A Robust GA/PSO-Hybrid Algorithm in Intelligent Shipping Route Planning Systems for Maritime Traffic Networks

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Abstract

The development of intelligent shipping route planning systems is important for maritime traffic networks, and has attracted considerable attention in the field of marine traffic engineering. In practical applications, the traditional experience-based planning scheme has been widely used due to its simplicity and easy implementations. However, the traditional manual procedure is experience-dependent and time-consuming, which may easily lead to unstable shipping route planning in different waters. The purpose of this study automatically and robustly determines that the optimal shipping route is based on artificial intelligence approaches. It is general that Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are almost the most popular methods in route planning. These two heuristic-based optimization techniques benefit from their specific advantages when solving different optimization problems. In this paper, we proposed a hybrid heuristic scheme by integrating GA and PSO to improve the accuracy and robustness of shipping route planning in restricted waters. The experimental results about both synthetic and real-world problems have demonstrated that our proposed hybrid approach outperforms the existing schemes in terms of both accuracy and robustness, and the approach is helpful for optimizing maritime traffic network for the links of terminals.

Keywords: Intelligent systems engineering, Maritime traffic network, Shipping route planning, Restricted waters, Artificial intelligence algorithm

1 Introduction

With the rapid development of economy and society, the maritime traffic network is becoming more and more complex in restricted waters. Meanwhile, with the development and the application of wireless mesh networks [1-2], sensor networks [3-4], information storage [5-6], big data technology [7-8], cloud computing [9-10] and intelligence computation [11-14], the navigation information storage and transmission is have made great progress. And, they laid a solid foundation for the maritime traffic network.

It is very important to optimize the structure of maritime traffic network for promoting water transportation efficiency. The shipping route optimization is an important foundation of optimizing maritime traffic network, to improve the intelligence of marine traffic. Furthermore, the research work of shipping route planning could be implemented in support of ship collision avoidance decisions, to enhance the safety of marine traffic [15]. The traditional experience-based planning scheme has been widely used due to its simplicity and easy implementation. However, the traditional manual method may easily lead to unstable shipping route planning for different people in different waters since it is essentially experience-dependent and time-consuming [16-17]. To overcome these limitations, there is a great potential to use the artificial intelligence techniques to solve the problem of shipping route planning in restricted waters.

In current literature, a large number of artificial intelligence methods have attracted increasing attention due to their great potential for solving complex networks and real-world problems, such as genetic algorithm (GA) [18], particle swarm optimization (PSO) [19], ant colony optimization (ACO) [20], artificial neural network (ANN) [21], artificial fish swarm algorithm (AFSA) [22], artificial bee colony algorithms (ABCA) [23], and so on. These artificial intelligence methods have obtained successful applications on solving route planning of different networks, and they are also well applied to solve the

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road traffic and tail traffic by combining with entropy, fuzzy mathematics or other theories [24-25]. The GA and PSO are compared to study real-time unmanned aerial vehicle path planning [26]. In this work, we mainly focus our attention on the first two methods (i.e., GA and PSO) due to their essential features of robustness and easy implementation.

In order to reduce the shipping costs and ship collision risks in restricted waters [27], it is necessary to optimize shipping route for improving the maritime traffic network. For instance, Braekers et al. [28] proposed a decision support model to determine the optimal shipping route along a single waterway. A multi-input fuzzy inference system was introduced to optimize the transoceanic route [29]. Zhang et al. [30] handled the path control problem for a ship steering in restricted waters using sliding model technique. The evolutionary algorithm-based decision support systems have also been used to help the operator to choose safer ship trajectories [15, 31-32]. Due to the great success of GA in solving complex optimization problems, GA-based methods have gained increasing attention in optimal shipping route planning [33-34]. PSO is typically able to solve the shortest path routing problems [19]. Thus it could be naturally extended to assist the operator to determine the safe shipping route to avoid ship collision in restricted waters [35]. However, the disadvantage of local minima trapping has constrained the further practical usage of GA. One drawback of PSO is that it often suffers from undesirable premature convergence and slow convergence rate [36]. In contrast, GA and PSO have a similar property in their inherent parallel characteristics, whereas several experiments have demonstrated that they have their specific advantages when dealing with different problems [37]. In order to improve the shipping route planning, there is a huge potential to combine GA with PSO to maximum the advantages of each individual heuristic approach while simultaneously overcoming their specific limitations. The basic idea behind the hybrid strategy of artificial intelligence algorithms is to overcome critical problem such as local minima trapping, premature convergence and memory loss.

During the past years, many researchers have tried to combine GA with PSO to solve complex network and real-world problems. For instance, the hybrid GA-PSO algorithm was used to improve solution accuracy for traveling salesman problems (TSPs) [38-39]. Marinakis and Marinaki [40] proposed a hybrid algorithmic nature inspired methodology for the effective handling of vehicle routing problem in road traffic network. This algorithm generated satisfactory results in two set of benchmark instances. By taking the advantages of both GA and PSO algorithms into account, Sheikhalishahi et al. [41] presented a novel GA-PSO algorithm for reliability redundancy allocation problem in series, series-parallel, and complex (bridge) systems. Although these hybrid GA-PSO algorithms have been widely studied, to the best of our knowledge, no research has been conducted on optimal planning of shipping route for maritime traffic networks thus far. In this paper, a hybrid GA-PSO approach will be used to help ship handlers to choose the optimal shipping route for realizing maritime traffic network optimization in restricted waters. To evaluate the proposed approach, numerical experiments will be performed on both synthetic and real-world problems.

The remainder of this paper is organized into several sections. Section 2 briefly explains the GA and PSO algorithms. The hybrid heuristic approach by integrating GA and PSO is also proposed in this section. In Section 3, the proposed hybrid GA-PSO approach is effectively used for intelligent shipping route planning systems. Experimental results on both synthetic and real-world problems are illustrated in Section 4. Finally we conclude this paper by summarizing our contributions and discussing the future work in Section 5.

2 Hybrid Framework for GA and PSO Algorithms

In this section, we will briefly explain the basics of GA and PSO heuristic methods. To improve the performance of shipping route planning, the hybrid heuristic approach is presented by integrating GA and PSO. The combined GA and PSO can generate a better performance than either GA or PSO alone.

2.1 Genetic Algorithm

Originated from the pioneering work of J.H. Holland in the 1970s [42], GA has emerged as one of the most powerful computational method for solving complex real-world problems. Commonly GA contains three different stages in the process of global solution searching [43]:

- **Stage 1**: generating an initial population.
- **Stage 2**: evaluating a fitness function.
- **Stage 3**: producing a new population.

For a specific problem, the populations in GA are formulated as the chromosomes of potential solutions (called individuals). This algorithm is an iterative process where new populations are generated based on individual adaption and some heuristic operators (crossover and mutation). In each generation, the fitness function[1] of each individual in the population is calculated. The individuals with the best fitness values have a higher probability of reproducing and generating new individuals by crossover and mutation. In contrast, the individuals with lower fitness values could be eliminated with a higher probability. The

1 The fitness function denotes a measure of the quality of the represented solution [44].

crossover operator creates two offsprings (new candidate solutions) by recombining the information from two randomly selected individuals of the population. It is generally thought that a good GA performance is closely associated with a high crossover probability. The mutation operator generates a new individual by introducing a small change in a single individual. Since frequent application of this operator would lead to non-robust solution, a low mutation probability is usually assigned to enhance GA performance.

Using these search operators (i.e., selection, crossover and mutation), the detailed flow chart of the algorithm is sketched in Figure 1. This procedure is repeated several times until a specified topping criterion is satisfied, and the optimal chromosome of the last generation is then selected as the final solution.

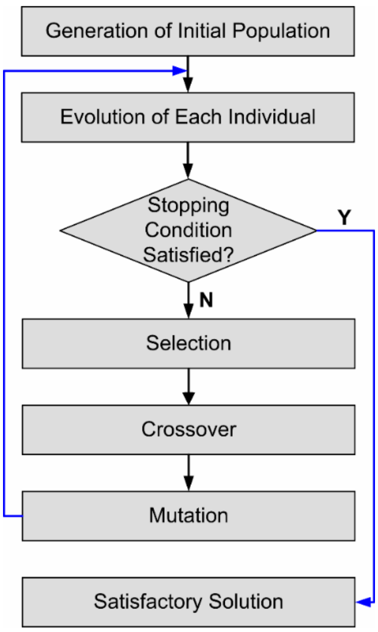

Figure 1. The detailed flow chart of GA algorithm

2.2 Particle Swarm Optimization

It is well known that PSO is an evolutionary computation technique which is based on swarm intelligence. This artificial intelligence technique is developed by Kennedy and Eberhart who was inspired by the simulation of social behavior [45]. Analogous to GA, PSO is initialized with a population of particles (or, individuals) being randomly generated. Each particle in PSO represents a potential solution and has a position denoted by a position vector x_i. The moving velocity of each particle can be represented by a velocity vector v_i. The particles have memory and each particle keeps track of its own previous position, which is associated with the best fitness in a vector p_i. Furthermore, the best position among the population of particles is kept track of as p_g. In conventional PSO approach, each particle moves in the problem space according to its own experience and other particles' experiences [15]. At each time step k, by using the individual best position p_i^k, and the global best position p_g^k, the i-th particle is manipulated according to the following equations

$$v_i^{k+1} = w^{k+1} + v_i^{k+1} + c_1 r_{1,i}^k (p_i^k - x_i^k) + c_2 r_{2,i}^k (p_g^k - x_i^k) \quad \textbf{(1)}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad \textbf{(2)}$$

where i = 1, 2, …, N, and N is the size of the population; w is the inertia factor; c_1 and c_2 respectively denote the cognitive and social parameters; r_1 and r_2 are random numbers uniformly distributed in the range [0, 1]. Figure 2 illustrates the description of velocity and position updates for a two-dimensional (2D) problem space.

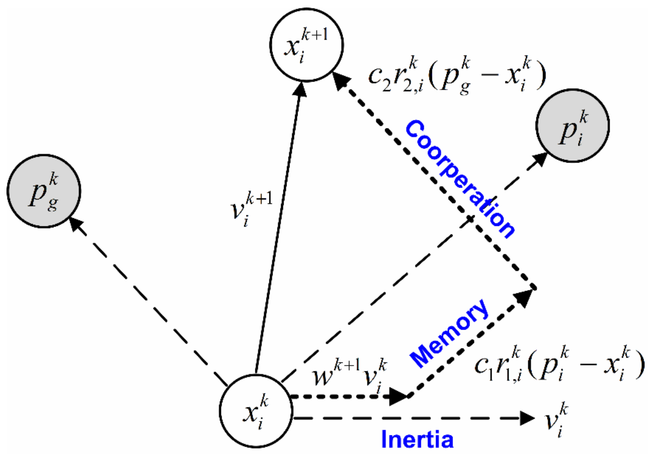

Figure 2. Description of velocity and position updates in PSO for a 2D problem space

To enhance the exploration and exploitation capacities of the PSO, a linear evolution with respect to the algorithm iteration has been introduced in [46] to update the inertia factor, i.e.,

$$w^{k+1} = w_{\max} - \frac{k}{k_{\max}} (w_{\max} - w_{\min}) \quad \textbf{(3)}$$

where $k_{\max}$ is the maximum iteration number, $w_{\max}$ =0.9 and $w_{\min}$ =0.4 denote the maximum and minimum inertia factor values, respectively. Based on Eqs. (1) and (2), the population of particles could converge quickly and tens to cluster together from different directions. Compared to GA, the advantages of PSO are that PSO is much easier to implement and there are only a few parameters to tune. Moreover, the flexibility of PSO to maintain the trade-offs between local and global exploration of the problem space helps to suppress the premature convergence of elite strategy in GA, and also promotes searching ability [47]. Therefore there is a great potential to combine GA with PSO to form a hybrid algorithm. In the next section, the hybrid GA-PSO algorithm will be proposed to enhance the optimization performance in practice.

2.3 GA/PSO-Hybrid Algorithm

Based on the above description, we proposed a hybrid GA-PSO algorithm by taking the advantages of both GA and PSO. As shown in Figure 3, this proposed algorithm is initialized by a population of random solutions and searches for the optimal solution through an iterative scheme. During this searching process, an evolution of the solution is performed by combining GA with PSO. In particular, the optimal solution can be found by the following steps:

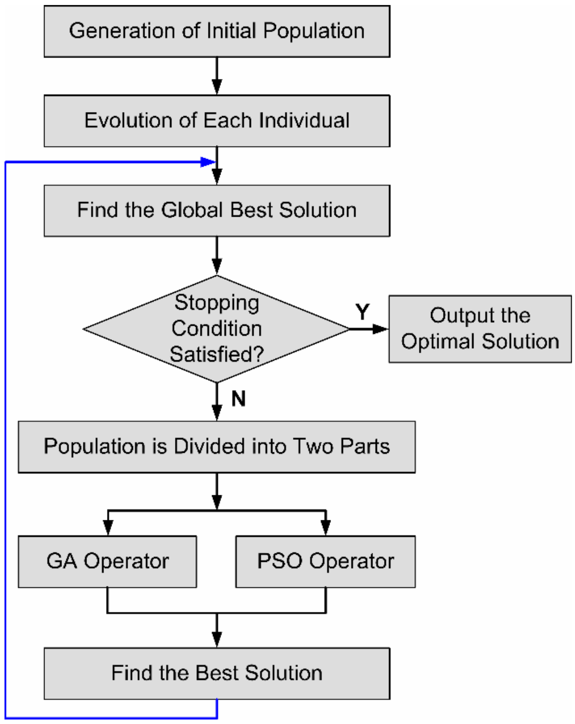

Figure 3. The detailed flow chart of hybrid GA-PSO algorithm

- **Step 1** (**Initialization**): Randomly initialize the population of individuals according to several limitations including individual dimensions, searching positions and velocities. These individuals are regarded as chromosomes in GA operator and particles in PSO operator.
- **Step 2** (**Evaluation**): The evaluation function (or, fitness function) should be defined to measure each individual's fitness value. We sort the individuals according to the calculated fitness value. The individual with the minimum fitness value is regarded as the global best individual.
- **Step 3** (**Partition**): The individuals are divided into two groups based on a predefined partition strategy. In this work, GA is used to update the top half of individuals. The bottom half of individuals are fed into PSO to update the velocities and positions.
- **Step 4** (**GA Operator**): As shown in Figure 1, GA commonly uses three operators (i.e., selection, crossover and mutation) to update each individual. Let $\mathbf{G}_{\mathrm{GA}}$ denote the best position in GA.
- **Step 5** (**PSO Operator**): Particles update their velocities and positions according to Eqs. (1) and (2). Let $\mathbf{G}_{\mathrm{PSO}}$ denote the best position in PSO.
- **Step 6** (**Comparison and Updating**): Comparing $\mathbf{G}_{\mathrm{GA}}$ and $\mathbf{G}_{\mathrm{PSO}}$, if $\mathbf{G}_{\mathrm{GA}} \leq \mathbf{G}_{\mathrm{PSO}}$, the global best position becomes $\mathbf{Gbest}_{\mathrm{GA}}$. The $\mathbf{Gbest}_{\mathrm{PSO}}$ and $\mathbf{G}_{\mathrm{PSO}}$ are respectively replaced by $\mathbf{Gbest}_{\mathrm{GA}}$ and $\mathbf{G}_{\mathrm{GA}}$. Otherwise, the global best position becomes $\mathbf{Gbest}_{\mathrm{PSO}}$. The $\mathbf{Gbest}_{\mathrm{GA}}$ and $\mathbf{G}_{\mathrm{GA}}$ can be replaced by $\mathbf{Gbest}_{\mathrm{PSO}}$ and $\mathbf{G}_{\mathrm{PSO}}$, respectively.
- **Step 7** (**Recursion**): If a specified topping criterion is not satisfied, repeat Step 2 to Step 6 until the topping criterion is met.
- **Step 8** (**Output**): If a specified topping criterion is satisfied, we can obtain the final optimal solution accordingly.

3 GA/PSO-Hybrid Algorithm for Robust Optimal Planning of Shipping Route

In this section, the hybrid GA-PSO algorithm will be used to design the optimal shipping route for maritime traffic networks in restricted waters. It is well known that many constraints limit the optimal route planning, such as distance, environmental and maneuverability constraints. To combine these different constraints, it is important to design a proper fitness function to enhance the satisfactory performance of shipping route planning. In this paper, our fitness function is composed of three parts related to the considered constraints. The detailed information is as follows:

3.1 Distance Constraint

In current literature, distance constraint has been widely used in optimal shipping route planning. This constraint is also considered into our fitness function. Let x and y denote the horizontal and perpendicular directions, the total distance for the shipping route is defined as follows

$$f_n = \sum_{i=1}^{I} \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} \tag{4}$$

where I denotes the total number of points in shipping route. The shorter route brings lower oil consumption to reduce economic cost.

3.2 Environmental Constraint

Let N denote the number of dangerous sources, such as islands, shoals and submerged rocks et al. The closest distance between ship and any dangerous source is given by D_n . By considering all the dangerous sources, we define the environmental constraint in this work as follows

$$f_E = \frac{1}{\min_{1\le n\le N} D_n} \quad \textbf{(5)}$$

Generally speaking, the small distance D_n could bring high risk of stranding. To improve the ship navigation safety, it is necessary to keep a proper distance between the moving ship and any dangerous source.

3.3 Maneuverability Constraint

Besides the distance and environmental constraints, maneuverability constraint has also become an obstacle in optimal shipping route planning. In this work, we only consider the limitation of steering angle, which is visually illustrated in Figure 4.

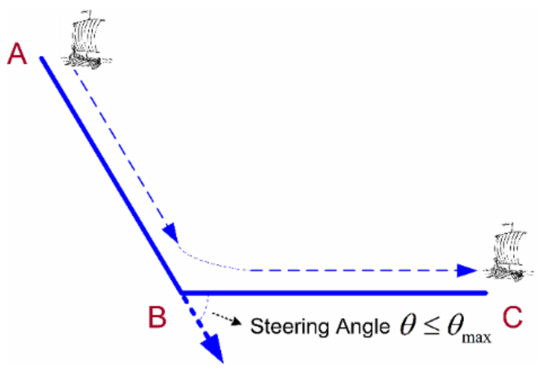

Figure 4. Description of steering angle θ

Let D_{AB} , D_{BC} and D_{AC} denote the distances between two corresponding points. According to the law of cosines, the steering angle in Figure 4 can be obtained, i.e.,

$$\theta = \pi - \arccos\left(\frac{D_{AB}^2 + D_{BC}^2 - D_{AC}^2}{2D_{AB}D_{BC}}\right) \quad \textbf{(6)}$$

In practice, the steering angle θ should be less than or equal to the maximum angle $\theta_{\max}$. Therefore, the maneuverability constraint is defined by considering the following cost function

$$f_M = \begin{cases} epx(\max_{1\le j\le J} \theta_j / \theta_{\max} - 1) & \max_{1\le j\le J} \theta_j < \theta_{\max} \\ +\infty & \max_{1\le j\le J} \theta_j < \theta_{\max} \end{cases} \quad \textbf{(7)}$$

where J denotes the total number of steering angles.

3.4 Fitness Function

As discussed aforementioned, the fitness function defined in our hybrid GA-PSO algorithm is composed of three terms. By combining the distance, environmental and maneuverability constraints, the final fitness function is defined as follow

$$f_{\cos t} = \alpha f_D + \beta f_E + \lambda f_M \quad \textbf{(8)}$$

where $\alpha, \beta, \lambda > 0$ denote weight parameters, which play important roles in intelligent shipping route planning systems for maritime traffic networks. In practical applications, these parameters are preselected according to the operator preference. If distance constraint is more important in route planning, α should be larger in the hybrid GA-PSO algorithm. In contrast, we should pay more attention on β and λ, if these two parameters play more important roles.

4 Experimental Results and Discussion

In this section, the hybrid GA-PSO algorithm for optimal shipping route planning was evaluated on both synthetic and real-world problems. For both synthetic and real-world problems, the parameter values in the fitness function (8) were set as $\alpha = 2\times10^{-2}$, $\beta = 5\times10^{-1}$ and $\lambda = 5\times10^{-1}$. The iterative scheme in Figure 3 was stopped when the maximum number of iterations (K=200) was reached. All experiments mentioned in this paper were implemented using Matlab R2014a (The MathWorks, Natick, Inc., MA) on a machine with 3.10 GHz Intel Core i5-2500 CPU and 4GB RAM.

4.1 Validation on Synthetic Data

In synthetic data experiment, a 20×20 searching region was used as the restricted waters shown in Figure 5. In addition, four different kinds of dangerous sources were considered, such as two circles, one square and one trapezoid. These dangerous sources were located in different waters and resulted in increased risk of shipping. Before implementation of shipping route planning, the searching region could be discretized with multiple scales of grids. As shown in Figure 5, A and B denote the starting and end points, respectively. The searching regions near dangerous sources were discretized with small scale of grids to enhance searching accuracy; whereas the other homogeneous regions were discretized with large scale of grids to reduce computational cost. Thus, this adaptive scheme of discretization setting for the hybrid GA-PSO algorithm could maintain a good balance between computational cost and accuracy.

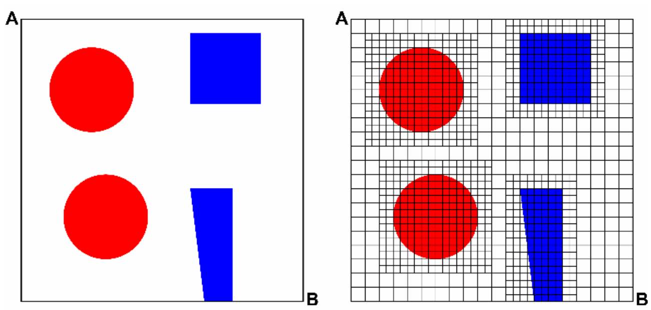

Figure 5. From left to right: searching region in synthetic restricted waters and its corresponding discretization setting

The simulation results of shipping route planning in maritime traffic network are summarized in Table 1. To reduce randomness, GA, PSO and GA-PSO algorithms ran 10 times to obtain the average results. As illustrated in Table 1, PSO yielded the best searching performance if we only considered the distance constraint as fitness function in this paper. However, this simple assumption could significantly increase the risk of shipping due to complex environmental conditions in restricted waters. By taking distance, environmental and maneuverability constraints into consideration, the proposed hybrid GA-PSO algorithm generated the best shipping route planning with the highest level of robustness. In Figure 6, we considered a general case of shipping route planning in restricted waters. Its discretization setting for optimal route searching could be found in Figure 5. It can be observed that GA resulted in the longest shipping route and PSO generated the shortest version. However, the shipping route generated by PSO was very close to the dangerous source, which brought high risk of stranding in practice. In contrast, the hybrid GA-PSO algorithm could keep a proper distance between the moving ship and dangerous sources. Thus this proposed algorithm is capable of maintaining a good trade-off between optimizing shipping route length and reducing shipping risk.

Table 1. The optimal route lengths and fitness vales (Mean±Std) of different methods for one synthetic data

Methods	GA	PSO	GA-PSO
Lengths	33.602±4.625	29.998±3.628	30.318±3.267
Fitness Values	1.822±0.285	1.701±0.278	1.406±0.239

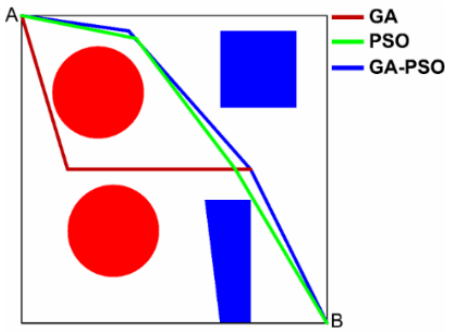

Figure 6. Optimal shipping routes generated by GA, PSO and GA-PSO, respectively

4.2 Validation on Real-World Data

In order to verify the consistency of hybrid GA-PSO algorithm on real-world data, the experiment was carried out on the maritime traffic network between Penglai City and Nanchangshan Island. As shown in Figure 7, A and B respectively denote the starting and end points. A to B is one route of the maritime traffic network, the ship should sailing through the restricted waters between Penglai City and Nanchangshan Island. Much attention has been paid to the optimal planning of shipping route in these important waters. The traditional method was implemented according to the operators' experience and subjective judgments. However, the time-consuming and operator- dependent operations in manual methods would lead to decision error and reduce the shipping route planning reproducibility. In particular, the decision error could bring a negative effect on the shipping cost. Therefore, developing an automatic method to optimize the shipping route is an interesting and demanding research topic in practice. In this paper, the hybrid GA-PSO algorithm will be used to deal with the problem of optimal shipping route planning.

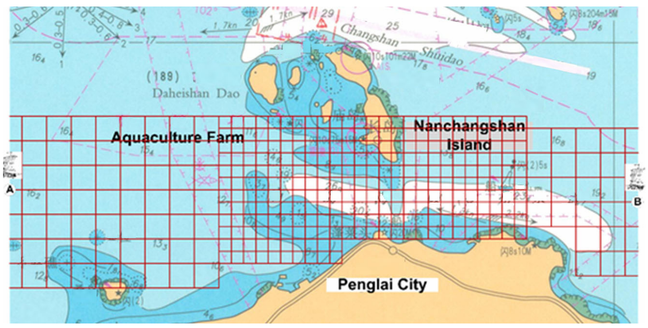

Figure 7. Searching region in real-world restricted waters and its discretization setting (shown by red grids)

The planning performance of our automatic GA-PSO algorithm was verified by the comparison with traditional operator-dependent method. The final optimal results of shipping route planning could be found in Figure 8. It can be observed that the shipping route generated by GA-PSO (labeled in blue) is roughly similar to the manual result (labeled in red). This optimization result illustrates that the proposed GA-PSO algorithm could play an important role in the practical traffic network optimization. Compared with traditional manual method, GA-PSO could improve the work efficiency and reduce the economic cost. Moreover this automatic algorithm could be easily extended to different restricted waters only if we could collect the corresponding environment parameters. In Figure 8, our shipping route looks smoother because the depth of water was not considered in this work. This limitation may result in increased risk of stranding in restricted waters. To further enhance the safety of maritime navigation, in our future work the depth of water will be taken into consideration during optimal shipping route planning.

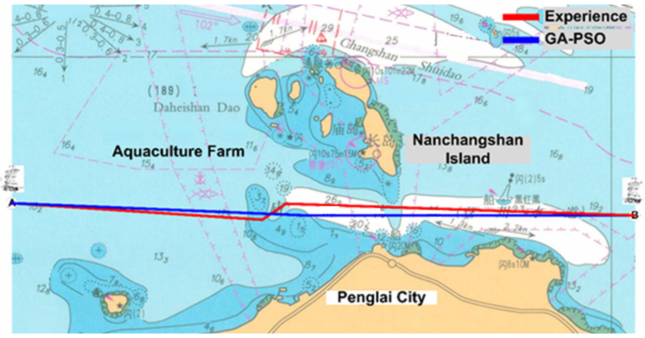

Figure 8. The final optimal results of shipping route planning generated by operator's experience and hybrid GA-PSO algorithm, respectively

5 Conclusions and Future Research

In this paper, a hybrid GA-PSO algorithm is proposed to deal with the problem of shipping route planning for maritime traffic networks. Numerical experiments performed on both synthetic and real-world problems are presented to indicate how the proposed hybrid algorithm may be used in practical applications. The proposed robust GA/PSO-hybrid algorithm could significantly outperform other competing shipping route planning methods (e.g., GA and PSO) in terms of both qualitative and quantitative evaluations. Furthermore, the proposed method is capable of generating planning results with higher accuracy and robustness. However, the proposed method has several potential limitations in its current version. To further improve the performance of intelligent shipping route planning for maritime traffic networks, our work will be extended in the following directions:

- The optimal shipping route planning proposed in this work was implemented by considering only static constraints, such as distance, environmental and maneuverability constraints. In practice, both water velocity and wind speed can be changed dynamically in real-time. These dynamic constraints could cause more difficulties and constrain the further practical usage of hybrid GA-PSO algorithm in accurate and robust route planning. It is specifically expected that further work will incorporate the dynamic constraints into our fitness function (8) to ensure more satisfactory performance of shipping route planning in restricted waters.
- In this work we only considered the two-dimensional (2D) searching region in restricted waters for shipping route planning in maritime traffic network. The 3D information, e.g., depth of water, is ignored in the proposed hybrid GA-PSO algorithm. It is well known that the depth of water also plays an important role in guaranteeing high-level safety of maritime navigation. Therefore it is also important to study the depth of water to make route planning more available in practical applications.

Although there remain limitations in our proposed method for intelligent shipping route planning, we still believe there is a great potential to use the hybrid GA-PSO algorithm to optimize shipping route for maritime traffic networks in practical applications. In the future, the hybrid GA-PSO algorithm can be used to optimize the whole maritime traffic network by optimizing shipping route of terminals.

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Author Contributions

The work presented in this paper corresponds to a collaborative development by all authors. All authors conceived and designed the experiments; Zhao Liu and Ryan Wen Liu performed the numerical experiments; Zhao Liu, Jingxian Liu, Feng Zhou, Ryan Wen Liu and Naixue Xiong analyzed the experimental results; Ryan Wen Liu, Zhao Liu and Naixue Xiong wrote the manuscript.

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