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Ship Navigation Optimization Using Detailed Oceanographic Information Based on the S-100 Standards

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Maritime transport is a globally interconnected mode of logistics that enables large-scale cargo movement across nations. Unlike land or air transport, ships operate in an open and borderless domain, which necessitates the adoption of standardized operational frameworks across countries. However, this global standardization also constrains the rapid integration of emerging digital technologies into maritime operations. Recently, international organizations, such as the International Maritime Organization (IMO) and the International Hydrographic Organization (IHO), have been actively promoting next-generation maritime navigation systems and the implementation of unified data standards, such as the S-100 framework. These efforts align with global environmental goals, including decarbonization and sustainable shipping. In this study, we propose an integrated framework for estimating ship fuel consumption by utilizing detailed oceanographic information predicted through the Coastal Korea Operational Oceanographic System. The predicted fuel usage is intended to be delivered to ship operators in real time to assist in navigation decisions. Furthermore, referring to environmental forecasts, the system is designed to provide optimized navigation guidelines, with the ultimate aim of reducing fuel usage and improving overall operational efficiency. The present work is focused on establishing the data acquisition infrastructure and preliminary integration of real ship sensor data with high-resolution oceanographic forecasts, laying the foundation for future AI-based optimization models.

1. Introduction

1.1 Research background

According to UN Trade and Development shipping statistics published in 2025,[1] maritime transport accounts for more than 80% of the volume of goods traded worldwide. As shown in Fig. 1, country-level seaborne trade data are therefore critical for designing effective transport,

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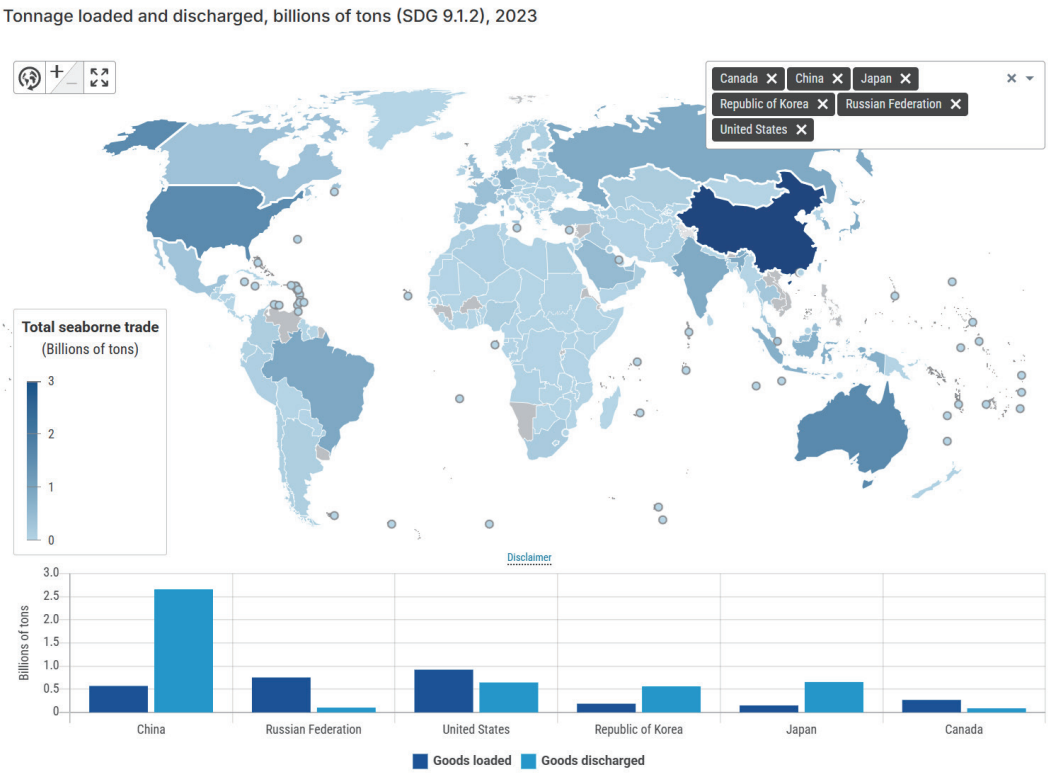


Fig. 1. (Color online) UN trade and development. Data Hub, 2025

trade, and investment policies. Although freight movement via rail, road, and air transport remains important, sea transport continues to dominate global logistics in terms of volume.

As the oceans connect the entire world as one, all nations employ common standards and frameworks. However, the standards currently in use were developed more than twenty years ago and thus fail to reflect the latest industrial technologies. While on land, model development using digital twins and AI is advancing rapidly, but the maritime sector lags behind.

Recently, the International Maritime Organization, International Hydrographic Organization, and International Organization for Marine Aids to Navigation (IALA) have been developing next-generation standards aimed at providing ships with real-time maritime data and enabling the exchange of harmonized data according to standardized formats, thereby improving operational efficiency. In this study, we seek to utilize the S-100/10X standards to supply ships with detailed marine data and to develop a model that predicts fuel consumption under various environmental conditions by leveraging the relationship between ship motion characteristics and fuel use during operations.

At the same time, the relative importance of safe and efficient ship operation has increased as maritime logistics have become more central to national economies. In countries like the Republic of Korea, a large majority of import and export cargo is transported by sea, making the reliability and efficiency of maritime transport a key strategic factor. The growing need for high-precision ocean forecasting technologies is widely recognized in domains such as maritime disaster response, port operations, and logistics optimization. This shift goes beyond simple data

provision and moves toward real-time, operational oceanography-based prediction and decision-support systems.

From an environmental perspective, climate change and the increasing frequency of extreme weather events are amplifying the variability of ocean conditions, particularly in coastal and shelf seas. Strong winds, tides, waves, and sharp temperature gradients directly influence route selection and the safety of ship operations. The inaccurate prediction of such localized phenomena can pose significant risks to maritime safety. Nevertheless, existing forecasting systems are largely weather-centric and operate at relatively coarse spatial resolutions, which are insufficient to meet the needs of ship operators who require detailed oceanographic information at the scale of specific routes (on the order of a few kilometers or less). As a result, many mariners still rely on experience or global, relatively low-resolution visualization tools (e.g., generic web-based weather maps), which limit the potential for fuel savings and operational optimization.

In addition, there is a lack of unified platforms for integrated, multimodal maritime information. Such platforms are essential for digital-twin and AI-based maritime services. In the Republic of Korea, numerical prediction models for weather, ocean circulation, and waves typically operate independently. This limited interoperability hinders the development of holistic navigation-support services. Specifically, it is difficult to combine ship-specific operational data with high-resolution environmental information. While existing numerical models are suitable for basin-scale prediction, they are often inadequate for producing route-specific or vessel-specific conditions. Furthermore, technologies for generating customized oceanographic information tailored to individual vessels, routes, or operating patterns remain in their early stages.

In response to these challenges, the International Maritime Organization (IMO), the International Hydrographic Organization (IHO), and IALA have been developing next-generation standards that provide ships with real-time maritime data and support the exchange of harmonized information in standardized formats, thereby enhancing operational efficiency and safety. Among these, the S-100 framework plays a central role as a universal standard for hydrographic and maritime data. We aim to utilize the S-100/10X standards to deliver detailed oceanographic information to ships and to build a framework for predicting fuel consumption under varying environmental conditions, by coupling ship motion characteristics with fuel usage during operations. Ultimately, the goal is to provide ship operators with operational guidelines that account for both environmental conditions and vessel state, enabling the optimization of fuel consumption and the enhancement of safety.

1.2 Literature review

Digital maritime services that leverage oceanographic and meteorological information for enhancing ship operating efficiency have been the subject of extensive research. Kytariolou and Themelis[2] proposed a weather-routing system that finds optimal ship routes using forecasted wind, wave, and current data while simultaneously considering safety criteria. Fuel consumption is computed through a physics-based resistance/propulsion model and optimized with a genetic algorithm across route segments.

Han *et al.*[3] integrated a seakeeping model into weather routing, accounting for ship motions and fuel consumption influenced by waves, wind, and currents. An improved lattice-based search using motion primitives identifies safe and energy-efficient routes. In their study, they focused on route optimization and ship motion but do not use high-resolution coastal ocean models or standardized S-100 data structures.

Charalambopoulos *et al.*[4] applied probabilistic roadmaps (PRMs) to ship routing under uncertain environmental conditions, enabling efficient path planning. These PRMs are used to evaluate route options on the basis of fuel consumption and travel time using probabilistic environmental fields.

Golsefidi *et al.*[5] analyzed how uncertain weather conditions affect fuel consumption and logistics cost, presenting a probabilistic optimization model for container ship routing. Multiple weather scenarios are incorporated to minimize total voyage cost. Zhou *et al.*[6] merged onboard sensor data with external metocean datasets to predict ship speed through water (STW) and subsequent fuel consumption. A two-step modeling approach improved prediction accuracy during real operations.

Zhang *et al.*[7] developed a deep-learning model to predict ship fuel consumption using high-frequency real-world operational data. The model captures nonlinear relations among operational and limited environmental variables. Luo *et al.*[8] proposed a deep-learning-based transfer learning strategy to apply fuel-consumption models trained on large datasets to ships with limited data availability. It demonstrates improved performance through ANN-based transfer learning.

Gao *et al.*[9] proposed an adaptive online-learning framework that updates fuel consumption models on the basis of evolving time-series data. They demonstrated near-perfect prediction performance using incremental learning across various machine learning (ML) models. In our study, we focus on how the model will be applied following condition and time (online learning), but environmental dynamic information plays a minor role in their framework.

Aljahdali *et al.*[10] employed emotional artificial neural network (Emotional ANN) models to incorporate climate-change variables, such as wave period, wind intensity, and sea-level rise, into long-term fuel consumption predictions. Results show significant fuel consumption decrease under future scenarios in which fuel efficiency improves by around 19–22%.

Giglio *et al.*[11] evaluated how S-100-based services influence ship operations, cost efficiency, safety, and environmental performance using scenario analyses. They highlighted S-100 as a key component of next-generation e-Navigation. The study is conceptual and policy-oriented as operational ship data were not used.

Park *et al.*[12] proposed new routes available to passenger ferries operating in South Korea, verifying reduced voyage times. Their findings indicate that if shipping companies apply the seven alternative and improved routes suggested in this study, on the basis of next-generation hydrographic information, there could be annual fuel cost savings of approximately 1 billion won from a long-term perspective.

Choi *et al.*[13] equipped an S-100 ECDIS prototype with a ship behavior prediction algorithm to forecast ship movement in response to rudder operation during navigation. They predicted the ship's position at intervals from 10 to 60 s in the future. Through user satisfaction surveys, they assessed how the S-100 ECDIS and ship behavior prediction model can reduce accidents.

Choi *et al.*[14] developed a model that estimates ship fuel consumption using high-resolution oceanographic variables, including surface currents, wave height, and swell direction. The system delivers real-time predictions of fuel usage to ship operators, enabling more informed and energy-efficient navigation decisions. By integrating environmental forecasts, the model further provides optimized navigation guidelines tailored to expected sea conditions. Following the preliminary research of Coastal Korea Operational Oceanographic System (Coastal-KOOS) by Kim *et al.*[15] and Park *et al.*,[16] in this study, we were able to use an enhanced model and system based on the Korea Institute of Ocean Science & Technology (KIOST)'s Coastal-KOOS with high quality resolution.

On the basis of the above review, the existing literature can be grouped into four main categories, as summarized below.

1.2.1 Weather-routing-based ship navigation optimization

Weather routing has been continuously developed as a technique for determining optimal routes while accounting for meteorological and oceanographic conditions during ship operations. Early studies mainly involved the calculation of the increase in ship resistance owing to wind and waves using physics-based models and then identifying routes that minimize fuel consumption and voyage time. For example, Kytariolou and Themelis[2] proposed route optimization that simultaneously ensures safety and energy efficiency using forecasted wind, wave, and current fields, whereas Han *et al.*[3] increased the precision of route search by incorporating a seakeeping model so that ship motion characteristics and energy consumption could be jointly considered. Charalambopoulos *et al.*[4] used PRMs to achieve efficient path planning under uncertain weather conditions, and Sang *et al.*[17] formulated cost-based route optimization by probabilistically modeling the impact of weather uncertainty on fuel consumption.

Those studies were generally focused on optimizing routes using medium-to-coarse-resolution environmental forecast fields across broad ocean areas. However, there is a lack of work on using high-resolution oceanographic fields—such as detailed coastal currents, wave conditions, and wind fields—for specific coastal routes, or on connecting such data to standardized S-100–based marine information structures. In this regard, the present study addresses this notable gap by directly extracting and matching high-resolution Coastal-KOOS fields to a specific coastal route (Gunsan–Shidao) and integrating them with real ship operational data for detailed analysis.

1.2.2 ML-based ship fuel consumption prediction

In recent years, research combining ship operational data with ML techniques to predict fuel consumption has grown rapidly. One model learns the relationship between STW and fuel consumption using onboard sensor data together with external metocean information in a multistage modeling scheme. Also, other researchers developed a deep-learning-based model that predicts fuel consumption by capturing the nonlinear characteristics of real operational data and estimating the specific fuel consumption under various operating conditions.

However, most ML-based fuel consumption studies treat environmental data as relatively simple explanatory variables (e.g., wave height and wind speed) or rely on global or basin-scale oceanographic products (e.g., CMEMS and NOAA). As a result, they have limited ability to represent fine-scale coastal ocean dynamics such as tidal currents, coastal reflection waves, or complex bathymetric effects that are particularly important along coastal routes. Our study differs in that it is designed to eventually combine detailed Coastal-KOOS forecasts (with grid resolutions from 300 m to 2 km) with real ship operational and fuel data so that ML models can be trained on high-quality, high-resolution environmental inputs tailored to a specific route.

1.2.3 S-100 and e-Navigation-based data standardization and navigation support

S-100 is a universal standard for next-generation electronic charts and maritime data exchange, and constitutes a core element of the e-Navigation strategy led by IMO and IHO. Existing S-100 research primarily focuses on the need for data standardization and the associated operational and economic benefits in applications such as electronic charts, navigational information services, port operations, and vessel traffic services (VTS). These studies show that S-100-based services can enhance navigational safety, decision-making efficiency, and environmental performance (e.g., by reducing emissions). However, there are few studies on applying high-resolution oceanographic data directly in S-100–compliant structures and using them explicitly for fuel savings and navigation optimization in real ship operations.

This paper goes beyond S-100 as a mere data-exchange standard and seeks to implement S-100/10X as a core component of an integrated operational framework that can be directly linked to fuel-consumption prediction models and navigation support algorithms. By integrating real ship data (VDR/ECDIS), fuel monitoring systems, and Coastal-KOOS data, our study provides an application-oriented contribution within S-100 research, targeting the realization of a practical "navigation optimization service."

1.2.4 Detailed oceanographic information prediction for digital maritime services

Coastal-KOOS, operated by KIOST is the national operational oceanographic forecasting system for Korean waters. It provides high-resolution predictions by coupling ocean circulation (MOHID), atmospheric (WRF), and wave (SWAN) models. Previous KOOS-related studies have primarily focused on public-interest applications such as evaluating current forecast performance, supporting coastal search and rescue operations, predicting oil-spill dispersion, and supporting maritime disaster response. For instance, Jeong *et al.*[18] used 153 drifters to verify the accuracy of Coastal-KOOS surface current forecasts across large areas, and Kim *et al.*[15] summarized the operational achievements and industrial/public applications of KOOS.

However, the direct use of KOOS outputs for ship navigation and energy optimization is still in its infancy, both in Korea and internationally. In this study, we aim to pioneer a new application domain for Coastal-KOOS by matching its high-resolution environmental fields to an actual ferry route and combining them with real fuel consumption and operational data, so

that detailed oceanographic information can be systematically exploited for navigation optimization.

2. Research Methods

2.1 Acquisition of ship operational data

For this study, a passenger–cargo vessel regularly operating between Gunsan, Republic of Korea, and Shidao, China, was selected as a test case. A custom-built device was installed on board to collect ship operational data during actual voyages. The device was connected to the vessel's ECDIS and VDR systems to acquire key operational variables—including engine-specific RPM, speed over ground, STW, and heading—which were recorded at 1 s intervals and stored in CSV format. The collected data were automatically uploaded to a designated server while the vessel was berthed, allowing researchers to access and utilize the information.

2.2 Measurement of fuel consumption

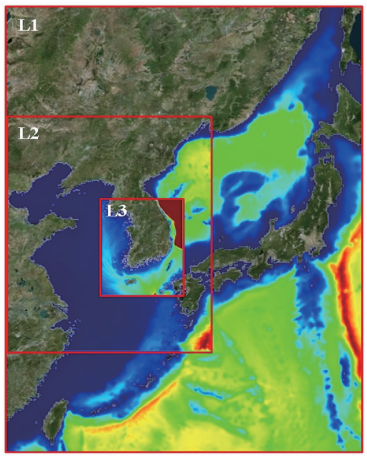
Traditionally, ship fuel consumption has been monitored using analog gauges or by reading digital values derived from sounding-based tank-level measurements. In this study, an automated system was developed to read and record digital outputs from onboard fuel monitoring equipment. The system is designed to capture real-time fuel consumption rates and remaining fuel quantities at user-defined intervals and to store the results in a digital database for subsequent analysis.

To support legacy systems, a self-developed AI-based OCR module was also employed to read and digitize fuel-related displays when direct digital interfaces were not available. The resulting time-series fuel data are then synchronized with the operational dataset described in Sect. 2.1.

2.3 Detailed oceanographic information

Detailed oceanographic data are being generated using the Coastal-KOOS developed and operated by KIOST. Data are processed for the ship's operating routes and waypoint locations, using grid resolutions between 300 m and 2 km depending on the temporal and spatial domains. These data will be integrated with observed fuel consumption records, and an AI-based learning approach will be applied to develop a predictive model for fuel use under varying environmental conditions.

The Coastal-KOOS circulation component is based on the MOHID model, the atmospheric component on WRF, and the wave component on SWAN. Figure 2 shows the specifications of these Coastal-KOOS models, including their domains and grid resolutions. For the regular service route between Gunsan and Shidao, which passes through the Yellow Sea, as shown in Fig. 3, model domains covering the entire Yellow Sea were prioritized to ensure consistent forcing along the route. In this study, the following configurations are used.



(1) Model : SWAN

- Domain : Territorial seas of the Korean Peninsula
- Resolution : (L1) 1/12° x 1/12° (about 9 km) & (L2) 1/48°x1/48° (about 2 km) & 1/288°x1/288° (about 300 m)
- Running period : Forecast 3 days

(2) Model : MOHID

- Domain : Territorial seas of the Korean Peninsula
- Resolution : (L2) 1/48° x 1/48° (about 2 km) & (L4) 1/288°x1/288° (about 300 m) in horizontal & 40 vertical layers
- Running period : Forecast 3 days

Fig. 2. (Color online) Specifications of Coastal-KOOS for detailed oceanographic data.

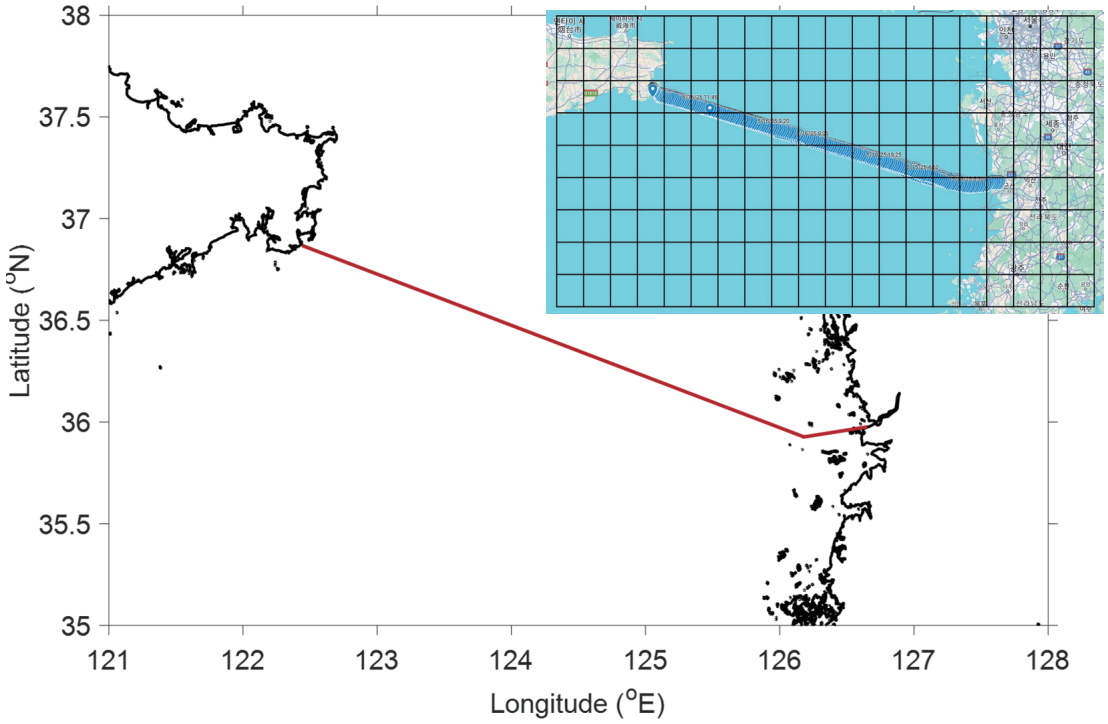


Fig. 3. (Color online) Route plan for sea trial of research.

(1) Ocean circulation model (MOHID): The Level-3 domain with approximately 2 km horizontal resolution provides surface current, temperature, and salinity fields.
(2) Atmospheric model (WRF): The D02 domain with approximately 4 km resolution provides 10 m wind speed and direction.

(3) Wave model (SWAN): Coarser domains (e.g., 9 and 2 km) and, where necessary, nested high-resolution domains (down to 300 m) provide significant wave height, wave period, and wave direction.

The available variables and domains were catalogued, and the physical units and extraction methods for each parameter were standardized to construct a consistent ocean–meteorological database for navigation optimization. Table 1 shows the key characteristics of the selected Coastal-KOOS domains—such as spatial extent, grid resolution, and temporal interval—and provides the basis for extracting environmental data along the ship's track and at predefined waypoints.

3. Sea-trial-based Detailed Oceanographic Information and Real Ship Data

3.1 Preliminary setup of detailed oceanographic information

Once the sea-trial plan using the selected vessel was finalized, detailed oceanographic information for the ship's operating area and time period was generated using Coastal-KOOS. For the first sea trial, 72 h forecast datasets were produced, focusing on the Level-2 or comparable resolution domains appropriate for the Gunsan–Shidao route.

For each forecast cycle, environmental variables such as surface currents, wind, and wave conditions were extracted along the planned route and at relevant spatial grids. Figure 4 shows the extracted surface current vectors and water temperature fields along the route, while the corresponding significant wave height fields are presented in Fig. 5. These data were then co-registered with the ship's operational records to enable the subsequent analysis of the relationships among environmental forcing, ship dynamics, and fuel consumption.

3.2 Ship navigation optimization model

The proposed "Ship Navigation Optimization Using Detailed Oceanographic Information" framework is aimed at developing a model that predicts ship fuel consumption by considering external forces such as currents, waves, and swell, in conjunction with ship-specific operating conditions. To achieve this objective, three main groups of datasets are required.

Table 1
Detailed operational information of Coastal-KOOS model.

Model	Domain	Resolution	Lat-min	Lat-max	Long-min	Long-max	Numbers of grids	Time interval
WRF	D01	20 km	13.87	52.04	95	155.27	218 × 218	1 h
WRF	D02	4 km	29.69	42.96	116.5	133.91	361 × 361	1 h
SWAN	L2	9 km	20	50	117	143	313 × 361	1 h
SWAN	L3	2 km	32	39.02	124	133.02	346 × 351	1 h
SWAN	L4	300 m	32.92	38.54	124.5	130.13	1620 × 1620	1 h
MOHID	L3	2 km	28.67	43.5	117.5	132.5	720 × 720	1 h
MOHID	L2	300 m	32.92	38.54	124.5	130.13	1620 × 1620	1 h

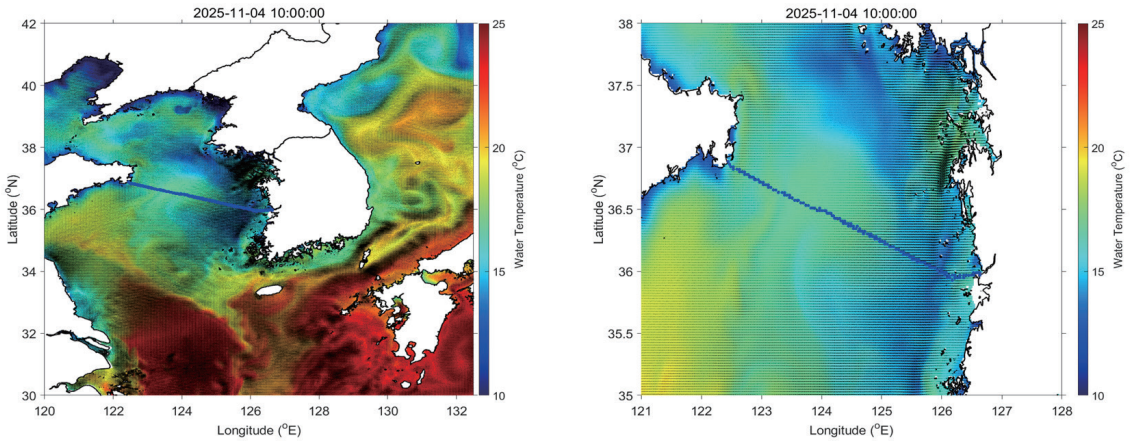


Fig. 4. (Color online) Vector data of surface currents and water temperature.

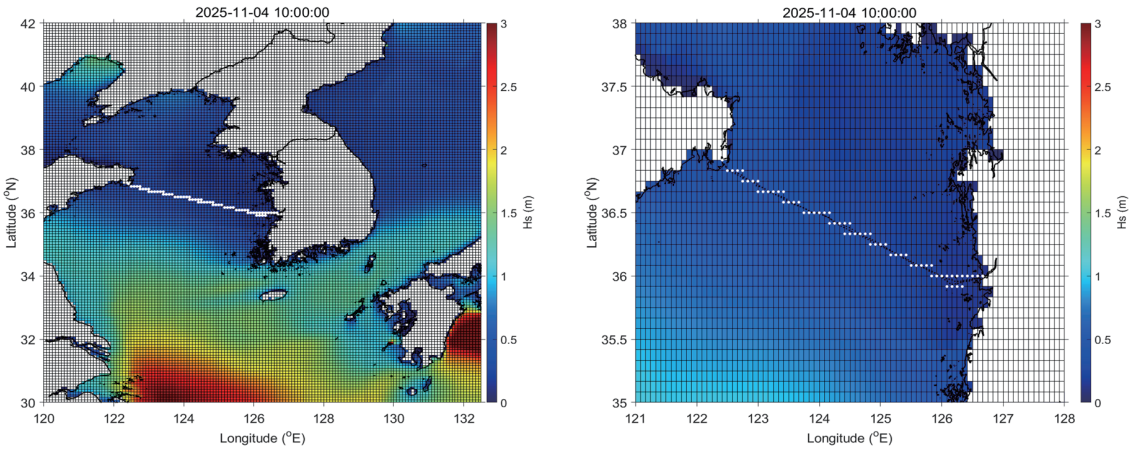
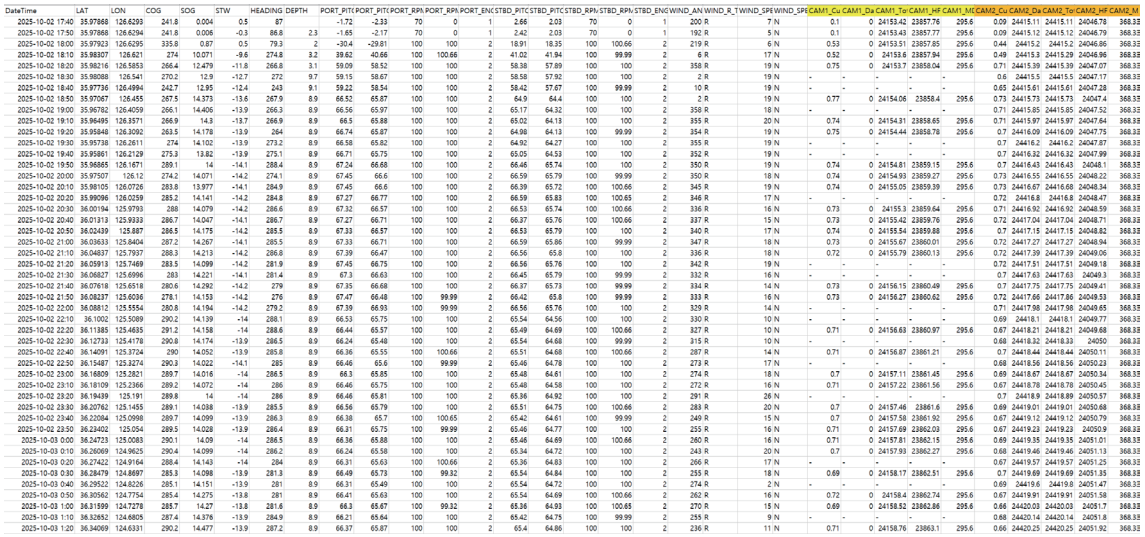


Fig. 5. (Color online) Grid data of ocean waves.

(1) Ship operational data – includes engine RPM, speed over ground, STW, heading, and other motion-related variables, sampled at high frequency.
(2) Fuel consumption data – includes instantaneous fuel flow and cumulative fuel usage, synchronized with the operational data so that fuel consumption can be related to specific operational states and environmental conditions.
(3) Detailed oceanographic information – includes surface current vectors, wave height and direction, swell characteristics, and wind fields, obtained from Coastal-KOOS at appropriate spatial and temporal resolutions.

In 2025, the research team developed a ship–shore data interface and installed a fuel-consumption monitoring system in order to acquire the above three datasets in an integrated manner. As a result, a unified database has been established in which ship operational data, fuel measurements, and detailed oceanographic information are stored with consistent time stamps and formats. Figure 6 shows an example of this integrated dataset, combining detailed oceanographic information with ship data and fuel consumption.



DateTime	LAT	LON	COG	SOG	STW	HEADING	DEPTH	PORT_PITCH	PORT_PITCH	PORT_RPM	PORT_RPM	PORT_ENGINE	STBD_PITCH	STBD_PITCH	STBD_RPM	STBD_RPM	STBD_ENGINE	WIND_ANGLE	WIND_R	TWIND_SPEED	WIND_SPEED	CAM1_Cu	CAM1_Da	CAM1_To	CAM1_HF	CAM1_MI	CAM2_Cu	CAM2_Da	CAM2_To	CAM2_HF	CAM2_MI
2025-10-02 17:40	35.97868	126.6293	241.8	0.004	0.5	87		-1.72	-2.33	70	0	1	2.66	2.03	70	0	1	200	R	7	N	0.1	0	24153.42	23857.76	295.6	0.09	24415.11	24415.11	24046.78	368.33
2025-10-02 17:50	35.97868	126.6294	241.8	0.006	-0.3	86.8	2.3	-1.65	-2.17	70	0	1	2.42	2.03	70	0	1	192	R	5	N	0.1	0	24153.43	23857.77	295.6	0.09	24415.12	24415.12	24046.79	368.33
2025-10-02 18:00	35.97923	126.6295	335.8	0.87	0.5	79.3	2	-30.4	-29.81	100	100	2	18.91	18.35	100	100.66	2	219	R	6	N	0.53	0	24153.51	23857.85	295.6	0.44	24415.2	24415.2	24046.86	368.33
2025-10-02 18:10	35.98307	126.621	274	10.071	-9.6	274.8	3.2	39.62	40.66	100	100.66	2	41.02	41.94	100	99.99	2	6	R	17	N	0.52	0	24153.6	23857.94	295.6	0.49	24415.3	24415.29	24046.96	368.33
2025-10-02 18:20	35.98216	126.5853	266.4	12.479	-11.8	266.8	3.1	59.09	58.52	100	100	2	58.38	57.89	100	100	2	358	R	19	N	0.75	0	24153.7	23858.04	295.6	0.71	24415.39	24415.39	24047.07	368.33
2025-10-02 18:30	35.98088	126.541	270.2	12.9	-12.7	272	9.7	59.15	58.67	100	100	2	58.58	57.92	100	100	2	2	R	19	N	-	-	-	-	-	0.6	24415.5	24415.5	24047.17	368.33
2025-10-02 18:40	35.97736	126.4994	242.7	12.95	-12.4	243	9.1	59.22	58.54	100	100	2	58.42	57.67	100	99.99	2	10	R	19	N	-	-	-	-	-	0.65	24415.61	24415.61	24047.28	368.33
2025-10-02 18:50	35.97067	126.455	267.5	14.373	-13.6	267.9	8.9	66.52	65.87	100	100	2	64.9	64.4	100	100	2	2	R	19	N	0.77	0	24154.06	23858.4	295.6	0.73	24415.73	24415.73	24047.4	368.33
2025-10-02 19:00	35.96782	126.4059	266.1	14.406	-13.9	266.3	8.9	66.56	65.97	100	100	2	65.17	64.32	100	100	2	358	R	18	N	-	-	-	-	-	0.71	24415.85	24415.85	24047.52	368.33
2025-10-02 19:10	35.96495	126.3571	266.9	14.3	-13.7	266.9	8.9	66.5	65.88	100	100	2	65.02	64.13	100	100	2	355	R	20	N	0.74	0	24154.31	23858.65	295.6	0.71	24415.97	24415.97	24047.64	368.33
2025-10-02 19:20	35.95848	126.3092	263.5	14.178	-13.9	264	8.9	66.74	65.87	100	100	2	64.98	64.13	100	99.99	2	354	R	19	N	0.75	0	24154.44	23858.78	295.6	0.7	24416.09	24416.09	24047.75	368.33
2025-10-02 19:30	35.95738	126.2611	274	14.102	-13.9	273.2	8.9	66.58	65.82	100	100	2	64.92	64.27	100	100	2	355	R	19	N	-	-	-	-	-	0.7	24416.2	24416.2	24047.87	368.33
2025-10-02 19:40	35.95861	126.2129	275.3	13.82	-13.9	275.1	8.9	66.71	65.75	100	100	2	65.05	64.53	100	100	2	352	R	19	N	-	-	-	-	-	0.7	24416.32	24416.32	24047.99	368.33
2025-10-02 19:50	35.96865	126.1671	289.1	14	-14.1	288.4	8.9	67.24	66.68	100	100	2	66.46	65.74	100	100	2	350	R	19	N	0.74	0	24154.81	23859.15	295.6	0.7	24416.43	24416.43	24048.1	368.33
2025-10-02 20:00	35.97507	126.12	274.2	14.071	-14.2	274.1	8.9	67.45	66.6	100	100	2	66.59	65.79	100	99.99	2	350	R	18	N	0.74	0	24154.93	23859.27	295.6	0.73	24416.55	24416.55	24048.22	368.33
2025-10-02 20:10	35.98105	126.0726	283.8	13.977	-14.1	284.9	8.9	67.45	66.6	100	100	2	66.39	65.72	100	100.66	2	345	R	19	N	0.74	0	24155.05	23859.39	295.6	0.73	24416.67	24416.68	24048.34	368.33
2025-10-02 20:20	35.99096	126.0259	285.2	14.141	-14.2	284.8	8.9	67.27	66.77	100	100	2	66.59	65.83	100	100.65	2	346	R	17	N	-	-	-	-	-	0.72	24416.8	24416.8	24048.47	368.33
2025-10-02 20:30	36.00194	125.9793	288	14.079	-14.2	286.6	8.9	67.32	66.57	100	100	2	66.53	65.74	100	100.66	2	336	R	16	N	0.73	0	24155.3	23859.64	295.6	0.71	24416.92	24416.92	24048.59	368.33
2025-10-02 20:40	36.01313	125.9333	286.7	14.047	-14.1	286.7	8.9	67.27	66.71	100	100	2	66.37	65.76	100	100.66	2	337	R	15	N	0.73	0	24155.42	23859.76	295.6	0.72	24417.04	24417.04	24048.71	368.33
2025-10-02 20:50	36.02439	125.887	286.5	14.175	-14.2	285.5	8.9	67.33	66.57	100	100	2	66.53	65.79	100	100	2	340	R	17	N	0.74	0	24155.54	23859.88	295.6	0.7	24417.15	24417.15	24048.82	368.33
2025-10-02 21:00	36.03633	125.8404	287.2	14.267	-14.1	285.5	8.9	67.33	66.71	100	100	2	66.59	65.86	100	99.99	2	347	R	18	N	0.73	0	24155.67	23860.01	295.6	0.72	24417.27	24417.27	24048.94	368.33
2025-10-02 21:10	36.04837	125.7937	288.3	14.213	-14.2	286.8	8.9	67.39	66.47	100	100	2	66.56	65.8	100	100	2	336	R	18	N	0.72	0	24155.79	23860.13	295.6	0.72	24417.39	24417.39	24049.06	368.33
2025-10-02 21:20	36.05913	125.7469	283.5	14.099	-14.2	281.9	8.9	67.45	66.75	100	100	2	66.56	65.76	100	100	2	342	R	19	N	-	-	-	-	-	0.72	24417.51	24417.51	24049.18	368.33
2025-10-02 21:30	36.06827	125.6996	283	14.221	-14.1	281.4	8.9	67.3	66.63	100	100	2	66.45	65.79	100	99.99	2	332	R	16	N	-	-	-	-	-	0.7	24417.63	24417.63	24049.3	368.33
2025-10-02 21:40	36.07618	125.6518	280.6	14.292	-14.2	279	8.9	67.35	66.68	100	100	2	66.37	65.73	100	99.99	2	334	R	14	N	0.73	0	24156.15	23860.49	295.6	0.7	24417.75	24417.75	24049.41	368.33
2025-10-02 21:50	36.08237	125.6036	278.1	14.153	-14.2	276	8.9	67.47	66.48	100	99.99	2	66.42	65.8	100	99.99	2	333	R	16	N	0.73	0	24156.27	23860.62	295.6	0.72	24417.66	24417.86	24049.53	368.33
2025-10-02 22:00	36.08812	125.5554	280.8	14.194	-14.2	279.2	8.9	67.39	66.93	100	99.99	2	66.56	65.76	100	100	2	329	R	14	N	-	-	-	-	-	0.71	24417.98	24417.98	24049.65	368.33
2025-10-02 22:10	36.1002	125.5089	290.2	14.139	-14	288.1	8.9	66.53	65.75	100	100	2	65.54	64.56	100	100	2	330	R	10	N	-	-	-	-	-	0.69	24418.1	24418.1	24049.77	368.33
2025-10-02 22:20	36.11385	125.4633	291.2	14.158	-14	288.6	8.9	66.44	65.57	100	100	2	65.49	64.69	100	100.66	2	327	R	10	N	0.71	0	24156.63	23860.97	295.6	0.67	24418.21	24418.21	24049.68	368.33
2025-10-02 22:30	36.12733	125.4178	290.8	14.174	-13.9	286.5	8.9	66.24	65.48	100	100	2	65.54	64.68	100	99.99	2	315	R	10	N	-	-	-	-	-	0.68	24418.32	24418.33	24050	368.33
2025-10-02 22:40	36.14091	125.3724	290	14.052	-13.9	285.8	8.9	66.36	65.55	100	100.66	2	65.51	64.68	100	100.66	2	287	R	14	N	0.71	0	24156.87	23861.21	295.6	0.7	24418.44	24418.44	24050.11	368.33
2025-10-02 22:50	36.15487	125.3274	290.3	14.022	-14.1	285	8.9	66.46	65.6	100	99.99	2	65.46	64.78	100	100	2	273	R	17	N	-	-	-	-	-	0.68	24418.56	24418.56	24050.23	368.33
2025-10-02 23:00	36.16809	125.2821	289.7	14.016	-14	286.5	8.9	66.3	65.85	100	100	2	65.48	64.61	100	100	2	274	R	18	N	0.7	0	24157.11	23861.45	295.6	0.69	24418.67	24418.67	24050.34	368.33
2025-10-02 23:10	36.18109	125.2366	289.2	14.072	-14	286	8.9	66.46	65.75	100	100	2	65.48	64.58	100	100	2	272	R	16	N	0.71	0	24157.22	23861.56	295.6	0.67	24418.78	24418.78	24050.45	368.33
2025-10-02 23:20	36.19439	125.191	289.8	14	-14	286	8.9	66.46	65.81	100	100	2	65.36	64.92	100	100	2	291	R	26	N	-	-	-	-	-	0.7	24418.9	24418.89	24050.57	368.33
2025-10-02 23:30	36.20762	125.1455	289.1	14.038	-13.9	285.5	8.9	66.56	65.79	100	100	2	65.51	64.75	100	100.66	2	283	R	20	N	0.7	0	24157.46	23861.6	295.6	0.69	24419.01	24419.01	24050.68	368.33
2025-10-02 23:40	36.22084	125.0998	289.7	14.099	-13.9	286.3	8.9	66.38	65.7	100	100.65	2	65.42	64.61	100	99.99	2	249	R	15	N	0.7	0	24157.58	23861.92	295.6	0.67	24419.12	24419.12	24050.79	368.33
2025-10-02 23:50	36.23402	125.054	289.5	14.028	-13.9	286.4	8.9	66.31	65.75	100	99.99	2	65.46	64.77	100	100	2	255	R	16	N	0.71	0	24157.69	23862.03	295.6	0.67	24419.23	24419.23	24050.9	368.33
2025-10-03 0:00	36.24723	125.0083	290.1	14.09	-14	286.5	8.9	66.36	65.88	100	100	2	65.46	64.69	100	100.66	2	260	R	16	N	0.71	0	24157.81	23862.15	295.6	0.69	24419.35	24419.35	24051.01	368.33
2025-10-03 0:10	36.26069	124.9625	290.4	14.099	-14	286.2	8.9	66.24	65.58	100	100	2	65.34	64.72	100	100	2	243	R	20	N	0.7	0	24157.93	23862.27	295.6	0.68	24419.46	24419.46	24051.13	368.33
2025-10-03 0:20	36.27422	124.9164	288.4	14.143	-14	284	8.9	66.31	65.63	100	100.66	2	65.36	64.83	100	100	2	266	R	17	N	-	-	-	-	-	0.67	24419.57	24419.57	24051.25	368.33
2025-10-03 0:30	36.28479	124.8697	285.3	14.098	-13.9	281.3	8.9	66.49	65.73	100	99.32	2	65.54	64.84	100	100	2	255	R	18	N	0.69	0	24158.17	23862.51	295.6	0.7	24419.69	24419.69	24051.35	368.33
2025-10-03 0:40	36.29522	124.8226	285.1	14.151	-13.9	281	8.9	66.31	65.49	100	100	2	65.54	64.72	100	100	2	274	R	2	N	-	-	-	-	-	0.69	24419.8	24419.8	24051.47	368.33
2025-10-03 0:50	36.30562	124.7754	285.4	14.275	-13.8	281	8.9	66.41	65.63	100	100	2	65.54	64.69	100	100.66	2	262	R	16	N	0.72	0	24158.4	23862.74	295.6	0.67	24419.91	24419.91	24051.58	368.33
2025-10-03 1:00	36.31599	124.7278	285.7	14.27	-13.8	281.6	8.9	66.3	65.67	100	99.32	2	65.36	64.93	100	100.65	2	270	R	15	N	0.69	0	24158.52	23862.86	295.6	0.66	24420.03	24420.03	24051.7	368.33
2025-10-03 1:10	36.32652	124.6805	287.4	14.376	-13.9	284.9	8.9	66.21	65.64	100	100	2	65.42	64.75	100	99.99	2	255	R	9	N	-	-	-	-	-	0.68	24420.14	24420.14	24051.8	368.33
2025-10-03 1:20	36.34069	124.6331	290.2	14.477	-13.9	287.2	8.9	66.37	65.87	100	100	2	65.4	64.86	100	100	2	236	R	11	N	0.71	0	24158.76	23863.1	295.6	0.66	24420.25	24420.25	24051.92	368.33

Fig. 6. (Color online) Detailed oceanographic information with ship data and fuel consumption.

However, the development of a robust ship navigation optimization model based on AI requires a large quantity of training data. In practice, thousands of synchronized data samples and at least six months of continuous operation are needed to capture seasonal variability and a wide range of environmental and operational conditions. Since the present study is focused on the design and installation of the measurement infrastructure and only a limited amount of data has been collected to date, it is not yet possible to train and validate a full AI-based optimization model.

Instead, in this study, we emphasize the conceptual design of the model and the establishment of the integrated data pipeline that will support future model development. Once sufficient data have been accumulated, AI-based learning algorithms will be applied to this database to predict fuel consumption under various environmental states and to derive optimized navigation guidelines tailored to the vessel and route.

3.3 Ship location prediction model evaluation

Because the construction of a ship navigation optimization model requires extensive datasets, an auxiliary experiment on ship location prediction was conducted in parallel with the sea trials. Using the acquired operational data (speed, position, heading, and STW) and environmental information from Coastal-KOOS, a short-term ship location prediction model was implemented to forecast the vessel position 5 min into the future, as shown in Fig. 7. The predicted positions were then compared with the actual positions observed during the sea trials.

The test utilized the same onboard data acquisition module described in Sect. 2.1 to capture the vessel's dynamic state, while Coastal-KOOS forecasts supplied wind and current information for the corresponding time and location. In addition, the ship's master was asked to provide

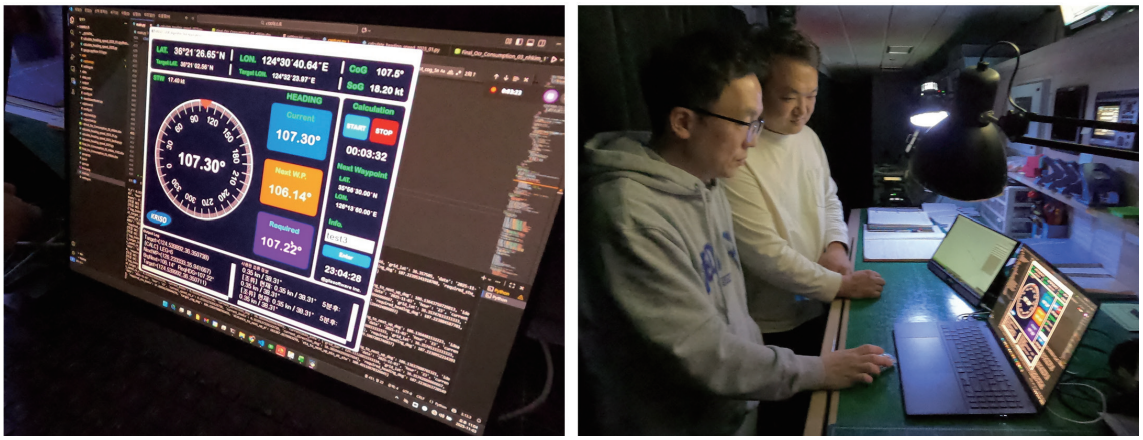


Fig. 7. (Color online) Onboard experiment for ship location prediction.

qualitative feedback on the usefulness and perceived reliability of the prediction results. This evaluation served as a preliminary verification of the integrated data pipeline and demonstrated the potential of combining detailed oceanographic forecasts with real-time ship data for advanced decision-support applications.

4. Conclusions

The aim of this study was to develop and implement a framework for predicting ship fuel consumption using detailed oceanographic information and for providing optimized operational guidelines to ship operators. As a first step, a comprehensive data acquisition infrastructure was designed and installed on a passenger–cargo vessel operating between Gunsan and Shidao. The system integrates high-frequency ship operational data, automated fuel-consumption measurements, and high-resolution environmental forecasts from Coastal-KOOS within an S-100–oriented data structure.

The current work was focused on defining the required datasets, constructing the ship–shore data pipeline, and performing initial sea trials to verify the feasibility of integrating real ship data with detailed oceanographic information. These efforts lay the groundwork for future AI-based ship navigation optimization models that can exploit multimodal maritime data. Once a sufficiently large and diverse dataset has been collected, the proposed framework is expected to support accurate fuel-consumption prediction and the generation of route-specific, environmentally aware navigation guidance, thereby contributing to both economic efficiency and environmental performance in maritime transport.

As the International Organization has agreed to enforce the implementation of next-generation ship navigation systems until 2029 following the previous research of Choi and Oh,[19] a new ship navigation system shall be developed with S-100 hydrographic data and detailed oceanographic information.

5. Future Work

The development of a practical ship navigation optimization model based on AI requires a substantial volume of high-quality training data. In the context of this study, the integrated model must learn complex relationships among ship operational variables, fuel consumption, and detailed oceanographic conditions along the Gunsan–Shidao route. To achieve this, several key future research directions are identified.

(1) Long-term data acquisition and dataset expansion

The current dataset, although sufficient for testing the data pipeline and conducting preliminary analyses, is not large enough to train a robust AI model. At least six months of continuous operation and thousands of synchronized samples are required to adequately capture seasonal variability, diverse weather and sea-state conditions, and different loading and operational regimes. Future work will therefore focus on sustaining long-term data collection, ensuring the consistent logging of ship operational data, fuel consumption, and Coastal-KOOS forecasts.

(2) Data quality control and multimodal data integration

As the dataset grows, systematic procedures for data quality assessment, outlier detection, gap filling, and synchronization across modalities (ship sensors, fuel monitoring, and oceanographic models) will become increasingly important. Future research will be directed toward designing and implementing a multimodal data processing framework that can automatically classify, clean, and align heterogeneous maritime datasets. This framework will also include an AI-based OCR for obtaining fuel consumption values and generate a combined database of detailed oceanographic information and ship operation data.

(3) AI-based ship navigation optimization model development

Once sufficient data have been accumulated and quality-controlled, various AI and ML approaches—such as deep neural networks, sequence models, and hybrid physics–ML schemes—will be applied to build fuel-consumption prediction models conditioned on both operational and environmental variables. The goals are to estimate fuel usage for candidate operating profiles (speed, heading, and RPM) under forecasted environmental conditions and to identify operating strategies that minimize fuel consumption while satisfying safety and schedule constraints.

(4) Portrayal rule for dynamic predicted information

As IHO has developed new symbols for S-100 standards and S-10X Product Specification, symbols and interoperability rule shall be researched for dynamic and predicted information. This is because the vessel's fuel consumption and surface currents and wave information during operation should be easily recognized by the navigator taking into consideration weather information and ship characteristics.

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