INTELLIGENT LAYOUT DESIGN OF SHIP PIPELINE USING A PARTICLE SWARM OPTIMISATION INTEGRATED GENETIC ALGORITHM

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Yunlong Wang, Dalian University of Technology, School of Naval Architecture, China
Hao Wei, Dalian University of Technology, School of Naval Architecture, China
Guan Guan, Dalian University of Technology, School of Naval Architecture, China
Kai Li, Dalian University of Technology, School of Naval Architecture, China
Yan Lin, Dalian University of Technology, School of Naval Architecture, China
Shuhong Chai, University of Tasmania, Australia Maritime College, Australia

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SUMMARY

This paper proposes a Particle Swarm Optimisation Integrated Genetic (PSOIG) algorithm to define ship pipeline layout, where the pipeline layout environment is complex and changeable. The pipeline layout space model includes a cabin model, an obstacle model, a pipe model and a regional model of layout. Given the characteristics of ship pipeline layout, the direction guidance mechanism for automatic pipeline layout is introduced, and a direction parameter setting are put forward to further improve the efficiency of the algorithm. At the same time, the crossover and mutation strategies of the genetic algorithm are introduced into the particle swarm optimisation to establish the PSOIG algorithm for ship pipeline intelligent layout. This fully optimises the advantages of particle swarm optimisation and genetic algorithms to improve the diversity of solutions and the convergence speed of the algorithm. Finally, the simulation results demonstrate the feasibility and efficiency of the proposed algorithm.

NOMENCLATURE

GA	Genetic Algorithm
PLD	Pipeline layout design
PSO	Particle Swarm Optimisation
PSOIG	Particle Swarm Optimisation Integrated Genetic
SPLD	Ship pipeline layout design
3D	Three-dimensional

1. INTRODUCTION

Pipeline layout design（PLD） is the process of finding the optimal pipeline layout scheme under the geometry, topology, technology, rules and other constraints. In a geometric view, it is to find a non-collision path from the specified starting point to the ending point in a limited three-dimensional (3D) layout space, which does not interfere with other arranged objects (such as bulkheads, machinery and equipment, aisles, laid pipes.), and satisfies various constraints such as physical, economic, and it should satisfy various constraints such as physical, economic, safety and specification, production and installation, operation and maintenance constraints. PLD plays a significant role in industry especially in ship design (Cao *et al*., 2019). The research of pipeline layout design has developed from simple constraints in two dimensions to multi-objective constraints in 3D space since 1970s (Nguyen *et al*., 2016). The conventional methods include the maze running algorithm (Lee, 1961), escape algorithm (Hightower, 1969), network optimisation (Nicholson,1966), network optimisation algorithm (Wangdahl & Pollock, 1974), dynamic programming method (Van & Koopmans, 1976), expert system (Vakil & Zargham, 1988), genetic algorithm (Ito,1999), ant colony algorithm (Fan *et al.*, 2006), co-evolutionary algorithm (Jiang *et al*., 2015), human-computer cooperation approach (Wang *et al.*, 2015) and particle swarm optimisation (Dong & lin, 2017). These research results are very helpful and valuable to the further research of PLD.

PLD is one of the main contents of ship design, it is very important to the safety, economy, maneuverability, maintenance, safe navigation and normal operation of all kinds of machinery and equipment. With the development of computer technology and intelligent algorithm, intelligent layout design of ship pipeline has become a hot and difficult problem in ship intelligent design. Several intelligent algorithms have been used to solve it. To reduce designer workload and human errors, Kang *et al*. (1999) prososed a design expert system to automate the ship pipeline design process. Fan *et al*. (2007a) put forward a genetic algorithm of variable length coding suitable for 3D layout optimisation of ship pipeline. Based on this algorithm, an adaptive annealing genetic algorithm was proposed for the layout of ship pipeline to improve the diversity of solutions and the convergence speed of the algorithm (Fan *et al.*, 2007b). Jiang *et al*. (2014) proposed an improved ant colony genetic algorithm to find the optimal layout scheme of ship single pipeline. Fan and Lin (2006) introduced the ant colony algorithm into ship piping layout optimisation design. And then combined the ant colony algorithm with the cooperative algorithm to present a multi-ant colony cooperative co-evolutionary algorithm model for the parallel pipeline layout, which can obtain better results (Fan *et al.* 2009). The Dijkstra’s algorithm with some improvements was used to reduce the calculation time, occupied memory and the shortest paths which were exported by this method would have a minimum number of bend and elbow, at the same time, a new algorithm of mesh sizes are not restricted by pipe diameter was proposed (Ando, 2011, Nguyen, 2016). Qu and Jiang (2011) established a dynamic ant colony algorithm, and built dynamic heuristic information with modeling space and ant location change. An ant colony-shuffled frog leaping algorithm is proposed to optimize the piping results of orthogonal pipelines in three-dimensional space(Cao *et al*.,2019). Liu *et al*. (2009) proposed an improved particle swarm algorithm and introduced a particle coding mechanism based on the grid to solve the problem of ship pipeline layout. Wu *et al*. (2008) introduced the layout of ship branch pipes with co-evolutionary ant colony algorithm. According to the characteristics of ship pipe routing, Jiang *et al*. (2015) presented a multi ant colony optimisation algorithm integreted with co-evolution mechanism to solve the multi and branch pipe routing problem, and achieved good results. Wang *et al*. (2018) proposed a human-computer cooperation improved ant colony optimisation algorithm for SPLD, it could take full advantages of designers' expertise and experience as well as computers' calculation ability, the simulation results demonstrated that the new method can improve the convergence speed and the quality of the solution. The optimal shortest path A* algorithm is introduced to the field of pipeline placement optimisation (Haytham *et al*., 2019). To cope with branch-pipe routing widely existing in engineering, a new pipe router is put forward using a modified Steiner Tree framework in combination, it is more versatile and can effectively balance the layout quality and time efficiency (Dong *et al*., 2020). From the research results for SPLD, we can find that it is difficult to obtain the stable solution which can meet engineering requirements. Most studies are only similar to robot path optimisation, and do not study the layout environment and direction guidance mechanism of ship pipeline layout. Further research is needed to improve the convergence speed and solution quality.

In this paper, a Particle Swarm Optimisation Integrated Genetic (PSOIG) algorithm is presented to solve SPLD problem in 3D space. This paper has researched the ship pipeline layout space model including a cabin model, an obstruction model, a pipe model and a regional model of layout. The direction guidance mechanism is introduced to further improve the convergence speed. The crossover and mutation strategies of GA are introduced into the PSO to constitute the PSOIG algorithm, which fully optimizes the advantages of PSO and GA to improve the diversity of solutions and the convergence speed for the SPLD.

This paper is organized as follows: Section 2 introduces SPLD optimisation model; Section 3 describes the process of PSOIG algorithm for solving the problems of SPLD; Section 4 Shows the simulation results to demonstrate the feasibility and efficiency of the proposed algorithm; Finally, Section 5 contains the conclusion of this paper.

2. SHIP PIPELINE LAYOUT DESIGN OPTIMISATION MODEL

2.1 SPACE DATA MODEL OF CABIN

The cabin layout space model refers to the mathematical model of the cabin space to be arranged by pipeline. In this paper, the grid method is used to establish the space model of cabin layout. The steps are as follows:

(1) Simplify the cabin space into a regular cuboid according to the length, width and height of the compartment.

(2) The cuboid model is divided into 3D grid nodes by grid method, and a unique coordinate (position) value (x, y, z) is given to each grid node by rectangular coordinate system identification (Cartesian coordinate system).

(3) The space model is modified according to the actual conditions of the cabin space. In fact, most of the cabin space is not usually a regular cuboid. For example, the side cabin is usually an irregular shape with curved bulkhead. At this point, the model should be modified to set the space in the model that does not belong to the cabin layout space into a forbidden layout area. Figure 1 shows the process of building spatial data model of side cabin.

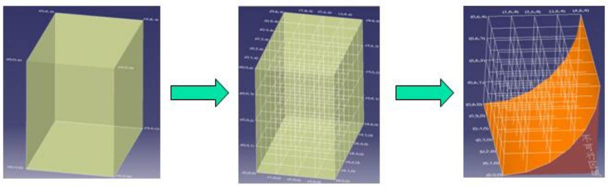


Figure 1: The side cabin data model

When dividing grids, grid size is an important factor to determine the quality of space data models. If the grid is too large, the space division is not detailed enough, which will lead to the difficulty of automatic layout. If the grid is too small, it will increase the amount of data in the model space, and then increase the time of subsequent automatic optimisation layout calculation. Therefore, the grid size should be set according to the following key elements:

(1) Radius of the pipe. Because the center line of the pipe will be used to replace the pipe in the automatic layout, the size of the grid should not be less than the radius of the pipe, otherwise, the layout will be wrong, for example, side-by-side pipelines will interfere.

(2) Reserved interval between pipelines. A gap should be left between two adjacent pipes and pipe fittings for insulation, installation, maintenance, etc.. So the grid size should not be less than the sum of the pipe radius and the reserved clearance between the pipes. When multi-pipe layout, the grid size can be selected, then

the actual arrangement can be adjusted according to the pipe diameter.

2.2 PIPE MODEL

Central line theory is used in pipeline layout design, that is, the radius and wall thickness of pipeline are reduced to 0, and the central line of pipe is used to represent the line of pipe in the intelligent layout design (Park & Richard, 2002). Figure 2 shows the pipe model.

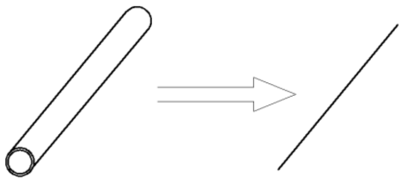


Figure 2: The pipe model

2.3 OBSTACLE MODEL

Obstacle model refers to the model established according to the layout of machinery and equipment, bulkhead, aisle, laid pipeline and hull structure in the cabin, which are defined as prohibited areas. The shape of most obstacles is not regular. If the model is built based on the actual shape, it will not only have a large modeling workload, but also increase computational workload in the optimisation, so most researchers simplify obstacles to regular shape modeling. However, this simplification usually only considered the geometric size of the obstacle in modeling, and did not take into account the inherent characteristics and maintainability of the obstacle itself. Therefore, this paper proposes a pose space modeling method: the obstacle is completely included by establishing one or more regular cuboids, and posture space should be built on the following principles.

(1) The posture space is an envelope of the obstacle, that is, the obstacle is completely contained in the posture space, and there is no part outside the posture space.

(2) The posture space should be set according to the inherent properties of the obstacle. The obstacle, for example, is a cable and requires a distance of at least 100mm between the cable and the pipeline, so the posture space of the cable should contain 100 mm of space around the cable.

(3) The posture space should consider the maneuverability and maintainability of the mechanical equipment. That is, it can also be calculated in the envelope of the posture space when a certain operation and maintenance space is reserved around the obstacle.

2.4 DIRECTION GUIDANCE MECHANISM

In the pipeline intelligent layout design, each individual in the initial population corresponds to a pipe path which must go from the starting point to the end point. In the layout space model established by the grid method, there are six directions to choose when the path enters the next node through one node. If the path is generated completely randomly in the layout space, the probability of selecting the six directions is the same, which may cause the direction of the path to deviate from direction of the end point (Fan *et al*., 2007a).

In this paper, a direction guidance mechanism is established to guide the direction of the path. When the initial path is generated, the probability of setting forward to the end point is greater than that in the opposite direction, so as to improve the convergence rate of the initial individual. The six directions (Figure 3) are divided into two groups: the three directions consistent with the end point direction are P_1 group, and the other three directions deviate from the end point direction are P_2 group. The probability of P_1 group is greater than that of P_2 group, and the probability of direction in the same group is same. The ratio of P_1 to P_2 is defined as direction parameter P.

$$P = \frac{P_1}{P_2} \quad (1)$$

$$P_1 + P_2 = 1 \quad (2)$$

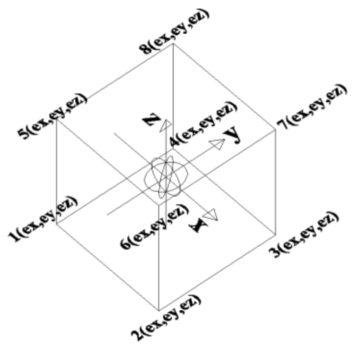


Figure 3: Six directions and relative positions of starting and end point of the pipe

The choice of direction parameter P should be appropriate. If it is too small, the direction guidance is not obvious, and the convergence rate can't be effectively improved. If it is too large, the diversity of the initial population will decrease, which is not conducive to the evolution of the population. After multi-test, we set the direction parameter P to 16 and obtained good experimental result (Wang & Lin, 2017).

$$P = \frac{P_1}{P_2} = 16$$

$$P_1 = \frac{16}{51} + \frac{16}{51} + \frac{16}{51} = \frac{48}{51}$$

$$P_2 = \frac{1}{51} + \frac{1}{51} + \frac{1}{51} = \frac{3}{51}$$

Let the *U*(*ux*, *uy*, *uz*) be the starting point coordinate and the *V*(*vx*, *vy*, *vz*) as the goal point coordinate. The spatial position of any two points in the layout space can be summarized into 8 cases shown in Table 1. Table 2 lists the probability values of each position in different direction when the direction parameter P=16.

Table 1: Relative positions of starting point and goal point of SPLD

Position	*X* direction	*Y* direction	*Z* direction
1	$ux \leq vx$	$uy \leq vy$	$uz \leq vz$
2	$ux \leq vx$	$uy \leq vy$	$uz \geq vz$
3	ux ≤ vx	uy ≥ vy	uz ≤ vz
4	ux ≤ vx	uy ≥ vy	uz ≥ vz
5	ux ≥ vx	uy ≤ vy	uz ≤ vz
6	ux ≥ vx	uy ≤ vy	uz ≥ vz
7	ux ≥ vx	uy ≥ vy	uz ≤ vz
8	ux ≥ vx	uy ≥ vy	uz ≥ vz

Table 2: Probabilities of six running directions

Position	*x*	*-x*	*y*	*-y*	*z*	*-z*
1	16/51	1/51	16/51	1/51	16/51	1/51
2	16/51	1/51	16/51	1/51	1/51	16/51
3	16/51	1/51	1/51	16/51	16/51	1/51
4	16/51	1/51	1/51	16/51	1/51	16/51
5	1/51	16/51	16/51	1/51	16/51	1/51
6	1/51	16/51	16/51	1/51	1/51	16/51
7	1/51	16/51	1/51	16/51	16/51	1/51
8	1/51	16/51	1/51	16/51	1/51	16/51

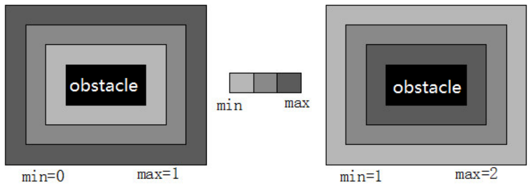
2.5 REGIONAL MODEL OF LAYOUT

The regional model of a ship pipeline layout consists of a state value model and an energy value model. The state value model is used to determine whether the pipeline can be arranged in this region. The energy value model is used to determine whether the region is suitable for the layout of the pipeline. In the pipeline layout design, the cabin space to be arranged is usually divided into two categories: the layout region and the forbidden layout region. In the cabin space, the forbidden layout region refers to the area which can not be arranged because of the cabin environment or the pipeline functional characteristics. The mentioned areas outside the cabin space and obstacles are prohibited regions.

In order to distinguish the forbidden area from the configurable area, each grid node is given a state value. The size of the grid node state value is used to determine whether the grid node is located in the forbidden layout area, and then to determine whether the pipeline can pass through the area. In this paper, the state value of the grid node in the forbidden layout area is set to 1, while the state value of the grid node in the configurable region is 0.

According to the layout requirements and functional characteristics of the pipe to be arranged, as well as the cabin space environment, the energy value method divides the cabin space to be arranged into different energy regions, and gives these energy regions different energy values. Then based on the energy value, the computer can judge whether the area is suitable for pipeline layout. In this paper, the energy region model is established by giving each grid node energy value. In the design of pipeline layout, the smaller the energy value, the greater the priority weight of the node; and the smaller the energy value of the grid node, the more suitable it is to arrange the pipeline. Because the pipeline is usually arranged along the bulkhead or obstacle, the energy value of the area near the bulkhead or obstacle is smaller than that of other areas. According to the layout rules and constraints of the pipeline, the layout space can be divided into dominant area, transition area, general area and forbidden area according to the difference of energy value. The energy value increases gradually from the minimum energy value of the dominant area to the maximum value of the general area, and the state value of the grid node is set at the same time.

For SPLD in 3D space, main constraints are obstacles divided into two categories shown in Figure 4. Figure 4(a) is obstacle surface with low node energy value *e* such as wall, supporter and pipe routes laid. Figure 4(b) is obstacle surface with high node energy value *e* including heat sensitive region. Pipe route is expected to lay closely to the former obstacle surface and keep away from the latter.



（a） （b）

Figure 4: Energy zone around obstacles for pipeline to (a) desire and (b) reject

2.6 LAYOUT OPTIMISATION MODEL

Pipeline layout design is automatically searching a path with minimum length from the start location to the ending locationm, meanwhile, different kinds of constraint conditions in aspects of physics, economy, safety and regulations, manufacture and installation, operation and maintainance are satisfied. For single pipeline, main task is to find a path with minimum length and elbows (Kimura, 2017). Besides, state value *o* of all nodes should be 0 and energy value *e* should be kept as lower as possible. So the path is determined around obstacles of the first category. A fitness function is defined for single pipe optimisation design as the following:

$$fitness(p) = e^{-(a \cdot L(p) + b \cdot B(p) + c \cdot E(p) + d \cdot O(p))} \quad (3)$$

Where

$$L(p) = \sum_{i=1}^{n} (node_i, node_{i+1}), \quad E(p) = \sum_{i=1}^{n} e_i$$

$L(p)$ denotes the path length. $B(p)$ denotes the number of elbows on path. $E(p)$ represents the total energy value of path p, and e_i is the energy value on node i of path p. $O(p)$ is penalty function, representing the number of nodes located on the forbidden regions (namely obstacles) on path p. a, b, c, d are their weights respectively. According to the fitness function introduced, the pipe route is more preferred when fitness value is higher.

3. THE PSOIG ALGORITHM FOR SHIP PIPELINE LAYOUT DESIGN

3.1 THE PSOIG ALGORITHM

Particle Swarm Optimisation (PSO) is an unconstrained optimisation algorithm proposed by Kennedy and Eberhart (1995). It uses the characteristics of bionics to simulate the trajectory of birds in nature when looking for food. Scientists have found that birds can find food efficiently and quickly in the process of foraging, that is, first find the area around the individual closest to the food, through the cooperation of the group, constantly adjust, correct the location and direction of flight, until the location of the food is found (Wang *et al*., 2013). This behaviour among birds provides a powerful biological basis for human to construct of PSO framework. Because of its simple concept and few parameters, PSO is a convenient and efficient group search optimisation method with fast convergence speed, it has been paid more attention by many scholars. The mathematical description of PSO is generally as follows.

Suppose the solution space of the solved problem is D dimension, the number of particles is N, they are initialized as $X=(x_1,x_2,x_3,...x_N)$, the position of the particle i in the iteration k process can be expressed as a vector $x_i=(x_{i1},x_{i2},x_{i3},...x_{iD})$, the speed is expressed as a vector $v_i=(v_{i1},v_{i2},v_{i3},...v_{iD})$, each iteration requires a new round of evaluation of the fitness values of individual particles. Define the position of the optimal fitness value of the particle i at the moment T as the individual extremum $pbest_i=(pbest_{i1},pbest_{i2},pbest_{i3},...pbest_{iD})$. At this time, the position of the entire population with historical optimal fitness value during evolution is defined as the global extremu $gbest_i=(gbest_{i1},gbest_{i2},gbest_{i3},...gbest_{iD})$. The specific calculation formula is as follows.

$$pbest_i=\begin{cases} pbest_i(k-1),\ f(x_i(k)) \geq f(pbest_i(k-1)) \\ x_i(k),\ f(x_i(k)) < f(pbest_i(k-1) \end{cases} \quad (4)$$

$$gbest(k)=\arg\min\{f(gbest(k-1)),\ f(x_1(k)),...f(x_N(k))\} \quad (5)$$

The following two expressions are used to update the speed and position of each particle separately.

$$v_{ij}(k+1)=wv_{ij}(k)+c_1r_1(pbest_{ij}(k)-x_{ij}(k))+c_2r_2(gbest_j(k)-x_{ij}(k)) \quad (6)$$

$$x_{ij}(k+1)=x_{ij}(k)+v_{ij}(k+1) \quad (7)$$

Where: w represents the inertia weight; c_1 and c_2 represents learning factors or accelerating factors, generally set to constants in the interval (0, 2), respectively representing the ability of the particles to self and social cognition; r_1, r_1 usually referred to as a random number in the interval [0,1], used to maintain diversity during evolution; k is the current number of iterations.

Genetic Algorithm (GA) is based on natural selection. GA is an optimisation method in line with the law of survival of the fittest in species' evolution. It's proposed first by Holland in 1975 (Holland, 1975). Due to its vast search field, strong search capability, simplified calculation process, parallelism and expandability, GA is widely applied in various engineering field (Dong *et al*., 2020).

PSO is simple, fast and easy to realize, convergence occur early in the later stage (Das *et al*., 2016, Hu *et al*., 2020). GA has a unique efficiency in the search of global optimal solution, but it has a deficiency in local search ability (Zhang & Zhang, 2020). PSO and GA have strong complementary in optimisation. GA has strong exploration accuracy and variable ability, and good global search ability, but its local search ability is insufficient, while PSO algorithm has random characteristics in the global optimisation algorithm, and the function of the optimisation objective does not require analytic ability. In this paper, an improved particle swarm optimisation-PSOIG algorithm is presented. The crossover operator of GA is introduced into PSO, so that the paired particles can exchange information with each other, and make particles have the ability to fly to new search space. At the same time, in order to enhance the ability of PSO to jump out of local solution, the mutation operation of GA is introduced into PSO. This new method not only enhances the global search ability of particles, but also improves the convergence rate.

3.2 ENCODING

In SPLD, work space model of cabin is divided into 3D cubic grid cells. Each node has a unique special coordinate sequence number (x, y, z). Pipelines from start point to goal points will go through these nodes, and in return, these nodes line up together to form these pipelines. Therefore, float-point number encoding is selected in the PSOIG algorithm. Each particle swarm includes a string of coordinates and represents a pipeline. The encoding of particle swarm is shown in Figure 5.

x_1,y_1,z_1	x_2,y_2,z_2	x_3,y_3,z_3	$\cdots$	x_n,y_n,z_n

Figure 5: Particle swarm encoding

3.3 INHERITANCE STRATEGY

In this paper, the solution for each pipeline is obtained using PSOIG algorithm. The PSOIG algorithm selects operators through roulette and elitism selection rules. Each particle selected performs crossover operations with the global and local optimal particles in PSO. Then the two hybrid particles are randomly selected for mutation operation.

Crossover operation adopts the random point crossing method, shown in Figure 6, which based on asymmetric single point hybridization strategy to prevent the creation of illegal individuals. Asymmetry means that the individual chromosome length of the individual hybridization does not have to be equal, and the hybridization does not have to be in the same position. Individuals with greater fitness after crossover operation will be selected into the next generation population.

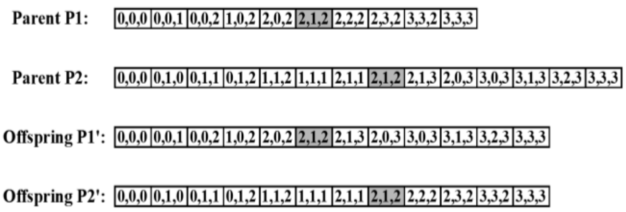


Figure 6: Crossover mode

Mutation operator can determine the way of chromosome transforms, and mutational operation is an important means to keep colony diverse and avoid premature. The PSOIG algorithm proposed in this paper adopts random point mutation mode, viz. randomly choose two nodes except start point and goal points, and then replace the sub-pipeline between to achieve mutational operation, shown in Figure 7.

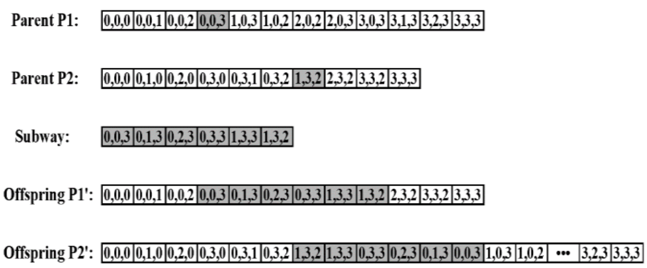


Figure 7: Mutation mode

Two methods can be used as the stopping criterion: One is to use the maximum iteration number as the stopping criterion of PSOIG algorithm, and another is to use the no-evolutionary generations as the stopping criterion.

The flowchart of proposed PSOIG algorithm is shown in Figure 8.

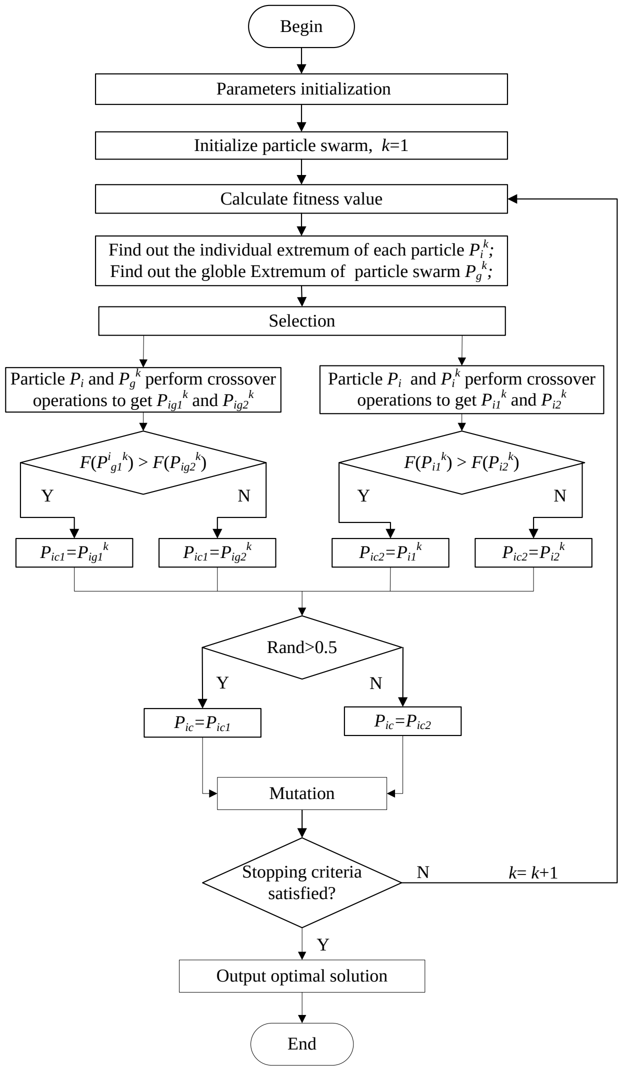


Figure 8: Flowchart of PSOIG algorithm

4. SIMULATION AND RESULTS

The proposed PSOIG algorithm for SPLD is simulated with two kinds of tested model spaces using the Matlab compiler on an Intel-i3 3.5GHz computer. In order to test and observe the feasibility and effectiveness of the proposed algorithm, this section selects two numerical models used in similar subject papers (Fan *et al*., 2007c) as the research object to facilitate the comparison of experimental results.

4.1 SIMULATION MODEL DESCRIPTION

Two model spaces are used in this simulation, namely Model A and Model B which were used in literature Fan et al. (2007c). Their diagonal coordinates are (0,0,0), (19,19,19) and (0,0,0), (49,49,49), respectively. The first one is divided into 19×19×19 cube units, and the second 49×49×49. In Model A, eight obstacles are scattered. The diagonal coordinates of them are (0,2,0), (2,8,5); (4,2,0), (10,8,5); (2,11,0),(9,17,10); (13,8,0), (19,14,8); (13,17,0), (19,19,5); (0,3,14), (3,10,17); (16,0,11), (19,9,16); (0,16,16), (7,19,19), respectively. Points (0,19,0) and

(19,0,19) are the coordinates of the starting point and ending point of the pipeline. Seven obstacles are set in Model B which is larger than Model A. The diagonal coordinates of these obstacles are (0,4,0), (20,16,10); (30,0,35), (49,15,49); (4,30,0), (18,40,25); (30,10,0), (45,24,20); (26,38,0), (38,46,25); (0,0,34), (10,20,49); (40,20,30), (49,49,40), respectively. The would-be-routed pipe will travel from the starting point (0, 0, 0) toward the ending point (49, 49, 49). The parameters of simulation experiments are obtained by experience (Fan *et al*. 2007c) and a large number of experiments, shown in Table 3. In this simulation, experiments are implemented 10 times for each algorithm. The maximum number of iterations o is set as 150 for Model A, and 500 for the Model B.

Table 3: Parameters of calculation for the test algorithm

Parameter	Values
Fitness function parameters	a=0.003,b=0.003, c=0.004, d=20
Number of particles	N=50
Number of runs of each algorithm	10
Maximum number of iterations	Model A: 150, Model B: 500
Fixed non-evolution generation	20
Mutation probability parameters	0.05

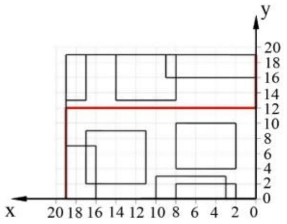
4.2 SIMULATION RESULTS

The overall results obtained are listed in Table 4 and Table 5. The best value means the best solution found in the 10 runs, and the averaged value collects the average of 10 best solutions generated in the 10 trials. The averaged convergence number of generations represents the average times of iteration when the algorithms converge to the best across the 10 conducted trials. The percent of convergence to optimum indicates the times of the algorithms converging to the optimal solutions out of the 10 trials. The average running time of each algorithm per 150 (500) generation is provided by the averaged CPU time (sec)/150 (500) generation. Figure 9 and Figure 10 showed the final results of the ship pipeline layout.

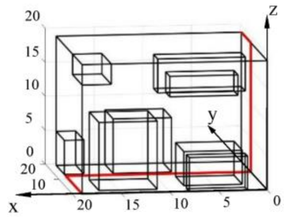
Table 4: Comparison of simulation results for model A

Subjects	PSOIG	Literature algorithms		
		AS	ACS	ACOIPU
Best value of the Obj(p)	61	61	61	61
Averaged convergence number of generation	19.5	67.1	39.9	41.2
Percent of convergence to optimum (%)	80	60	60	90
The averaged CPU time (sec)/150 generation	17.53	129.2	26.5	23.2

AS=Ant System; ACS=Ant Colony System; ACOIPU= Ant Colony Optimisation with Iterative Pheromone Updating



(a)



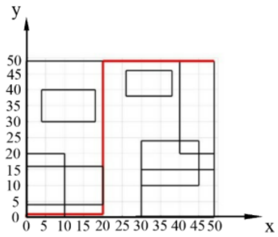
(b)

Figure 9: The top view (a) and front view (b) of Model A pipe layout by PSOIG algorithm

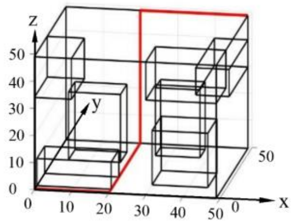
Table 5: Comparison of simulation results for model B

Subjects	PSOIG	Literature algorithms		
		AS	ACS	ACOIPU
Best value of the Obj(p)	151	151	151	151
Averaged convergence number of generation	42.5	233.3	224	228.7
Percent of convergence to optimum (%)	80	80	70	90
The averaged CPU time (sec)/500 generation	448.9	2137	591.3	517.2

AS=Ant System; ACS=Ant Colony System; ACOIPU= Ant Colony Optimisation with Iterative Pheromone Updating



(a)



(b)

Figure 10: The top view (a) and front view (b) of Model B pipe layout by PSOIG algorithm

From Table 4 and Table 5, it is evident that the results obtained by the proposed algorithm are much better than those of AS, ACS and ACOIPU. These algorithms all could find the optimal solutions during the set times of iterations for the 10 time trials, but the averaged convergence number of generation and the averaged CPU time from the proposed PSOIG algorithm are best ones among them. It is illustrated that the optimum search efficiency of the proposed algorithm is highest. At the same time, the percentage of convergence to optimum of the proposed algorithm is stable and good, namely 80%.

By analyzing the simulation results and performance comparison of ship pipeline layout, it can be seen that the PSOIG algorithm has good operation effect, the pipeline can effectively avoid obstacles, maintain orthogonal attitude, and can meet the constraints of pipeline layout. The optimal solution can be found quickly within the set number by the proposed algorithm. Through the comparison with the results of similar topic papers, we can see that the average convergence iteration of PSOIG algorithm is greatly improved compared with other algorithms. Combined with the simulation results, PSOIG algorithm is good in terms of search performance and convergence speed.

5. CONCLUSIONS

With the development of computer technology and intelligent algorithm, there is a strong demand for intelligent layout design of ship pipeline in order to further improve the quality and efficiency of ship design. Ship pipeline layout design in 3D space is a multi-objective combination optimisation problem with various constraints of performance. In this paper, a layout space model, an obstacle model, and a regional model of layout are established for ship pipeline layout space structure, and the direction guidance mechanism of ship pipeline automatic layout is introduced. Then the crossover and mutation strategy of genetic algorithm is introduced into PSO to form a new PSOIG algorithm. Finally, the feasibility of the presented algorithm in solving the pipeline layout problem is verified by simulation experiments, and through the comparison and analysis of the results with the similar research literature, such as the averaged CPU time (sec)/150 generations saved more than 24%. The advantages of the proposed algorithm are verified. The research results of this paper can be used for reference in the future research of ship intelligent design. The future work will aim to improve the proposed method and apply it to the intelligent layout of ship branch and parallel pipelines to meet the needs of practical engineering design.

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