Onboard weather routing model and algorithm based on ant colony optimization

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Abstract. Due to many limitations and deficiencies in the onshore weather routing, the onboard weather routing based on ant colony optimization (ACO) is proposed in this paper. Firstly, this work analyses the similarities and differences between weather route optimization and TSP, proposes a more appropriate heuristic function which makes ants tend to search for grids nearer to the destination. Secondly, an onboard weather routing algorithm based on ant-cycle model is established, including constraint criteria, path search strategy and smoothing strategy. At last, the history meteorological data was used to simulate the forecast information, and the feasibility and rationality of the model and algorithm is verified based on an experimental ship. As the simulation shown, the final optimal route solved in this paper can be in line with the actual situation of navigation and having practical significance.

1. Introduction
At present, onshore weather routing has found wide applications in the shipping field. However, there are still many ships that have difficulty in using weather routing service due to such factors as cost, confidentiality. The weather route plays a very important role in the navigation safety and economic benefits of the ship. Due to many limitations and deficiencies in the onshore weather routing, the onboard weather routing is particularly necessary.

Route optimal problem belongs to the researching of weather routing in some extents, and the route optimization is the key technology of weather routing[1]. Within specified limits of weather and sea conditions, the term optimum is used to mean maximum safety and crew comfort, minimum fuel consumption, minimum time underway, or any desired combination of these factors[2-3]. In this study, the least deviation for heavy storm and wave sea area is taken as optimization object.

The development of the computer, the internet and communications technology has since then improved weather observation and prediction, and the highly accurate and real-time environmental data has provided a crucial basis for ship routing optimization[4]. The current ship routing optimization studies have mainly focused on onshore weather routing using intelligent optimization algorithms, such as Simulated Annealing[5], Genetic Algorithm[6-7] and ACO[8] provide new ways to determine the optimum route, but few researches for onboard weather routing are available. In this paper, this problem is modeled and abstracted into a mathematical model via an intelligent ACO, and the onboard weather routing is proposed.
2. Weather routing problem analysis

2.1. Weather routing and TSP
Ship weather routing develops an optimum track for ocean voyages based on forecasts of weather, sea conditions, and a ship’s individual characteristics for a particular transit. The weather routing in this paper focuses on avoiding the heavy storm and wave sea area to ensure the safety of ship and cargo, finding a safety and the least deviation route. It is no exception a optimization problem, and has the similarity with TSP, the goal of TSP is to find a path have the least distance to travel each city, and weather routing in this paper is to find a least deviation route, their optimization object are all least distance. But the differences between them are:

1) In TSP, the traveler should travel all the city nodes in the graph, while the weather routing just find a path from starting point to destination point, unnecessary to travel all nodes
2) Comparing with TSP, the weather routing has more constraints.

2.2. Constraint criteria
The conditions for restricting the safe navigation of ships, damage causing to ships or cargo varies from ship to ship. Therefore, the zone of the heavy storm and wave defined in this paper is not simply a maritime or meteorological stormy area, but means that as long as the wind and wave environment of one sea area exceeds the capacity of the given ship (including the ship and cargo), then these zones are called “non-navigable”, this given ship can’t sail on them, and must take some deviations.

2.3. Grid mesh
In this paper, the ACO is used to solve the onboard weather routing. For ACO, the grid or graph is the basis for optimization path, and the grid span is the step that the ants move once time. For weather routing, the grids can divide the ocean into several cells, and some particular cells are particularly suited as sailing regions. For grid span, considering the navigation safety factors, algorithm speed factors and route accuracy factors, is set to 0.5°. In this way, the number of grids is not large, and the search speed of the algorithm can be guaranteed. At the same time, the actual geographic size of the grid is more suitable for ship sailing and avoiding the zone of the heavy storm and wave, thus can meet the actual needs of navigation well.

2.4. Heuristic function
Heuristic function $n_y$ play the key role to ACO. In TSP, heuristic function reflects the expected usage of ants travel from city $i$ to $j$, which is given by $n_y(t) = 1/d_y$, where $d_y$ is the distance between city $i$ and $j$.

In weather routing problem, the ants needs to have tendency to search the grids near destination point for finding an optimal route, so the heuristic function in this paper for weather routing is given by $n_{jD}(t) = 1/d_{jD}$, where $d_{jD}$ is the distance between grid $j$ and destination grid $D$.

3. Weather routing algorithm based on ant-cycle model
Considering the characteristic of the weather routing, the ant-cycle model was used to solve the weather routing problem in this section, and the detailed solution process including symbol definition, state transition rule and pheromone update mechanism will be discussed.

3.1. Symbol definition
The $\text{Ants} = \{1, 2, \cdots, k, \cdots, m\}$ is defined as the ants set, where $k$ is the kth ant, $m$ is the amount of the ants.

The $\tau_{ij}(t)$ is defined as the pheromone concentration between the grid $i$ and $j$ at the given time $t$. 


The $\eta_{jD}(t)$ is defined as the heuristic function of the selected grid, where $\eta_{jD}(t) = \frac{1}{d_{jD}}$.

The Tabu$_k$ is defined as the set of visited grids by the $k$th ant up to the time $t$, which is route list, and also called “tabu list”. So, it stores the path information(geo coordinates of the visited grids) of the $k$th ant.

The allow$_k$ is defined as the set of reachable grids that the $k$th ant can visit at the later time.

3.2. Improved pheromone update mechanism
When the ant select the next grid, the transition probability of each reachable grids must be calculated firstly, and then the roulette wheel selection is used to decide which grid is selected finally. So, according to the above defines, which is given by:

$$j = \left\{ \begin{array}{ll} \arg \max_{j \in \text{allow}_k} \left[ \left( \tau_0(t) \right)^{\alpha} \cdot \left( \eta_{jD}(t) \right)^{\beta} \right], & \text{if } q < q_0 \\
J, & \text{otherwise} \end{array} \right. \quad (3)$$

Where $J = P_{j}^{s}(t)$, and

$$P_{j}^{s}(t) = \left\{ \begin{array}{ll} \left( \frac{\tau_0(t)}{\sum_{s \in \text{allow}_k} \left( \tau_0(t) \right)^{\alpha} \cdot \left( \eta_{jD}(t) \right)^{\beta}} \right)^{\beta}, & s \in \text{allow}_k \\
0, & s \notin \text{allow}_k \end{array} \right. \quad (4)$$

At the based ACO, $q_0$ dominates the select probability, and is often set to constant. When the $q_0$ is set higher, such as $q_0 = 0.9$, the ant will choose the next grid which has the highest pheromone concentration. In this case, with the increasing of iteration, the pheromone concentration of the path with higher concentration progressively increase, and the gap between paths are widening, so, other ants lose the ability of global search, and the weather routing algorithm will fall into local optima. But while the $q_0$ is set smaller, such as 0.1, the ant will chooses the next grid stochastically. In this case, the pheromone concentration in each route has little difference, the search space in optimizing process is extended, and the optimal direction is ambiguous, which cause the positive feedback of pheromone-oriented has little effect, lead to the weather routing algorithm slow convergence and difficult to obtain a global optimal solution.

So, setting inappropriate value(too high or small) to $q_0$ will inevitably lead to the algorithm falling into local optimum or slow convergence. To avoid this situation, the dynamic adjustment model for $q_0$ setting is introduced:

$$q_0 = \left\{ \begin{array}{ll} 0.7, & 0 < \text{iter} \leq 0.25 * \text{iter}_{\text{max}} \\
0.3, & 0.25 * \text{iter}_{\text{max}} < \text{iter} \leq 0.73 * \text{iter}_{\text{max}} \\
0.7, & 0.75 * \text{iter}_{\text{max}} < \text{iter} \leq \text{iter}_{\text{max}} \end{array} \right. \quad (5)$$

As equation (5) shown, given higher value to $q_0$ in the early iterations, this insure the algorithm has more powerful capacity of finding optimal solutions and improve convergence speed. Given smaller value to $q_0$ as iterations increasing, this avoid the algorithm falling into local optimum, extend the search space and improve the capacity of finding global solution. In later iteration, increasing the value of $q_0$ to make the algorithm accelerate convergence to the optimum solution.

3.3. Pheromone update mechanism
The ant-cycle model is introduced to pheromone update mechanism, which can be formulated:

\[
\begin{align*}
\tau_{ij}(t+1) &= (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) \\
\Delta\tau_{ij}(t) &= \sum_{k=1}^{n} \Delta\tau^{k}_{ij}(t), (0 < \rho < 1)
\end{align*}
\]  

(6)

Where \(\Delta\tau_{ij}(t)\) is the sum of pheromone concentration deposited by all ants between grid \(i\) and \(j\), while \(\Delta\tau^{k}_{ij}(t)\) is the pheromone concentration deposited by the \(k\)th ant, which is given by:

\[
\Delta\tau^{k}_{ij}(t) = \begin{cases} 
Q/L_k & \text{if the } k\text{th ant travels across } (i, j) \text{ in this iteration} \\
0 & \text{otherwise}
\end{cases}
\]

(7)

Where \(Q\) is pheromone intensity, and \(L_k\) is the sum distance of traveled path by \(k\)th ant in this iteration.

3.4. Route smoothness method

The solved optimal route from ACO is jagged line, as shown in figure 1, and this is inconvenient for ship maneuvering and navigating, so the solved route must smoothed to meet navigation practice. Suggested that the solved waypoints set of the solved route is \(\{P_0, P_1, ..., P_{n-1}, P_n\}\), where \(P_0\) and \(P_n\) are the starting and destination point separately, and others are the waypoints in the route, the route smoothness method is described as below.

Taking \(P_0\) as the start point and connecting \(P_0\) and \(P_n\), the connecting line crosses the non-navigable grids does or not is judged, if not, this is called the route between \(P_0\) and \(P_n\) can smoothed, the connecting line is the smoothed route then the other waypoint are deleted as figure 2 is shown, the routes between points \(A\) and \(B\) can be smoothed. Else, as figure 1 shown, the route between points \(A\) and \(B\) can’t be smoothed, then \(P_0\) and \(P_{n-1}\) is connected, the waypoints between them can delete or not is decided, and in turn, waypoints between \(P_0\) and anyone waypoint can delete or not should be decided sequentially. In the judgement, if the route between \(P_0\) and \(P_x\) can smoothed, then \(P_x\) is connected with \(P_n\), then the waypoints between \(P_x\) and \(P_n\) can delete or not is decided , and so on.

4. Simulation Results

The characteristics information of the experimental ship is supposed that its velocity is fixed to 20kn, maximum resisting wind scale ability is 7(14.0m/s), maximum resisting wave height is 4.0m. In order to meet the above model, the simulation experiment is simplified that the ship is taken as a point mass and sails at the fixed velocity, its locations of each step is the grids’ center in grid mesh.
The wind and wave grid data in this paper are from UCAR (University Corporation for Atmospheric Research), the date format is GRIB2 which can be read and displayed by the using of NC toolbox provided in Matlab. By the using of NC toolbox, wind and wave data can be loaded directly and stored in a matrix, which is very important for computing the wind grids indexes and displaying them together with the route. M-map toolbox were also used to implement the algorithm for projection, mapping and to draw ship routes on computers using only the Geo coordinates.

This work takes the meteorological data of 0000UTC and 0600UTC in 28/9/2016 as experimental date, and 25.0°N~35.0°N, 145.0°E~155.0°E as experimental sea area. It is assumed that the ship receive the weather forecast at 25.25°N, 145.25°E in 0000UTC, and its destination point is 34.75°N, 154.75°E. So, the mesh matrix size is 20×20, and the index of its first grid is 1, and last one is 400.

By amounts of simulation experiments, the parameter in ACO are set as Table 1 shows, and the value of these parameters are used in the simulation, the simulation results are shown in figure 3 and figure 4.

Table 1. Ant colony algorithm parameter settings.

|   |   |   |   |   |   |
|---|---|---|---|---|---|
| m | τ | α | β | ρ | Q  |
| 40 | 0.01 | 1 | 5 | 0.1 | 100 |

The optimal route solved by ACO is shown in figure 3, the gray grids are the zone of the heavy storm and wave for experimental ship. By the using of the model and algorithm achieved in this paper, the experimental ship can automatically optimize its route to avoid the zone of heavy storm and wave and arrive the shortest path to destination when receive the newest weather forecast. The figure 4 is the simulation convergence diagram of the shortest voyages (red line) and average voyages (blue line) for each generation of ants.

Figure 3 shows the wind field of experimental sea area, and the figure 6 shows the optimal route after smoothed. Comparing with figure 3 and figure 6, it can be clearly reflected that the smoothed route has a shorter voyage and less waypoints, is more in line with navigation practice. When the ship sails for 6 hours along the optimized new route, once the newest weather forecast formation is received, the grid where the ship's current position located will be taken as the starting point, and the real-time route optimization according the above description will executed.
5. Conclusion

Through analysing the optimization objective and the meteorological data in the form of grid, the ant colony algorithm is used to solve the problem about onboard weather routing in this paper. In order to improve the algorithm’s searching speed, this paper proposed a more appropriate heuristic function makes ants tend to search for grids nearer to the destination, and established an optimization model of ship weather routing including path search strategy, constraint criteria, and route smoothing strategy. Finally, an experimental ship is used to simulate the model and algorithm mentioned in this paper, the simulation result shows that the ship can avoid the rough sea area to reach the destination safely with the shortest voyage when sails along the optimized route, and the final optimal route can be in line with the actual situation of navigation and have practical significance.

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