Dynamic Optimization Method for Unmanned Ship Weather Route Based on Multi-stage Inverse Reasoning

Xiaoyuan Wang¹,² *, Xinyue Zhao², Gang Wang¹,², Quanzheng Wang¹,² and Guowen He¹,²

¹College of Electromechanical Engineering, Qingdao University of Science and Technology, Qingdao, China
²Intelligent Shipping Technology Innovation and Comprehensive Experimental Base, Qingdao, China

*Corresponding author e-mail: wangxiaoyuan@qust.edu.cn

Abstract. Route is an important factor for safe and efficient navigation of ships. In this paper, unmanned ship navigation environment under complex marine meteorological conditions was analyzed. Wind, wave conditions were integrated considered. Dynamic optimization model of unmanned ship weather route was established, in which meteorological and hydrological information was considered, unfavorable influences of which on ship navigation were reduced, energy and sailing time were saved, and route was found. Simulation results showed that initial fixed weather route could be optimized, and the model could be applied to dynamic optimization of weather routes of unmanned ships in large areas under complex meteorological conditions.

1. Introduction

With rapid development of global shipping industry, it has become increasingly crucial to ensure safe and efficient navigation of unmanned ships. As we know, safety and economy are two important indicators to evaluate route performance. In traditional route optimization methods, static weather information was widely adopted. The route couldn’t be ensured to be always optimal, which couldn’t automatically change according to real-time weather information. Dynamic optimization of weather route refers to dynamic adjustment of the route, based on real-time meteorological information, to reduce the impact of adverse meteorological factors and make the vessel always sail on optimal route. Energy consumption and sailing time were dynamically optimized, which reduced navigation cost and met practical needs of sailing. Therefore, to deeply study dynamic optimization methods of weather routes would be of great practical significance. And the method can be adopted to provide theoretical basis for autonomous decision-making process of unmanned ships.

On research of the shortest sailing time weather route optimization method, Zhang et al. [1] proposed an improved algorithm for automatic generation of shortest time routes based on instantaneous water depth model. Invalid point definition and dynamic envelope rectangle strategy were utilized to improve searching efficiency. Fang et al. [2, 3] considered factors of land boundary, effective wave height and engine speed, and designed the shortest route by using three-dimensional correction isochronal method of ship track floating network system. Mannarini et al. [4] proposed route design model based on sea state forecasting, which was used to resist wave resistance and loss of
ship stability by speed optimization. Padhy et al. [5] used Dijkstra algorithm to find out the shortest time route by evaluating the influence of wind, wave, and current.

On research of the safest weather route optimization method, Krata et al. [6] proposed a motor-driven scheme for hybrid ships in hazardous weather based on evolutionary SPEA algorithm, considering impact of meteorological conditions. Kim et al. [7] proposed a method based on genetic algorithm. Ship navigation resistance was obtained by calculating the average traction generated by wind and wave data. Ship safety constraints were added to get the route.

On research of the lowest energy consumption weather route optimization method, Zaccone et al. [8] calculated wave-resistance index and fuel consumption by observing ship motion and resistance caused by waves to obtain the lowest energy consumption route. Park et al. [9] proposed a method of saving fuel consumption. A* algorithm was used to obtain the best route at each planning time node, and geometric methods were used to determine the best speed plan for ships.

On research of multi-objective optimization method of weather route, Delitala et al. [10] proposed to optimize navigation time and energy consumption on the premise of ensuring ship safety and comfort. Fluid dynamics based ship database was built to calculate ship's sailing resistance. Walther et al. [11] further considered ship characteristics and geographical conditions based on minimizing fuel costs. The speed plan of the ship was formulated based on hydrodynamic model, which could reflect speed changing and fuel consumption. Veneti et al. [12] proposed two-target weather route optimization method that considered fuel consumption and route safety. The method of improving simulation efficiency was proposed. Joanna [13] combined with meteorological information to define the sailing constraints of ships, and to solve the optimal route of ship safety and economy based on Pareto optimal method.

On research of route dynamic optimization method, Nie et al. [14] introduced spatial data index structure to realize rapid retrieval of navigation information and proposed an improved ant colony algorithm based on navigation information space connectivity matrix to realize dynamic optimization of maritime search and rescue routes. Experimental results demonstrated feasibility of the proposed algorithm. Krata et al. [15] proposed a dynamic constrained ship meteorological path optimization based on synchronous roll prediction, which compared wave period prediction with actual wave period and optimized meteorological route in real-time.

Shortcomings of previous studies on weather routes were as follows. Firstly, static meteorological information was mostly used instead of time-varying information. So, it was difficult to always keep optimal sailing condition. Meanwhile, when the ship was yawed, the route was resumed to original route, thus increased sailing cost, which was difficult to meet actual navigation needs of ships. Secondly, previous studies lacked comprehensive consideration of energy consumption and sailing time, only achieved optimal single goal. Thirdly, isochronal method, variational method and mesh model constructed method were used in existing research. Isochronal method is a recursive algorithm. When meteorological data is large, storage space will be consumed and complexity will be increased. Therefore, it could only be used to design route with short-range, and it's hard to program. Variational method was to construct function of sailing time or energy consumption, and Euler equation was used to acquire extreme values. Solution was difficult due to too many constrains. When second-order differential was needed, equation solution would be inaccurate. Mesh model constructed method was to transform the problem into network path. Lots of data needs to be read and processed when the route was calculated with a long-range, which led to low operating efficiency. Finally, Great Circle Route was the shortest route between two points on the earth, based on which route optimization was realized with little change in total voyage. Sailing time and energy consumption were reduced.

Aiming at above shortcomings, dynamic optimization weather route model for unmanned ship based on multi-stage inverse reasoning was proposed. Dynamic planning points were set. According to real-time marine weather information, combined with optimization rule of the route and comprehensively considered impact of energy consumption and sailing time, positions of points in initial route were adjusted. Properly "deviating" or changing course to reduce the impact of adverse weather factors for ship's sailing. Energy and time were saved, and the route was optimized.
2. Method

2.1. The dynamic optimization principle of weather route

2.1.1. Analysis of core problem. Weather route is the best route recommended for ships crossing the ocean [16], according to accurate marine environment forecasts, combining with factors of ship performance, loading characteristics, technical conditions and so on. Economy of the route was a significant indicator, which could be affected by factors of energy consumption and sailing time. Dynamic planning was to solve the problem of multi-stage decision optimization. Route multi-stage decision process meant to divide the whole route into several segments. When arriving at dynamic planning point, position should be adjusted to optimize the whole route. According to principle of optimality, if decision of each waypoint was made according to optimal principle, the final route was multi-segment optimal decision. Route dynamic optimization process was shown in Figure 1.

![Figure 1. Route dynamic optimization flow chart.](image)

2.1.2. Mathematical expression of route dynamic optimization. Essence of route design was process of waypoints selection. The model belonged to dynamic programming of discrete control systems. There were N waypoints between starting point and target point, which meant N times of course decisions. As shown in Figure 2, at the (k+1)th stage, global route was regarded as two parts of the first k-segment sub-route and latter N-k sub-route. For the latter sub-route, \( x(k) \) can be regarded as initial state formed by \( x(0) \) and k-segment initial decisions \( u(0), u(1) \ldots u(k-1) \). Thus, the optimal strategy for route multi-segment decisions had characteristics as follows: decisions of latter segments were always the optimal strategy for the state formed based on initial decision regardless of the initial state and decision. Dynamic equation for N-stage decision was shown as formula 1.

![Figure 2. N-stage decision process.](image)

\[
x(k + 1) = f[x(k), u(k), k] \quad k = 0,1,\ldots,N
\]

Where, \( u(k) \) was weather condition of the k-th point. \( x(k) \) was position decision. By connecting selected grid points, optimal route was obtained.

2.2. Weather route optimization model based on Multi-stage Dynamic Inverse Reasoning

2.2.1. Principle of Multi-stage Dynamic Inverse Reasoning. Dynamic programming was an important method in optimal control theory, which can be used to solve the optimization problem in the process of multi-stage decision. As shown in Figure 3, each waypoint of the route was a dynamic planning point. When the ship reached a dynamic planning point, it acquired real-time meteorological information and re-planned the route. Point A was current position of a dynamic planning point. It was assumed to pass through k route points to reach endpoint S. At this time, calculate from endpoint S,
select the optimal waypoint $F_1$, and then from $F_1$ to find the next waypoint until $F_k$ near point A was selected. By connecting all these waypoints, the dynamic optimal route would be achieved.

![Figure 3. Waypoints selection.](image)

Figure 3. Waypoints selection.  
Figure 4. Waypoints optimization.

2.2.2. Model construction. When unmanned ship reached waypoint $i$, the next waypoint $j$ should be selected to be the best one. As shown in Figure 4, longitude and latitude of initial waypoint were randomly perturbed within a specified range. Specific adjustment rule was to generate a random value in the range of 0-1, and determined whether it was greater than 0.5. If correct, longitude of current waypoint was increased by a random value in the range of 0.25 to 1.25. Otherwise, current longitude of route point was reduced by the same way. So as latitude value. After disturbance, new possible waypoints were generated. Connect waypoint $i$ and the adjusted $n$ new waypoints to get $n$ constant lines. Energy and time required to pass each segment of constant line was calculated. And objective function value $h$ would be calculated through ideal point model. After comparison, waypoint with the smallest $h$ would be selected as the optimal one. Set N-stage decision evaluation function $J^*_N$:

$$J^*_N[x(i), m] = h[x(i), m] + \sum_{i=1}^{N} h[x(i-1)]$$

(2)

Where, $m$ was the number of waypoints to be calculated. $x(i)$ indicated the waypoint to be selected. $h[x(i), m]$ was evaluation function of the waypoint $x(i)$, expressed as follows:

$$h[x(i), m] = \sqrt{\omega_1 \gamma_1 \left( \sum_{i=1}^{N} T_e S_i - f^*_a \right)^2 + \omega_2 \gamma_2 \left( \sum_{i=1}^{N} \frac{S_i}{\nu_i} - f^*_b \right)^2}, (i = 1, 2, ..., N, \gamma_1 = \gamma_2 = \gamma, A)$$

(3)

s.t. $0 < \nu_i \leq \nu_{\text{max}}, N > 0$, $S_i > 0$, $T_e \geq 0$, $\omega_1 + \omega_2 = 1$

(4)

Where, $\omega_1$ and $\omega_2$ were weighting factors of energy consumption and sailing time. $\gamma_1$ and $\gamma_2$ were transform factors, to convert energy consumption and sailing time into economic indicators for evaluating routes. $A$ was a constant. Number of constant lines was $N$. $\nu_i$ was actual speed of the ship on i-th constant line. Ship critical speed was $\nu_{\text{max}}$. Length of the i-th constant line was $S_i$. The main engine thrust of the i-th constant line was $T_e$. $f^*_a$ and $f^*_b$ were the optimal solutions for energy consumption and sailing time in single-target route model.

In actual navigation, hydrological environment was complex and variable, and ship’s performance was different. Therefore, in route planning, critical speed of the ship in wind and waves needed to be determined, which shouldn’t be exceeded. Provided by [17] as formula 5.

$$\nu_{\text{max}} = e^{0.11}[1.4 \times 10^{-4} q^{23} + 12.0 - h]^{0.4} + 4.0 \times 10^{-4} q^{23} + 7.0$$

(5)

Where, $h$ was wave height, $q$ was relative wave direction, angle between ship’s course and wave direction.
3. Results

3.1. Data processing and calculation.

Wind field data of March 2010 was adopted. Data [18] comes from SCOW (Scattermeter Climatology of Ocean Winds) published by UCAR (University Corporation for Atmospheric Research). Wind field data of 10m above ocean surface was obtained by sea-air scatter meter mounted on QuikSCAT satellite by NASA (National Aeronautics and Space Administration). Monthly average wind data was obtained by establishing a regression model for data analysis and processing. Data followed Network Common Data Form.

3.1.1. Windfarm data processing.

After reading the wind field data, a raster map of latitude -69.875° ~ 69.875°, longitude 0.125° ~ 359.875° was obtained. Wind direction and speed data from longitude and latitude components were recorded. In order to facilitate the intuitive understanding of the wind field distribution, data needed to be pre-processed to provide a foundation for route design.

**Figure 5.** Global wind speed distribution map of March 2010.  **Figure 6.** Wind direction calculation.

As shown in Figure 5, direction of horizontal axis represented direction of longitude changing, while vertical axis represented latitude changing. The gray region represented constraint set \( \mathbb{R}_c \) of terrain area. Wind speed was expressed by the number below horizontal color bar, with unit of \( 1 \text{ms}^{-1} \).

From Figure 5, distribution conditions of wind field about whole Marine environment can be clearly obtained. Values of regions of land and islands were expressed as “-9999”. The direction on which longitude was increased was taken as the positive direction of horizontal axis, similarly, latitude corresponded to vertical axis. In wind field data, at a grid point, direction of wind was calculated from wind direction data of longitude and latitude components, which can be expressed as follows:

\[
\alpha = \arctan \frac{\text{Lon}}{\text{Lat}}
\]  

(6)

Where, \( \alpha \) was wind direction angle, \( \text{Lon} \) was wind direction value of longitude direction wind, \( \text{Lat} \) was wind direction value of latitude direction wind, and result angle range was \( [-\pi, \pi] \).

3.1.2. Calculation of hull upwind angle.

Measurement datum of wind direction was positive direction of x-axis, however, that of heading \( C \) was positive direction of y-axis, and angle range of both directions is the same, expressed as \( [0, \pi] \). Therefore, unified measurement basis or method was necessary. Firstly, change metrics by \( \alpha = \frac{\pi}{2} - \alpha \). Thus, benchmark of wind direction was changed to north. Measured range became \( [-\frac{\pi}{2}, 3\frac{\pi}{2}] \). Secondly, measured range was changed by \( \alpha = \text{rem}(\alpha + \pi, \pi) \). The \( \alpha = \text{rem}(\alpha, \pi) \) function acted as:

\[
\alpha = \begin{cases} 
\alpha & \alpha < \pi \\
\alpha - \pi & \alpha \geq \pi 
\end{cases}
\]  

(7)

The hull upwind angle \( \beta \) referred to the angle between ship’s heading \( C \) and wind direction \( \alpha \). As shown in Figure 6, coordinate system of Cartesian was established. Set positive direction of y-axis to the direction of the North. Upwind angle can be expressed as follows:
\[ \beta = \left| 180^\circ - |C - \alpha| \right| \]  \hspace{1cm} (8)

Where, \( \alpha \) represented wind direction angle, \( C \) represented ship's heading. The range of angles obtained was \([0, \pi)\).

### 3.1.3. Wave data processing

In actual Marine meteorological environment, data of wind and wave can be separately obtained. Owning to the difference of timeliness, data of wind and wave of the same time can’t be obtained accurately. Therefore, in order to ensure the accuracy of wave data, according to literature [19], wave height was expressed as follows:

\[ h = \frac{0.7 \left( \frac{gF}{v_{\text{wind}}} \right)^{\frac{1}{2}} \times v_{\text{wind}}^{2}}{g} \]  \hspace{1cm} (9)

Where, \( g \) represented gravity acceleration, and \( g = 9.8 \text{m/s}^2 \). \( F \) represented the length of the wind zone, which referred to the area of the sea, in which wind condition was nearly the same.

### 3.1.4. Ship loss-speed data processing

In sailing process, ships would be affected by factors of meteorology and hydrology, among which wind and waves had the greatest impact. Ship resistance in actual voyage was always greater than that in still water, which was known as natural loss-speed. According to literature [20], actual speed could be calculated by formula 10 as follows:

\[ v = v_0 - \left( a_1 h - a_2 gh + a_3 v_{\text{wind}} \cos \beta \right) \left( 1 - a_4 D v_0 \right) \]  \hspace{1cm} (10)

Where, \( v \) represented actual speed of the ship, \( v_0 \) represented speed in still water, \( v_{\text{wind}} \) represented speed of the wind, \( h \) represented wave height, \( \beta \) represented ship upward angle, \( D \) represented ship displacement, and \( a_1, a_2, a_3, a_4 \) represented undetermined coefficients. To simplify the process of calculation, it was assumed that direction of wave and wind were consistent with each other. Therefore, relative wave direction \( q \) and hull upward angle \( \beta \) were the same.

### 3.2. Model Solution

Japan Yokohama Port (34°40'N, 140°E) and US Long Beach Port (34°25'N, 120°W) were separately selected as initial and terminal port. The number of waypoints \( N \) was set to 10. Great circle route was selected to be initial route, and initial waypoints were shown in Table 1.

**Table 1.** Latitude and longitude values of initial waypoints.

| Num. | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   |
|------|------|------|------|------|------|------|------|------|------|------|
| Lat. | 34.7 | 39.2 | 42.8 | 45.5 | 46.8 | 45.4 | 45.5 | 39.0 | 34.5 | 34.5 |
| Lon. | 140  | 149  | 159  | 171.3| 163  | 151  | 129  | 120  | 120  | 120  |

Ordinary container ship "Long Lin" was selected, of which parameters were shown in Table 2.

**Table 2.** Parameters of "Long Lin" wheel.

| PARM         | Length of the ship | Width of the ship | Ship draft | Ship full displacement | Gross tonnage | Design speed | Propeller design speed |
|--------------|--------------------|-------------------|------------|------------------------|---------------|--------------|-----------------------|
| Values       | 153.60m            | 21.83m            | 14.20m     | 15702m³                | 13433         | 17.4kn       | 101r/min              |

According to parameters of Table 2, iterative method was used to solve the parameters in ship's stall formula. And the loss-speed of the ship can be expressed as follows:

\[ v = v_0 - (1.08h - 0.126gh + 2.77v_{\text{wind}} \cos \beta)(1 - 2.33Dv_0) \]  \hspace{1cm} (11)

It was assumed that weight value of energy consumption was equal to that of sailing time. Ordered \( \omega_1 = 0.5, \omega_2 = 0.5, \gamma_1 = 1, \gamma_2 = 1.725 \times 10^8 \).

Dual-objective optimization route model was solved by ideal point method, latitude and longitude values of waypoints were shown in Table 3, which was used as initial route of dynamic optimization.
The proposed model based on multi-stage dynamic inverse method was used to solve the above route. Corresponding values were shown in Table 4, so as simulation results in Table 5.

**Table 3.** Latitude and longitude values of dual-objective optimization route waypoints.

| Num. | Lat. | Lon. |
|------|------|------|
| 1    | 34.7 | 140  |
| 2    | 39.125 | 149.375 |
| 3    | 42.875 | 159.625 |
| 4    | 45.625 | 171.375 |
| 5    | 46.875 | -176.125 |
| 6    | 45.375 | -151.125 |
| 7    | 42.625 | -139.625 |
| 8    | 39.125 | -129.375 |
| 9    | 34.5  | -120  |

**Table 4.** Latitude and longitude values of dynamically optimized route waypoints.

| Num. | Lat. | Lon. |
|------|------|------|
| 1    | 34.7 | 140  |
| 2    | 39.125 | 149.375 |
| 3    | 42.875 | 159.625 |
| 4    | 45.625 | 171.375 |
| 5    | 46.875 | -176.125 |
| 6    | 45.375 | -151.125 |
| 7    | 42.625 | -139.625 |
| 8    | 39.125 | -129.375 |
| 9    | 34.5  | -120  |

**Table 5.** Statistical Table of Dynamic Optimization Route Simulation Results.

| Name                                      | Voyage (km) | Energy consumption (kJ) | Sailing time(h) |
|-------------------------------------------|-------------|--------------------------|-----------------|
| Dynamic optimization of route model      | 8764.1529   | 4.5137×10^7              | 256.83          |

4. **Discussion**

4.1. **Model verification**

In order to confirm reliability of the proposed model, it was necessary to be further compared with other single-target and dual-target models. In this paper, lowest energy consumption, shortest sailing time and dual-target route models were compared with the proposed model, respectively.

Two single-target route models were solved by intelligent water droplet algorithm [19]. Parameters selected in the algorithm were shown in Table 6. Results were shown in Table 7 and Table 8. The total voyage, energy consumption and sailing time were shown in Table 9.

**Table 6.** Parameters of intelligent water droplet algorithm.

| Parameters | Number of water drops | Number of iterations | Initial sediment amount | Initial velocity of water droplets | Water droplets contain initial sediment |
|------------|-----------------------|----------------------|-------------------------|-----------------------------------|----------------------------------------|
| Symbols    | \( N_{\text{total}} \) | \( \text{Itermax} \) | init\textit{soil} \( t \) | init\textit{vel} \( \text{soil}^{\text{init}} \) |
| Values     | 50                    | 100                  | 100                     | 0                                 |

**Table 7.** Some of waypoints’ latitude and longitude values of the lowest energy consumption route.

| Num. | Lat. | Lon. |
|------|------|------|
| 1    | 34.7 | 140  |
| 2    | 39.125 | 149.375 |
| 3    | 42.875 | 159.625 |
| 4    | 45.625 | 171.375 |
| 5    | 46.875 | -176.125 |
| 6    | 45.375 | -151.125 |
| 7    | 42.625 | -139.625 |
| 8    | 39.125 | -129.375 |
| 9    | 34.5  | -120  |

**Table 8.** Some of waypoints’ latitude and longitude values of the shortest sailing time route.

| Num. | Lat. | Lon. |
|------|------|------|
| 1    | 34.7 | 140  |
| 2    | 39.125 | 149.375 |
| 3    | 42.875 | 159.625 |
| 4    | 45.625 | 171.375 |
| 5    | 46.875 | -176.125 |
| 6    | 45.375 | -151.125 |
| 7    | 42.625 | -139.625 |
| 8    | 39.125 | -129.375 |
| 9    | 34.5  | -120  |

**Table 9.** Statistics of simulation results.

| Name                                      | Voyage (km) | Energy consumption (kJ) | Sailing time(h) |
|-------------------------------------------|-------------|--------------------------|-----------------|
| The Great Circle route model             | 8698.7359   | 4.6572×10^7              | 269.94          |
| Lowest energy consumption route model     | 8799.7030   | 4.6092×10^7              | 273.08          |
| Shortest sailing time route model         | 8735.8216   | 4.6372×10^7              | 260.58          |
| Dual-objective optimization route         | 8774.2519   | 4.6219×10^7              | 264.16          |
| Dynamic optimization route               | 8764.1529   | 4.5137×10^7              | 256.83          |
Results in Table 9 showed that total voyage of Great Circle route was the shortest, but energy consumption and sailing time were higher than other three routes. Lowest energy route model had most obvious optimization of energy consumption value, which was lower than Great Circle route by $4.8 \times 10^7$ kJ, but sailing time was 3.14h higher; shortest time route model optimized the sailing time, which was 9.36h lower than that of Great Circle route. Dual-target route had significant effects on energy consumption and navigation time. It was $3.53 \times 10^7$ kJ and 5.78h lower than that of Great Circle route respectively. Dynamic optimization route adopted dual-target route model, and considered real-time meteorological information. Compared with common dual-target route, it was reduced by $1.082 \times 10^8$ kJ and 7.33h respectively, which indicated reliability and applicability of proposed model.

4.2 Comments

In this paper, dynamic optimization model of unmanned ship global weather route considering meteorological conditions during ship's sailing process was established. Firstly, route can be adjusted to an optimal state according to real-time marine meteorological conditions. In this model, impact of marine meteorological conditions on ship navigation was analyzed, sailing time and energy consumption were comprehensively considered, and dynamic optimization of weather routes under complex wind and wave conditions were simulated, and differences were analyzed compared with static weather routes. Meanwhile, in order to reduce complexity of the model, it was assumed that main thrust of the ship was constant, adjusted windward angle of the hull by means of orbiting or changing the heading, maximized the use of meteorological resources, reduced sailing resistance, and improved speed under the premise of ensuring safety, and achieved optimal dual goal. However, once main thrust was changed, so was the route. Secondly, it was assumed that wind direction was consistent with wave direction and calculated ship stall data. Although wave data in this paper was reckoned from wind speed and direction, strictly speaking, wave direction did not depend entirely on wind direction, but it also depended on air pressure situation and inertia of waves, which had less influence, so it was temporarily approximated expressed, which had little effect on calculation of ship loss-speed. Thirdly, higher number of route point disturbances might cause lower calculating speed of route model, and lower number of disturbances might lead to insufficient route searching in a long route, which resulting in reduced model accuracy and difficulty in achieving double-objective optimization of the route Therefore, segmented route design method can be further studied to improve speed of the model while ensuring its accuracy. Finally, weight values of energy consumption and sailing time were assumed the same. In actual voyages, weight values can be changed depending on missions. Simulation results showed that dynamic optimization of weather routes had significant optimization effect on energy consumption and voyage time compared with static weather routes, which effectively saved sailing cost, and better solved weather route problems.

5. Conclusions

In this paper, navigation environment of unmanned ships under complex marine meteorological conditions was analyzed. Influence of wind, wave and ship's own conditions on navigation were considered synthetically. Dynamic optimization model of unmanned ship global weather route was established. Secondly, dynamic planning points were set up, initial route was divided into several constant lines, and dynamic optimization of the route was realized by establishing a multi-level dynamic decision-making inverse equation. Finally, optimization effect of the proposed model on initial dual-target route was verified by simulation. Results showed that the model could be used to optimize unmanned ship global weather route and provide decision-making method for route dynamic optimization under complex ocean meteorological conditions.

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