

# A two-criteria weather routing method based on neural network and A-star algorithm

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## Original Research

## Abstract:

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This paper presents the construction of a method to find the optimal route for ships with two criteria: fuel consumption and sailing time. Unlike most previous studies, the data used in this research was generated from a simulation model using the HIL (Hardward-In-The-Loop) technology instead of real operational data. The HIL simulator is built from equations of the ship's 6 degrees of freedom (6-DOF), models of environmental disturbances, propulsion systems, and technical records of the real ship. In fact, operating data of the real ship is collected from noon reports, which are often incomplete in terms of environmental disturbances acting on the ship, not to mention the large sampling time (usually updated once a day). Meanwhile, the dataset generated from the HIL simulator will fully include the three main environmental components acting on ships, including waves, wind, and currents, with various scenarios. Based on that dataset, an algorithm to find optimal routes with two criteria is proposed using neural networks and the A-star algorithm. Test results show that the proposed algorithm operates reliably and has low errors. This research can be applied to find the optimal routes for small and medium-sized ships in Vietnam before each voyage at a low cost instead of using high-cost weather routing services.

**Keywords:** Weather routing; Neural network; A-star; HIL; Weather routing services

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## 1. Introduction

Vietnam is a country that aims to develop its marine economy strongly in the future. In recent years, the number of fleets has continuously increased. When operating a ship, fuel costs can be up to 70% of the total operating cost, depending on the type of ship and its parameters [1]. Furthermore, to comply with Appendix VI/resolution MEPC.328(76) of 2021 on “Regulations on preventing air pollution from ships,” current shipping companies in Vietnam have been looking for methods to minimize fuel consumption when operating ships. To save fuel when operating ships, it is often divided into two main groups of solutions. Firstly, the solution group helps improve fuel efficiency from the ship design process. Secondly, a group of solutions to improve fuel efficiency during the operation of the ship [2, 3].

Solutions to help improve the ship's fuel efficiency from the design process include: Optimizing the ship's hull shape [4–7], optimizing main machine operation [8, 9], using a

hybrid propulsion system [10], and using alternative energy sources [11]. The most significant advantage of ship design modifications is that once implemented, they do not require constant monitoring and adjustment for optimal performance, requiring only regular ship maintenance. This gives the ship optimal efficiency from design through to later use.

Methods to improve energy efficiency during ship operation often include the following main solutions: operating the ship at low operating speeds [12], choosing the optimal trim value for the ship depending on each specific load case [13, 14], controlling the ship to follow a predetermined trajectory [15, 16], building models to calculate fuel consumption to support voyage planning [17–19], developing decision-making support software for ship officers [20–22], and methods to find the optimal route before each voyage for the ship based on the weather forecast systems [23–27]. Among these methods, the method of finding the optimal route based on weather forecast information is the method that is being widely used due to the great efficiency it brings

by not only helping ships save fuel but also helping make ship operations safer. There have been many different algorithms proposed in these methods, such as the ant colony optimization algorithm [26], genetic algorithms and swarm optimization algorithms [23], Dijkstra algorithm [24], A-star algorithm [25], etc. However, most of the above studies use data sets of past ship operations, which often have large sampling times and do not have enough major disturbance components affecting the ship.

Many shipping companies in Vietnam now hire weather routing services to help operate ships more efficiently. However, medium-sized and small domestic ships do not use this service due to its high cost. Therefore, this study proposes to develop a method to find the optimal route with two criteria, fuel consumption and sailing time, that can be applied to small and medium-sized ships at low cost.

The rest of the article is organized as follows: section 2 presents research methods, results and discussion will be presented in section 3, and section 4 draws some conclusions and future works.

## 2. Methods

### 2.1 Research framework

Fig. 1 shows the research framework of this study. Firstly, a HIL simulator is built based on the technical profile of the real ship, 6-DOF equations of motion, mathematical models of the propulsion system, and environmental disturbances. Secondly, based on the built HIL simulator, a dataset with 3456 data samples is generated with various scenarios, like when ships operate at sea.

Finally, an algorithm to find the optimal route with two criteria is proposed based on the neural network, the A-star

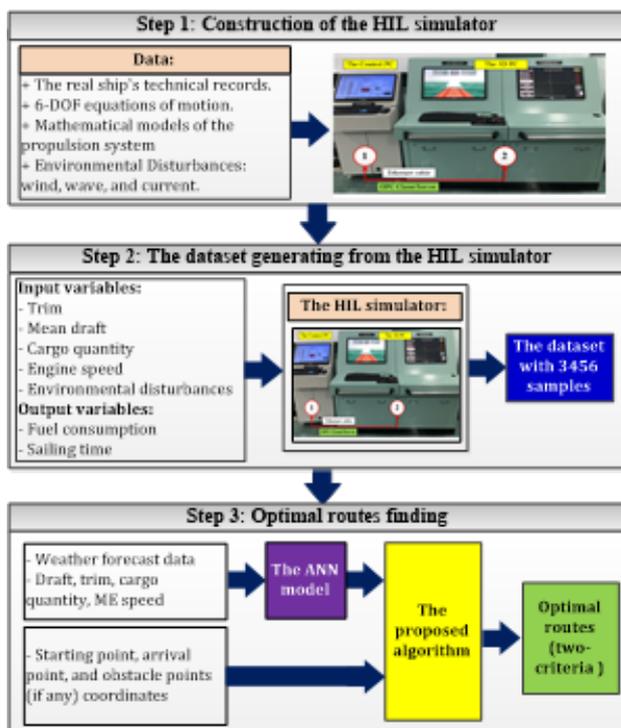


Figure 1. Research framework

algorithm, and the built dataset.

The inputs to the algorithm are the coordinates of the starting waypoint, arrival waypoint, obstacles (if any), weather forecast data, and ship parameters (draft, trim, cargo quantity, main engine (ME) speed).

### 2.2 The developed HIL simulator

#### 2.2.1 The 3D dynamic model

The 3D dynamic model simulating a real ship is built based on the 6-DOF equations as below [28]:

$$\begin{aligned} \dot{\eta} &= J(\eta)v \\ M\dot{v} + C(v)v + D(v) + G\eta &= \tau_E + \tau \end{aligned} \quad (1)$$

where  $\eta$  denotes the position and orientation vector;  $J(\eta)$  is a transformation matrix;  $v$  is the body-fixed linear and angular velocity vector;  $M$  is the inertia matrix,  $C$  is Coriolis and Centripetal matrix,  $G$  is a constant matrix,  $D(v)$  is the damping matrix,  $\tau_E$  is the environmental forces and moments; and  $\tau$  is the propulsion forces and moments.

When a ship operates at sea, environmental disturbances acting on it consist largely of three main components: waves, wind, and currents. Therefore, the forces and moments of the environmental disturbances in Equation (1) can be written as follows:

$$\tau_E = \tau_{\text{currents}} + \tau_{\text{waves}} + \tau_{\text{wind}} \quad (2)$$

where  $\tau_{\text{currents}}$ ,  $\tau_{\text{waves}}$ ,  $\tau_{\text{wind}}$  are the forces and moments of currents, waves, and wind acting on the ship, respectively. These components can be found in detail in the documents [28, 29].

In addition, because the research scope is cargo ships with one main propeller and one rudder while ignoring the forces and moments of the bow thruster (the bow thruster is only used in ship maneuvering mode), the force and moment components of the propulsion system in Equation (1) are synthesized from the literature [30–32] into a vector like the equation below:

$$\tau = [\tau_U, \tau_V, 0, 0, 0, \tau_R]^T \quad (3)$$

where  $\tau_U$  is the force acting on the ship along the longitudinal axis. This force will include the force from the main propeller and the force when turning the rudder;  $\tau_V$  is the rudder force acting on the ship along the horizontal axis and  $\tau_R$  is the rudder moment.

From 6-DOF equations of the ship, models of environmental disturbances, and propulsion systems according to Equations 1 ÷ 3 combined with the real ship's technical records, the 3D dynamic model was built by Unity software to replace the real ship.

Details on building this 3D dynamic model have been presented in the document [33].

#### 2.2.2 The fuel consumption calculation model

To build a dataset with fuel consumption as the output, a fuel consumption calculation model for 3D virtual ships will need to be built.

When the ship is traveling at sea, most of the energy is consumed by the main engine in addition to the generator.

While the generator’s consumption usually does not change much when the ship is at sea, the main engine’s fuel consumption depends greatly on weather factors such as waves, wind, and current. Therefore, in the proposed fuel calculation model, only the fuel consumed by the main engine is considered, and the fuel consumed by the generators is ignored (considering the fuel consumed by the generators is a constant when ocean-going ships).

The fuel consumed by the main engine in one day can be calculated as the equation below:

$$TFC = \int_{i=0}^{24h} P_i \cdot SFOC_i \cdot dt \quad (4)$$

where  $TFC$  is the total fuel consumed in a day (tons),  $P_i$  is the instantaneous power of the main engine (kW), and  $SFOC_i$  is the fuel consumption rate (g/kWh).

Thus, to calculate real-time fuel consumption, the instantaneous power values  $P_i$  and fuel consumption rate  $SFOC_i$  need to be calculated at each sampling time  $i$ .

The fuel calculation model based on that basis has been presented in the document [34]. In that model, the instantaneous power of the main engine is calculated based on calculating the added resistance acting on the ship (due to waves and wind) using semi-empirical formulas. Meanwhile, the fuel consumption rate is calculated by interpolation from the  $SFOC$  curve in the sea trial data of the real ship.

### 2.2.3 The proposed trajectory controller

In this research, a trajectory controller, designed based on the fuzzy logic algorithm and the PID controller, will provide an appropriate course sent to the steering system as in Equation (5) [16].

$$\psi_0 = \psi_1 + (\psi_2 - \psi_1) \times FZ \quad (5)$$

where  $\psi_1$  is the course of the shortest path to the next waypoint and the north direction,  $\psi_2$  is the course of the shortest path to the second next waypoint and the north direction,  $\psi_0$  is the order of course change sent to the controller. Meanwhile,  $FZ$  is a fuzzy coefficient  $\in [0 \ 1]$ . This coefficient was calculated using fuzzy logic.

Fig. 2 is the control structure. The trajectory controller in this structure will be used to control the ship when creating

the dataset in Section 2.3. Moreover, it is also used to verify the proposed algorithm in section 3.2.

The proposed algorithm in this structure diagram will find the optimal route according to two criteria. Meanwhile, the set speed value for the main engine will be assumed to be constant at 70 rpm. This speed is commonly used in the eco mode of the real ship.

### 2.2.4 The built HIL simulator

The HIL simulator is built as shown in Fig. 3, with specific blocks as follows:

- Block 1 (on the left): this block includes a computer acting as a trajectory controller. This controller is built on Matlab/Simulink software;
- Block 2 (on the right): this block includes a computer running the 3D dynamic model. This computer is connected to two screens. The left screen is designed to show the forward view of the ship using a camera located in the virtual ship’s bridge. Meanwhile, the screen on the right is the screen to set up simulation situations such as ship coordinates, weather conditions, etc.

Block 1 and Block 2 are connected by an ethernet cable with OPC Client/Server communication protocol.

This simulator will be used to generate the dataset and test the proposed algorithm, which will be presented in the following sections.

### 2.3 Creating the dataset from the HIL simulator

In this section, a dataset will be generated to replace the real operational data as in most previous works. With the purpose of limiting the research scope, some assumptions are made as follows:

- The cargo on the 3D virtual ship is arranged so that the ship’s draft is 14.429 m, corresponding to the summer draft of the real ship;
- The ship is on an even keel;
- Waves are created entirely by wind, ignoring the rogue wave component;
- Wind speed and wave height are programmed according to the Beaufort scale of the International Meteorological Organization (WMO).

With the above assumptions, the dataset is created by changing the specific input variables as follows:

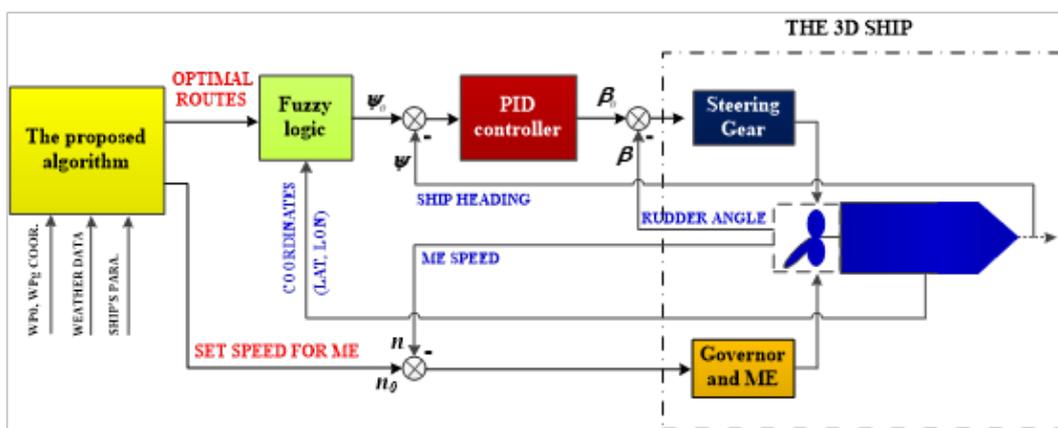


Figure 2. The control structure

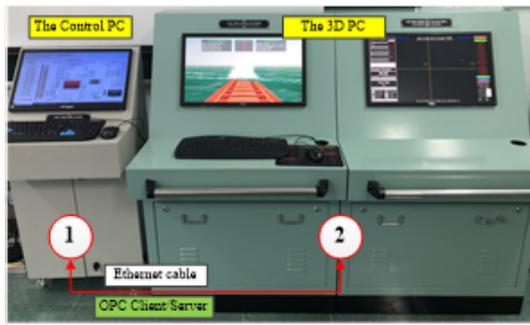


Figure 3. The built HIL simulator

- Main engine speed: since the most common operating speed of the real ship named The Prosperity (a bulk carrier) is 70 rpm (eco mode), 03 main engine speed values are selected, including 65 rpm, 70 rpm, and 75 rpm.
- Wind speed: there are 04 wind levels used: levels 0, 3, 5, and 7 (Beaufort scale);
- Wind direction: 12 directions (0°:30°:360°);
- Current speed: 03 speeds: 0, 1.5, 3 knots;
- Current direction: 08 directions (0°:45°:360°). Thus, after running the HIL simulator by changing input variables, as illustrated in Fig. 4, a dataset with 3456 cases will be collected. Meanwhile, the output signals in each case will include fuel consumption, sailing time, and the ship's X coordinates and Y coordinates. In all cases, the ship is controlled by a controller that uses fuzzy logic combined with a PID controller mentioned in section 2.2.3 to keep the ship heading along the same sample route of 2241 m between two waypoints: A and B.

2.4 The proposed algorithm

2.4.1 The predictive ANN model

With the built dataset, a prediction model using an MLP feedforward neural network is built for use in the proposed algorithm. The network structure is shown in Fig. 5. The prediction model is built with five input signals and two output signals corresponding to the number of inputs and outputs of the dataset.

The selected prediction model is an MLP network model with three layers, including one input layer (5 neurons), one hidden layer (30 neurons), and one output layer (2 neurons). This model was chosen among 30 different models with

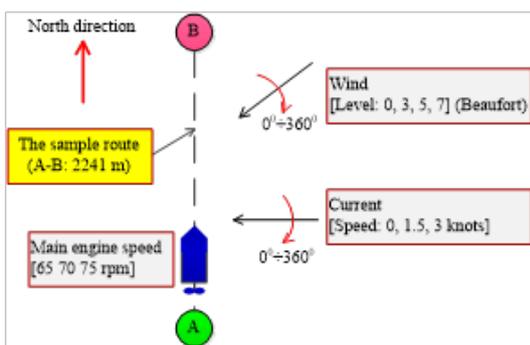


Figure 4. The dataset is created by changing variables.

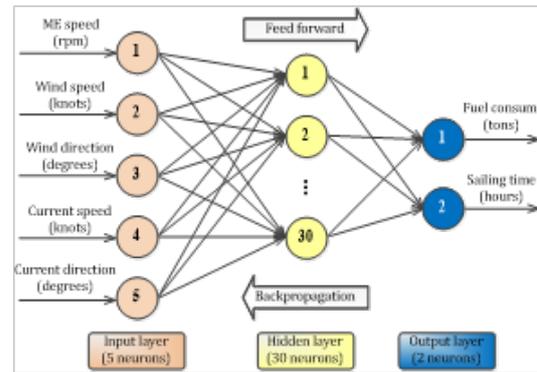


Figure 5. Structure of the proposed ANN model.

the smallest MAPE error (Mean Absolute Percentage Error) when testing with a testing dataset (the 30 models with different numbers of hidden layers and the number of neurons in each hidden layer). Details on the construction and testing of this model are presented in the study [35]. This ANN model is trained with the dataset built in section 2.3 and will be used to calculate the actual cost matrix *G* used in the proposed algorithm mentioned in section 2.4.3.

2.4.2 Introduction of A-star algorithm [36, 37]

In fact, some search algorithms, such as the Bellman-Ford, Dijkstra, Floyd-Warshall, and A-star algorithms, can be applied to find the optimal paths in a graph according to different criteria. Among these algorithms, Dijkstra and A-star are the two most popular graph search algorithms often applied in optimal route search problems, such as the research studies cited in section 1. A-star is an improved algorithm from Dijkstra's Algorithm with higher search speed and performance.

Invented in 1964 by Nils Nilsson to increase the search speed of Dijkstra's Algorithm. A-star algorithm uses a heuristic evaluation to rank each node according to its estimate of the shortest path through that node. The A-star algorithm will browse the nodes in priority order based on heuristic values. The basic principle of this algorithm is based on minimizing the following cost function:

$$\text{Minimum} : f(N_n) = h(N_n) + g(N_n) \tag{6}$$

where  $f(N_n)$  is the smallest possible cost to go from starting node to arrival node via node  $N_n$ ,  $g(N_n)$  is the actual cost to go to node  $N_n$  from starting node,  $h(N_n)$  is the estimated cost from node  $N_n$  to arrival node. minimum cost when the estimated values are acceptable, always satisfying the equation below:

$$h(N_n) \leq h^*(N_n) \forall n \tag{7}$$

where  $h^*(N_n)$  is the actual cost from node  $N_n$  to arrival node.

2.4.3 Build moving graph and cost matrices

When the ship travels through short routes, these routes can be considered straight lines. Therefore, when building movement graphs for ships, some studies use Euclidean distance to calculate the distance between waypoints in the

graph [38–40]. However, the method will reduce its accuracy if the distance between the waypoints is large because, in reality, the shortest route between any two points on the earth is curved.

Therefore, to build a moving graph as a basis for the proposed algorithm, a curved grid will be constructed between starting waypoint  $WP_0$  and arrival waypoint  $WP_g$ , as shown in Fig. 6. Depending on each specific case and the level of detail of the weather forecast data available, the resolution of the grid will be selected accordingly. The shortest arc length  $D_{WP_n-WP_p}$  between any two points,  $WP_n$  and  $WP_p$ , will be calculated based on the Haversine formula according to Equation (8).

$$D_{WP_n-WP_p} = R \cdot c \tag{8}$$

where  $R$  is earth’s radius (mean radius = 6371 km),  $c$  is a coefficient calculated as the following equations:

$$c = 2 \cdot a \cdot \tan(\sqrt{a} \sqrt{1-a})$$

$$a = \sin^2(\Delta\phi/2) + \cos\phi_1 \cdot \cos\phi_2 \cdot \sin^2(\Delta\lambda/2) \tag{9}$$

where  $\Delta\phi = \phi_{WP_n} - \phi_{WP_p}$ ;  $\Delta\lambda = \lambda_{WP_n} - \lambda_{WP_p}$ ;  $(\phi_{WP_n}, \lambda_{WP_n})$  is coordinates of  $WP_n$  (longitude and latitude); and  $(\phi_{WP_p}, \lambda_{WP_p})$  is coordinates of  $WP_p$ .

Besides, to help the algorithm operate accurately and reliably according to Equation (7), the estimated fuel consumption and estimated sailing time between any two waypoints,  $WP_n$  and  $WP_g$ , are calculated as the equations below:

$$h(WP_n)_{FC} = D_{(WP_n-WP_g)} \cdot FC_{unit} \tag{10}$$

$$h(WP_n)_{ST} = D_{(WP_n-WP_g)} \cdot ST_{unit} \tag{11}$$

where  $h(WP_n)_{FC}$  and  $h(WP_n)_{ST}$  are the estimated fuel consumption and the estimated sailing time from  $WP_n$  to  $WP_g$ ;  $D_{WP_n-WP_g}$  is the shortest arc between  $WP_n$  and  $WP_g$ ;  $FC_{unit}$  is the fuel consumption per unit length corresponding to the assumption that the ship operates in the calm sea (no wind, no waves, and no current); and  $ST_{unit}$  is the sailing time per unit length of the ship assuming the ship operates with heavy seas.

If we know the coordinates of  $WP_0$  and  $WP_g$ , a curved grid will be constructed between  $WP_0$  and  $WP_g$ , as shown in Fig. 6. The red arc is the shortest route between  $WP_0$  and  $WP_g$ . From any waypoint  $WP_n$ , the ship can be moved in three directions:  $WP_p$ ,  $WP_q$ , and  $WP_r$ . Meanwhile, waypoints located on Edge 1 and Edge 4, such as  $WP_u$ , have only one direction of travel, from  $WP_u$  to  $WP_v$ .

The algorithm will start from waypoints that are neighbors of  $WP_0$  until it reaches  $WP_g$ .

Besides, two following cost matrices will be created first before implementing the proposed algorithm:

- Actual cost matrix  $G$ : This matrix will be calculated based on the length of the shortest arcs between adjacent waypoints in the grid and weather data. The values in this matrix are predicted from the ANN model built in section 2.4.1.
- Heuristic cost matrix  $H$ : estimated fuel consumption and sailing time from any  $WP_n$  to  $WP_g$  are calculated according to Equations (10) and (11).

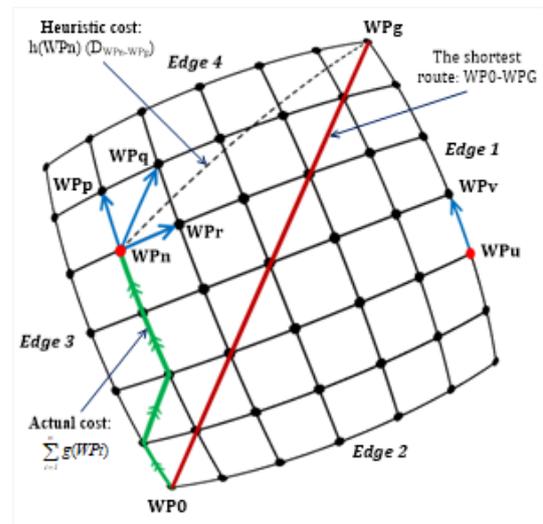


Figure 6. The proposed moving graph for the ship

### 2.4.4 Build the objective function

The proposed algorithm will minimize the proposed objective function as follows:

$$f(WP_n) = \left[ \frac{h(WP_n)_{FC}}{FC_{average}} + \frac{\sum_{i=1}^n g(WP_i)_{FC}}{FC_{average}} \right] \alpha$$

$$+ \left[ \frac{h(WP_n)_{ST}}{ST_{average}} + \frac{\sum_{i=1}^n g(WP_i)_{ST}}{ST_{average}} \right] (1 - \alpha) \tag{12}$$

where  $h(WP_n)_{FC}$ ,  $h(WP_n)_{ST}$  are the estimated fuel consumption and sailing time to go from  $WP_n$  to  $WP_g$ , respectively;  $g(WP_i)_{FC}$ ,  $g(WP_i)_{ST}$  are the actual fuel consumption and actual sailing time to reach waypoint ( $i$ ) from its parent waypoint ( $i-1$ ), respectively;  $FC_{average}$ ,  $ST_{average}$  are the average fuel consumption and sailing time, respectively; and  $\alpha$  is the optimal coefficient.

between two optimal criteria. If  $\alpha = 1$  then only find the fuel-optimal route. On the contrary, if  $\alpha = 0$ , then only find the route that optimizes the sailing time. Meanwhile, if  $0 < \alpha < 1$ , then the suggested route will be optimal according to both criteria depending on the value of  $\alpha$ .

### 2.4.5 The proposed algorithm

The proposed algorithm to find the optimal route with two criteria, fuel consumption and sailing time, is presented in Table 1. When executed, the algorithm will create two lists: open-list and closed-list. Open-list is used to record all waypoints that we need to consider to find the optimal route. Meanwhile, closed-list is a list that stores waypoints that we no longer need to review. Initially, the starting waypoint  $WP_0$  will be added to open-list, and closed-list will initially be empty. The algorithm will start searching from neighboring waypoints of  $WP_0$  so that the ship can move to the arrival waypoint  $WP_g$  to satisfy the objective function according to Equation (12).

## 3. Results and discussion

### 3.1 Testing scenarios

For the purpose of testing the proposed algorithm, the authors built a testing scenario to find the optimal routes for

**Table 1.** The proposed algorithm

Input: A graph with the starting waypoint (WP0) and the arrival waypoint (WPg)
Output: The route with the least cost from WP0 to WPg
<pre> Initial: open-list= WP0; closed-list= ∅; g(WP0)=0; h(WP0)= heuristic-cost(WP0,WPg); f(WP0)= h(WP0)+g(WP0); While open-list ≠∅ find the waypoint with the least f(WPn) in the open-list; if (WPn == WPg) return "Route is found"; else remove WPn from open-list; add WPn to closed-list; for Wpm ∈ neighbors(WPn) do %m=p, q, or r current-cost = g(WPn)+cost(WPn,Wpm); %based on matrix G; if (Wpm ∈ open-list &amp; g(Wpm) &gt; current-cost) remove Wpm from open-list; endif; if (Wpm ∈ closed-list &amp; g(Wpm) &gt; current-cost) remove Wpm from closed-list; endif; if (Wpm ∈ open-list &amp; g(Wpm) &gt; closed-list) remove Wpm from closed-list; endif; if (Wpm ∉ open-list &amp; Wpm ∉ closed-list) add Wpm to open-list; g(Wpm) = current-cost; h(Wpm) = heuristic-cost(Wpm,WPg); % based on matrix H. f(Wpm) = g(Wpm) + h(Wpm); endif; endfor endwhile; return "Route can not be found"; </pre>

ships between two points,  $WP0$  and  $WPg$ , which are two locations on the Vietnam East Sea with coordinates, as shown in Fig. 7. The shortest distance between them is a circular arc in the great circle of 20.953 km. A moving graph will be constructed between these two points with assumptions about the weather conditions for each area shown in Fig. 8.

In Fig. 8, waves and wind will appear in areas with different colors. With red arrows, dashed lines represent the direction of waves and wind. Wind speed and wave height will correspond to the Beaufort scale of the International Meteorological Organization (WMO). The wind level in this scale is represented by different colors placed on the right. For example, the pink area in the middle of the grid

will correspond to wind level 9/12. At this level, wind speed will be about  $41 \div 47$  knots, and wave height will be about  $7 \div 10$  m.

Meanwhile, the current area is represented by the blue dashed rectangle. The blue dashed arrows show the current direction. The current speed is assumed to be 2 knots throughout this rectangular area.

### 3.2 Results and discussion

To test the algorithm proposed in Table 1, the optimal coefficient  $\alpha$  in the objective function will be assumed with 03 different values, specifically:

- Case 1:  $\alpha = 0$ . This case corresponds to the goal of only



Figure 7. Coordinates of two waypoints: WP0 and WPg

optimizing the ship’s sailing time;

- Case 2:  $\alpha = 0.58$ . This case corresponds to the optimal purpose of both fuel consumption and sailing time;
- Case 3:  $\alpha = 1$ . This last case fits the goal of only optimizing fuel consumption.

When running the algorithm with the above three cases. The algorithm proposes three routes shown in Fig. 9, specifically:

- For case 1, the algorithm proposes Route 1 through waypoints 1-11-21-31-41-51-61-71-81. This route is the short-

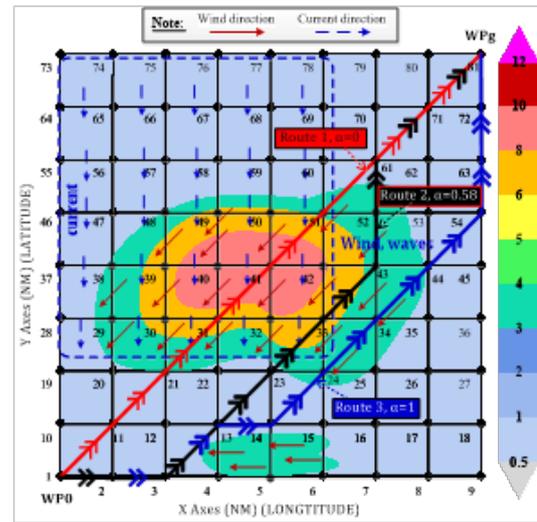


Figure 9. Three suggested routes

est distance on the great circle between 2 waypoints, WP0 and WPg;

- For case 2, the algorithm proposes Route 2 through waypoints 1-2-3-13-23-33-43-52-61-71-81;
- Meanwhile, in case 3, the algorithm proposes Route 3 through waypoints 1-2-3-13-14-24-34-44-54-63-72-81.

With three suggested routes, the HIL simulator will be used to control the ship through each route for each case to verify the results. Table 2 and Fig. 10 show the results of running the HIL simulator through the proposed routes. At the same time, these results are also compared with the predicted results by the ANN model proposed in section 2.4.1.

From Table 2, we see that when we only care about optimal time ( $\alpha = 0$ ) in case 1, the ship’s sailing time is the smallest at only 3623.5 s. However, the ship consumes the most fuel with 840.773 kg FO. Besides, we also see that Route 1 has the worst weather among all three routes. The average speed of the ship is also the smallest among all three routes when it only reaches 11.424 knots.

In case 3, when only optimal fuel consumption is con-

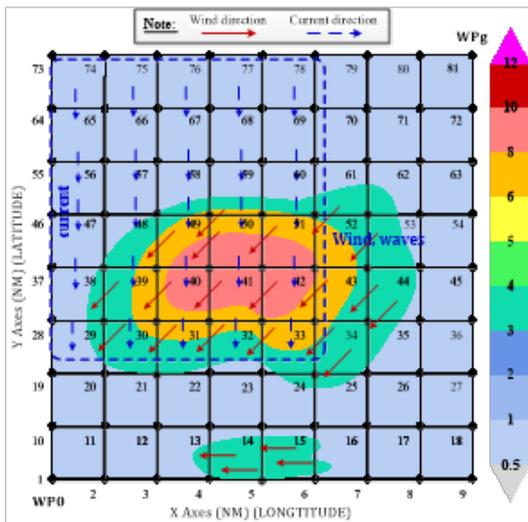


Figure 8. Weather conditions in the testing area

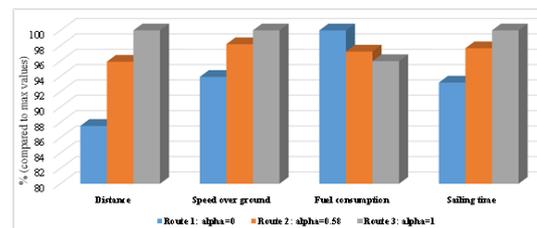
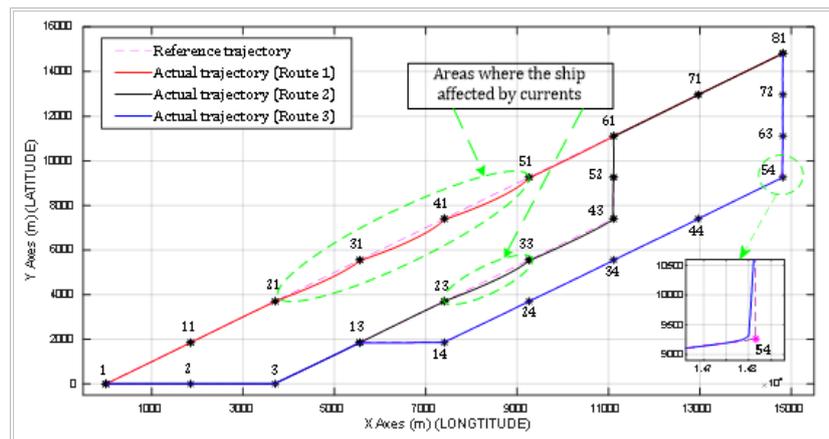


Figure 10. Distance, speed over ground, fuel consumption, and sailing time as a percentage of their max values.

Table 2. Compare results between the proposed ANN model and the data collected from running the HIL simulator

Routes	Optimal coefficient ( $\alpha$ )	Distance and average SOG		Fuel consumption(kg)			Sailing time(s)		
		Distance(nm)	SOG(knots)	Predict	The HIL simul.	Error(%)	Predict	The HIL simul.	Error (%)
Route 1	0	11.499	11.424	855.477	840.773	1.749	3664.793	3623.5	1.14
Route 2	0.58	12.599	11.943	828.249	817.513	1.313	3832.798	3797.75	0.923
Route 3	1	13.136	12.162	813.703	807.048	0.825	3913.682	3888.25	0.654



**Figure 11.** Actual moving trajectories of the 3D dynamic ship compared to set trajectories.

cerned ( $\alpha = 1$ ), fuel consumption in this case is the smallest when consuming 807.048 kg FO. However, in contrast to case 1, the ship's sailing time in this case is 3888.25 s, the largest of all three cases. Besides, because of favorable weather conditions, the average speed of the ship was the largest in the three cases when it reached 12.162 knots.

In case 2, when considering optimization according to both criteria, fuel and time with the optimization coefficient  $\alpha = 0.58$  (more inclined towards fuel optimization). Both the output fuel consumption and sailing time values are approximately average values, with the corresponding values for case 1 and case 3 being 817.513 kg FO and 3797.75 s, respectively.

From this table, we also see that the error between the proposed ANN model and the data collected from running the HIL simulator is quite small in all cases. The largest error is 1.749 % for fuel consumption with Route 1. This can also be explained because Route 1 is a route with areas with terrible weather, such as in areas of waypoints 31, 41, and 51. These areas all have large waves and currents acting on the ship.

Fig. 11 shows the actual moving trajectories of the 3D ship when running the HIL simulator through all three routes. In areas with bad weather, such as Route 1, the ship fluctuates quite largely around the set trajectory. Meanwhile, in areas with good weather, such as Route 3, because the ship is not much affected by environmental disturbances, the actual trajectory almost coincides with the set trajectory.

#### 4. Conclusion

In this article, the authors have presented a method to build optimal routes for ships according to two criteria: fuel consumption and sailing time. The proposed method is based on the application of neural networks and the A-star search algorithm. In addition, the dataset created from the HIL simulator is very useful as it can be applied to newly built ships that have not been in operation long enough and also to ships that have been in operation for a long time when most of the ship's past operational data was incompletely collected.

The next research direction of the article is to create a dataset with more diverse ship operating conditions,

especially ship parameters such as different draft values and more main engine speeds. Additionally, the recommendation algorithm will need to be compared with actual suggested routes by weather routing services to ensure objectivity in the future.

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#### Authors Contributions

All the authors have participated sufficiently in the intellectual content, conception and design of this work or the analysis and interpretation of the data (when applicable), as well as the writing of the manuscript.

#### Availability of data and materials

Data presented in the manuscript are available via request.

#### Conflict of Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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