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A co-evolutionary improved multi-ant colony optimization for ship multiple and branch pipe route design

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ABSTRACT

This paper presents a co-evolutionary improved multi-ant colony optimization (CIMACO) algorithm for ship multi and branch pipe route design. The purpose of CIMACO algorithm is to design appropriate pipe routes to connect the starting points and ending points in the layout space under various kinds of constraints. The ant colony optimization (ACO) algorithm is improved according to the characteristics of ship pipe routing which is used to solve the single pipe routing problem. Based on the improved ACO algorithm, the multi ant colony optimization (MACO) algorithm with co-evolution mechanism is used to solve the multi and branch pipe routing problem. In this paper, the pheromone direction information and pheromone extension process are developed in the proposed algorithm to improve the calculation performance. Compared with conventional method, CIMACO algorithm is better at avoiding the problem of local optimum and accelerating the convergence rate. Finally, the simulation results demonstrate the feasibility and efficiency of the proposed algorithm.

1. Introduction

Pipe route design (PRD) plays an important role in industry, especially in the ship design. The purpose of PRD is to figure out an optimal route from a start location to an ending location in an environment with obstacles under various kinds of constraints. PRD has been a hot research field all over the world since 1970s. The existing methods include maze running algorithm (Lee, 1961), escape algorithm (Hightower, 1969), network optimization (Nicholson, 1966), A⁎ algorithm (Zhu and Latombe, 1991), ant colony optimization (ACO) (Dorigo and Gambardella, 1997), particle swarm optimization (PSO) (Kennedy and Eberhart, 1995), genetic algorithm (GA) (Ito, 1999), expert system (Vakil and Zargham, 1988) and multi-agent (Fan et al., 2006).

Ship pipe route design (SPRD) is one of the most important steps in ship design since it can take over 50% of the total detail-design man-hours and all other detail designs depend on it (Park and Storch, 2002). It has not only general characters of PRD problem, but also its own individual characters. Some of intelligent methods have been used to solve SPRD problem. Wu et al. (1998) applied fuzzy functions and sequential coordination to optimization of machinery arrangement and pipe routing. Kang et al. (1999) described an expert system to get the pipelines automatically. Park and Storch (2002) proposed a cell-generation method to optimize pipelines in ship room. Roh et al. (2006) developed a pipe model using the generation method. Lu et al. (2008, 2010) developed several algorithms to solve the pipe-routing arrangements using free spaces models. Fan et al. (2006, 2007, 2009, 2010 proposed several methods to solve the SPRD problem. Liu and Lu (2009) used a 3D digital simulation environment to optimize the pipelines automatically. Zou et al. (2010) presented an orientation-location distribution algorithm to evaluate the spatial effect of pipe-routing. Liu and Wang (2008, 2012) presented a new branch pipe routing algorithm based on the Steiner tree theory. Wu et al. (2012) constructed an auto-routing ship ventilation system to build the round pipe components in the 3D environment. Asmara and Nienhuis (2006, 2007, 2008, 2013) developed the framework of pipe routing in process of the detailed ship design. Kim et al. (2013) developed an automatic pipe routing system in a shipbuilding CAD environment using network optimization. Kimura and Ikehira (2009, 2011) presented some methods for pipe arrangement. Many research results have been proposed so far.

In this paper, a CIMACO algorithm is present to solve the SPRD problem. ACO was first introduced by M. Dorigo to solve the combinatorial optimization problems. It has been proven powerful for optimization problems. Many research studies have been carried out to solve PRD problem using ACO algorithms (Fan et al., 2006, 2007). But ACO algorithms have the disadvantages of premature convergence and slow convergence rate. Hence, ACO algorithm is improved in some ways to overcome the defects in this paper, enhancing the performance of the proposed algorithm. The direction information is added in pheromone to improve the influence of the pheromone. The pheromone extension process is

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introduced to expand influence extent of the pheromone. Based on the improved ACO algorithm, MACO algorithm is proposed to solve the problem of the multi and branch pipe routing in which the pipelines are represented by different populations. Furthermore, a co-evolution mechanism is embedded into the process of the MACO to strengthen the cooperation of populations.

The remaining part of this paper is organized as follows. Section 2 describes the process of the IACO algorithm for solving the problem of single pipe routing. Section 3 describes the process of CIMACO algorithm for solving the problems of multiple pipes and branch pipe routing. Section 4 shows the simulation results to demonstrate the feasibility and efficiency of the proposed algorithm. Finally, Section 4 contains the conclusion of this paper.

2. Improved ACO for single pipe routing

In this section, the improved ACO algorithm is presented to solve the problem of single pipe routing. ACO algorithm is improved according to the characteristics of SPRD. Compared with ACO algorithm, some steps in ACO algorithm are modified. The pheromone direction information and pheromone extension process are developed in the proposed algorithm to enhance computing performance. The flowchart of improved ACO algorithm is presented in Fig. 1.

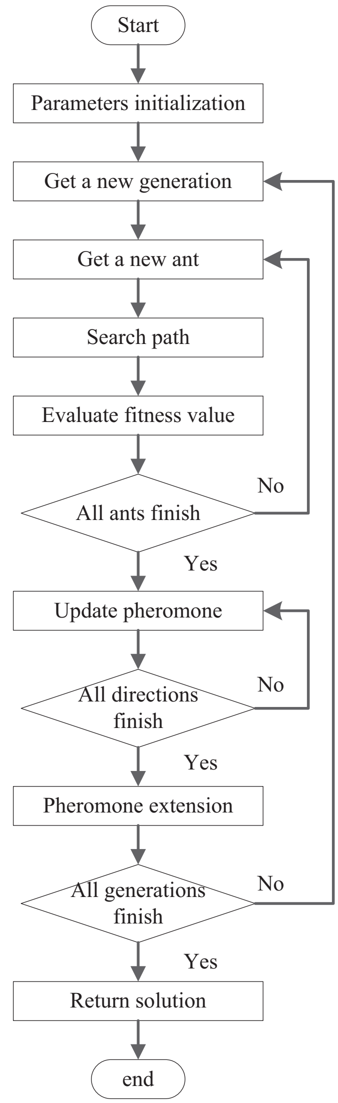

Fig. 1. Flowchart of IACO algorithm.

2.1. Data structure

The purpose of PRD is to figure out an optimal route from a start location to an end location in an environment with obstacles under various kinds of constraints. In SPRD problem, the main constraints include (Fan et al., 2006): avoid obstacles; minimize the length of pipeline and the number of elbows; arrange pipes orthogonally and along walls if possible; consider the convenience of installation and frequent maintenance.

In SPRD problem, the search environment can be simplified to a cubic model space in the coordinate system. The space is meshed according to pipeline diameters and interval distance. The data structure is defined as follows and shown in Fig. 2.

$$path = \{vertex_1, vertex_2, ..., vertex_n\}$$
$$vertex = (x, y, z) \tag{1}$$

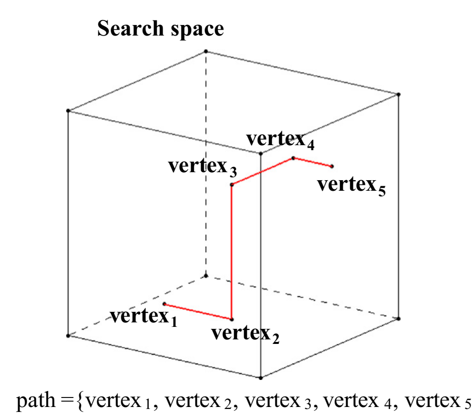

Fig. 2. Data Structure.

2.2. Search path

In ACO, ants move from node to node based on the probability which is involved with pheromone intensity and heuristic information. In this paper, a novel addressing method is proposed to accelerate the search process.

2.2.1. Select exploration direction

Ants select an exploration direction firstly when they want to move from current node to next node. The exploration direction is selected from the directions of three coordinate axes. In this paper, the direction information is added in the pheromone. When the current node is determined by the pheromone, its exploration direction is along to the direction of the pheromone. Otherwise, the exploration direction of the current is determined using the method of roulette selection.

The exploration direction of node j is defined as follows:

$$D_j = \begin{cases} D_{pt}^{\alpha 1} & \text{if } node_j \text{ is determined by } pt \text{ and } \alpha 1 = 1 \\ RS(X, Y, Z) & \text{otherwise} \end{cases} \tag{2}$$

D_{pt} represents the direction of the pheromone track. When node j is determined by the pheromone track, its exploration direction D_j is along to this pheromone track. $\alpha 1$ is the weight, which is defined as follows:

$$\alpha 1 = \begin{cases} 0 & \text{if} \quad q < q_0 \\ 1 & \text{otherwise} \end{cases}$$

$$q_0 = 0.6^{round(\tau_{pt}/60)} \tag{3}$$

q is a uniform random in [0, 1]. q_0 is the direction threshold value which is determined based on pheromone intensity. τ_{pt} is the pheromone intensity of pheromone track, which can actuate the direction threshold value.

$RS(X,Y,Z)$ represents the method of roulette selection, in which the probability of each direction is defined as follows. When $q<q_0$ or the node j is not determined by the pheromone track, the exploration direction D_j is determined using the method of roulette selection.

$$p_i=\frac{RL_i\times FR_i}{\sum RL\times FR},\quad i\in\{X,Y,Z\} \tag{4}$$

RL_i is the ratio of the location distance. FR_i is the ratio of the feasible region.

2.2.2. Calculate displacement

When the exploration direction has been determined, the displacement from current node in this exploration direction is calculated. In this paper, the direction information is added in the pheromone. The pheromone intensities on each node in three directions are executed, respectively. They are relatively independent. All of them involve in the calculation of the displacement together.

The probability of the current node moving to the node j in direction i is defined as follows:

$$p'_{ij}=\begin{cases}\frac{\tau_{ij}^{\alpha 2}\times\eta_j^{\beta}}{\sum_J \tau^{\alpha 2}\times\eta^{\beta}} & \text{if}\quad j\in J,\quad i\in\{X,Y,Z\}\\ 0 & \text{otherwise}\end{cases} \tag{5}$$

J is the feasible region from current node in the exploration direction. τ_{ij} is the pheromone intensity on node j in direction i. η_j is the heuristic information on node j when node j is determined by p'_{ij}, the exploration direction of node j is direction i. $\alpha 2$ is the weight, which is defined as follows:

$$\alpha 2=\begin{cases}0 & \text{if}\quad q<q_1\\ \alpha 2 & \text{otherwise}\end{cases}$$
$$q_1=0.6^{round(\max(\tau)/60)} \tag{6}$$

q is a uniform random number in [0, 1]. q_1 is the intensity threshold value. $\max(\tau)$ is the maximum of pheromone intensity in feasible region in three directions, which can actuate the intensity threshold value.

The heuristic information is set based on the potential preference of selecting a specific point. It is generally defined as the reciprocal of the distance between the alternative point and end point. In this paper, the heuristic information of the node j is defined as follows:

$$\eta_j=\frac{1}{d+1} \tag{7}$$

d is the distance between node j and the end node in exploration direction.

When the current point and the end point can be connected by line or broken line, the process of searching path is over.

2.3. Evaluate fitness value

The purpose of PRD is to figure out an optimal route from a start location to an end location in an environment with obstacles under various kinds of constraints. Considering the economic factors, the fitness function is defined as follows:

$$f_1(path)=E_1\times L(path)+E_2\times B(path)+E_3\times IL(path)+E_4\times W(path) \tag{8}$$

$L(path)$ denotes the path length. $B(path)$ denotes the number of elbows on path. $IL(path)$ denotes the length of installation path. $W(path)$ denotes the length of path which is not along wall which is used to arrange pipes along walls if possible. E_1–E_4 are their weights.

2.4. Pheromone updating rules

The pheromone is accumulated and updated on the optimal path solution during the iterative process. In this paper, the direction information is added in the pheromone. The pheromone intensities in direction X, Y and Z are updated. Firstly, pheromone is evaporated, by which the impact of the pheromone on the sub-optimal paths is gradually weakened. Secondly, the pheromone is accumulated on the best path of current generation. The updating rule is defined as follows:

$$\tau_{i,t+1}=\rho\times\tau_{i,t}+\Delta\tau_{i,t},\quad i\in\{X,Y,Z\} \tag{9}$$

τ_{t+1} and τ_t are the pheromone intensities in generation $t+1$ and t at direction i, respectively. $\Delta\tau_t$ is the intensity increment. ρ is the pheromone residual parameter which is actuated by the fitness values.

$$\rho=\max\left(\frac{fitness_b}{fitness_c},0.5\right)\times\rho_b \tag{10}$$

$fitness_b$ is the fitness value of the optimal solution path. $fitness_c$ is the fitness value of current path. ρ_b is a base value of the pheromone residual parameter.

The pheromone intensity is limited in the maximum τ_{max} and minimum τ_{min}.

$$\tau=\begin{cases}\tau_{max} & \text{if}\quad \tau\geq\tau_{max}\\ \tau_{min} & \text{if}\quad \tau\leq\tau_{min}\end{cases} \tag{11}$$

2.5. Pheromone extension

In ACO algorithm, the pheromone is accumulated on the optimal path. In this paper, the pheromone is accumulated not only on the points of the optimal path, but also on the points around the optimal path. The pheromone track is expanded into pheromone cuboid to expand the influence range of pheromone. The length of the extension sl is defined as follows. Fig. 3 shows the pheromone extension strategy in 2D search space.

$$sl=round(\tau/60) \tag{12}$$

τ is the pheromone intensities, which actuates the length of the extension. The stronger the pheromone intensity is, the wider the influence range is. The pheromone is accumulated on the points in

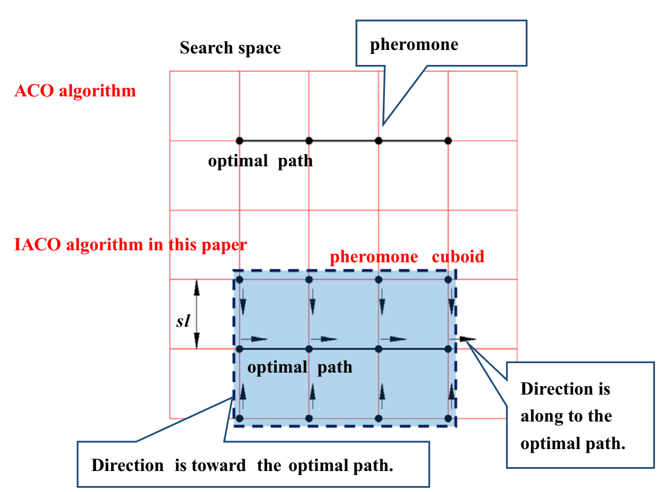

Fig. 3. Pheromone cuboid.

the pheromone cuboid. In this paper, the direction information is added in the pheromone. The pheromone direction of the point on the optimal path is along to the direction of the path. Meanwhile, the pheromone direction of the point in the pheromone cuboid is toward the pheromone track which is shown in Fig. 3.

3. CIMACO for multiple pipe routing and branch pipe routing

The pipe routing optimization problem includes single pipe routing, multiple pipe routing and branch pipe routing. In this section, based on IACO algorithm, CIMACO algorithm is proposed to solve the multiple pipe routing and branch pipe routing.

In the CIMACO algorithm, the problem is decomposed into several sub problems. Each sub problem represents a population of ant colony, which is in an ecological system. The evolutionary proceeding of populations is under the influence of circumstances and resources in the ecological system. Meanwhile, the evolutionary consequences provide feedback to the environment of the ecological system. The solution of the whole problem can be obtained finally.

In this paper, the multiple pipe routing optimization problem is decomposed into several single pipe routing optimization problems, which are represented by different populations. It assumes that all of the populations have the same function and share the resources of pheromone. The purpose of collaboration and interaction among different populations is to minimize the length of installation path. The pipeline is installed by the supporters. The length of installation path can be shorten by arranging the pipelines together as shown in Fig. 4.

The branch pipe is a one-to-many problem, namely, which has one starting point and many end points. In this paper, branch pipe routing is the same as the multiple pipe routing through connecting the corresponding points. But the purpose of collaboration and interaction among different populations is to minimize effective length. Effective length is the total length of all the pipelines without repetitive parts. Neither of the location of branch points and the sequence order of branch pipes is considered.

In this paper, CIMACO algorithm is developed to solve SPRD problem. The flowchart of proposed CIMACO algorithm is presented in Fig. 5.

3.1. Data structure

The data structure in the CIMACO algorithm involves multiple paths. Hence, based on Eq. 1, the data structure is defined as

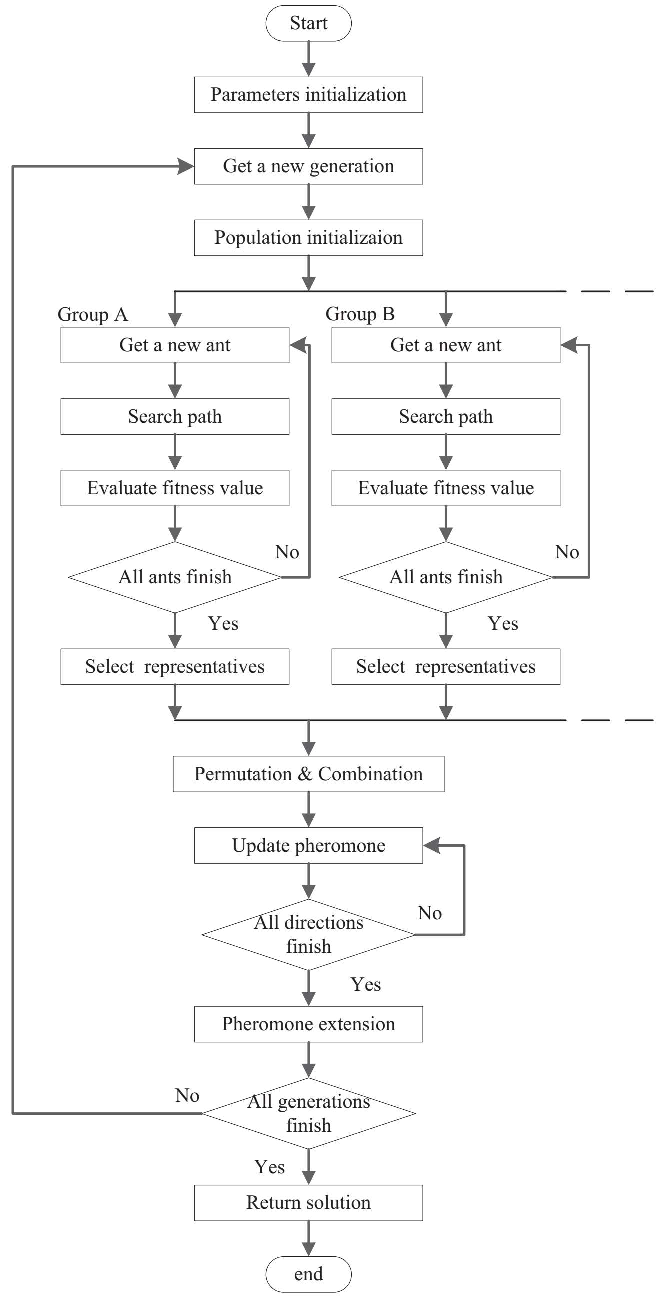

Fig. 5. Flowchart of CIMACO algorithm.

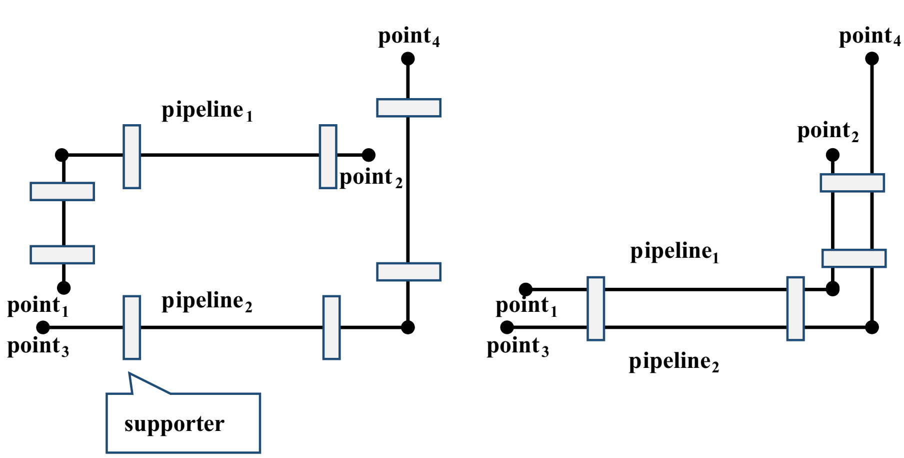

Fig. 4. Installation path.

follows:

$$path = \{path_1,\ path_2, \ldots,\ path_m\}$$
$$path_i = \{vertex_1,\ vertex_2, \ldots,\ vertex_n\} \tag{13}$$

3.2. Population initialization

In this paper, branch pipe is broke down into multiple pipes by connecting the corresponding points. Any one of the points can be used as the starting point for ants' search process. Hence, the point which is the closest to all the other points is defined as the starting point for ants' search process. Through this method, the sum length of the searching paths is the shortest, which can reduce the searching time.

The ant can select randomly the starting point from the two endpoints of the path to start the search the path, which can vary the solution paths and improve the convergence speed of the optimization.

3.3. Select representatives

The evolutionary of each population is executed according to the IACO algorithm introduced in the previous section. When all ants in a population have finished the paths, several paths are selected as the represents of this population for current generation. The individual fitness value and the global fitness value are taken into account in the principle of selection.

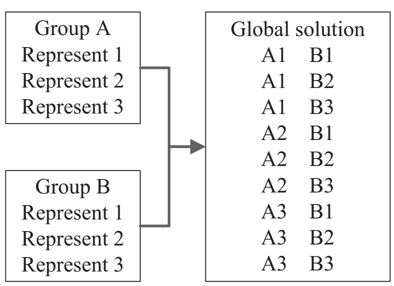

Fig. 6. Permutation and combination.

Table 1
The diagonal coordinates of the obstacles.

No.	Coordinate value
1	(6,12,1)–(24,16,40)
2	(32,12,1)–(40,16,40)
3	(1,26,1)–(8,30,40)
4	(16,26,1)–(34,30,40)
5	(1,1,12)–24,40,16)
6	(16,1,26)–(40,40,30)

The individual fitness of pipeline i is defined as follows:

$$f_2(path_i) = E_1 \times L(path_i) + E_2 \times B(path_i) + E_4 \times W(path_i) \tag{14}$$

The global fitness is defined in Eq. (8). The different between them is that the installation path is regardless in the individual fitness. In

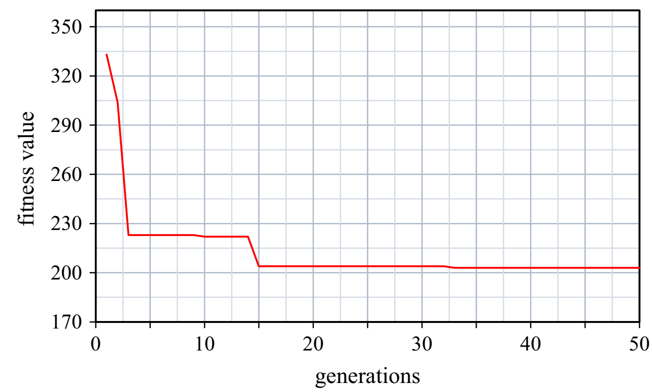

Fig. 7. Fitness value curve of single pipe routing.

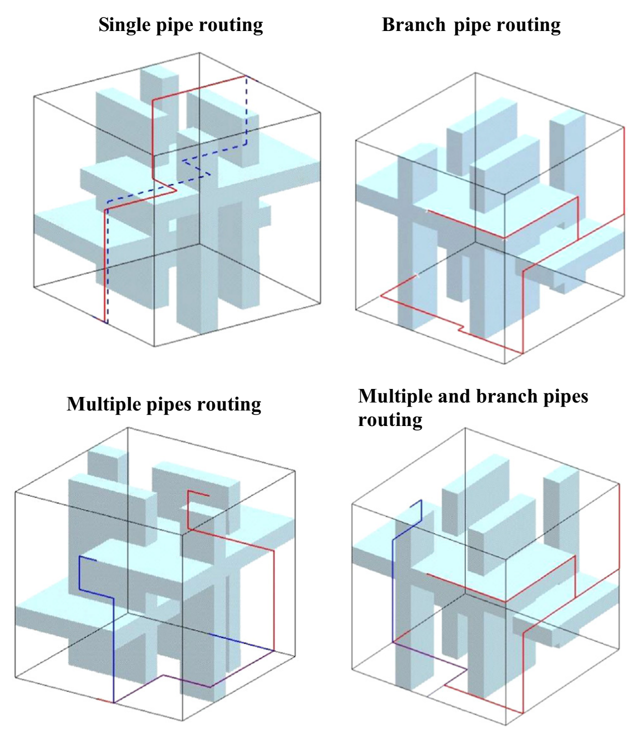

Fig. 8. Solution paths. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

Table 2
The parameters set for single pipe routing.

Parameters	Value
Endpoints	(20,1,1)–(20,40,40)
Directions of endpoints	X, X
Maximum step size	50
Number of ants in population	10
Number of generations	50
Weights of fitness function	$E_1=1$; $E_2=2$; $E_3=0.5$; $E_4=1$
Weights of pheromone and heuristic information	$\alpha_{2'}=1$; $\beta=1$
Base value of the pheromone residual parameter	$\rho_b=0.8$
Maximum and minimum of pheromone intensity	$\tau_{max}=300$; $\tau_{max}=0$;

Table 3
The parameters set for multiple pipes routing.

Parameters	Value
Endpoints	(20,1,1)–(20,40,30) (20,1,30)–(20,40,1)
Directions of endpoints	*X*, *X* *X*, *X*
Maximum step size	50
Number of ants in population	30
Number of generations	100
Weights of fitness function	$E_1=1$; $E_2=2$; $E_3=0.5$; $E_4=1$
Weights of pheromone and heuristic information	$\alpha_{2'}=1$; $\beta=1$
Base value of the pheromone residual parameter	$\rho_b=0.8$
Maximum and minimum of pheromone intensity	$\tau_{max}=300$; $\tau_{max}=0$;

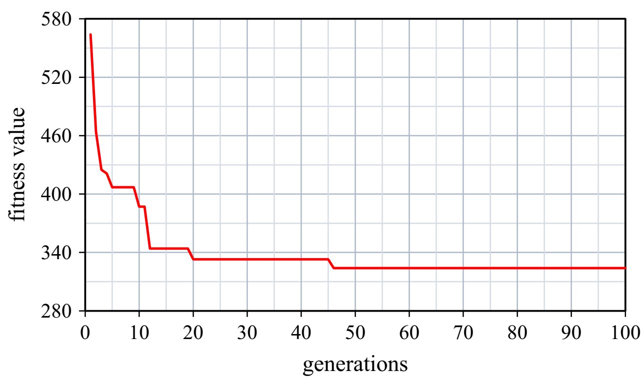

Fig. 9. Fitness value curve of multiple pipes routing.

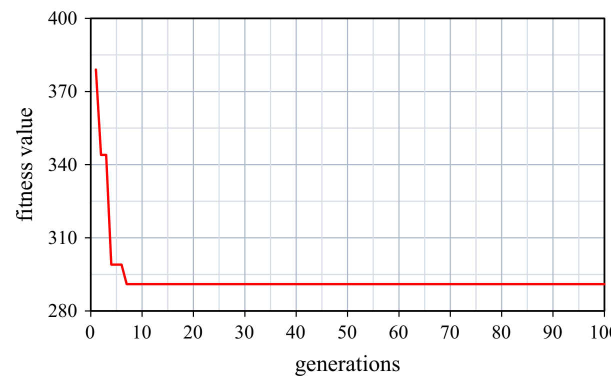

Fig. 10. Fitness value curve of branch pipe routing.

Table 4
The parameters set for branch pipe routing.

Parameters	Value
Endpoints	(20,1,1)–(40,20,30)–(20,40,20)–(1,40,40)
Directions of endpoints	*X*, *X*, *X*, *X*
Maximum step size	50
Number of ants in population	30
Number of generations	100
Weights of fitness function	$E_1=1$; $E_2=2$; $E_3=0.5$; $E_4=1$
Weights of pheromone and heuristic information	$\alpha_{2'}=1$; $\beta=1$
Base value of the pheromone residual parameter	$\rho_b=0.8$
Maximum and minimum of pheromone intensity	$\tau_{max}=300$; $\tau_{max}=0$;

CIMACO algorithm, the global solution is a set of solutions which are representatives of all groups in the ecological system. The global fitness value is calculated by all the pipelines in the search space. Hence, during the evolvement of the population, the global fitness value of current solution is computed by itself and the representatives of other populations in current global optimal solution.

In this paper, three cases of solution paths are selected as the represents.

(1) The paths with better global fitness value.
(2) The paths with better individual fitness value.
(3) The representative of this population in current global optimal solution.

3.4. Permutation and combination

When all groups in a generation have finished the paths, the representatives of all groups are put together. A global solution set is generated by permutation and combination shown in Fig. 6. The global fitness values of the global solutions in this set are calculated. By comparison, the solution with the best global fitness value is used as the global optimal solution path of current generation.

4. Simulation and results

The experiments are made in order to demonstrate the feasibility and effectiveness of the proposed algorithm. The algorithm is compiled in the MATLAB software.

4.1. Search space

In order to compare the simulation results, the experiments are executed in the same search space. The search space is (1,1,1)–(40,40,40). The diagonal coordinate of the obstacles in search

Table 5
The parameters set for combination pipes routing.

Parameters	Value
Endpoints	(20,1,1)–(40,20,30)–(20,40,20)–(1,40,40) (20,1,30)–(40,20,1)
Directions of endpoints	X, X, X, X X, X
Maximum step size	50
Number of ants in population	40
Number of generations	150
Weights of fitness function	$E_1=1$; $E_2=2$; $E_3=0.5$; $E_4=1$
Weights of pheromone and heuristic information	$\alpha_{2'}=1$; $\beta=1$
Base value of the pheromone residual parameter	$\rho_b=0.8$
Maximum and minimum of pheromone intensity	$\tau_{max}=300$; $\tau_{max}=0$;

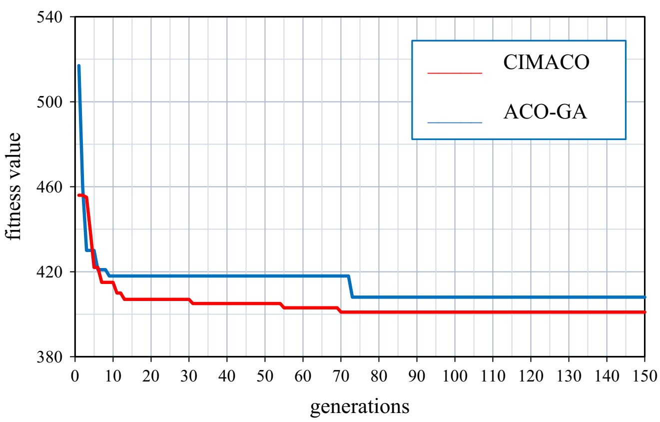

Fig. 11. Fitness value curve of combination pipes routing. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

space are listed in Table 1. Each experiment is executed 10 times. The result of the best one is selected to show here.

4.2. Simulation for single pipe routing

The parameters are set in Table 2.

The fitness value curve is shown in Fig. 7.

The coordinate values of the points on optimal solution path are listed as follows:

(20,40,40)–(16,40,40)–(16,18,40)–(16,18,24)–(24,18,24)–(24,1,24)–(24,1,1)–(20,1,1).

The optimal solution path is shown using the red solid line in Fig. 8. The blue dotted line is the solution path using the fitness function without $W(path)$. By comparison, the red solution is better than the blue one in the arrangement along wall.

4.3. Simulation for multiple pipes routing

The parameters are set in Table 3.

The fitness value curve is shown in Fig. 9.

The coordinate values of the points on optimal solution path are listed as follows:

(20,40,30)–(15,40,30)–(15,40,22)–(35,40,22)–(35,40,1)–(35,18,1)–(24,18,1)–(24,1,1)–(20,1,1).

(20,1,30)–(16,1,30)–(16,1,23)–(24,1,23)–(24,1,1)–(24,18,1)–(35,18,1)–(35,40,1)–(20,40,1).

The optimal solution path is shown in Fig. 8.

4.4. Simulation for branch pipes routing

The parameters are set in Table 4.

The fitness value curve is shown in Fig. 10.

The coordinate values of the points on optimal solution path are listed as follows:

(20,40,20)–(34,40,20)–(34,40,1)–(34,23,1)–(32,23,1)–(32,1,1)–(20,1,1).

(40,20,30)–(40,40,30)–(16,40,30)–(16,40,20)–(20,40,20).

(1,40,40)–(1,40,20)–(20,40,20).

The optimal solution path is shown in Fig. 8.

4.5. Simulation for combination pipes routing

The parameters are set in Table 5.

The fitness value curve is shown in Fig. 11. The red one and the blue one are obtained using the method of CIMACO algorithm and ACO-GA, respectively. The experiments are executed 150 times. The average values of the two methods are compared. The averaged convergence number of generations and the averaged fitness value are better in the results of CIMACO algorithm.

The coordinate values of the points on optimal solution path are listed as follows:

(20,1,1)–(24,1,1)–(24,20,1)–(34,20,1)–(34,40,1)–(34,40,20)–(20,40,20).

(40,20,30)–(40,40,30)–(16,40,30)–(16,40,20)–(20,40,20).

(1,40,40)–(1,40,20)–(20,40,20).

(20,1,30)–(16,1,30)–(16,1,25)–(24,1,25)–(24,1,1)–(24,20,1)–(40,20,1).

The optimal solution path is shown in Fig. 8.

5. Conclusion

In this paper, a new algorithm is presented to solve ship multi and branch pipe route design. Based on the ACO algorithm, IACO is developed for single pipe routing problem; CIMACO is developed for multiple and branch pipes routing problem. In this paper, the direction information is added in pheromone to improve the influence of the pheromone. The pheromone extension process is introduced to expand influence extent of the pheromone. They are developed in the proposed algorithm to improve the calculation performance. Some cases are calculated using the proposed algorithm. The simulation results demonstrate the feasibility and effectiveness of the proposed algorithm.

Further work will focus on studying the combination between equipment layout and pipe routing in main engine block.

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