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Factor analysis of icebreaker assistance operation for ice-going ships in the Baltic Sea

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ABSTRACT

Merchant vessels navigating the Baltic Sea in winter often require assistance from icebreakers to create safe pathways and improve navigational efficiency. Given icebreaker resources are limited, assistance decision is important. The requirement for assistance depends on multiple factors, including ice conditions, weather, and ship characteristics. In this paper, we explore how data-driven techniques can enhance the current understanding of factors influencing the decision-making of icebreaker assistance. Firstly, the paper identifies multiple factors from previous winter navigation operations research. Then different data sources containing traffic data, environmental conditions, and ship characteristics are explored to find data about the identified factors. Finally, an integrated database containing these factors is established. Using a multi-step clustering method, data points in the database are classified as either assistance or independent navigation. Preliminary statistical analysis of the factors is performed to understand how they vary between independent navigation and assistance cases. Results show that weather and ship factors do not significantly vary compared to ice factors. Among the ice factors, ridge ice thickness and level ice concentration vary the most between independent navigation and assistance. These findings are aligned well with empirical knowledge and previous studies. The database and the empirical findings in this paper can provide insights for quantifying factor effects on the decision-making of icebreaker assistance and support the intelligent decision-support system for winter navigation.

KEYWORDS: Icebreaker assistance; Merchant vessels; Statistical analysis; Factor analysis; ice-covered waters; Baltic Sea.

INTRODUCTION

Icebreaker (IB) assistance operation is significant for winter navigation safety and efficiency in the Baltic Sea region (BSR), which is necessitated due to the presence of ice (Zhang et al., 2019). IB assistance is provided to create ice channels for the merchant ship(s), to reduce the risk of it getting stuck in ice or damage on the hull. For ships with low engine power and new ships with Energy Efficiency Design Index (EEDI), IB assistance operations are important (Bergström & Kujala, 2020). IB operations in BSR are managed by the Finnish Swedish Winter Navigation System (FSWNS) (Valdez Banda et al., 2016). The IB captains decide whether a merchant vessel in BSR needs to be assisted in accordance with the regulations and their own expert knowledge (BIM, 2011). However, to develop a data-driven intelligent decision support system for winter navigation, quantitative criteria should be available as input to instruct a machine.

Previous studies have directly assessed or indirectly referred to factors that trigger the request of IB assistance. Existing factors can be classified in three broad categories, ice factors, ship characteristics, and weather factors (Lu et al., 2021). For example, studies focusing on ship performance in ice quantitatively assessed how ice variables impact ship hull in ice, referring to a situation in which IB assistance would be needed (Kuuliala et al., 2017). Weather factors and ice factors are preferably discussed simultaneously by studies aiming to assess navigational risks (e.g., besetting risk), indicating a situation leading to the request of IB assistance (Valdez Banda et al., 2016). To plan a route on ice or simulate a winter navigation system, the threshold for launching the IB assistance is commonly a minimum ship speed, rather than a reflection of actual operational conditions (An et al., 2022). However, when considering decision-making of winter navigation operations, the information about influencing factors is limited. A holistic identification of influencing factors is still needed to guide a data-driven method to better understand the decision-making of winter navigation operations.

Thus, the primary goals of the current paper are to identify factors that lead to the need of IB assistance and to figure out how a data-driven method can enhance the current understanding of those factors. To achieve the goals, a list of factors that impact decision-making is identified by reviewing previous studies in the field of winter navigation. Using the list as a guide, data presenting the factors are collected from different sources, and a novel database is established to quantitatively present the operational conditions. The approach is to employ a multi-step clustering model to label IB assistance and independent cases (Liu et al., 2022). The database consists of IB assistance and independent navigation scenarios based on different data sources, including traffic data, environmental data, and ship information. Preliminary statistical analysis is conducted, and the outcomes give trend values of the factors leading to the request of IB assistance.

LITERATURE REVIEW FOR FACTOR COLLECTION

This paper starts with a brief review of studies that considered factors that influence the request of IB assistance. To figure out search queries to get literature, topics mentioning the IB assistance consideration are sorted out. They can be described from four aspects. Firstly, IB assistance can help merchant ships sailing through challenging ice fields. Thus, to manage risk and improve navigations safety, IB assistance would be needed. With the help of IB assistance, ice resistance on the ship hull can be reduced, reducing the risk of getting damaged on the hull and optimizing ice-going ship design. Studies involving the context of ship performance investigation in ice are considered for the literature search. Then, winter navigation efficiency can be optimized with the help of IB assistance. On one hand, efficient decision-making of IB assistance can optimize icebreaker resources and optimize the waiting time of merchant vessels. On the other hand, the requirement of ship's output power can be reduced by being assisted by an IB. Finally, route planning in ice contributes to the influencing factors investigation regarding the decision-making of IB assistance. Thus, as shown in Table 1, search queries cover the topics of winter navigation safety, ship performance in ice, winter navigation efficiency, and route planning in ice.

The literature search was performed in December 2022, using Web of Science and Scopus as data sources. By screening titles and keywords, all English-written articles in the search results referring to factors linked to the need of IB assistance are deemed as relevant articles for further review. Initially, 226 articles were selected, including scientific journal papers, conference papers, book chapters, and reports. The next step was to screen the abstract and the part describing IB assistance in the full-length paper, 111 articles were left in the article database after the filtering.

Table 1. Search queries for literature collection

Topics	Search queries
Topic 1	TS = (‘Ice’ OR ‘Winter navigation’ OR ‘Polar’ OR ‘Northern Sea’ OR ‘Baltic Sea’)
Topic 2	TS = (‘Efficiency’ OR ‘Safety’ OR ‘Polar’ OR ‘Risk’)
Topic 3	TS = (‘Ship*’ OR ‘Vessel’ OR ‘Maritime’ OR ‘Marine’)
Topic 4	TS = (‘Beset*’ OR ‘Stuck’ OR ‘Decision mak*’ OR ‘Ship performance’ OR ‘Ice resistance’ OR ‘Ice loads’ OR ‘Route’ OR ‘Path’ OR ‘Navigation’ OR ‘Maneuvering’ OR ‘Engine’ OR ‘Fuel’)
Note:	TS presents topic search ‘AND’ is used between different topics. Ship* denotes ship or shipping. Beset* denotes beset or besetting or besetment. mak* denotes make or making.

As shown in Figure 1, there are 20 factors classified into four categories: ice factors, weather factors, ship factors, and human factors. These factors are mentioned in different topics. Ice factors and ship factors have been investigated by studies focusing on safety or ship performance in ice using theoretical or semi-empirical methods. Route planning studies tend to consider a specific ship type and ice thickness as a threshold to refer to the IB assistance plan. Some valuable papers aim to develop on board navigation assistant tools (Frydenberg et al., 2021). Factors, such as wind, ship type, and ice thickness, are indirectly mentioned. Wind is considered by various topics, as it can not only force ice drift and compression but also impact ship navigational performance. Almost all the responses of human factors come from the topic of risk assessment. Human factors are complex, which can be affected by ice, weather, technical issues on board, and the experience level of the expert (Xu et al., 2021).

Among ice factors, ice concentration, and thickness are the two most frequently mentioned in the studies. Ice concentration represents a fraction of a measured area covered by ice, and ice can be categorized into diverse groups (e.g., ice new, grey ice, etc.) according to ice thickness (Milaković et al., 2019). The condition with high ice concentration and thick ice would increase the navigation difficulty of merchant vessels, leading to a high probability of being assisted by IB. Ice type is another influencing factor, which is described specifically in articles. It can be classified into level ice, ridge ice, and rafted ice based on the ice appearance. All these types of ice can move under the force of the wind, forming dynamic ice. Usually, dynamic ice moving perpendicular to the midship section is considered as hazardous situation, such as high risk of getting stuck, indicating the need of IB assistance (Lu et al., 2021). Ice drift can be referred to ice deformation. Ice would deform from the undeformed ice (e.g., level ice). Based on the different thicknesses of deformed ice, thin deformed ice would be called rafted ice, while thicker one would be called ice ridges (Kubat et al., 2016). Ice compression or pressure is another factor. Although its definition is still imprecise, ice ridges and wind have been identified as the main forces leading to ice compression (Kubat et al., 2012). It is assessed to investigate ship performance in ice or predict besetting probability (Pärn et al., 2007). Ice distribution is mentioned once in route planning research (Wang et al., 2021). This terminology can be presented by the location of an ice-covered area using latitude and longitude.

For ship factors, ice class is the most frequent. Ice class refers to the icebreaking capacity of a ship. In BSR, there are five ice classes, IA SUPER (IAS), IA, IB, IC, and II. IAS has the strongest icebreaking capability, followed by IA. Ships with these two ice classes can be assisted without restrictions in severe ice conditions. While for IB, IC, and II, there are regulations restricting these ice classes to enter the ports in BSR during peak winter due to their low ice-going capacity (BIM, 2011). Ship types, dimensions, and deadweight have been statistically analyzed by studies focusing on risk management in ice (Valdez Banda et al., 2015). Different accident rates of different ship types can refer to the impact of ship type on the need of IB assistance (e.g., loose a ship stuck in ice). Engine power partly presents the ship's ice-going capability. Ships being assisted by IB can reduce the power output when sailing in ice. To balance the navigation cost and efficiency, IB assistance can be used to help ship proceeding with navigation in ice (Kondratenko et al., 2021).

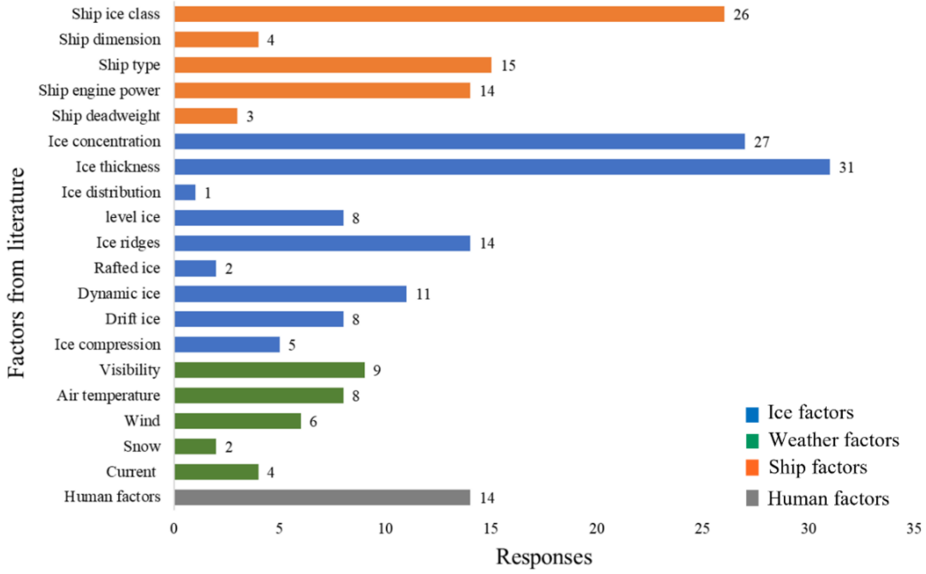

Figure 1. Factors collected from literature until the end of 2022

For weather factors, there are five factors identified by the literature search. The wind is the factor considered by ice movement investigation (e.g., the formation of ice compression) and navigational risk assessment (e.g., the risk of besetting in ice because of ice movement forced by wind) (Lensu et al., 2013). The remaining factors are qualitatively considered by risk assessment studies (e.g., the probability of getting beset) (Fu et al., 2016).

FRAMEWORK FOR STATISTICAL ANALYSIS

Based on the identified factors, to quantitatively understand these variables, this paper proposes a framework to establish a database presenting assistance and independent navigation and analyze the variables. The framework includes three steps, as shown in Figure 2. The framework is now described in detail.

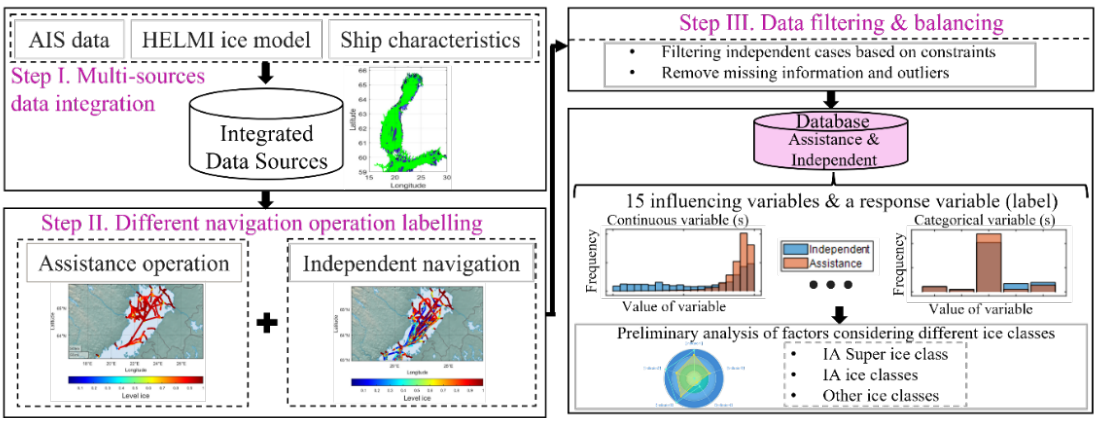

Figure 2. Flowchart for statistical analysis of presenting variables

Step I. Multi-source data integration: To gather data about the identified factors in Figure 1 , multiple data sources such as traffic information, environmental conditions, and ship characteristics need to be integrated. The traffic data in the current study are from winter 2018. The ice condition during this winter is adequate to present a typical average ice season. To present traffic scenarios, Automatic Identification System (AIS) data is used. Information on dynamic positions corresponding to timestamps and Marine Mobile Service Identity (MMSI) is used in this study. It is notable that as shown in Figure 1, human factor is one of the influencing factors according to the literature review. However, given that this study aims to explore how data-driven techniques can improve decision-making, the human factor is beyond the scope of the paper.

According to the guidance of factors in Figure 1, factors collected from multi-data sources, including ship factors (SF), ice factors (IF), and weather factors (WF) are shown in Table 2. To collect SFs, information from Icebreaker Net (IBNet) is used. IBNet is a system jointly operated and maintained by the Finnish Transport Infrastructure Agency (FTIA) and Swedish maritime administration to coordinate icebreaking operations (BIM, 2011). From IBNET, all the 5 SFs in Figure 1, namely ship ice class, dimension (length and width), type, engine power, and deadweight, can be obtained and they are included in Table 2.

To collect ice factors (IF) and weather factors (WF), Helsinki Multi-category sea-ice model (HELMI) is used. The model includes numerical gridded environmental data, such as various ice variables and other weather factors. Variables from HELMI are expressed in a latitude/longitude matrix with one nautical mile grid size and updated hourly. Among the 5 WFs identified in Figure 1, wind speed, snow thickness, and air temperature are readily available in HELMI and are included in Table 2. Although visibility and currents are WFs mentioned frequently in risk management, data on these two variables are currently not available.

HELMI model quite accurately estimates ice conditions as validated by real-life observations (Haapala et al., 2005). Ice distribution can be presented using the spatial matrix. In HELMI, undeformed ice presents level ice and deformed ice presents ridge ice and rafted ice. When ice deforms from the level ice, ridge ice and rafted ice is classified by different thickness (Haapala et al., 2005). Thus, undeformed ice concentration represents concentration of level ice, while deformed ice concentration demonstrates the concentration of ridge and rafted ice. Instead of having general ice concentration and ice thickness as shown in Figure 1, through HELMI more specific data such as undeformed and deformed ice concentration and thickness of level, ridge, and rafted ice can be obtained and are included in Table 2. However, ice compression, dynamic ice, and drift ice cannot be directly obtained from HELMI. Drift ice refers to ice floe or small pack ice, which can affect ice loads on ship hull. When there is wind as a force to move drift ice, dynamic ice appears. To our knowledge, currently there is no data source available to accurately obtain information on ice compression and dynamic ice. However, the wind speed in the WF category partially mediates this issue. This is because ice speed is highly correlated with wind speed, and ice compression is also mainly driven by wind and ice ridges (Pärn *et al.*, 2007).

To integrate traffic data with ship characteristics, the MMSI index is used to bridge the relevant information from AIS data and ship characteristic data. Ice and weather variables are integrated with the temporary and spatially nearest AIS position message to integrate dynamic ship positions with corresponding ice conditions. In this way, the spatial and temporal integration accuracy is of the order of the grid size of ice variables or better. Lensu & Goerlandt, 2019 indicated that uncertainties in this integration method come almost exclusively from the model's inaccuracy.

Table 2. Independent variables used in the analysis

No	Factors from the integrated dataset	No	Factors from the integrated dataset
IF 1	Undeformed ice concentration (in tenths)	WF 3	Wind speed (m/s)
IF 2	Deformed ice concentration (in tenths)	SF 1	Ship length (m)
IF 3	Real thickness of level ice (m)	SF 2	Ship width (m)
IF 4	Real thickness of ridge ice (m)	SF 3	Ship engine power (Kw)
IF 5	Real thickness of rafted ice (m)	SF 4	Ship deadweight (T)
WF 1	Real snow thickness (m)	SF 5	Ship ice class
WF 2	Air temperature (°C)	SF 6	Ship type
Note:	IF presents Ice Factor. WF presents Weather Factor. SF presents Ship Factor.		

Step II. Different navigation operation labeling: After the data integration, each data point reflects traffic information in actual operational conditions. However, the data points are not classified as assistance or independent cases by default and labelling needs to be done. Labeling assistance case is the process of identifying assistance cases based on big data and adding a label indicating that the identified data point presents either an assistance case or an independent case. Our previous study (Liu et al., 2022) adopted a multi-step clustering method to identify assistance cases and validated the outcomes using the IBNet assistance records. Details can be referred to Liu et al., 2022.

Step III. Data filtering: The number of independent navigation cases is much greater than that of assistance cases in BSR. To select appropriate independent cases for factor analysis, there are two constraints to be followed. First, to ensure smooth and safe winter navigation, the minimum deadweight and ice class of merchant vessels entitled to IB assistance are mandatory, which is regulated by FSWNS. Ships proceeding with independent navigation are supposed to reach the same deadweight and ice class requirement as assistance ones, ensuring the consistency of data points. Generally, the minimum deadweight for ships entering the Baltic Sea area is set to 1300 DWT. For the ice class, depending on ports, the minimum ice class varies from IB, IC to II (TRAFI, 2011). Thus, only merchant vessels larger than 1300 DWT and ice class higher than II are included. Second, 98% percent of assistance cases happened $63^{\circ}N$ and above in the study period. Thus, to keep navigational areas of assistance and independent operations comparable, $63^{\circ}N$ northwards is used to filter independent merchant ship voyages. Further, types of assisted ships within the study period include bulk, container ship, general cargo, RoRo cargo, and tankers. For data consistency purposes, ship types are used to further filter independent cases.

To ensure the integrity and validity of the established dataset, data cleaning is further conducted by checking each data point in the database. Data points with missing information, such as missing ship deadweight and unavailable ice data at a certain position, and obvious outliers are removed from the dataset. To avoid a skewed class proportion in the classified database during the variable analysis procedure, random under-sampling is employed (Brownlee, 2020). The same number of independent data points can be selected as that of assistance data points.

RESULT AND ANALYSIS

Based on the framework proposed above, a database presenting assistance and independent operations was established, and variables were preliminarily analyzed.

Database of Assistance And Independent Navigation

According to the method introduced above, this study established a new winter navigation database covering an average winter month in 2018. As shown in Figure 3, after data integration, each data point includes 14 variables as influencing variables described in Table 2. The label refers to operation mode categories (assistance operation or independent navigation) assigned in the data labeling step. Based on the method in Liu et al., 2022, 321 trajectories were classified and validated as assistance cases and 33231 cases were independent. Among 321 trajectories, there are 6535 data points included. After selecting independent cases and filtering missing information and outliers in step III, there were 63900 data points reserved in the dataset, including 5899 assistance and 58001 independent points. Figure 3 shows the balanced dataset obtained by random under-sampling method, and 11798 points were kept in the dataset. It is observed that the variable distribution of different navigation modes varies significantly, specifically for ice variables. For ship variables, IB, IC, and II ice classes ships visited BSR less frequently during the study period compared to ships with IAS and IA ice classes. To further obtain the diverse operation conditions experienced by distinct ice classes, a preliminary statistical analysis was conducted. The results are demonstrated in the following section.

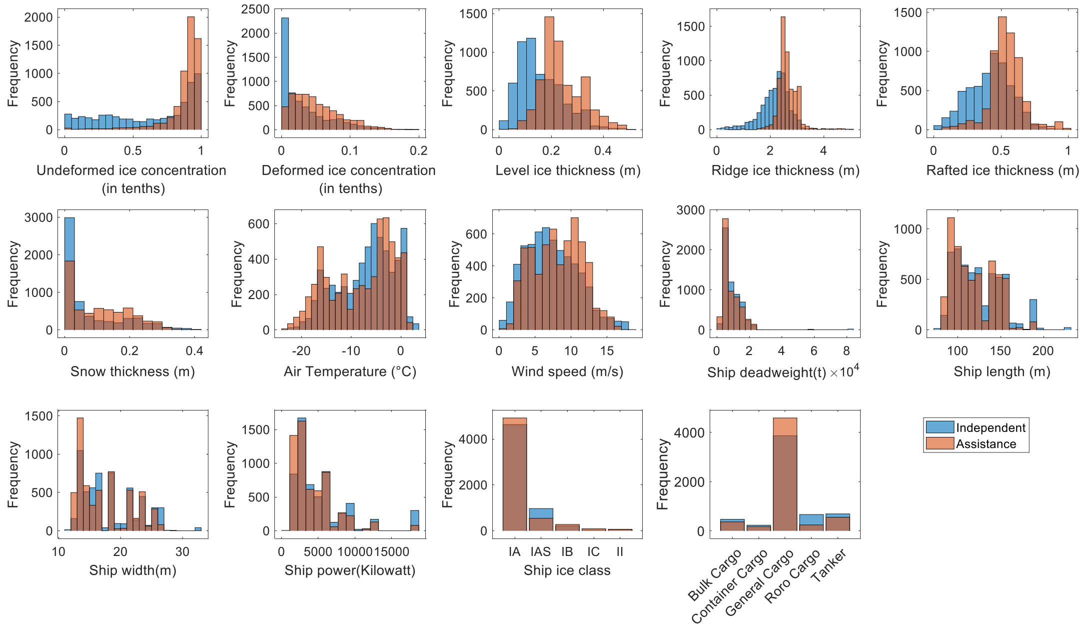

Figure 3. Variables distribution of the database of assistance and independent operations

Preliminary Analysis of Variables

Based on the established database, the mean values give insight into the central measures of the variable distribution. Figure 4 shows the mean values of variables for assistance and independent navigation. Figure 4(a) shows the observations of ships with IA ice class, Figure 4(b) shows the observations of ships with IA ice class, and Figure 4(c) shows these of ships with other ice classes. The indicators of each variable can be referred to in Table 2.

For all ice classes, ice factors show the most significant difference between assistance and independent navigation compared to weather and ship factors. For ships with IAS ice class, compared to conditions of independent navigation, different ice types, concentration, and thickness all demonstrate significant changes. The undeformed ice concentration is 0.89 which is around 20% higher than that during independent navigation. Deformed ice concentration is 39% higher during assistance than that during independent navigation. The ice thickness is around 20% thicker during assistance compared to the thickness during independent navigation. For ships with IA ice class, ice conditions during assistance are more severe compared to that during independent navigation, and the general trend is similar to that for IAS ships. Compared to ships with high ice class, low ice class ships tend to navigate in ice conditions where ridge ice is thinner even being assisted by IB. The deformed ice concentration that the low ice class has experienced is lower than that of the high ice classes. This finding is aligned with empirical knowledge and previous knowledge. Coverage and height of ice ridge pose threat to navigation, which is more hazardous for ships with low ice-breaking capability (Kubat et al., 2015). Low ice class ships are preferable to be assisted before reaching such severe ice conditions.

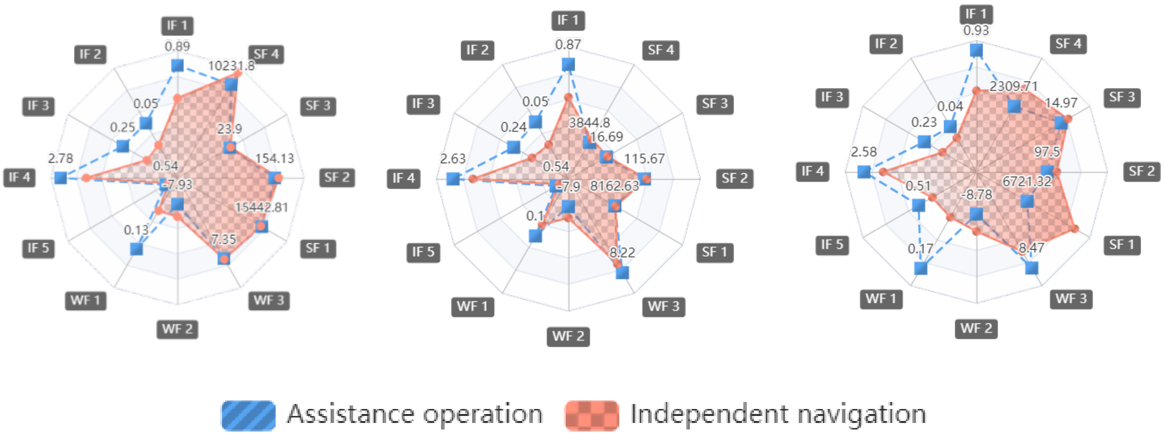

Figure 4(a). Observations of IAS. Figure 4(b). Observations of IA. Figure 4 (c). Observations of others.

Figure 4. Mean value distributions of each factor regarding different ice classes

CONCLUDING REMARKS AND FUTURE WORK

By reviewing existing articles covering four different topics, factors influencing the requirement of IB assistance were identified and discussed. This paper then presented these identified factors using variables defined from data analytics. Based on our previous data mining study (Liu et al., 2022), a novel database with examples from distinct navigation modes was established for the first time.

Concluding Remarks

Decision-making in winter is complex, involving frequent and recurring analysis of multiple factors. The big data available in current times from different sources can be a useful aid in guiding experts to make safer and more efficient decisions if analyzed correctly. The enlisting of factors and the creation of the database described in this article is the first step in advancing data-driven decision support. Information regarding factors influencing operations is scattered across literature and industry sources. This work attempts to combine insights across these multiple sources to provide academics and end users with a comprehensive and exhaustive source for all known influencing factors. This lays the foundation for building a data-driven decision support system. Preliminary statistical analysis conducted in this work shows that inferences can be made regarding ship operational modes based on the magnitude of statistical parameters. The current results are aligned well with the previous studies and empirical knowledge. Ice concentration and thickness vary more significantly between the two navigation categories compared to weather and ship factors. Factors perform differently for ships with different ice classes. Further investigation including deeper statistical and correlation analysis would help gauge the effectiveness of these parameters in predicting operational modes.

Future Work

This study is part of an ongoing project on prediction of IB assistance requirements using machine learning methods. The current study introduces the concept of a data-driven framework to understand winter navigation operations. The immediate extension of this study is to quantify the effect of each influencing factor on the decision-making in BSR based on the established database. Another important extension of this study is to distinguish the effects of factors for specific ship ice classes. This quantitative knowledge can support precise decision-making regarding ships with different icebreaking capabilities. In the near future, the analyzed influencing factors would be adopted as inputs to supervised machine learning models. A comparative prediction study would be conducted to explore to what extent emerging techniques can contribute to improving efficient and safe decision-making of winter navigation, such as icebreaker scheduling optimization and winter navigation efficiency improvement.

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