

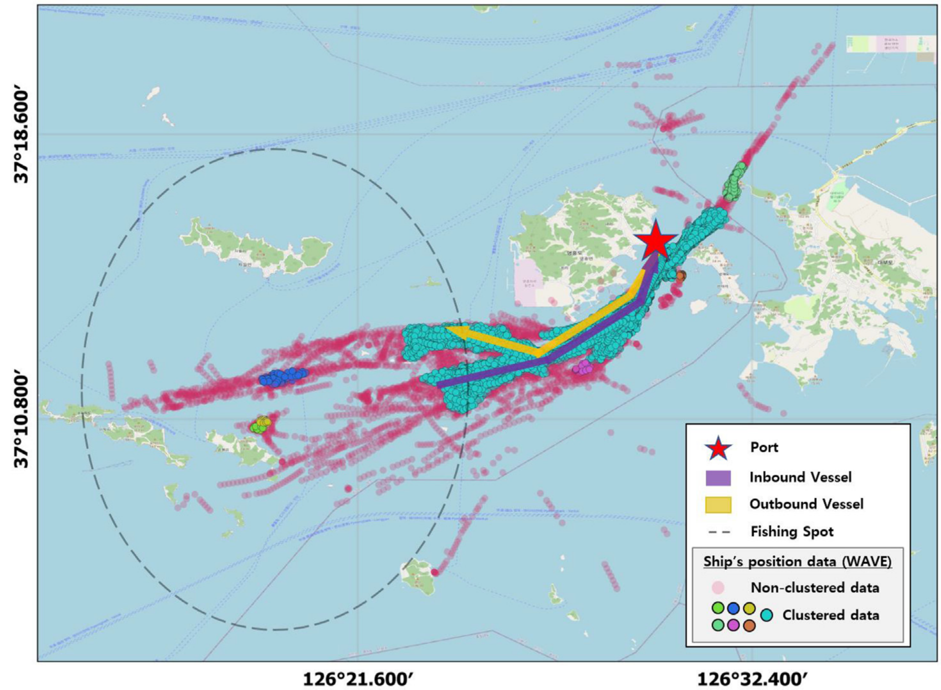

Fig. 3. Main flow of ships in the research area.

based notion of clusters designed to discover clusters of arbitrary shape, was employed to identify the navigation and fishing operation segments of ships equipped with the WAVE device [35]. In this study, the DBSCAN algorithm was implemented through Python (Jupyter Notebook, anaconda 3). Figure 3 visualizes the primary operational areas as well as the patterns of ship arrivals and departures derived from applying the DBSCAN algorithm.

To ensure the accuracy of the analysis, data points with speeds ranging from 0 to 3 knots were excluded from the DBSCAN algorithm, as they corresponded to speeds observed during fishing operations based on feedback from, ship operators [36]. Moreover, to address gaps in data coverage and facilitate comprehensive analysis, interpolation was performed on all data points at 30 s intervals. Finally, clustering was performed based on 24,812 ship position data, where 7 major clusters were recognized.

The main cluster of the highest density of ships identified through DBSCAN included data associated with the departure and arrival of ships. By examining the collected data in chronological order, it was observed that ships typically departed in the early morning and entered the port in the evening on a daily basis. Therefore, on September 20, the date for which the most reliable WAVE data were available in September 2022, predictions were made for four target ships using 24 h data, and the results were subsequently verified. Table 2 provides further details regarding the target-ship predictions.

Table 2. Description of ships for prediction.

Name	ARA2	LUREFISHING	MANSU2	NICE
Picture				
Length(m)	14.2	15.85	13.9	16.5
Breadth(m)	4.12	3.58	4.1	3.6
Grosston(t)	9.77	9.77	9.77	9.77

3.2. Prediction method

Through the exhaustive review of previous studies presented in Section 2, various prediction methods have been explored, ranging from elementary position predictions made through calculations to sophisticated ship track predictions utilizing deep-learning and artificial intelligence technologies. Within this spectrum, Ibadurrahman et al. [13] classified ship position prediction techniques from 19 literatures into three distinct approaches: point-based, motion-based, and trajectory-based approaches. However, for small vessels such as fishing boats or leisure ships, which often lack well-defined navigation patterns, the application of the trajectory-based method is anticipated to be complex. Therefore, the focus of this study is on conducting predictions employing the point-based and motion-based approaches.

3.2.1. Past time data of small ship

The dataset used for prediction consists solely of actual navigation data from small fishing boats. Specifically, data points corresponding to ship navigation states, excluding those with speeds of 0 knots (indicating operational status), were extracted and utilized for prediction. The WAVE data, collected as navigation data, were segmented into separate ship navigation data files at intervals of 5, 10, 15, 20, and 30 s. Establishing a communication period of 5–30 s allowed for evaluating the suitability of the dynamic information transmission cycle of a ship equipped with Class B type AIS. Each file was subsequently subjected to prediction. A comparison between the predicted data and the original data was then conducted to assess the appropriateness of small ship position and risk prediction when a specific time interval was guaranteed. Figure 4 illustrates the ship data processing procedure for position prediction.

3.2.2. Point-based prediction

The point-based prediction method involves predictions derived from previously received data on position, speed over ground (SOG), and course over ground (COG). To implement point-based prediction, the dynamic information of the ship is first needed, necessitating pre-processing steps such as time period division and unit conversion for prediction. After making a prediction using this data, the RMSE serves as a verification tool for the result. A more comprehensive explanation with equations is provided in the following text.

The navigation data collected through the WAVE device utilizes the WGS-84 coordinate system, which is based on latitude and longitude in degree form. To facilitate calculations, these coordinates are converted into the Cartesian location coordinate system with units in meters, as shown in (1). Here, $Latitude_a$ and $Longitude_a$ represent the coordinates in the WGS-84 system, while $Latitude_{datumpoint}$ and $Longitude_{datumpoint}$ denote the reference point in the WGS-84 system.

$$x = \left(\text{Latitude}_a - \text{Latitude}_{datumpoint}\right) \times 1852 \times 60.$$
$$y = \begin{bmatrix} \left(\text{Longitude}_a - \text{Longitude}_{datumpoint}\right) \\ \times \\ \left\{\text{COS}\left(\text{Latitude}_{datumpoint} \times \pi \div 180\right)\right\} \end{bmatrix} \times 1852 \times 60. \tag{1}$$

Likewise, speed values are converted from knots to meters per second (m/s) unit.

$$\text{sog}\left(\frac{\text{m}}{\text{s}}\right) = 0.514444 \times \text{SOG}(\text{knot}). \tag{2}$$

Using (3), the movement of the object during the time (s) required for the next data reception is calculated.

$$s = \text{time}(\text{sec}'') \times \text{sog}. \tag{3}$$

Subsequently, the distance traveled until the next data reception is obtained using the most recent COG and SOG values. This distance (Δx and Δy) is then added to the previous position to determine the future position coordinates, as shown in (4) and (5).

$$\Delta x = s \times \sin\left(COG \times \frac{\pi}{180}\right). \tag{4}$$

$$\Delta y = s \times \cos\left(COG \times \frac{\pi}{180}\right).$$
$$x' = x + \Delta x. \tag{5}$$
$$y' = y + \Delta y.$$

3.2.3. Motion-based prediction

In contrast to the point-based prediction method that predicts the next position based on the most recent position, SOG, and COG, the motion-based prediction method forecasts the next position by considering the average speed and bearing of past position data received over a specific period. In this study, the past 3 min of data were used for position prediction, given that the maximum communication period for small ships equipped with Class B AIS is 3 min. This differs from the point-based prediction method, as it calculates the average speed and bearing over the past 3 min and utilizes it as the previous position for prediction. Figure 5 outlines

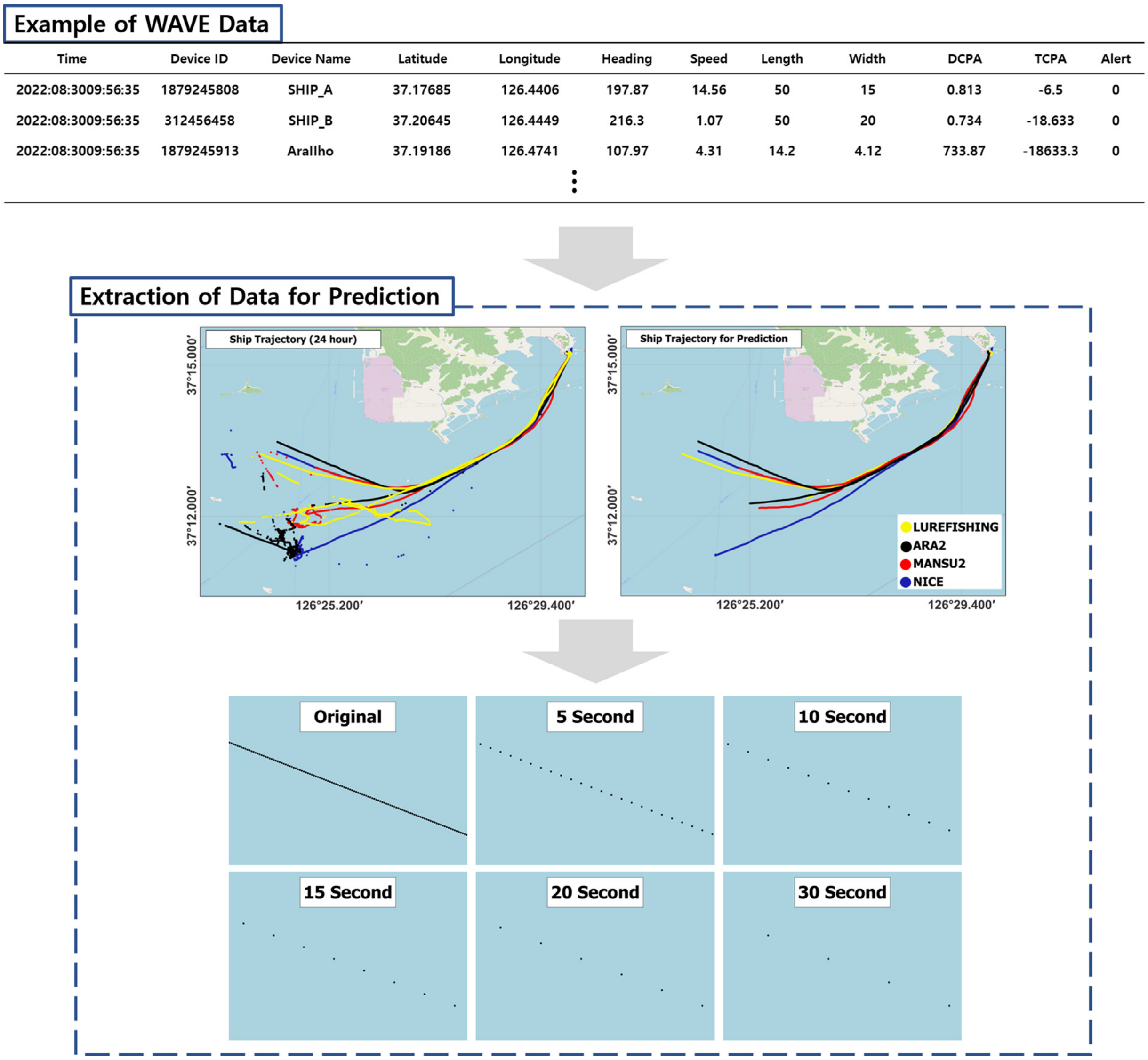

Fig. 4. Flow of data processing for prediction.

the calculation procedure for the point-based and motion-based prediction.

Similar to the process in point-based prediction, position and speed data units are converted into meters using (1) and (2). Subsequently, to determine the object's movement during the time required until the next data reception, the average SOG for the past 3 min is utilized.

$$s = \text{time}(\text{sec}'') \times sog_{3\ min}. \tag{6}$$

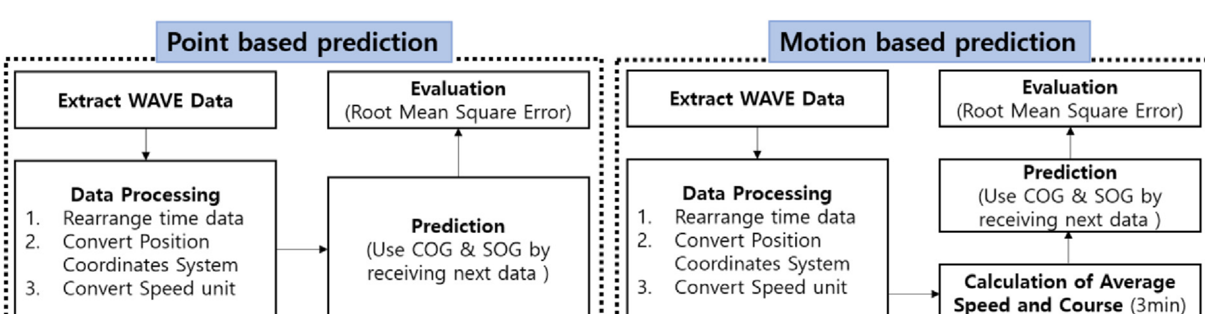

Fig. 5. Flow chart of prediction methods.

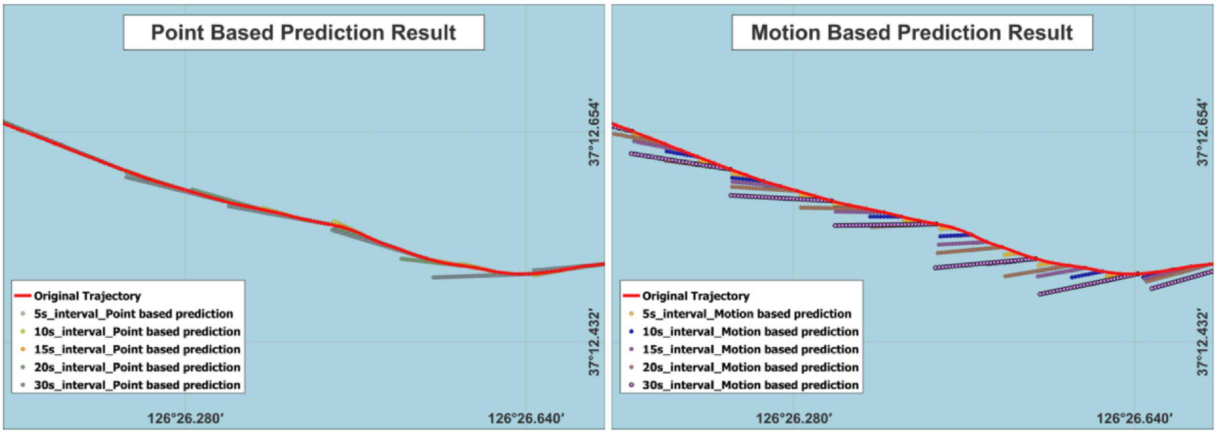

Fig. 6. Result of ship position prediction (sample).

Similarly, utilizing the average COG over the past 3 min, the distance traveled until the next data reception was determined. This distance was then added to the previous location to obtain the future location coordinates, as depicted in (5).

$$\Delta x = s \times \sin\left(COG_{3\ min} \times \frac{\pi}{180}\right).$$
$$\Delta y = s \times \cos\left(COG_{3\ min} \times \frac{\pi}{180}\right). \tag{7}$$

3.3. Results of prediction

Figure 6 illustrates the position prediction results for ships operating on September 20, 2022, using point-based and motion-based methods at intervals of 1 s until the next data reception.

By comparing the actual tracks with the tracks predicted by the prediction methods, it becomes evident that the motion-based prediction exhibits a greater deviation from the actual track compared to the point-based prediction. Figure 6 confirms the difficulty in accurately predicting future positions, especially near bends, when relying on data from the past 3 min. Through this, it is seen that it is very difficult to predict the future risk with the average bearing and speed of the past 3 min because small ships such as fishing boats and leisure ships have characteristics such as sudden changes in their intention that are difficult to predict. Furthermore, in the prediction results of each method, it appears that the method utilizing data generated at the shortest interval of 5 s yields predictions that most closely align with the original track. However, to objectively assess the accuracy of the predicted data, RMSE was employed as a measure.

3.4. Verification of results

In this study, the RMSE, a commonly used parameter for evaluating model errors in various fields such as natural environment measurements, map measurements, and surveying, was employed to assess the accuracy of the previously predicted location data. The RMSE quantifies the discrepancy between actual and predicted values by calculating the squared errors, summing them, and obtaining the average value. To obtain the RMSE, the squared errors are then squarely rooted. In this context, a smaller RMSE value indicates a smaller error, with a value closer to 0 indicating higher accuracy [37]. The formula for calculating the RMSE is expressed in (8), where N represents the total number of samples, i represents the sample order, $P\_measure$ denotes the actual value, and $P\_predict$ signifies the predicted value.

$$RMSE = \sqrt{\frac{1}{N} \times \left(\sum_{i=1}^{N} \left(P\_measure_i - P\_predict_i\right)^2\right)}. \tag{8}$$

3.4.1. Results of verification

Table 3 presents the results of summing the RMSE between the location coordinates of the original data

Table 3. Sum of RMSE by factors.

Sum of RMSE (m)							
	By Prediction method		By Time interval				
	Point based	Motion based	5 s	10 s	15 s	20 s	30 s
ARA2	36.7	76.9	6.2	13.6	21.3	29.2	43.4
LUREFISHING	28.2	62.8	5.0	10.7	16.9	22.7	35.7
MANSU2	37.0	98.6	7.0	15.8	24.7	33.3	54.8
NICE	34.0	106.5	7.7	16.9	25.6	35.9	54.5

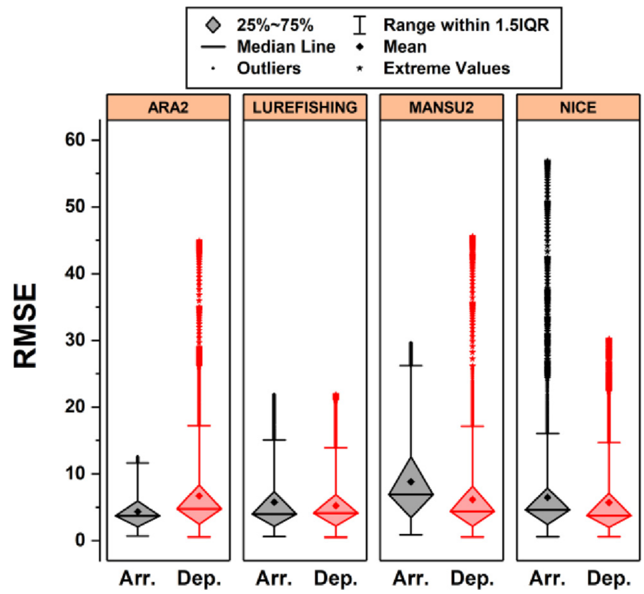

Fig. 7. Boxplot of RMSE by ships.

and the data predicted by the ship, communication period, and prediction method.

Through RMSE calculations, it was observed that the errors associated with a communication period of 5 s and the point-based prediction data were relatively low, exhibiting a trend similar to that of the original data. Notably, it was evident that there were variations in each element, and the shorter the communication period, the greater the likelihood of the predicted data resembling the original data when utilizing the point-based prediction method.

Figure 7 presents a boxplot illustrating the distribution of RMSE for each ship's arrival and departure tracks. The plot reveals that 75% of the RMS errors are below 10 m, with RMSE values exceeding 20 m identified as outliers.

3.4.2. Calculation of RMSE by time

To identify the sections with the highest RMSE, indicating the most challenging prediction scenarios, the RMSE was calculated for each ship by categorizing the prediction methods. Figure 8 illustrates the RMSE values over time for one ship as an example.

Considering the ARA2 arrival and departure tracks and their corresponding RMSE values by time zone as an example, it was observed that the RMSE values for arrival tracks fell within a relatively lower range compared to those for departure tracks. This discrepancy can be attributed to specific track characteristics, such as sharp turns during departure due to unberthing operations and significant heading changes while moving towards fishing operation areas.

Analyzing the RMSE values in chronological order for each communication period, it became evident that the error between the predicted and actual data decreased in the following order: 5, 10,

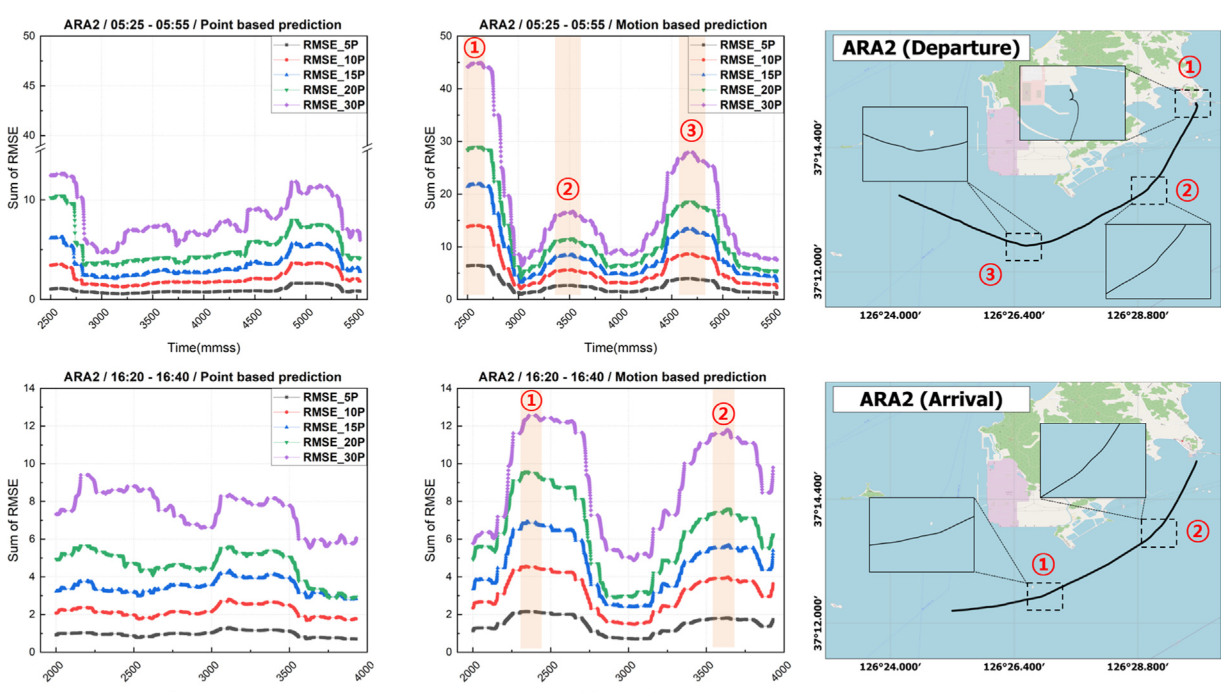

Fig. 8. Comparison of RMSE and ship trajectories.

15, 20, and 30 s. Thus, recording ship position data at intervals of 5 s appeared to be a prerequisite for accurate position prediction.

Furthermore, examining the RMSE values in chronological order for each prediction method, the point-based prediction method displayed smaller errors compared to the motion-based prediction method. Hence, the point-based prediction technique seems suitable for forecasting the future positions of small ships.

When comparing Fig. 7, which displays the RMSE boxplot, with Fig. 8, illustrating the RMSE results for each time zone, it becomes apparent that the accuracy of predictions using the motion-based method significantly decreases when the communication period is prolonged or when there are abrupt changes in bearing. Consequently, it is challenging to provide accurate danger warnings to small ships using this method.

4. Analysis of maritime traffic risk

Using the aforementioned RMSE calculations, the error magnitude between the actual track and the predicted track for each communication period was determined. Additionally, the sections with the largest RMSE in each time zone, indicating areas where position prediction was more challenging, were identified. To assess potential differences in maritime traffic risk between the original data and the predicted data from a maritime traffic perspective, the maritime traffic risk was calculated by simulating random encounter situations according to the COLREG regulations using each ship's operational data, including the predicted data.

4.1. Potential assessment of risk model [38]

In this study, the potential assessment of risk (PARK) model, a tool that integrates subjective risks associated with the type of ship-to-ship encounter and overall ship conditions based on a survey of Korean ship operators was employed. The PARK model proved effective in this study as it represents a maritime traffic risk assessment model specifically tailored to the characteristics of coastal regions in Korea, along with the awareness and needs of Korean ship operators. Furthermore, the model's ability to select a fishing boat as a vessel type allows for a more refined determination of the collision risk of a small vessel using predicted data. The model was further validated through ship-handling simulation experiments [39]. The PARK model was calculated using (9) and adjusted using the closest point of approach (CPA) and time to the closest point of approach (TCPA). Table 4 presents the classification of Subjective Judgment (SJ) values derived from the PARK model, categorized by risk and tolerance levels.

Table 4. Stress ranking of PARK model.

SJ	Mariners' Judgement	Stress ranking	Acceptable criteria
1	Extremely safe	Negligible	Acceptable
2	Fairly safe	Negligible	Acceptable
3	Somewhat safe	Negligible	Acceptable
4	Neither safe nor dangerous	Negligible	Acceptable
5	Somewhat dangerous	Marginal	Acceptable
6	Fairly dangerous	Critical	Unacceptable
7	Extremely dangerous	Catastrophic	Unacceptable

$$\begin{aligned}\text{Risk Value} = {} & 5.081905 + \text{Type factor} \\ & + \text{Tonnage factor} + \text{Length factor} + \text{Width factor} \\ & + \text{Career factor} + \text{License factor} + \text{Position factor} \\ & + 0.002517 \times \text{LOA} + \text{Crossing factor} + \text{Side factor} \\ & + \frac{\text{In}}{\text{Out}}\text{harbor factor} + \text{Speed factor} - 0.004930 \\ & \times \text{Speed difference} - 0.430710 \times \text{Distance}.\end{aligned} \quad (9)$$

4.2. Data for analysis of maritime traffic risk

4.2.1. Own ship data

The primary ship data used in the analysis consisted of eleven data points, encompassing the

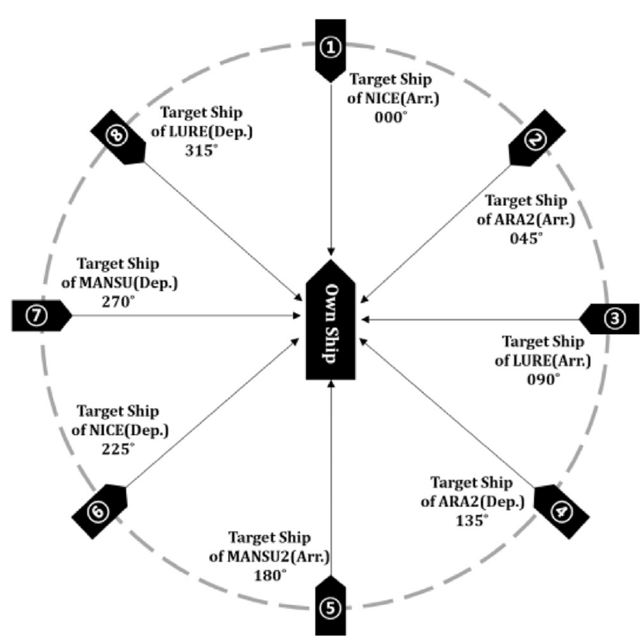

Fig. 9. Scenario of PARK model.

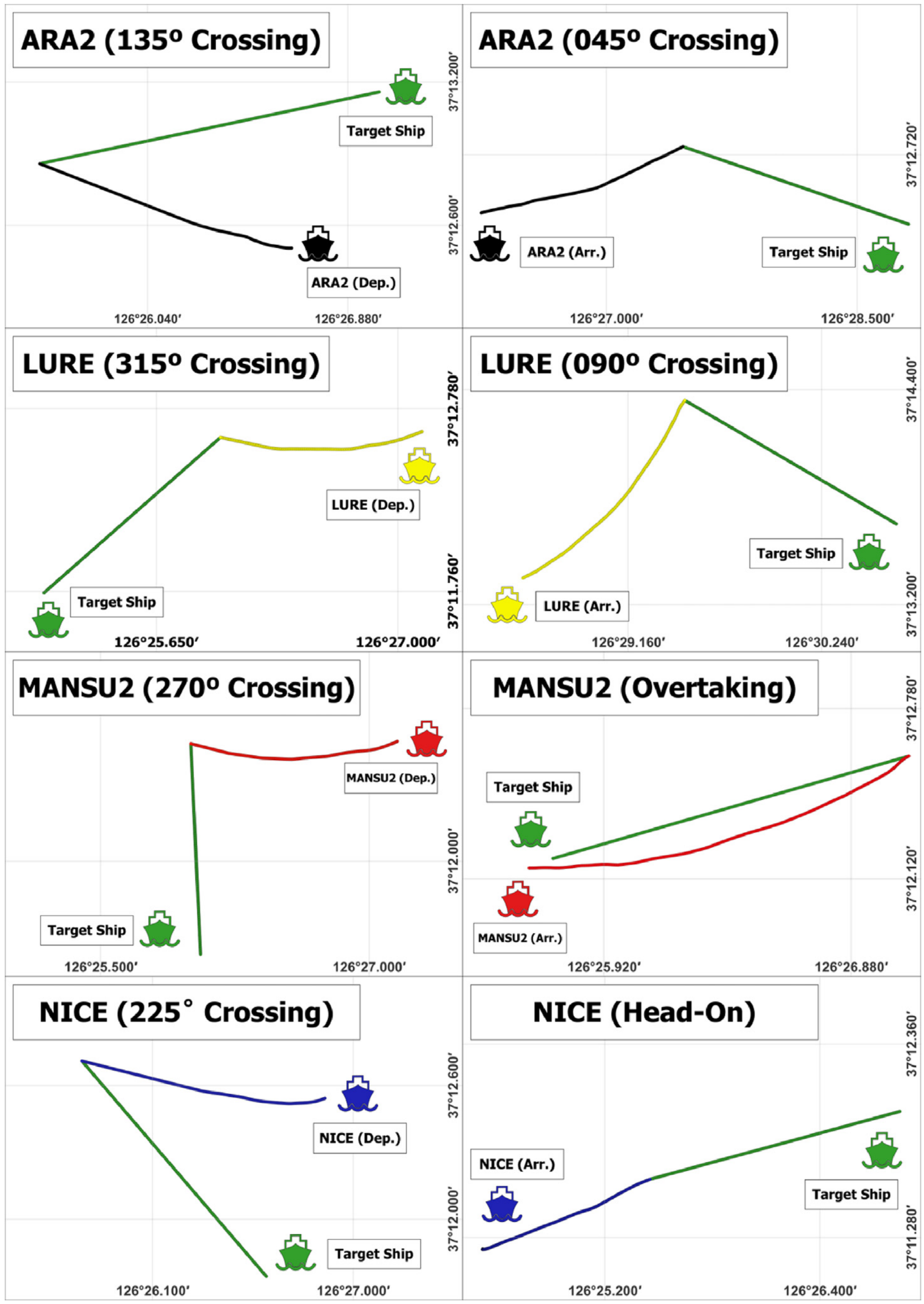

Fig. 10. Real trajectory of ship for PARK Model.

original WAVE data for each encounter, two prediction methods, and five communication periods. To examine the variation in maritime traffic risk between the original data and the data generated by each prediction method for different periods, the 5-min track exhibiting the largest RMSE (indicating the most significant position difference) was extracted from each dataset, including the original data. Sections with substantial RMSE values were selected as the focus of the maritime traffic risk analysis, as they were expected to yield different risk outcomes compared to sections with negligible position differences.

4.2.2. Target ship data

To calculate the maritime traffic risk, encounter situations prescribed by COLREGs were generated for the arrival and departure data of each ship at 45° angles. The specifications of the other ship were

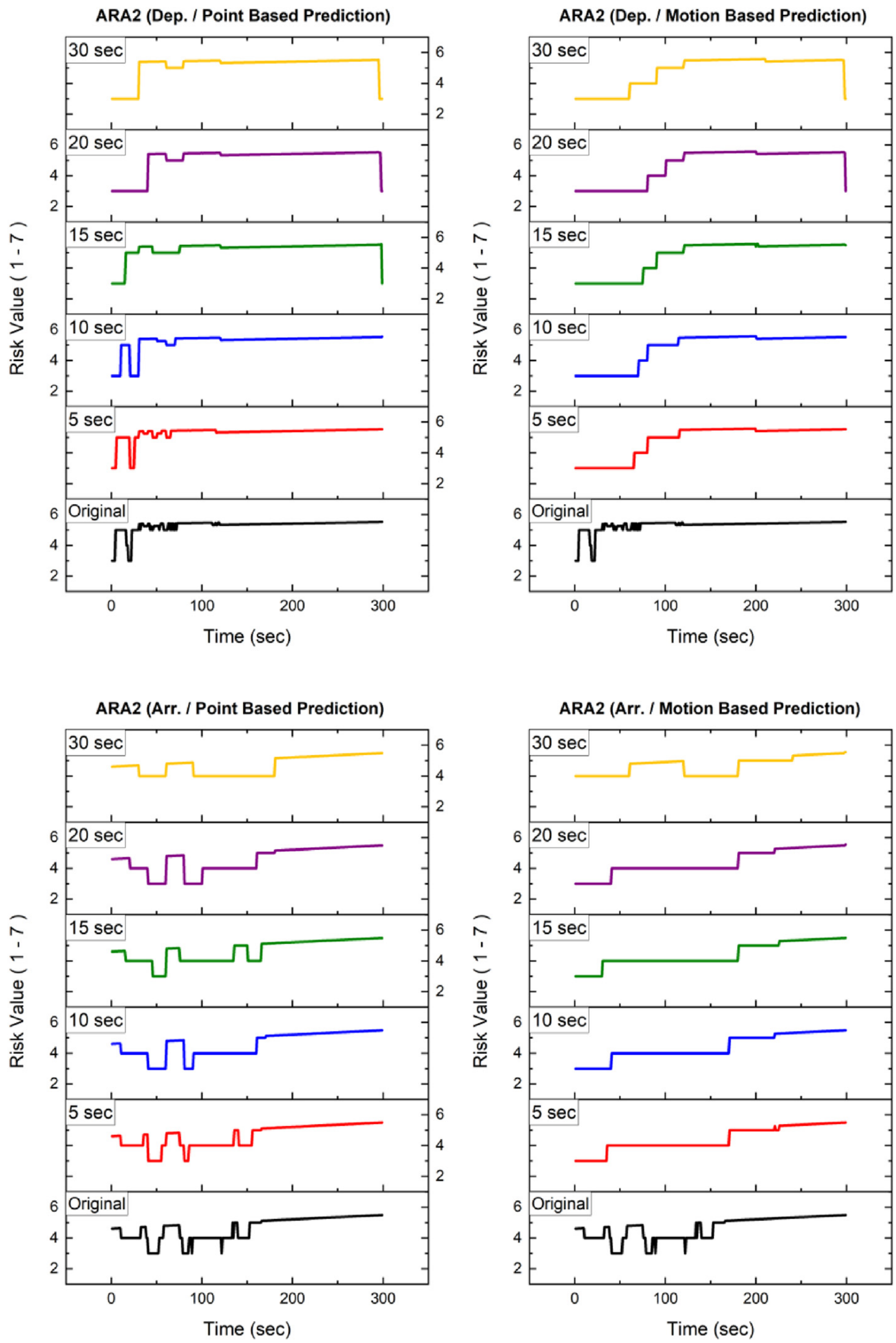

Fig. 11. Calculated risk of PARK Model.

configured to match those of the small ship, while the speed of the ship was set to 14 knots, which represents the average sailing speed of small ships [40]. Consequently, the other ship operated in a direction corresponding to each encounter situation relative to the average bearing of the ship at a point approximately 1.17 nautical miles away. Figure 9 provides an overview of the scenario used for the PARK model calculations, while Fig. 10 illustrates the actual track of the main ship and the target ship for each encounter situation.

4.3. Results of maritime traffic risk analysis

Figure 11 presents an example of the results of calculating maritime traffic risk for situations encountered by each ship using the prediction method and communication period.

Analyzing the maritime traffic risk in terms of the time until collision with the other ship, the risk values range from three to six across all encounter situations. This suggests that these encounter situations possess a certain level of inherent danger within an acceptable safety range. The absence of a higher risk value (7) even when simulating collision-like scenarios can be attributed to the maneuverability and small size of the analyzed fishing boat. These characteristics seem to be reflected in the PARK model, which incorporates factors such as the sizes and types of other ships during the risk calculation.

Examining the maritime traffic risk based on the prediction method, it was observed that the point-based prediction method can promptly detect and provide risks similar to the original data compared to the motion-based prediction method. When considering the maritime traffic risk in relation to the communication period, it becomes apparent that the data generated at the shortest period (5 s) aligns closely with the risk levels of the original data. However, in the case of motion-based prediction, even the 5 s interval data exhibited a tendency to underestimate the actual danger, indicating that the point-based prediction method is more suitable for predicting the navigation risk of small ships.

5. Conclusion

Maritime transportation inherently faces numerous risks owing to its environmental characteristics. With the growing popularity of marine leisure activities and the emergence of autonomous ships, the risks associated with navigation at sea have further intensified. To effectively mitigate these risks, it becomes crucial to predict the future behavior of ships and take appropriate precautions. However, for small ships like, leisure ships and fishing boats, capturing their behavior accurately poses a challenge, particularly due to limitations in wireless communication. Hence, this study aimed to identify the optimal communication period and prediction method for predicting the navigation risk of small ships. The findings of this study confirm that the point-based prediction method, which relies on previous positional data, is the most suitable approach for predicting the future risk of small ships. Moreover, it was determined that a communication period of 5 s, the shortest among the periods examined in this study, should be supported to ensure accurate navigation prediction.

This study holds significance as it sheds light on prediction methods and wireless communication periods specifically tailored for small-ship navigation, a topic that has received limited attention in previous research. However, one limitation of this study lies in its limited geographical scope and focus on specific target vessels. Therefore, future research should aim to expand the analysis to include a more diverse range of vessels and regions. Additionally, it would be valuable to verify the suitability of the results derived from this study through real-world testing in different maritime areas.

Conflict of interest

There is no conflict of interest.

Appendix

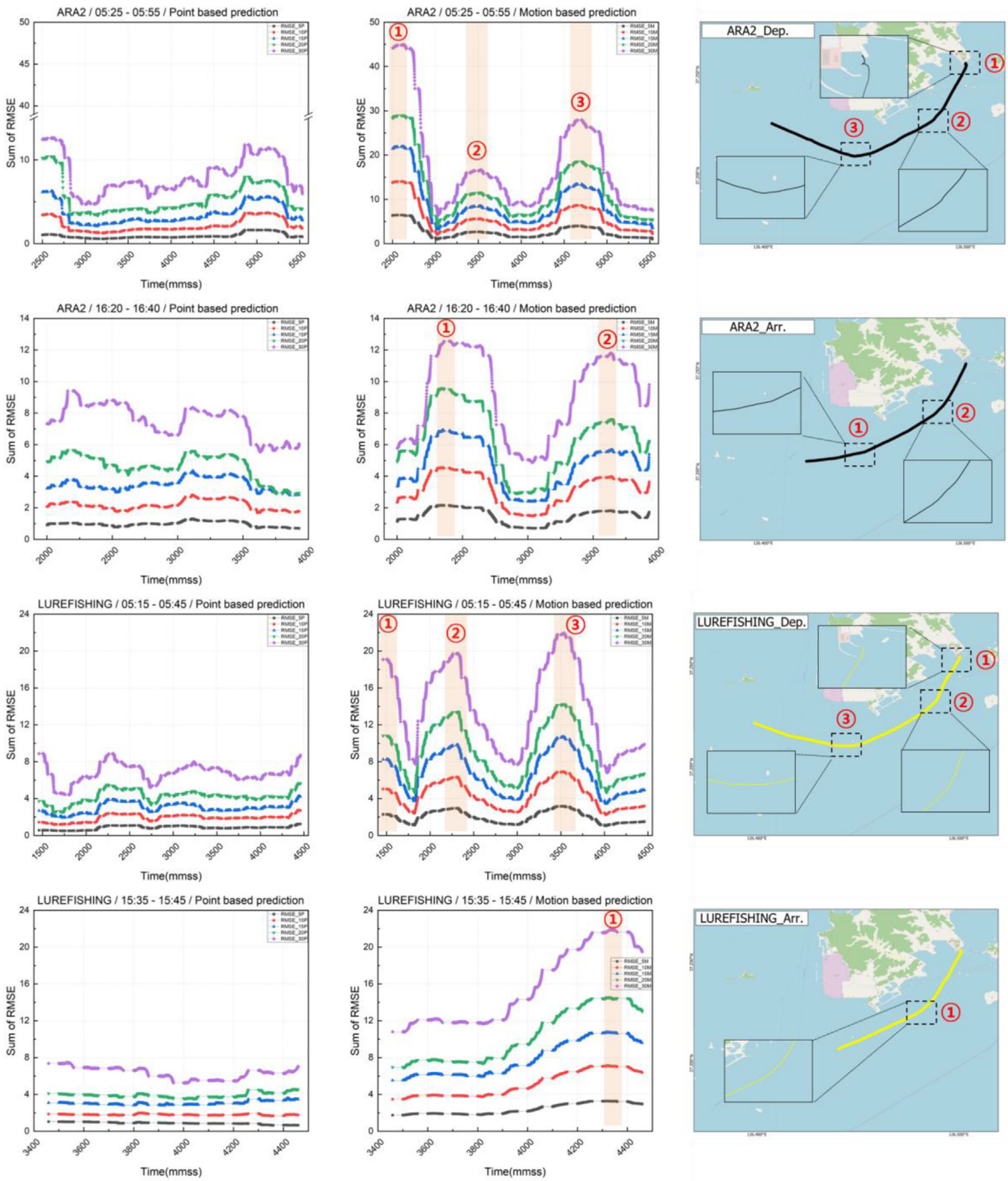

Figure a. Comparison of RMSE and ship trajectories.

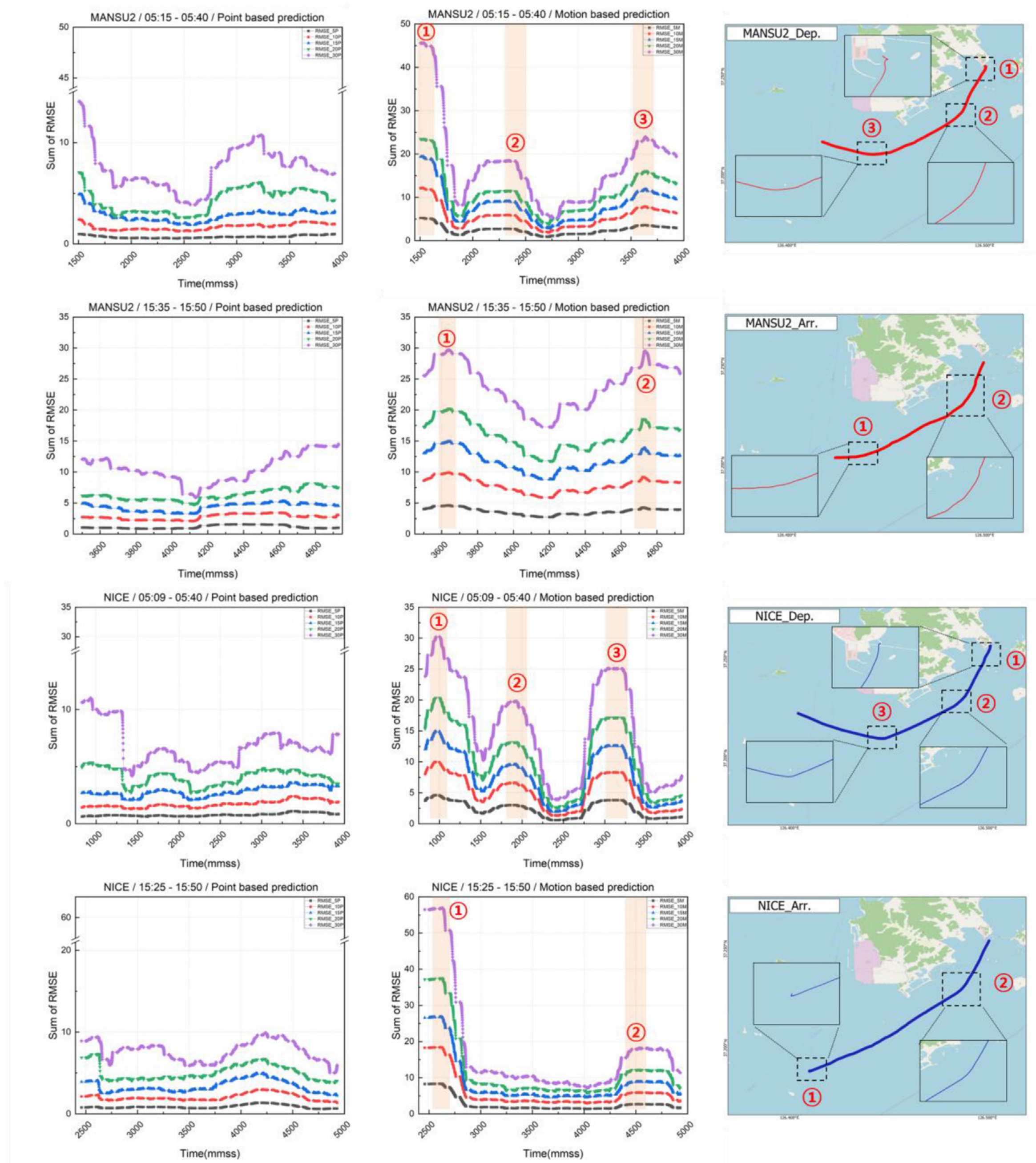

Figure a. (Continued).

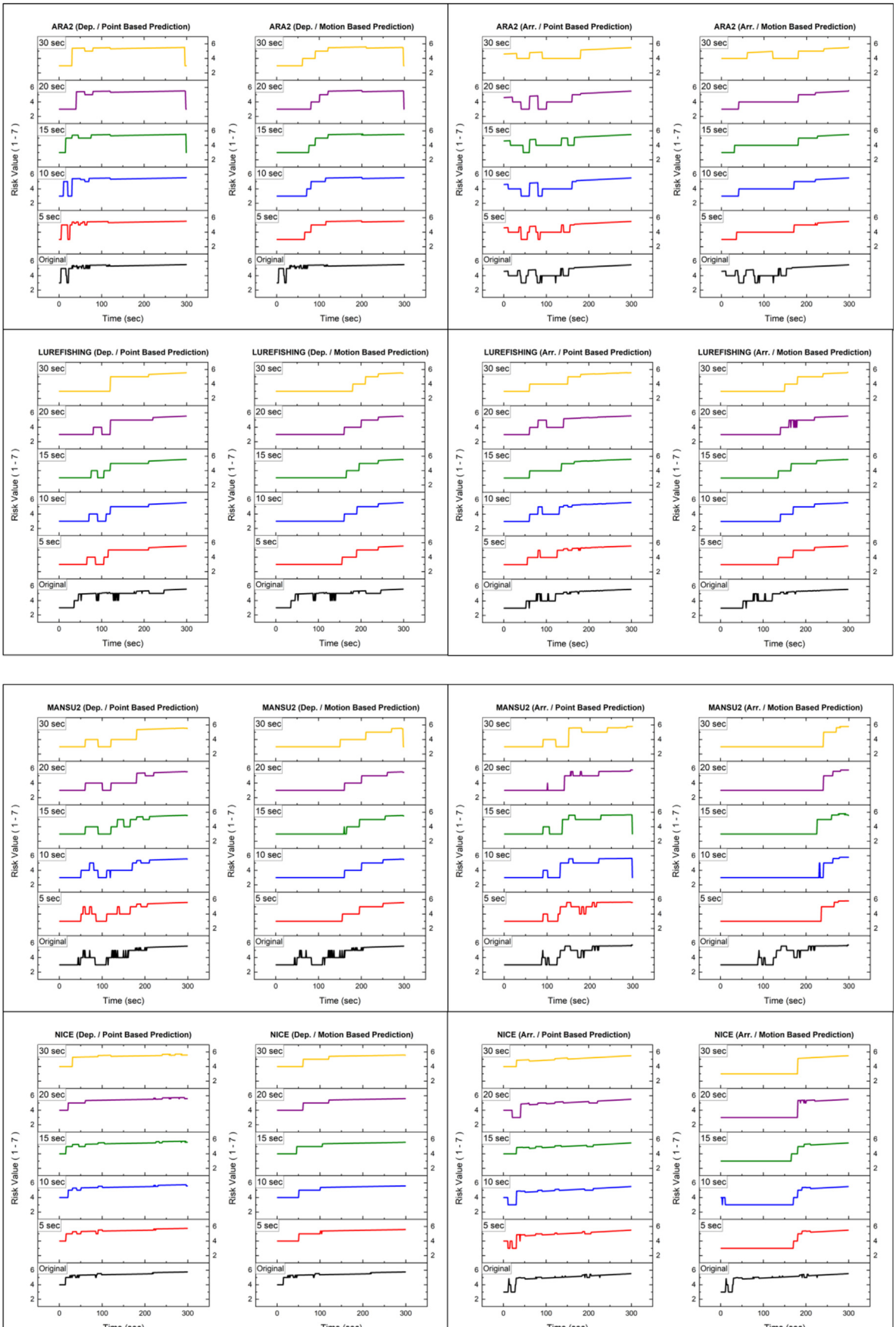

Figure b. Calculated risk of PARK Model.

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