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Data-Driven Ship Energy Efficiency Analysis and Optimization Model for Route Planning in Ice-Covered Arctic Waters

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Abstract: As increasing numbers of merchant ships navigate in the Arctic waters, more energy efficient navigation in the Arctic is needed for both economic and environmental purposes. This paper aims to provide a comprehensive analysis of energy efficiency of ice-going ships. Firstly, a data-driven model based on neural network theory is developed to predict the energy efficiency of ships in the Arctic. Then, a route with optimum energy efficiency is presented, intended to cut costs and be as environmentally friendly as possible. Finally, a case study is carried out to analyze the performance of a case study ship sailing at various environmental conditions. The results indicate that when planning the route for such an Arctic ship, it would be shortsighted only to focus on distance rather than energy efficiency. Moreover, the model shows good agreement between the simulation and real-life navigation. It is expected that the construction of this multi-angle, energy efficiency optimization model could help to improve Arctic navigation.

Keyword: Ship Energy Efficiency; Optimization Model; Route Planning; Arctic Navigation

1. Introduction

Maritime transportation in the Arctic waters has become more attractive since the Arctic sea ice is melting fast due to climate change. Because of shorter and faster sea routes between Northeast Asia and Northwest Europe/North America compared to the traditional Suez/Panama Canal, both maritime industries and academics have begun to pay significant attention to the utilization of Arctic sea routes: the Northwest Passage Route through Canada (Stoddard et al., 2016) and the Northeast Passage Route along Arctic coasts of Norway and Siberia (Fu et al., 2017; Zhang et al., 2017; Zhang et al., 2018) which is also the focus in the current paper. For merchant ships navigating in the Arctic, cutting down on voyage costs, is typically one of the most important objectives. This is compounded by the fact that, compared with other navigation areas, the Arctic environment is more fragile and sensitive. It means that the problem of carbon emissions needs more attention. The IMO (International Maritime Organization), in particular, has planned to propose several policies aiming to mitigate the emissions in the Arctic (Nelissen and Tol, 2018). Combined, the reasons noted here point to the necessity of conducting research into the improvement of ship energy efficiency in the Arctic.

Considering that the shipping industry has made significant contributions to global carbon emissions, and for the purposes of reducing fuel consumption and carbon emissions, ships' energy saving strategies are discussed in literatures (Ballou, 2013). A ship's energy efficiency optimization can be conducted from several perspectives, such as management, operation, ship design, etc. (Beşikçi et al., 2016). While optimization measurements in the design phase, such as propeller geometry optimization and engine

optimization, are not discussed in this paper, the focus here is on other operational approaches (namely, routing and speed optimization).

A number of indexes have been used to evaluate ship energy efficiency (e.g. total fuel consumption, fuel consumption per nautical mile, and the Energy Efficiency Operational Indicator) (IMO, 2011). Among those indexes, the Energy Efficiency Operational Indicator (EEOI) can monitor ship and fleet efficiency performance over time, and can reveal changes when certain measures are taken. Nowadays, there are some researches discussing EEOI analysis and optimization, mainly in the context of the inland river transport. To analyze the EEOI for ships operated in the inland river, figuring out how EEOI react to different navigation environment is critical. The data-driven model presented by Sun et al. (2013) contains a substantial amount of data pertaining to the ship performance (e.g., speed and oil consumption) and to the environment (e.g., current speed). This model proves that the actual navigation environment and sailing speed do influence energy efficiency of the inland water transport. In most cases, however, such a substantial amount of data is hard to come by; thus, simulation methods such as the Monte Carlo method (Andrea et al., 2014) can be conducted to simulate the stochastic parameters (displacement, speed), which can then be combined with deterministic parameters (propeller geometry, diesel generator map, sailed distance, etc.) (Tillig et al., 2017). The other reason for developing a data-driven model to analyze the relationship between energy efficiency and environment is that the specific relationship – namely, the computational formulation – may be difficult to discern, or the empirical formulations may contain too many uncertainties. Such a situation is discussed in Meng et al. (2016), which presents a regression model for analyzing fuel efficiency and emissions based on the shipping log data of actual ships. Therefore, for the energy efficiency optimization of ice-going ships, to find the relationship between environment and energy efficiency related parameters reveals the significance. The analysis of energy efficiency of ice-going ships can be more complex comparing with ships in the inland river or open sea, and there exists no specific guideline for the application of EEOI to Arctic navigation. Thus, in this paper, we develop a data-driven model to provide a relative clear reflection for the energy efficiency of ice-going ships.

To boost ship energy efficiency, two optimum proposals have been put forward in the current paper. One is the speed optimization model based on the aforementioned data-driven model, and the other is the ice route planning model, which may provide more efficient route selection for operators. Generally, the conventional ice routing model contains three aspects: the transit model, ice model and optimization model (Kotovirta et al., 2009; Guinness et al., 2014). The drawback of this approach is that the uncertainties in these three models would work together when they are integrated, thus decreasing the model's reliability. For example, transit models are mainly derived from empirical formulas, which contain numerous uncertainties. Although such uncertainties can be, to some extent, identified and evaluated in Li et al. (2018). Besides, the ice condition also injects a lot of uncertainties into ship navigation, namely, due to inaccurate ice data or measurement of the data. These uncertainties can be considered by quantitative uncertainty analysis, but they cannot be handled in Choi et al. (2015). However, to explain the uncertainty resulting from the transit model, Montewka et al. (2018) constructed an ice routing model based on two categories – the data-driven model and engineering model. These two sub-models contribute to the routing model in the aspects of safety and cost, respectively.

From the studies mentioned above, it is evident that the topic of ship energy efficiency in open water

and inland river has been widely discussed. However, research about the coupled relationship between energy efficiency and the Arctic environment is relatively scarce. The reason for this may be that it is difficult to express such a relationship in mathematical formulae. Moreover, while most research mainly focuses on risk and emergency responses (Mileski et al., 2018; Fu et al., 2017), there are few studies discussing the management of ship energy efficiency in the Arctic. It is expected that the developed model in this paper can provide some suggestions to fill the gap. In addition, it should be noted that most routing models, especially for ice-going ships, concentrate on obstacle-avoidance problems or minimum distance and time. Studies consider the route with the lowest fuel consumption to be either the shortest route or the fastest route (Nam et al., 2013; Tsou and Cheng, 2013). However, this cannot be applied to ice-covered waters given that ship resistance may change in different navigation environments, resulting in the value of fuel consumption also being changeable. Therefore, the current study proposes a new route planning model in the context of sea ice searching the route for ice-going ships that enable optimum energy efficiency, which may be more applicable for Arctic navigation.

The remainder of the paper is organized as follows. The problem and the data are described in Section 2. Section 3 introduces the methods of analysis and relative parameters choices. Section 4 describes the procedure of developing the energy efficiency prediction model and related strategies. Section 5 presents the ice routing model for optimum energy efficiency. The conclusions and future work are detailed in section 6.

2. Description of the research problem and data

Sea ice is the most critical factor in the Arctic navigation, especially for the energy efficiency. To achieve the purpose of optimizing ship energy efficiency, it is necessary to clarify a ship's performance in the Arctic sailing environment. In the current paper, we develop an energy efficiency prediction model to demonstrate such a relationship between ship performance and the Arctic environment. The information was drawn from the log data of the ship, Yong Sheng. It is noteworthy that the routing model was also attention paid to safety concerns, given that the route planned needed to keep a distance with obstacles such as icebergs or other severe ice conditions. The model construction is detailed in section 5.

Fig. 1. Yong Sheng trajectory.

In order to construct a data-driven model, data pertaining to ship performance first need to be collected. The basic characteristics of Yong Sheng are presented in the Table 1 and the trajectory of Yong Sheng's navigation in 2013 is shown in the Fig. 1. Moreover, Data relating to ice concentration and voyage speed were recorded as log data (Fig. 4), together with other environmental data such as wind speed, wave height, air temperature and water temperature. Specifically, the ice concentration data was retrieved by analyzing the forecast ice conditions given by NMEFC (National Marine Environmental Forecasting Center) and observation by crews on aboard. The aforementioned other hydrometeorology data (wind speed, wave height, air temperature and water temperature) was also from the NMEFC (Zhao, 2014), which were shown in Fig. 5 and 6. It was noteworthy that the data of wave condition was recorded as meteorological degree which referred to the Douglas Sea scale (Douglas, 1991). While, the information about ship speed during the voyage was obtained from the Automatic Information System (AIS). Another vital variable for analyzing energy efficiency in our model was fuel consumption during the voyage, which was calculated according to the given engine data (Fig. 2 and Fig. 3), using the fuel consumption model discussed in section 3.2.

Table 1

Yong Sheng characteristics.

Ship name	Yong Sheng
Type	General cargo
Ice class	PC6
DWT	14357
Length	159.985 m
Breadth	23.70 m
Draught	8.69 m
Operation power	7074 kW

Fig. 2. Engine specific fuel consumption curve.

Fig. 3. Time series of engine power.

Fig. 4. Time series of ship speed and ice concentration.

Fig. 5. Time series of wind speed and wave height.

Fig. 6. Time series of air temperature and water temperature.

It should be noted that we chose not to include data collected on ice thickness because this was deemed too rough and inexact to be utilized in modeling. The fuzziness here mainly emerged due to the data of ice thickness was obtained purely from crew's observation and it was only recorded as two states: more or less than 0.5 m, which can only give a crude knowledge (Fu et al., 2016). As such, this information was seen to be beyond the scope of this paper, and was not adopted to build the model for the simulation.

3. Methodology

3.1 Framework of establishing energy efficiency sailing in the Arctic

The Framework to plan a ship's energy efficiency sailing can be broken down into three steps:

Step 1: Correlation analysis. To find the correlation coefficients of energy efficiency and its influencing factors, the correlation analysis method was utilized to analyze factors including speed, wind speed, ice concentration, etc.

Step 2: Energy efficiency prediction model. The prediction model using the BP Neural Network was developed by selecting those factors which have a strong correlation with energy efficiency, as input parameters. Ship speed optimization strategies were then be proposed based on the model's prediction. This model also sets the foundations for the next step.

Step 3: Route planning model for optimum energy efficiency. Firstly, certain image processing methods were used to build a navigation environment model for simulation. The improved Ant Colony Algorithm was then adopted to solve the optimum energy efficiency route planning problem. Finally, recommendations were provided based on the model.

3.2 Ship Energy Efficiency Operational Indicator (EEOI)

As previously mentioned, the Energy Efficiency Operational Indicator (EEOI) was selected to measure energy efficiency in this paper, as this indicator can reflect changes in energy efficiency caused by operations during the voyage.

The EEOI is first proposed by the IMO in 2009 (IMO, 2009). Since then, it has been used to constrain the CO₂ emissions of most ships. According to the MEPC.1/Circ.684 resolution, the EEOI can be calculated as follows:

$$EEOI = \frac{\sum_j FC_j \times C_{Fj}}{m_{\text{cargo}} \times D} \quad (1)$$

where FC_j is the mass of consumed fuel during voyage j ; C_{Fj} is the fuel mass to CO_2 mass conversion factor during voyage j ; m_{cargo} is the cargo carried (tonnes) or work done (number of TEU or passengers) or gross tonnes of passenger ships; D is the distance in nautical miles corresponding to the cargo carried or work done.

From the formulation, it is clear that energy efficiency would improve with a decrease of EEOI, which is mainly influenced by four parameters— m_{cargo} , D , FC_j and C_{Fj} . Among them, m_{cargo} and D can be considered components of transport volume and are constants in most situations, making it difficult to decrease the EEOI by adjusting these two parameters. Therefore, in order to decrease the EEOI and improve ship energy efficiency, reducing the fuel consumption during the voyage would be the best strategy.

The fuel consumption F , measured in kg per hour, was calculated using the following equation (Veneti et al., 2017):

$$F = P \times SF_{OC} \quad (2)$$

where SF_{OC} and P refers to the specific fuel consumption (kg/kWh) and the engine power (kW) of the ship, respectively. Therefore, the total fuel consumption along a route F_C can be calculated as the product of the ship's travelling time, T , and fuel consumption per hour, F (Veneti et al., 2017):

$$F_C = F \times T \quad (3)$$

3.3 Back Propagation Neural Network

The Back Propagation (BP) neural network is a typical machine learning algorithm which is widely applied in prediction and classification problems. A general BP neural network includes three layers: the input layer, hidden layer and output layer. The network can be trained by adjusting the weight and activation function, termed the Gradient Decent Optimization Algorithm. This self-regulation method gradually decreases the network's error between the model output and desired output.

Assuming that the BP neural network input is $X, X = \{x_1, x_2, x_3, \dots, x_n\}$, the weight correlation is ω_{ij} and θ represents the threshold. The weighted input, namely, the output of the hidden layer, $H, H = \{h_1, h_2, h_3, \dots, h_n\}$ can be calculated as follows (Wang et al., 2015):

$$h_j = f\left(\sum_{i=1}^n \omega_{ij} x_i - \theta_j\right) \quad j = 1, 2, \dots, l \quad (4)$$

where l represents number of units of the hidden layer. f represents the activation function. And, the error of the whole network, E , can be calculated as follows (Deo and Jagdale, 2003):

$$E = \frac{1}{2} \sum_{k=1}^m (y_k - o_k)^2 = \frac{1}{2} \sum_{k=1}^m \left[y_k - g \left(\sum_{j=1}^l \omega_{jk} f \left(\sum_{i=1}^n \omega_{ij} x_i - a_j \right) - b_k \right) \right]^2 \quad (5)$$

The updated approach, that is, the Gradient Descent Optimization Algorithm, can be utilized to update ω_{ij} and ω_{jk} (Rumelhart et al., 1986). And, the change of weight between units of the hidden layer and output layer, ω_{jk} , can be calculated as:

$$\Delta \omega_{jk} = -\eta \frac{\partial E}{\partial \omega_{jk}} = -\eta \frac{\partial E}{\partial net_k} \frac{\partial net_k}{\partial \omega_{jk}} = \eta \cdot e_k \cdot g'(net_k - b_k) \cdot H_j \quad (6)$$

The change of weight between units of the input layer and hidden layer, ω_{ij} , can be calculated as:

$$\Delta\omega_{ij} = -\eta \frac{\partial E}{\partial \omega_{ij}} = -\eta \frac{\partial E}{\partial net_j} \frac{\partial net_j}{\partial \omega_{ij}} = \eta \cdot \left(\sum_{k=1}^m e_k \cdot g'(net_k - a_j) \cdot \omega_{jk} \right) \cdot f'(net_j - a_j) \cdot x_i \quad (7)$$

The change of threshold between the hidden layer and output layer, accumulated in all input-output processes, can be calculated as:

$$\Delta b_k = -\eta \frac{\partial E}{\partial b_k} = \eta \cdot e_k \cdot g'(net_k - b_k) \quad (8)$$

The change of threshold between the input layer and hidden layer, accumulated in all input-output processes, can be calculated as:

$$\Delta a_j = -\eta \frac{\partial E}{\partial a_j} = -\eta \cdot \left(\sum_{k=1}^m e_k \cdot g'(net_k - b_k) \cdot \omega_{jk} \right) \cdot f'(net_j - a_j) \quad (9)$$

A BP neural network was developed using data shown in section 2. This feed-forward neural network contains three layers, with ten neurons in the hidden layer, which were determined according to empirical formula and numbers of selected input variables, benefiting the fit performance (Stathakis, 2009). The transfer functions chosen for the hidden layer and output layer were the sigmoid function and linear function, respectively, which may have raised the working efficiency of the neural network. The core training algorithm was set as the Levenberg-Marquardt algorithm (Smith et al., 2018), and the MSE (Mean Squared Error) was selected in order to estimate the performance of the model (Du et al., 2019).

3.4 Ant Colony Algorithm – voyage optimization

The Ant Colony Algorithm (ACA) is an intelligent, heuristic optimization algorithm that can be applied to solve search problems, inspired by the actions of live ants in searching for food. At first, the ants wander around randomly. When the first ant finds a source of food, it goes back to the nest and lays down a chemical substance (called pheromones) on the path; the pheromones evaporate over time. Other ants are more likely to follow the path on which more pheromones have been left. The shorter the path, the faster the accumulation of pheromones, resulting in a higher probability that this route would be selected, that is how such a feedback mechanism works. Ultimately, the ant colony would collectively find the shortest route containing the highest amount of pheromones, hence optimizing the "solution". In this way, ants' pheromone-based communication is key to ACA (Abdulkader et al., 2015).

However, like other heuristic algorithms, the ACA has some constraints, such as slow convergence and easily falling into local extreme values (Wang et al., 2018). The current study conducts certain measurements to improve the performance of the ACA, to some extent.

3.4.1 Waypoint selection procedure and pheromone adjustment

The ACA procedure is as follows:

(1) Set the departure and destination on the navigation environment model. The original pheromone in every waypoint is set as the same amount. Empty the tabu table and initialize parameters.

(2) Sent artificial ants to search the path in the navigation environment grid model. In general, the probability of the k th ant moving from node i to j can be deduced as follows (Gao, 2016):

$$P_{ij}^k = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}{\sum_{k \in \{N-tabu_k\}} [\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}, & j \in \{N-tabu_k\} \\ 0 & j \notin \{N-tabu_k\} \end{cases} \quad (10)$$

Where η_{ij} is heuristic information related to edge (i, j) , $\tau_{ij}(t)$ is the density of pheromone of edge (i, j) . α and β are the weights of $\tau_{ij}(t)$ and η_{ij} , respectively. $N-tabu_k$ represents the grids that ants are allowed to select in the next movement.

(3) Update the best route in every iteration, and calculate the length of the route.

(4) Repeat step 2 and step 3 until the artificial ants either reach the destination or fell into a dead end.

(5) Repeat steps 2, 3 and 4 until every ant in the generation finishes their iteration.

(6) Update the pheromone density of every node; the pheromone adjustment formulas applied is as follows (Gao, 2016):

$$\tau_{ij}(t+1) = (1-\rho) * \tau_{ij}(t) + \Delta\tau_{ij} \quad (11)$$

$$\Delta\tau_{ij}(t) = \begin{cases} \frac{Q}{L_k(t)}, & \text{ant } k \text{ passes } (i, j) \\ 0, & \text{ant } k \text{ doesn't pass } (i, j) \end{cases} \quad (12)$$

Where ρ is the coefficient of pheromone evaporation and $\Delta\tau_{ij}$ is the increment of the pheromone in edge (i, j) .

(7) Repeat steps 2 to 6, when the n th generation finishes the iteration, the search mission is completed.

3.4.2 ACA parameter adjustment

Setting the ACA parameters is an important step that can influence the algorithm's performance to a large extent (Danchuk, 2017). Thus, we installed a simple test to find the best combination of parameters for this routing model. In this process, the parameters of weight of pheromone α , weight of heuristic information β and iteration times were set as 1, 7 and 1000.

Table 2

ACA parameter adjustment.

Parameters Adjustment	Quantity of ants M	volatile coefficient ρ	convergence
No.1	50	0.3	170
No.2	50	0.7	155
No.3	100	0.7	133
No.4	100	0.3	158
No.5	150	0.7	147

The results shown in Table 2 imply that when the quantity of ants and the volatile pheromone coefficient were set as 100 and 0.7, respectively, the model experienced better convergence compared with other combinations. The reason for this situation may be that the navigation environment model of

simulation contains a sufficient quantity of grids leading to the decrease of route search accuracy thus increasing amount of ants may improve it, and that an increase in the volatile coefficient may decrease the occurrence of the local convergence problem (Wang et al., 2018).

4. The energy efficiency prediction model architecture

This section describes the development of the energy efficiency prediction model, based on the BP Neural Network, representing the first step in the optimization model as a whole. Also, the prediction model is data-driven, while the data used is from Yong Sheng which was selected as a case study due to the typical type and size of this ship.

4.1 Analysis of factors influencing Arctic ship energy efficiency

The initial work (factors analysis) has been conducted prior to constructing the architecture of the model, since navigation in the Arctic is typically affected by various characteristics. After collecting data from the Yong Sheng and experts' knowledge (Fu et al., 2016), we conducted a Pearson correlation analysis based on several environmental parameters (including wind speed, air temperature, water temperature, wave height and ice concentration), as well as on speed and energy efficiency. The Pearson correlation analysis is a widely used approach that aims to find the linear relationship between variables. We thus chose this method in order to identify the factors that are strongly correlated with energy efficiency.

Table 3

Correlation coefficients between variables and ship energy efficiency for Yong Sheng, while each number corresponds to one factor, such as No.1 represents ship energy efficiency and No.2 represents ship speed.

Factor	No.	1	2	3	4	5	6	7
Ship energy efficiency	1	1.000						
Ship speed	2	0.835	1.000					
Wind speed	3	0.391	0.389	1.000				
Air temperature	4	0.163	0.381	0.033	1.000			
Water temperature	5	0.254	0.595	0.331	0.591	1.000		
Ice concentration	6	0.680	0.689	0.522	0.141	0.585	1.000	
Wave height	7	0.308	0.408	0.937	0.060	0.359	0.550	1.000

From the results in Table 3, it can be seen that ship speed is ranked first, making this the most important factor in ship performance. Ship speed is followed by ice concentration, which may be the major environmental factor. Simultaneously, other environmental factors such as wind speed and wave height can be seen to have a weak correlation with energy efficiency compared with ice conditions, similar to results found in other literature (Qian et al., 2016).

4.2 Energy efficiency prediction model for ships in Arctic waters

In line with the results of the correlation analysis, the parameters of ice concentration and ship speed were set as the inputs in the prediction model, which characterizes the strong correlation with EEOI. We thus constructed a BP neural network (a black box model) to demonstrate their relationship.

The database collected from Yong Sheng, containing 179 rows of data, was divided into two sets – 149 rows for the training set and 30 for the test set. The data were then input into the neural network for the model training.

Fig. 7. Neural network fitting condition.

The default training data set was randomly divided into three mutually exclusive sets in the network: training set, validation set and test set. The scatter graph (Fig. 7) shows the comparison between the prediction output data and the actual data at the three databases of training, verification and testing. The model was seen to have a good performance during the training process, whose fitting rate achieved nearly 0.97. The fitting rate of validation was set near 0.96, which is evidence of appropriate parameters having been set up in the neural network. The reason why the fitting rate of the training set is higher than other two sets is that the training set is utilized to update the parameters, while the other two are used to estimate the network's prediction capability (Vasiliki et al., 2018).

We input the test data into the trained neural network model to measure its generalization. The result is shown in Fig. 8.

Fig. 8. Accuracy test of model's prediction capability.

As illustrated in Fig. 8, the model was able to predict EEOI with high accuracy, within an acceptable error of 5%. This, in turn, also proves that those two parameters (speed and ice concentration) were strongly

correlated with EEOI. This data-driven model can, therefore, help us to understand how EEOI reacts with the environment.

The prediction model, based on our results so far, was thus found able to assist in adjusting ship speed to optimize energy efficiency for ships in the Arctic. A simple simulation was then conducted to find the ship speed for optimum energy efficiency under various ice conditions.

Before the navigation of Yong Sheng, the navigation strategies including the speed range in deferent ice conditions was discussed by managers and captains (Cai and Lin, 2016). After consulting the captain of Yong Sheng who had 15 years longer navigation experience, we combined the information from experts' consultation and actual navigation data presented in section 2 to set the speed limits in various ice conditions. The details are shown in Table 4.

Table 4
Speed limitations in deferent ice conditions.

Ice concentration	Speed variation (kn)
1/10	8-14
3/10	6-12
5/10	5-10
7/10	4-8

In line with the prediction model and the speed limitation in ice waters, we were able to develop the simulation to find the speed for the corresponding optimum energy efficiency in various degrees of ice concentration. Taking into account the actual operation of the ship, the speed was set to increase by 0.5 kn, which may be more acceptable for the operators to maneuver ships.

Fig. 9. Simulation results of ship speed for optimum energy efficiency.

Table 5
The ship speed for optimum energy efficiency in different ice concentration.

Ice concentration	Optimal speed (kn)	EEOI (t/(t nm))
1/10	9.5	1.23×10^{-5}
3/10	9.0	1.52×10^{-5}
5/10	5.5	1.83×10^{-5}
7/10	5.0	2.44×10^{-5}

Fig. 9 and Table. 5 demonstrate the consequence of the simulation. For example, at an ice concentration of 7/10, the EEOI varies with the speed, reaching a minimum at 2.44×10^{-5} t/(t nm) with the speed of 5.0 kn which would be the most appropriate speed in that ice condition.

In real-life Arctic navigation, when the ice becomes denser ship resistance will increase, which in turn decreases ship speed and leads to higher power required, as well as more fuel. Eventually, the EEOI would grow greater and ships manifest poor energy efficiency, indicating that our simulation conforms to the actual situation.

5. Route planning method for energy efficiency optimization of ice-going ships

Generally, a ship's route selection is made by navigators according to their experience accumulated in previous voyages. While this strategy sometimes functions well, but human decision making can be affected by certain unfavorable factors, especially in the Arctic area, such as extreme cold, light nights in the summertime and dark days in the winter (V. Lehtola et al., 2018). Those factors may cause inefficiency of navigation. Therefore, having a routing model could be of great assistance for operators in the Arctic area.

In the previous section, the prediction model developed was applied to find the most suitable speed for optimum energy efficiency in diverse areas. Following this step, and to optimize Arctic navigation, the ice routing model was developed to improve ship energy efficiency in the context of the shipping lane.

For real-life navigation in ice-covered waters, the ice condition is the most significant environmental factor. It is, therefore, important to confirm that the navigation environment model developed can reflect actual ice conditions. This aspect of our work was undertaken using Matlab.

5.1 Navigation environment modeling

In general, ship routing model consists of several aspects, including modelling the environment under navigation, a route search using the appropriate algorithm. Developing a navigation environment model is fundamental to the study. To achieve this, image processing approaches were utilized to build the navigation environment model.

To describe this process, an example is depicted. Fig. 10 is the ice concentration prediction image provided by NMEFC for support Yong Sheng's navigation in 2013, which is conducted by analyzing original data from the database of University of Bremen (Spren et al., 2008). The section of the chosen simulation area shown in Fig. 10 is located in the Laptev Sea. The black marked square denotes the area we chose for the environmental simulation from longitude 99.5° E and latitude 80.5° N to longitude 101.1° E and latitude 80.1° N. However, such a figure (Fig. 10) is not appropriate for the direct application to the routing model as the figure contains too many details which may raise the complexity of the routing model and depress the efficiency of the computer's processing progress (Reimer, 2015). Considering these constraints, we simplified figures like Fig. 10 to make them the apt navigation environment models for the ice routing.

Fig. 10. Ice concentration prediction image (black marked rectangle area is taken as an example).

In order to process the chosen area in Fig. 10, approaches such as gray processing were utilized, enabling the chart to be discretized to a matrix sized 50×50 according to the scale of the figure. The entire process of image translation is shown in Fig. 11. Firstly, converting RGB image (Fig. 11(a)) to grayscale image (Fig. 11(b)), that was, the first step to simplify the image. Then, resizing the grayscale image and discretizing to a matrix sized 50×50 in which the image was further gridded according to the complexity (Einhäuser et al., 2007) and the side length of every grid is about 0.4 nautical miles according to the scale. Following this, the grids of the figure were filled with colors according to the original figure (Fig. 11(a)), which was finally converted to Fig. 11(c)). This step served to simplify the figure as far as possible, which was key to lowering the load of computerized programming. The entire process was conducted using Matlab. The gridded figure was thus able to reveal the distribution of various degrees of ice concentration using different colors. Namely, in the processed figure, the blue grids represented the open sea, while the red grids represented intensive ice area which need be avoided. The grids with different rest colors represented different ice concentrations, which was detailed in Table 6. Therefore, the figure processed was able clearly to reflect the key ice information while not being too complicated for a computer to work on.

Fig. 11. Image processing procedure.

Table 6

Explanation of the grids in the navigation environment model

Ice concentration	Color	Speed (kn)
0	blue	13.0
3/10	light green	9.0
5/10	green	5.5
7/10	yellow	5.0

5.2 Mathematical ACA modeling

While, as mentioned before, the core routing algorithm employed was the ACA. In this subsection, we described the assumptions and objective function of the algorithm we made to the ACA, which aimed to make it a better fit for the routing model discussed in this paper.

5.2.1 Assumptions

In the current simulation, the ship speed at each degree of ice concentration was assumed to keep constant, as well as the ship's fuel consumption per nautical mile. We also assumed that the speed in diverse areas was set by the prediction model developed in section 4, that is, referring to the optimum speed for optimum energy efficiency. Other assumptions made about the routing model were as follows:

(1) The influence of wind and waves was neglected. The most important environmental factor in Arctic navigation – ice – was set as the only environmental factor in the model.

(2) The case study ship used for the simulation was considered to be a mass point, meaning that the size of the ship was neglected.

5.2.2 Objective function of the routing model

With this model, we attempted to find the route enabling optimum energy efficiency. As the environmental information was known, the ice concentration in the study area and distribution of obstacles could be derived from the navigation environment model. Simultaneously, as far as safety was concerned, the planned route needed effectively to not only avoid obstacles but keep a distance with them, such as severe ice condition (the red part in the navigation environment model). Hence, the objective function was set as:

$$C = \text{Min} \frac{\sum d_n \cdot c_n \cdot C_{Fj}}{m_{\text{cargo}} \times D} \quad (13)$$

Where d_n is the distance of segment n and c_n is fuel consumption per nautical mile.

5.3 Ice routing simulation

According to ice forecast report from NMEFC, the NSR can be divided into several areas shown in Fig. 12 for a ship's navigation. The area E located in the Laptev Sea was the the most significant area due to its the relatively high ice conditions that brought Yong Sheng troubles to navigate (NMEFC, 2013). While, for the areas A, B, C and D, the Yong Sheng ship could navigate in weather conditions similar as those sailing in the open sea as the less ice in those areas during summertime. Many methods are available to plan a ship's routing with respect to less fuel consumption. Since the present study aims at proposing a routing model to save fuel for ice navigations, the proposed ice routing model for optimum energy efficiency has been conducted only in the area E.

Fig. 12. Areas divided in the NSR. The information is provided by the NMEFC.

Using the navigation environment modeling method in section 5.1, the area E is discretized to a 165×120 grid matrix with an aspect ratio 11:8, as shown in Fig. 13. The side length of every grid is about 1.65 nautical miles. The departure and destination are shown as black grids in the Fig. 13. The white grids in the navigation environment model represent land areas which also need to be avoided during the voyage.

Fig. 13. Area E navigation environment modeling (white grids refer to land area).

Then the development of the ice routing simulation using ACA in this area was presented. Firstly, the conventional ACA was employed to search for the shortest path from departure to arrival.

Fig. 14. The shortest route for the area E.

The iteration process was shown as Fig. 15:

Fig. 15. Process of iteration for the shortest route

From Fig. 15, it can be seen that the value of path length converged at around the 850th iteration, which represents the shortest path in the simulation. And, the path length was 267.81 nautical miles. The EEOI for the route was 1.40×10^{-5} t/(t nm) and the voyage took 25.76 hours.

Following this, in order to find the optimum energy efficiency route, the improved ACA was

employed. The result is shown in Fig. 16.

Fig. 16. Route for optimum energy efficiency for the area E.

Fig. 17. Process of iteration for optimum energy efficiency route.

According to Fig. 16 and Fig. 17, the value of the EEOI converged after about 940 generations and the smallest EEOI was 1.21×10^{-5} t/(t nm). The path length was 275.94 nautical miles and took 25.62 hours to navigate. A comparison of the performance parameters between the two paths is shown in Table 7.

Table 7

Parameters of two routes' comparison for area E.

Path	Distance (n mile)	Fuel consumption (t)	Time (hour)	EEOI (t/(t nm))
Shortest	267.81	16.86	25.76	1.40×10^{-5}
Best energy efficiency	275.94	14.92	25.82	1.21×10^{-5}

Table 7 demonstrates that the voyage time of two simulated routes is close. However, the distance for the optimum energy efficiency route is longer than the shortest route by a few nautical miles, but enable better energy efficiency as well as saving nearly two tons of fuel which is mostly on account of the avoidance of heavy ice conditions. The proposed routing model can thus be seen to have the capability to plan the more efficient routes for ships passing through ice-covered waters. Moreover, the results of the comparative simulation indicate that when operators select their navigation route in a particular ice region, it is worth selecting one enabling the best energy efficiency that considers the specific ice condition.

6. Conclusion and future work

The paper introduces an optimization model for ice-going ships' energy efficiency. The initial work of correlation analysis has been developed first since the complexity of the Arctic navigation may make it difficult to discern the relationship between all of the factors influencing energy efficiency in this area. The whole optimization model comprises two sub-models, one of which is the ship speed optimization model based on a data-driven, energy efficiency prediction model, the other is the ice routing model. With regard to the former, the index EEOI has been chosen as the tool with which to estimate ship energy efficiency, since it shows advantages compared with other indexes. According to the accuracy test, the model deviation was within 5%, implying that the prediction model performed well and could, in principle, be used for the purpose of predicting Arctic ships' energy efficiency. Based on this model, the speed corresponding to the best energy efficiency in various ice conditions could then be provided to operators.

To achieve further optimization, we constructed an ice routing model based on image processing methods and improved ACA. We chose the key area to develop the navigation environment model for routing simulation. The comparative simulation within deferent paths was also conducted; the results indicate that when planning the ship's route, it would be shortsighted only to focus on distance rather than energy efficiency.

The optimization model developed here could arguably solve energy efficiency improvement problems in terms of both ship speed and route. Notwithstanding this, there exist certain limitations that require further effort in future research. First of all, the input parameters of the current energy efficiency model would benefit from including a greater number of related components, such as displacement, trim, ice thickness; this would help to improve the applicability of the prediction model. Secondly, since the current study is ship specific (i.e. pertaining to the Yong Sheng), the applicability of the proposed model to other categories of ship would need to be validated. Such work would extend the usage scope of the current model. Thirdly, real-life navigation in Arctic ice-covered waters is not merely a cost-benefit issue but also includes risk analysis, which means that the value of risk would need to be added into the waypoint of the routing model, since it would be more meaningful to optimize energy efficiency under an acceptable level of risk. Finally, the proposed ice routing tool does not take users sufficiently into account. To improve the user's experience, certain measures can be taken, such as appropriately reducing the resolution of the navigation environment model so as to decrease computing time, or producing a graphical user interface (GUI) to satisfy users' various demands.

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Data-Driven Ship Energy Efficiency Analysis and Optimization Model for Route Planning in Ice-Covered Arctic Waters

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Abstract: As increasing numbers of merchant ships navigate in the Arctic waters, more energy efficient navigation in the Arctic is needed for both economic and environmental purposes. This paper aims to provide a comprehensive analysis of energy efficiency of ice-going ships. Firstly, a data-driven model based on neural network theory is developed to predict the energy efficiency of ships in the Arctic. Then, a route with optimum energy efficiency is presented, intended to cut costs and be as environmentally friendly as possible. Finally, a case study is carried out to analyze the performance of a case study ship sailing at various environmental conditions. The results indicate that when planning the route for such an Arctic ship, it would be shortsighted only to focus on distance rather than energy efficiency. Moreover, the model shows good agreement between the simulation and real-life navigation. It is expected that the construction of this multi-angle, energy efficiency optimization model could help to improve Arctic navigation.

Keyword: Ship Energy Efficiency; Optimization Model; Route Planning; Arctic Navigation

1. Introduction

Maritime transportation in the Arctic waters has become more attractive since the Arctic sea ice is melting fast due to climate change. Because of shorter and faster sea routes between Northeast Asia and Northwest Europe/North America compared to the traditional Suez/Panama Canal, both maritime industries and academics have begun to pay significant attention to the utilization of Arctic sea routes: the Northwest Passage Route through Canada (Stoddard et al., 2016) and the Northeast Passage Route along Arctic coasts of Norway and Siberia (Fu et al., 2017; Zhang et al., 2017; Zhang et al., 2018) which is also the focus in the current paper. For merchant ships navigating in the Arctic, cutting down on voyage costs, is typically one of the most important objectives. This is compounded by the fact that, compared with other navigation areas, the Arctic environment is more fragile and sensitive. It means that the problem of carbon emissions needs more attention. The IMO (International Maritime Organization), in particular, has planned to propose several policies aiming to mitigate the emissions in the Arctic (Nelissen and Tol, 2018). Combined, the reasons noted here point to the necessity of conducting research into the improvement of ship energy efficiency in the Arctic.

Considering that the shipping industry has made significant contributions to global carbon emissions, and for the purposes of reducing fuel consumption and carbon emissions, ships' energy saving strategies are discussed in literatures (Ballou, 2013). A ship's energy efficiency optimization can be conducted from several perspectives, such as management, operation, ship design, etc. (Beşikçi et al., 2016). While optimization measurements in the design phase, such as propeller geometry optimization and engine

optimization, are not discussed in this paper, the focus here is on other operational approaches (namely, routing and speed optimization).

A number of indexes have been used to evaluate ship energy efficiency (e.g. total fuel consumption, fuel consumption per nautical mile, and the Energy Efficiency Operational Indicator) (IMO, 2011). Among those indexes, the Energy Efficiency Operational Indicator (EEOI) can monitor ship and fleet efficiency performance over time, and can reveal changes when certain measures are taken. Nowadays, there are some researches discussing EEOI analysis and optimization, mainly in the context of the inland river transport. To analyze the EEOI for ships operated in the inland river, figuring out how EEOI react to different navigation environment is critical. The data-driven model presented by Sun et al. (2013) contains a substantial amount of data pertaining to the ship performance (e.g., speed and oil consumption) and to the environment (e.g., current speed). This model proves that the actual navigation environment and sailing speed do influence energy efficiency of the inland water transport. In most cases, however, such a substantial amount of data is hard to come by; thus, simulation methods such as the Monte Carlo method (Andrea et al., 2014) can be conducted to simulate the stochastic parameters (displacement, speed), which can then be combined with deterministic parameters (propeller geometry, diesel generator map, sailed distance, etc.) (Tillig et al., 2017). The other reason for developing a data-driven model to analyze the relationship between energy efficiency and environment is that the specific relationship – namely, the computational formulation – may be difficult to discern, or the empirical formulations may contain too many uncertainties. Such a situation is discussed in Meng et al. (2016), which presents a regression model for analyzing fuel efficiency and emissions based on the shipping log data of actual ships. Therefore, for the energy efficiency optimization of ice-going ships, to find the relationship between environment and energy efficiency related parameters reveals the significance. The analysis of energy efficiency of ice-going ships can be more complex comparing with ships in the inland river or open sea, and there exists no specific guideline for the application of EEOI to Arctic navigation. Thus, in this paper, we develop a data-driven model to provide a relative clear reflection for the energy efficiency of ice-going ships.

To boost ship energy efficiency, two optimum proposals have been put forward in the current paper. One is the speed optimization model based on the aforementioned data-driven model, and the other is the ice route planning model, which may provide more efficient route selection for operators. Generally, the conventional ice routing model contains three aspects: the transit model, ice model and optimization model (Kotovirta et al., 2009; Guinness et al., 2014). The drawback of this approach is that the uncertainties in these three models would work together when they are integrated, thus decreasing the model's reliability. For example, transit models are mainly derived from empirical formulas, which contain numerous uncertainties. Although such uncertainties can be, to some extent, identified and evaluated in Li et al. (2018). Besides, the ice condition also injects a lot of uncertainties into ship navigation, namely, due to inaccurate ice data or measurement of the data. These uncertainties can be considered by quantitative uncertainty analysis, but they cannot be handled in Choi et al. (2015). However, to explain the uncertainty resulting from the transit model, Montewka et al. (2018) constructed an ice routing model based on two categories – the data-driven model and engineering model. These two sub-models contribute to the routing model in the aspects of safety and cost, respectively.

From the studies mentioned above, it is evident that the topic of ship energy efficiency in open water

and inland river has been widely discussed. However, research about the coupled relationship between energy efficiency and the Arctic environment is relatively scarce. The reason for this may be that it is difficult to express such a relationship in mathematical formulae. Moreover, while most research mainly focuses on risk and emergency responses (Mileski et al., 2018; Fu et al., 2017), there are few studies discussing the management of ship energy efficiency in the Arctic. It is expected that the developed model in this paper can provide some suggestions to fill the gap. In addition, it should be noted that most routing models, especially for ice-going ships, concentrate on obstacle-avoidance problems or minimum distance and time. Studies consider the route with the lowest fuel consumption to be either the shortest route or the fastest route (Nam et al., 2013; Tsou and Cheng, 2013). However, this cannot be applied to ice-covered waters given that ship resistance may change in different navigation environments, resulting in the value of fuel consumption also being changeable. Therefore, the current study proposes a new route planning model in the context of sea ice searching the route for ice-going ships that enable optimum energy efficiency, which may be more applicable for Arctic navigation.

The remainder of the paper is organized as follows. The problem and the data are described in Section 2. Section 3 introduces the methods of analysis and relative parameters choices. Section 4 describes the procedure of developing the energy efficiency prediction model and related strategies. Section 5 presents the ice routing model for optimum energy efficiency. The conclusions and future work are detailed in section 6.

2. Description of the research problem and data

Sea ice is the most critical factor in the Arctic navigation, especially for the energy efficiency. To achieve the purpose of optimizing ship energy efficiency, it is necessary to clarify a ship's performance in the Arctic sailing environment. In the current paper, we develop an energy efficiency prediction model to demonstrate such a relationship between ship performance and the Arctic environment. The information was drawn from the log data of the ship, Yong Sheng. It is noteworthy that the routing model was also attention paid to safety concerns, given that the route planned needed to keep a distance with obstacles such as icebergs or other severe ice conditions. The model construction is detailed in section 5.

Fig. 1. Yong Sheng trajectory.

In order to construct a data-driven model, data pertaining to ship performance first need to be collected. The basic characteristics of Yong Sheng are presented in the Table 1 and the trajectory of Yong Sheng's navigation in 2013 is shown in the Fig. 1. Moreover, Data relating to ice concentration and voyage speed were recorded as log data (Fig. 4), together with other environmental data such as wind speed, wave height, air temperature and water temperature. Specifically, the ice concentration data was retrieved by analyzing the forecast ice conditions given by NMEFC (National Marine Environmental Forecasting Center) and observation by crews on aboard. The aforementioned other hydrometeorology data (wind speed, wave height, air temperature and water temperature) was also from the NMEFC (Zhao, 2014), which were shown in Fig. 5 and 6. It was noteworthy that the data of wave condition was recorded as meteorological degree which referred to the Douglas Sea scale (Douglas, 1991). While, the information about ship speed during the voyage was obtained from the Automatic Information System (AIS). Another vital variable for analyzing energy efficiency in our model was fuel consumption during the voyage, which was calculated according to the given engine data (Fig. 2 and Fig. 3), using the fuel consumption model discussed in section 3.2.

Table 1

Yong Sheng characteristics.

Ship name	Yong Sheng
Type	General cargo
Ice class	PC6
DWT	14357
Length	159.985 m
Breadth	23.70 m
Draught	8.69 m
Operation power	7074 kW

Fig. 2. Engine specific fuel consumption curve.

Fig. 3. Time series of engine power.

Fig. 4. Time series of ship speed and ice concentration.

Fig. 5. Time series of wind speed and wave height.

Fig. 6. Time series of air temperature and water temperature.

It should be noted that we chose not to include data collected on ice thickness because this was deemed too rough and inexact to be utilized in modeling. The fuzziness here mainly emerged due to the data of ice thickness was obtained purely from crew's observation and it was only recorded as two states: more or less than 0.5 m, which can only give a crude knowledge (Fu et al., 2016). As such, this information was seen to be beyond the scope of this paper, and was not adopted to build the model for the simulation.

3. Methodology

3.1 Framework of establishing energy efficiency sailing in the Arctic

The Framework to plan a ship's energy efficiency sailing can be broken down into three steps:

Step 1: Correlation analysis. To find the correlation coefficients of energy efficiency and its influencing factors, the correlation analysis method was utilized to analyze factors including speed, wind speed, ice concentration, etc.

Step 2: Energy efficiency prediction model. The prediction model using the BP Neural Network was developed by selecting those factors which have a strong correlation with energy efficiency, as input parameters. Ship speed optimization strategies were then be proposed based on the model's prediction. This model also sets the foundations for the next step.

Step 3: Route planning model for optimum energy efficiency. Firstly, certain image processing methods were used to build a navigation environment model for simulation. The improved Ant Colony Algorithm was then adopted to solve the optimum energy efficiency route planning problem. Finally, recommendations were provided based on the model.

3.2 Ship Energy Efficiency Operational Indicator (EEOI)

As previously mentioned, the Energy Efficiency Operational Indicator (EEOI) was selected to measure energy efficiency in this paper, as this indicator can reflect changes in energy efficiency caused by operations during the voyage.

The EEOI is first proposed by the IMO in 2009 (IMO, 2009). Since then, it has been used to constrain the CO₂ emissions of most ships. According to the MEPC.1/Circ.684 resolution, the EEOI can be calculated as follows:

$$EEOI = \frac{\sum_j FC_j \times C_{Fj}}{m_{\text{cargo}} \times D} \quad (1)$$

where FC_j is the mass of consumed fuel during voyage j ; C_{Fj} is the fuel mass to CO_2 mass conversion factor during voyage j ; m_{cargo} is the cargo carried (tonnes) or work done (number of TEU or passengers) or gross tonnes of passenger ships; D is the distance in nautical miles corresponding to the cargo carried or work done.

From the formulation, it is clear that energy efficiency would improve with a decrease of EEOI, which is mainly influenced by four parameters— m_{cargo} , D , FC_j and C_{Fj} . Among them, m_{cargo} and D can be considered components of transport volume and are constants in most situations, making it difficult to decrease the EEOI by adjusting these two parameters. Therefore, in order to decrease the EEOI and improve ship energy efficiency, reducing the fuel consumption during the voyage would be the best strategy.

The fuel consumption F , measured in kg per hour, was calculated using the following equation (Veneti et al., 2017):

$$F = P \times SF_{OC} \quad (2)$$

where SF_{OC} and P refers to the specific fuel consumption (kg/kWh) and the engine power (kW) of the ship, respectively. Therefore, the total fuel consumption along a route F_C can be calculated as the product of the ship's travelling time, T , and fuel consumption per hour, F (Veneti et al., 2017):

$$F_C = F \times T \quad (3)$$

3.3 Back Propagation Neural Network

The Back Propagation (BP) neural network is a typical machine learning algorithm which is widely applied in prediction and classification problems. A general BP neural network includes three layers: the input layer, hidden layer and output layer. The network can be trained by adjusting the weight and activation function, termed the Gradient Decent Optimization Algorithm. This self-regulation method gradually decreases the network's error between the model output and desired output.

Assuming that the BP neural network input is $X, X = \{x_1, x_2, x_3, \dots, x_n\}$, the weight correlation is ω_{ij} and θ represents the threshold. The weighted input, namely, the output of the hidden layer, $H, H = \{h_1, h_2, h_3, \dots, h_n\}$ can be calculated as follows (Wang et al., 2015):

$$h_j = f\left(\sum_{i=1}^n \omega_{ij} x_i - \theta_j\right) \quad j = 1, 2, \dots, l \quad (4)$$

where l represents number of units of the hidden layer. f represents the activation function. And, the error of the whole network, E , can be calculated as follows (Deo and Jagdale, 2003):

$$E = \frac{1}{2} \sum_{k=1}^m (y_k - o_k)^2 = \frac{1}{2} \sum_{k=1}^m \left[y_k - g \left(\sum_{j=1}^l \omega_{jk} f \left(\sum_{i=1}^n \omega_{ij} x_i - a_j \right) - b_k \right) \right]^2 \quad (5)$$

The updated approach, that is, the Gradient Descent Optimization Algorithm, can be utilized to update ω_{ij} and ω_{jk} (Rumelhart et al., 1986). And, the change of weight between units of the hidden layer and output layer, ω_{jk} , can be calculated as:

$$\Delta \omega_{jk} = -\eta \frac{\partial E}{\partial \omega_{jk}} = -\eta \frac{\partial E}{\partial net_k} \frac{\partial net_k}{\partial \omega_{jk}} = \eta \cdot e_k \cdot g'(net_k - b_k) \cdot H_j \quad (6)$$

The change of weight between units of the input layer and hidden layer, ω_{ij} , can be calculated as:

$$\Delta\omega_{ij} = -\eta \frac{\partial E}{\partial \omega_{ij}} = -\eta \frac{\partial E}{\partial net_j} \frac{\partial net_j}{\partial \omega_{ij}} = \eta \cdot \left(\sum_{k=1}^m e_k \cdot g'(net_k - a_j) \cdot \omega_{jk} \right) \cdot f'(net_j - a_j) \cdot x_i \quad (7)$$

The change of threshold between the hidden layer and output layer, accumulated in all input-output processes, can be calculated as:

$$\Delta b_k = -\eta \frac{\partial E}{\partial b_k} = \eta \cdot e_k \cdot g'(net_k - b_k) \quad (8)$$

The change of threshold between the input layer and hidden layer, accumulated in all input-output processes, can be calculated as:

$$\Delta a_j = -\eta \frac{\partial E}{\partial a_j} = -\eta \cdot \left(\sum_{k=1}^m e_k \cdot g'(net_k - b_k) \cdot \omega_{jk} \right) \cdot f'(net_j - a_j) \quad (9)$$

A BP neural network was developed using data shown in section 2. This feed-forward neural network contains three layers, with ten neurons in the hidden layer, which were determined according to empirical formula and numbers of selected input variables, benefiting the fit performance (Stathakis, 2009). The transfer functions chosen for the hidden layer and output layer were the sigmoid function and linear function, respectively, which may have raised the working efficiency of the neural network. The core training algorithm was set as the Levenberg-Marquardt algorithm (Smith et al., 2018), and the MSE (Mean Squared Error) was selected in order to estimate the performance of the model (Du et al., 2019).

3.4 Ant Colony Algorithm – voyage optimization

The Ant Colony Algorithm (ACA) is an intelligent, heuristic optimization algorithm that can be applied to solve search problems, inspired by the actions of live ants in searching for food. At first, the ants wander around randomly. When the first ant finds a source of food, it goes back to the nest and lays down a chemical substance (called pheromones) on the path; the pheromones evaporate over time. Other ants are more likely to follow the path on which more pheromones have been left. The shorter the path, the faster the accumulation of pheromones, resulting in a higher probability that this route would be selected, that is how such a feedback mechanism works. Ultimately, the ant colony would collectively find the shortest route containing the highest amount of pheromones, hence optimizing the "solution". In this way, ants' pheromone-based communication is key to ACA (Abdulkader et al., 2015).

However, like other heuristic algorithms, the ACA has some constraints, such as slow convergence and easily falling into local extreme values (Wang et al., 2018). The current study conducts certain measurements to improve the performance of the ACA, to some extent.

3.4.1 Waypoint selection procedure and pheromone adjustment

The ACA procedure is as follows:

(1) Set the departure and destination on the navigation environment model. The original pheromone in every waypoint is set as the same amount. Empty the tabu table and initialize parameters.

(2) Sent artificial ants to search the path in the navigation environment grid model. In general, the probability of the k th ant moving from node i to j can be deduced as follows (Gao, 2016):

$$P_{ij}^k = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}{\sum_{k \in \{N-tabu_k\}} [\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}, & j \in \{N-tabu_k\} \\ 0 & j \notin \{N-tabu_k\} \end{cases} \quad (10)$$

Where η_{ij} is heuristic information related to edge (i, j) , $\tau_{ij}(t)$ is the density of pheromone of edge (i, j) . α and β are the weights of $\tau_{ij}(t)$ and η_{ij} , respectively. $N-tabu_k$ represents the grids that ants are allowed to select in the next movement.

(3) Update the best route in every iteration, and calculate the length of the route.

(4) Repeat step 2 and step 3 until the artificial ants either reach the destination or fell into a dead end.

(5) Repeat steps 2, 3 and 4 until every ant in the generation finishes their iteration.

(6) Update the pheromone density of every node; the pheromone adjustment formulas applied is as follows (Gao, 2016):

$$\tau_{ij}(t+1) = (1-\rho) * \tau_{ij}(t) + \Delta\tau_{ij} \quad (11)$$

$$\Delta\tau_{ij}(t) = \begin{cases} \frac{Q}{L_k(t)}, & \text{ant } k \text{ passes } (i, j) \\ 0, & \text{ant } k \text{ doesn't pass } (i, j) \end{cases} \quad (12)$$

Where ρ is the coefficient of pheromone evaporation and $\Delta\tau_{ij}$ is the increment of the pheromone in edge (i, j) .

(7) Repeat steps 2 to 6, when the n th generation finishes the iteration, the search mission is completed.

3.4.2 ACA parameter adjustment

Setting the ACA parameters is an important step that can influence the algorithm's performance to a large extent (Danchuk, 2017). Thus, we installed a simple test to find the best combination of parameters for this routing model. In this process, the parameters of weight of pheromone α , weight of heuristic information β and iteration times were set as 1, 7 and 1000.

Table 2

ACA parameter adjustment.

Parameters Adjustment	Quantity of ants M	volatile coefficient ρ	convergence
No.1	50	0.3	170
No.2	50	0.7	155
No.3	100	0.7	133
No.4	100	0.3	158
No.5	150	0.7	147

The results shown in Table 2 imply that when the quantity of ants and the volatile pheromone coefficient were set as 100 and 0.7, respectively, the model experienced better convergence compared with other combinations. The reason for this situation may be that the navigation environment model of

simulation contains a sufficient quantity of grids leading to the decrease of route search accuracy thus increasing amount of ants may improve it, and that an increase in the volatile coefficient may decrease the occurrence of the local convergence problem (Wang et al., 2018).

4. The energy efficiency prediction model architecture

This section describes the development of the energy efficiency prediction model, based on the BP Neural Network, representing the first step in the optimization model as a whole. Also, the prediction model is data-driven, while the data used is from Yong Sheng which was selected as a case study due to the typical type and size of this ship.

4.1 Analysis of factors influencing Arctic ship energy efficiency

The initial work (factors analysis) has been conducted prior to constructing the architecture of the model, since navigation in the Arctic is typically affected by various characteristics. After collecting data from the Yong Sheng and experts' knowledge (Fu et al., 2016), we conducted a Pearson correlation analysis based on several environmental parameters (including wind speed, air temperature, water temperature, wave height and ice concentration), as well as on speed and energy efficiency. The Pearson correlation analysis is a widely used approach that aims to find the linear relationship between variables. We thus chose this method in order to identify the factors that are strongly correlated with energy efficiency.

Table 3

Correlation coefficients between variables and ship energy efficiency for Yong Sheng, while each number corresponds to one factor, such as No.1 represents ship energy efficiency and No.2 represents ship speed.

Factor	No.	1	2	3	4	5	6	7
Ship energy efficiency	1	1.000						
Ship speed	2	0.835	1.000					
Wind speed	3	0.391	0.389	1.000				
Air temperature	4	0.163	0.381	0.033	1.000			
Water temperature	5	0.254	0.595	0.331	0.591	1.000		
Ice concentration	6	0.680	0.689	0.522	0.141	0.585	1.000	
Wave height	7	0.308	0.408	0.937	0.060	0.359	0.550	1.000

From the results in Table 3, it can be seen that ship speed is ranked first, making this the most important factor in ship performance. Ship speed is followed by ice concentration, which may be the major environmental factor. Simultaneously, other environmental factors such as wind speed and wave height can be seen to have a weak correlation with energy efficiency compared with ice conditions, similar to results found in other literature (Qian et al., 2016).

4.2 Energy efficiency prediction model for ships in Arctic waters

In line with the results of the correlation analysis, the parameters of ice concentration and ship speed were set as the inputs in the prediction model, which characterizes the strong correlation with EEOI. We thus constructed a BP neural network (a black box model) to demonstrate their relationship.

The database collected from Yong Sheng, containing 179 rows of data, was divided into two sets – 149 rows for the training set and 30 for the test set. The data were then input into the neural network for the model training.

Fig. 7. Neural network fitting condition.

The default training data set was randomly divided into three mutually exclusive sets in the network: training set, validation set and test set. The scatter graph (Fig. 7) shows the comparison between the prediction output data and the actual data at the three databases of training, verification and testing. The model was seen to have a good performance during the training process, whose fitting rate achieved nearly 0.97. The fitting rate of validation was set near 0.96, which is evidence of appropriate parameters having been set up in the neural network. The reason why the fitting rate of the training set is higher than other two sets is that the training set is utilized to update the parameters, while the other two are used to estimate the network's prediction capability (Vasiliki et al., 2018).

We input the test data into the trained neural network model to measure its generalization. The result is shown in Fig. 8.

Fig. 8. Accuracy test of model's prediction capability.

As illustrated in Fig. 8, the model was able to predict EEOI with high accuracy, within an acceptable error of 5%. This, in turn, also proves that those two parameters (speed and ice concentration) were strongly

correlated with EEOI. This data-driven model can, therefore, help us to understand how EEOI reacts with the environment.

The prediction model, based on our results so far, was thus found able to assist in adjusting ship speed to optimize energy efficiency for ships in the Arctic. A simple simulation was then conducted to find the ship speed for optimum energy efficiency under various ice conditions.

Before the navigation of Yong Sheng, the navigation strategies including the speed range in deferent ice conditions was discussed by managers and captains (Cai and Lin, 2016). After consulting the captain of Yong Sheng who had 15 years longer navigation experience, we combined the information from experts' consultation and actual navigation data presented in section 2 to set the speed limits in various ice conditions. The details are shown in Table 4.

Table 4
Speed limitations in deferent ice conditions.

Ice concentration	Speed variation (kn)
1/10	8-14
3/10	6-12
5/10	5-10
7/10	4-8

In line with the prediction model and the speed limitation in ice waters, we were able to develop the simulation to find the speed for the corresponding optimum energy efficiency in various degrees of ice concentration. Taking into account the actual operation of the ship, the speed was set to increase by 0.5 kn, which may be more acceptable for the operators to maneuver ships.

Fig. 9. Simulation results of ship speed for optimum energy efficiency.

Table 5
The ship speed for optimum energy efficiency in different ice concentration.

Ice concentration	Optimal speed (kn)	EEOI (t/(t nm))
1/10	9.5	1.23×10^{-5}
3/10	9.0	1.52×10^{-5}
5/10	5.5	1.83×10^{-5}
7/10	5.0	2.44×10^{-5}

Fig. 9 and Table. 5 demonstrate the consequence of the simulation. For example, at an ice concentration of 7/10, the EEOI varies with the speed, reaching a minimum at 2.44×10^{-5} t/(t nm) with the speed of 5.0 kn which would be the most appropriate speed in that ice condition.

In real-life Arctic navigation, when the ice becomes denser ship resistance will increase, which in turn decreases ship speed and leads to higher power required, as well as more fuel. Eventually, the EEOI would grow greater and ships manifest poor energy efficiency, indicating that our simulation conforms to the actual situation.

5. Route planning method for energy efficiency optimization of ice-going ships

Generally, a ship's route selection is made by navigators according to their experience accumulated in previous voyages. While this strategy sometimes functions well, but human decision making can be affected by certain unfavorable factors, especially in the Arctic area, such as extreme cold, light nights in the summertime and dark days in the winter (V. Lehtola et al., 2018). Those factors may cause inefficiency of navigation. Therefore, having a routing model could be of great assistance for operators in the Arctic area.

In the previous section, the prediction model developed was applied to find the most suitable speed for optimum energy efficiency in diverse areas. Following this step, and to optimize Arctic navigation, the ice routing model was developed to improve ship energy efficiency in the context of the shipping lane.

For real-life navigation in ice-covered waters, the ice condition is the most significant environmental factor. It is, therefore, important to confirm that the navigation environment model developed can reflect actual ice conditions. This aspect of our work was undertaken using Matlab.

5.1 Navigation environment modeling

In general, ship routing model consists of several aspects, including modelling the environment under navigation, a route search using the appropriate algorithm. Developing a navigation environment model is fundamental to the study. To achieve this, image processing approaches were utilized to build the navigation environment model.

To describe this process, an example is depicted. Fig. 10 is the ice concentration prediction image provided by NMEFC for support Yong Sheng's navigation in 2013, which is conducted by analyzing original data from the database of University of Bremen (Spreen et al., 2008). The section of the chosen simulation area shown in Fig. 10 is located in the Laptev Sea. The black marked square denotes the area we chose for the environmental simulation from longitude 99.5° E and latitude 80.5° N to longitude 101.1° E and latitude 80.1° N. However, such a figure (Fig. 10) is not appropriate for the direct application to the routing model as the figure contains too many details which may raise the complexity of the routing model and depress the efficiency of the computer's processing progress (Reimer, 2015). Considering these constraints, we simplified figures like Fig. 10 to make them the apt navigation environment models for the ice routing.

Fig. 10. Ice concentration prediction image (black marked rectangle area is taken as an example).

In order to process the chosen area in Fig. 10, approaches such as gray processing were utilized, enabling the chart to be discretized to a matrix sized 50×50 according to the scale of the figure. The entire process of image translation is shown in Fig. 11. Firstly, converting RGB image (Fig. 11(a)) to grayscale image (Fig. 11(b)), that was, the first step to simplify the image. Then, resizing the grayscale image and discretizing to a matrix sized 50×50 in which the image was further gridded according to the complexity (Einhäuser et al., 2007) and the side length of every grid is about 0.4 nautical miles according to the scale. Following this, the grids of the figure were filled with colors according to the original figure (Fig. 11(a)), which was finally converted to Fig. 11(c)). This step served to simplify the figure as far as possible, which was key to lowering the load of computerized programming. The entire process was conducted using Matlab. The gridded figure was thus able to reveal the distribution of various degrees of ice concentration using different colors. Namely, in the processed figure, the blue grids represented the open sea, while the red grids represented intensive ice area which need be avoided. The grids with different rest colors represented different ice concentrations, which was detailed in Table 6. Therefore, the figure processed was able clearly to reflect the key ice information while not being too complicated for a computer to work on.

Fig. 11. Image processing procedure.

Table 6

Explanation of the grids in the navigation environment model

Ice concentration	Color	Speed (kn)
0	blue	13.0
3/10	light green	9.0
5/10	green	5.5
7/10	yellow	5.0

5.2 Mathematical ACA modeling

While, as mentioned before, the core routing algorithm employed was the ACA. In this subsection, we described the assumptions and objective function of the algorithm we made to the ACA, which aimed to make it a better fit for the routing model discussed in this paper.

5.2.1 Assumptions

In the current simulation, the ship speed at each degree of ice concentration was assumed to keep constant, as well as the ship's fuel consumption per nautical mile. We also assumed that the speed in diverse areas was set by the prediction model developed in section 4, that is, referring to the optimum speed for optimum energy efficiency. Other assumptions made about the routing model were as follows:

(1) The influence of wind and waves was neglected. The most important environmental factor in Arctic navigation – ice – was set as the only environmental factor in the model.

(2) The case study ship used for the simulation was considered to be a mass point, meaning that the size of the ship was neglected.

5.2.2 Objective function of the routing model

With this model, we attempted to find the route enabling optimum energy efficiency. As the environmental information was known, the ice concentration in the study area and distribution of obstacles could be derived from the navigation environment model. Simultaneously, as far as safety was concerned, the planned route needed effectively to not only avoid obstacles but keep a distance with them, such as severe ice condition (the red part in the navigation environment model). Hence, the objective function was set as:

$$C = \text{Min} \frac{\sum d_n \cdot c_n \cdot C_{Fj}}{m_{\text{cargo}} \times D} \quad (13)$$

Where d_n is the distance of segment n and c_n is fuel consumption per nautical mile.

5.3 Ice routing simulation

According to ice forecast report from NMEFC, the NSR can be divided into several areas shown in Fig. 12 for a ship's navigation. The area E located in the Laptev Sea was the the most significant area due to its the relatively high ice conditions that brought Yong Sheng troubles to navigate (NMEFC, 2013). While, for the areas A, B, C and D, the Yong Sheng ship could navigate in weather conditions similar as those sailing in the open sea as the less ice in those areas during summertime. Many methods are available to plan a ship's routing with respect to less fuel consumption. Since the present study aims at proposing a routing model to save fuel for ice navigations, the proposed ice routing model for optimum energy efficiency has been conducted only in the area E.

Fig. 12. Areas divided in the NSR. The information is provided by the NMEFC.

Using the navigation environment modeling method in section 5.1, the area E is discretized to a 165×120 grid matrix with an aspect ratio 11:8, as shown in Fig. 13. The side length of every grid is about 1.65 nautical miles. The departure and destination are shown as black grids in the Fig. 13. The white grids in the navigation environment model represent land areas which also need to be avoided during the voyage.

Fig. 13. Area E navigation environment modeling (white grids refer to land area).

Then the development of the ice routing simulation using ACA in this area was presented. Firstly, the conventional ACA was employed to search for the shortest path from departure to arrival.

Fig. 14. The shortest route for the area E.

The iteration process was shown as Fig. 15:

Fig. 15. Process of iteration for the shortest route

From Fig. 15, it can be seen that the value of path length converged at around the 850th iteration, which represents the shortest path in the simulation. And, the path length was 267.81 nautical miles. The EEOI for the route was $1.40 \times 10^{-5} \text{ t/(t nm)}$ and the voyage took 25.76 hours.

Following this, in order to find the optimum energy efficiency route, the improved ACA was

478 employed. The result is shown in Fig. 16.

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Fig. 16. Route for optimum energy efficiency for the area E.

Fig. 17. Process of iteration for optimum energy efficiency route.

According to Fig. 16 and Fig. 17, the value of the EEOI converged after about 940 generations and the smallest EEOI was 1.21×10^{-5} t/(t nm). The path length was 275.94 nautical miles and took 25.62 hours to navigate. A comparison of the performance parameters between the two paths is shown in Table 7.

Table 7

Parameters of two routes' comparison for area E.

Path	Distance (n mile)	Fuel consumption (t)	Time (hour)	EEOI (t/(t nm))
Shortest	267.81	16.86	25.76	1.40×10^{-5}
Best energy efficiency	275.94	14.92	25.82	1.21×10^{-5}

Table 7 demonstrates that the voyage time of two simulated routes is close. However, the distance for the optimum energy efficiency route is longer than the shortest route by a few nautical miles, but enable better energy efficiency as well as saving nearly two tons of fuel which is mostly on account of the avoidance of heavy ice conditions. The proposed routing model can thus be seen to have the capability to plan the more efficient routes for ships passing through ice-covered waters. Moreover, the results of the comparative simulation indicate that when operators select their navigation route in a particular ice region, it is worth selecting one enabling the best energy efficiency that considers the specific ice condition.

6. Conclusion and future work

The paper introduces an optimization model for ice-going ships' energy efficiency. The initial work of correlation analysis has been developed first since the complexity of the Arctic navigation may make it difficult to discern the relationship between all of the factors influencing energy efficiency in this area. The whole optimization model comprises two sub-models, one of which is the ship speed optimization model based on a data-driven, energy efficiency prediction model, the other is the ice routing model. With regard to the former, the index EEOI has been chosen as the tool with which to estimate ship energy efficiency, since it shows advantages compared with other indexes. According to the accuracy test, the model deviation was within 5%, implying that the prediction model performed well and could, in principle, be used for the purpose of predicting Arctic ships' energy efficiency. Based on this model, the speed corresponding to the best energy efficiency in various ice conditions could then be provided to operators.

To achieve further optimization, we constructed an ice routing model based on image processing methods and improved ACA. We chose the key area to develop the navigation environment model for routing simulation. The comparative simulation within deferent paths was also conducted; the results indicate that when planning the ship's route, it would be shortsighted only to focus on distance rather than energy efficiency.

The optimization model developed here could arguably solve energy efficiency improvement problems in terms of both ship speed and route. Notwithstanding this, there exist certain limitations that require further effort in future research. First of all, the input parameters of the current energy efficiency model would benefit from including a greater number of related components, such as displacement, trim, ice thickness; this would help to improve the applicability of the prediction model. Secondly, since the current study is ship specific (i.e. pertaining to the Yong Sheng), the applicability of the proposed model to other categories of ship would need to be validated. Such work would extend the usage scope of the current model. Thirdly, real-life navigation in Arctic ice-covered waters is not merely a cost-benefit issue but also includes risk analysis, which means that the value of risk would need to be added into the waypoint of the routing model, since it would be more meaningful to optimize energy efficiency under an acceptable level of risk. Finally, the proposed ice routing tool does not take users sufficiently into account. To improve the user's experience, certain measures can be taken, such as appropriately reducing the resolution of the navigation environment model so as to decrease computing time, or producing a graphical user interface (GUI) to satisfy users' various demands.

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