Genetic Algorithm Optimization in Ship Rapid Loading Planning

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With the rapid development of the global shipping industry, the planning of ship rapid loading is of great significance to improve the transportation efficiency and reduce the cost. In order to enhance the efficacy of ship fast loading planning, the simulated annealing algorithm is employed subsequently to the genetic algorithm, crossover, and mutation operations. The solution generated by the genetic algorithm is regarded as the initial solution of the simulated annealing algorithm to develop a hybrid algorithm, which will then be applied to the ship fast loading planning model. The results showed that compared with the comparison algorithm, the loss value and prediction fitting coefficient of the optimized genetic algorithm were 0.003 and 0.9632, respectively, which were better than the comparison algorithm. In addition, in the empirical analysis of the proposed ship rapid loading planning model, it was found that the maximum planning satisfaction rate of this model was 87.2%, which was better than the comparison algorithm. Its planning time was 12.1 s, which was significantly lower than the 31.2s of genetic algorithm model and 27.6s of ant colony optimization model. The above results indicate that the optimized genetic algorithm has good planning performance in the ship rapid loading planning, and has a good application prospect. This study provides a new way to solve the optimization problem in the field of ship transportation

Povzetek: Raziskava uporablja genetski algoritem in simulirano ohlajanje za optimizacijo načrtovanja hitrega nalaganja ladij, kar izboljša učinkovitost in zmanjša stroške prevoza.

1 Introduction

The rapid loading planning of ships is a crucial part of the shipbuilding process. A reasonable sequence of hull section loading can improve manufacturing efficiency, reduce manufacturing costs, and ensure the structural stability and quality safety of the hull [1, 2]. However, due to the complexity and diversity of ship rapid loading planning, determining the optimal loading plan is often challenging [3]. In the research of ship rapid loading planning, traditional planning methods often face problems such as large search space, low solving efficiency, and unstable results [4, 5]. In response to these issues, the study proposes the use of Genetic Algorithm (GA) for optimizing the rapid loading planning scheme of ships. As an optimization algorithm, GA can simulate the process of evolution and find potential optimization solutions in large-scale search spaces. Therefore, it has been widely applied in optimization problems in multiple fields [6-8]. The research aims to improve the efficiency of solving ship rapid loading planning problems by optimizing GA, and provide an efficient and accurate decision support tool for shipping enterprises. The innovation of the research is to improve the encoding method of GA, optimize crossover and mutation operations, and design adaptive selection strategies to enhance the adaptability and feasibility of ship rapid loading planning schemes. The objective of this study is to develop an efficient and accurate tool for ship rapid loading planning and decision-making for ship manufacturing enterprises. This tool is expected to enhance the efficiency and quality of ship manufacturing, reduce manufacturing costs, and enhance the competitiveness and market share of enterprises. The first part of the study briefly describes scholars' exploration of the application of GA and ship manufacturing issues in recent years. The second part elaborates on the optimization of GA and the optimization of ship rapid loading planning based on optimization algorithms. The third part is the performance comparison of optimized GA and the application effect analysis of ship rapid loading planning scheme. The fourth part makes an in-depth analysis and comparison of the research results. The final part is to summarize the entire study.

2 Related works

With the rapid development of science and technology, GA, as an optimization algorithm, is increasingly used in various fields. Its unique optimization ideas and adaptive search capabilities enable GA to solve many practical problems, especially those with complex constraints and high-dimensional search spaces. Nasrabadi et al. lacked research literature on parameter analysis and optimization of output power density, and designed a model based on GA and neural network particle swarm algorithm. After comparative experiments, the results showed that using this model increased power density by 46% [9]. Pongen et al. proposed an alloy theoretical density and experimental density prediction model based on GA grain refiner to address the issue of poor casting performance caused by density hysteresis in the aluminum alloy die-casting process. After empirical analysis, the results showed that the model was feasible [10]. The Owoyele team proposed a GA-based automatic active learning method to solve manual hyperparameter setting in computational fluid dynamics simulation technology based on machine learning proxy models. After comparative analysis, the results showed that this method can achieve better optimization results [11]. Ameer et al. proposed a hybrid GA-based setting and process planning constraint scheme to address the high cost of setting and process planning constraints in traditional reconfigurable manufacturing systems. After empirical analysis, the results showed that this scheme was practical and effective, improving economic benefits [12].

As science and economy develop, many high-tech applications have been made in shipbuilding. For example, Breuer proposed a new horizontal folding mechanism to address the issue of large widths of catamarans and trimarans leading to problems at docks. After simulation analysis, the results showed that this mechanism was simpler and more stable than many existing mechanisms [13]. Guan et al. proposed a simulation analysis method for engineering constrained assembly using an improved coherent point drift algorithm and Analytic Hierarchy Process (AHP) to address the issue of low assembly efficiency of ship blocks. After comparative analysis, results showed that this method reduced the workload of workers and improved the efficiency and quality of shipbuilding [14]. Li proposed a welding process based on friction stir welding to address the limitations of using metal inert gas welding technology in ship construction. After empirical analysis, the results showed that this welding process was effective for the connection of materials such as steel, titanium, lead, copper, and aluminum, among which the connection of aluminum was particularly advantageous [15]. The Vakil team proposed an energy management framework based on multiple decision criteria to improve energy efficiency in the shipbuilding industry, and applied the framework to practical cases for research. The results showed that the framework can effectively improve energy efficiency while improving the productivity and profitability of shipyards [16].

Table 1 is a research summary table organized according to relevant research content.

Table 1: Summary of relevant studies

Author	Year of publication	Method	Application field	Key result
Nasrabadi and Moghimi [9]	2022	Model based on GA and neural network particle swarm algorithm	Output power density optimization	Power density increased by 46%
Pongen et al. [10]	2022	Prediction model based on GA	Aluminum alloy die casting process	The model is feasible
Owoyele et al. [11]	2022	Automatic active learning method based on GA	Computational fluid dynamics simulation techniques	Get better optimization results
Ameer and Dahane [12]	2023	Hybrid GA-based setup and process planning	Reconfigurable manufacturing system	The scheme is practical and effective to improve economic benefit
Breuer [13]	2021	Horizontal folding mechanism	berth	The technical structure is simpler and more stable
Guan et al. [14]	2021	Improved coherent point drift algorithm and analytic hierarchy process	Hull assembly efficiency	Improve the efficiency and quality of shipbuilding
Li [15]	2022	Welding process based on friction stir welding	Ship welding technology	It is effective for the connection of various materials, especially for the connection of aluminum
Vakil et al. [16]	2022	Energy management framework based on multi-decision	Energy efficiency in shipbuilding	Effectively improve energy efficiency, productivity and

	criteria	profitability

As illustrated in Table 1, although GA has been demonstrated to possess optimization capabilities in a multitude of fields, its application in the context of ship fast loading remains relatively scarce. Currently, there is a paucity of research on the utilization of GA in the field of ship rapid loading planning. This study aims to address this gap and introduce a novel optimization method for the ship manufacturing industry. As evidenced by Table 1, there is scope for enhancement in the conventional ship carrying approach. The application of GA can facilitate the identification of more efficient loading schemes, thereby enhancing the speed and quality of ship construction. In addition, the effect of the existing GA application in ship loading is general, and the loading efficiency needs to be improved. The SA-GA hybrid algorithm proposed in this study demonstrates the potential to enhance the planning efficacy of the GA, thereby optimizing the efficiency of ship loading operations. This approach may serve as a valuable reference for other industries.

3 Ship rapid loading planning based on optimized GA

Ship rapid loading and unloading planning refers to the process of optimizing the loading sequence and location of ship cargo during ship loading and unloading operations, in order to maximize loading and unloading efficiency and reduce operation time. In order to facilitate more efficient planning of rapid loading of ships, an optimization GA integrating a simulated annealing algorithm is proposed in this chapter. The optimization GA is then applied to the planning process of rapid loading of ships.

3.1 Optimized GA based on simulated annealing algorithm

The optimization problem of ship rapid loading planning is a complex and challenging problem, which involves the optimization of multiple factors and constraints [17]. Due to its advantages such as global search ability, parallel computing ability, and wide applicability, GA can be applied to the optimization problem of ship rapid loading planning [18]. GA draws on Darwin's natural selection and genetic crossover and mutation principles to solve optimization problems. This algorithm simulates the natural evolution process and evolves through a population approach. In each iteration, individuals are evaluated based on the fitness function, and excellent individuals are selected for crossover and mutation to generate new individuals [19]. The basic process of GA is shown in Figure 1.

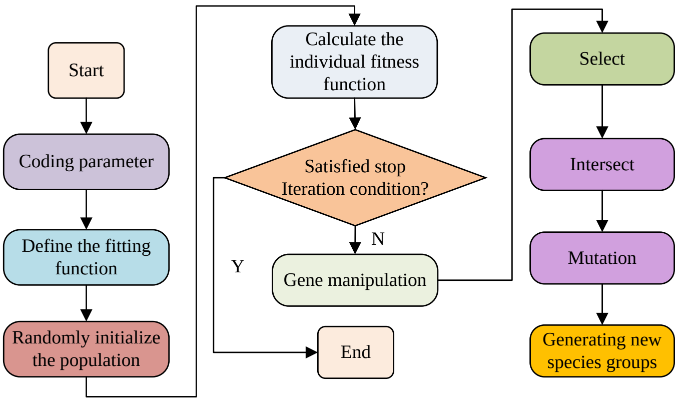

Figure 1: Flow chart of GA

In Figure 1, the operation process of GA mainly includes encoding, design of fitness functions, selection, crossover, mutation, and other operations. In the encoding operation, the binary encoding method is chosen for this study, and the encoding expression is shown in equation (1).

$$\begin{cases} \underbrace{000\cdots000}_{m\ individual} = 0 \rightarrow T_{\min} \\ \underbrace{000\cdots001}_{m\ individual} = 1 \rightarrow 1 \\ \underbrace{111\cdots111}_{m\ individual} = 2^m - 1 \rightarrow T_{\max} \end{cases} \tag{1}$$

In equation (1), $T_{\max}$ represents the maximum parameter value. $T_{\min}$ represents the minimum parameter value. m represents the encoding length. The calculation for encoding accuracy at this time is shown in equation (2).

$$\partial = \frac{T_{\max} - T_{\min}}{2^m - 1} \quad (2)$$

In the process of designing the fitness function, when optimizing the objective function $f(x)$ to solve the maximum problem, the fitness function $fit(f(x))$ is shown in equation (3).

$$fit(f(x)) = \frac{1}{c_{\max} - f(x)} \quad (3)$$

In equation (3), $c_{\max}$ represents the maximum value of the objective function. When optimizing the objective function $f(x)$ to solve the minimum problem, the fitness function $fit(f(x))$ is shown in equation (4).

$$fit(f(x)) = \frac{1}{f(x) - c_{\min}} \quad (4)$$

In equation (4), $c_{\min}$ represents the minimum value of the objective function. During the selection process, the fitness function generates fitness values $f(x_i)$ for each individual, with $i = 1, 2, \cdots, n$ representing the population size. Then the sum F of all individual fitness values is calculated using equation (5).

$$F = \sum_{i=1}^{n} f(x_i) \quad (5)$$

Then the selection probability and cumulative probability are calculated for each chromosome using equation (6).

$$\begin{cases} p_i = \dfrac{f(x_i)}{F} \\ q_i = \sum_{j=1}^{n} q_j \end{cases} \quad (6)$$

In equation (6), $j = 1, 2, \cdots, d$. d represents the number of iterations. After selection, a uniform crossover operation is performed on the parent individuals to generate new individuals through the combination of genes. Afterwards, a mutation operation is performed on the new individual, introducing randomness in a non-uniform manner to increase population diversity. The x'_m value rules for the mutation positions x_m after non-uniform mutation are shown in equation (7).

$$x'_m = \begin{cases} x_m + \Delta(t, x_{\max}^m - \lambda_m), random(0,1) = 0 \\ x_m - \Delta(t, \lambda_m - x_{\min}^m), random(0,1) = 1 \end{cases} \quad (7)$$

In equation (7), $x_{\min}^m$ represents the minimum gene value at the mutation position x_m. $x_{\max}^m$ represents the maximum gene value at the mutation position x_m. λ_m is a random number in $[x_{\min}^m, x_{\max}^m]$. Although GA has a wide search range and the advantages of adaptability and self-learning, in practical applications, due to its probabilistic operation and uncertain search direction, it is easy to fall into local optimal solutions. The Simulated Annealing algorithm (SA) has good local optimization ability, but is poor in global optimization [20]. Therefore, combining SA and GA can avoid the shortcomings of both algorithms. SA is an optimization algorithm based on the principle of solid annealing, whose basic idea is to simulate the annealing process of solid heating followed by gradual cooling. Figure 2 depicts the analogy between SA and the solid annealing process.

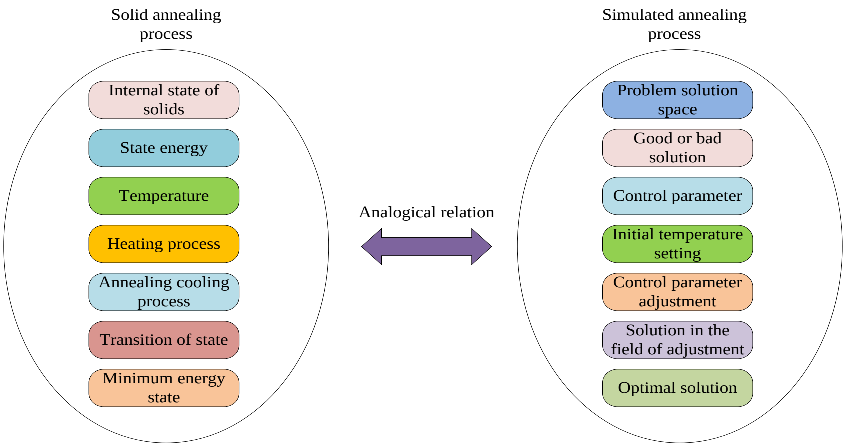

Figure 2: Analog relationship between simulated annealing algorithm and solid annealing process

At the beginning of SA, an initial solution is randomly selected and its corresponding objective value is calculated through the objective function. Then, the algorithm will randomly generate new solutions within the neighborhood of the current solution and calculate the corresponding target value. The neighborhood generation is shown in equation (8).

$$x_{new} = x_{current} + \varepsilon \quad (8)$$

In equation (8), $x_{current}$ represents the current solution. x_{new} indicates a new solution. ε represents a small random disturbance. The new solution is accepted as the current solution if its target value is better. Otherwise, the new solution is accepted with a certain probability, which is usually related to the difference in target values and temperature. This criterion is called the Metropolis acceptance criterion, and its expression is shown in equation (9).

$$P(accept) = \min 1, \frac{f(x_{new})}{f(x_{current})} \quad (9)$$

In equation (9), $f(x_{new})$ and $f(x_{current})$ represent the objective function values of the new solution and the current solution, respectively. As the algorithm iterates, the temperature will gradually decrease, and the probability of accepting a worse solution will also gradually decrease until the temperature drops to the preset minimum value and the algorithm terminates. In SAs, the temperature gradually decreases as iteration increases. The temperature update is shown in equation (10).

$$T_{new} = \alpha T_{current} \quad (10)$$

In equation (10), $T_{current}$ represents the current temperature. α is the cooling coefficient. The advantage of SA is that it can avoid falling into local optima and have the opportunity to find global optima. At the same time, it has little dependence on the initial solution and has a certain degree of robustness. The SA-GA hybrid algorithm proposed in this study mainly follows the genetic, crossover, and mutation operations of GA, followed by the SA algorithm. Treat the solution generated by GA as the initial solution in SA, and then perturb to generate a new solution. If the objective function of the new solution is better, the current solution is replaced. Firstly, the initial temperature, termination temperature, and number of internal loop iterations of the SA algorithm are set based on the set parameters, and the current individual of GA is used as SA's initial solution, then the internal loop of the SA algorithm is started. The increment of its objective function and objective function is calculated. The objective function increment is calculated in equation (3).

$$\Delta f = f(\omega') - f(\omega) \quad (11)$$

In equation (11), ω represents the initial solution. ω' indicates possible planning options. $f(\omega')$ represents the objective function of possible planning solutions. $f(\omega)$ represents the objective function of the initial solution. The SA-GA basic process is shown below.

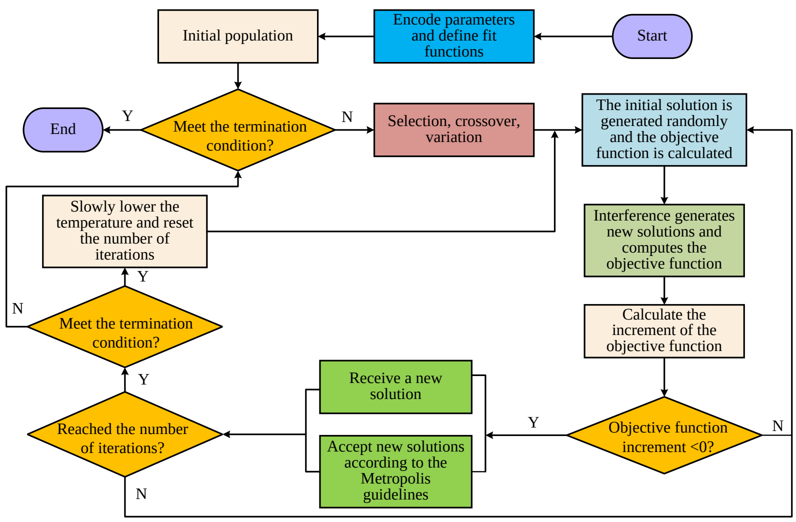

Figure 3: Flowchart of SA-GA

Figure 3 shows the running flowchart of the SA-GA. If the increment of the objective function is less than 0, the current solution is updated to a new solution, otherwise the current solution is accepted as a new solution according to Metropolis probability. The above operation is repeated until the number of inner loop iterations is met. After exiting the inner loop, whether the outer loop termination condition is met is determined. If not, it is cooled down to update the external circulation temperature, the new temperature is the product of the current temperature and annealing rate, and then the internal circulation is restarted. If the outer loop termination condition is met, the search is terminated. Finally, it is determined whether the current iteration count of GA reaches the set maximum iteration value. If so, the overall solution process will end and the optimal solution will be output. If it is not reached, iteration is continued from the selection operation.

3.2 Ship rapid loading planning optimization based on optimized GA

Ship rapid loading planning refers to the efficient and reasonable planning and optimization of the cargo loading process of a ship. The goal is to ensure that ships complete the loading and unloading of goods safely and efficiently in the shortest possible time, thereby improving the efficiency and economic benefits of the entire shipping process. Ship rapid loading planning involves the efficiency and economy of ship transportation. When carrying out ship rapid loading planning, multiple factors need to be comprehensively considered to ensure the safety of navigation, the integrity of goods, and the efficiency of transportation. The important factors affecting the rapid loading planning of ships are shown in Figure 4.

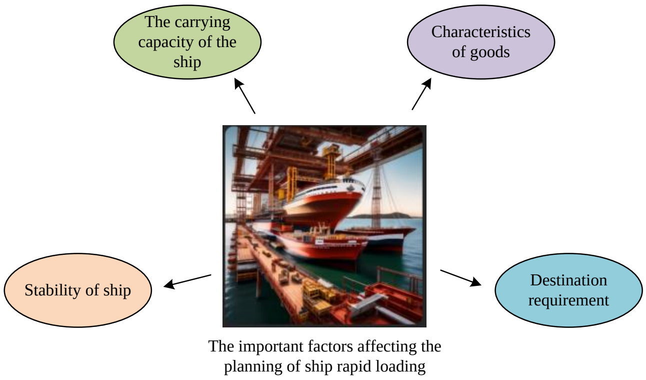

Figure 4: Important factors affecting the planning of rapid loading of ships

As shown in Figure 4, the most important influencing factors in ship rapid loading planning mainly include ship stability, ship load capacity, cargo characteristics, and destination requirements. The stability of ships is a factor that cannot be ignored in loading planning. By reasonably arranging the loading position and weight distribution of goods, the stability of the ship during navigation can be ensured. The ship stability is shown in equation (12).

$$GM = \frac{\sum(\omega_i \times z_i)}{\sum \omega_i} \tag{12}$$

In equation (12), GM represents the initial metacentric height of the ship. ω_i indicates the weight of the i cargo or equipment. z_i represents the vertical coordinate of the i cargo or equipment. Its application can help planners calculate the initial metacentric height of ships, judge their stability under different loading conditions, and take corresponding adjustment measures. Secondly, the load-bearing capacity of ships is also an important constraint in loading planning. To ensure the safety of navigation, the total loaded weight of a ship cannot exceed its deadweight tonnage. By making reasonable use of the ship's load-bearing capacity, the loading capacity of goods can be maximized and transportation efficiency can be improved. The ship load capacity is shown in equation (13).

$$\sum \omega_i \le DWT \tag{13}$$

In equation (13), $\sum \omega_i$ represents the total weight of all goods and equipment. DWT represents the deadweight tonnage of a ship. Its application can help planners monitor the total weight during the loading process, avoid overloading, and ensure that ships are transported within legal and compliant limits. In addition, rapid loading planning also needs to consider the characteristics of the goods and the requirements of the destination. Different goods have different sizes, weights, and transportation requirements, and need to be reasonably arranged in the loading plan. At the same time, according to the needs of the destination and the limitations of transportation time, suitable loading plans and routes can be selected to provide efficient and reliable transportation services. A comprehensive consideration of factors such as ship stability, load capacity, and cargo characteristics allows for the development of a fast, efficient, and safe loading plan. This will help improve the transportation efficiency of ships, reduce transportation costs, and ensure that goods arrive at their destination safely and on time. In order to better optimize ship rapid loading planning, the SA-GA is applied to it. The optimization process of ship rapid loading planning based on SA-GA is shown below.

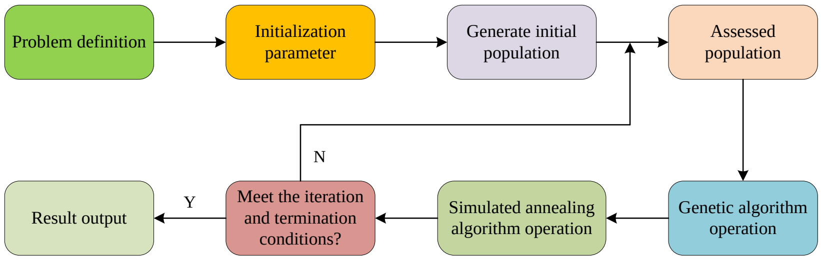

Figure 5: Optimization process of ship rapid loading planning based on SA-GA

From Figure 5, the optimization process for ship rapid loading planning based on SA-GA includes eight steps. The first step is to clarify the objective function and constraint conditions for ship loading planning. Then initialize the parameters, which mainly include the population size, crossover probability, mutation probability of GA, as well as the initial temperature and cooling coefficient of SA. The third step is to generate an initial population using GA. Each individual represents a ship loading plan. Then, the fitness function evaluates the fitness of each individual in the population. The fifth step is to use GA for selection, crossover, and mutation operations. The sixth step is to generate a new solution using SA and determine whether to accept it. After that, it is determined whether the termination conditions have been met. If the termination conditions have been met, the optimal ship carrying plan is output. If the termination conditions have not been met, the evaluation of population fitness is restarted until the termination conditions are met. This process combines the GA's global search ability with the SA's avoidance of local optima feature, aiming to more effectively solve the problem of ship rapid loading planning. Through this optimized ship rapid loading planning process, not only can the loading efficiency be improved, but also navigation safety can be ensured, achieving maximum economic benefits. In practical operation, the fitness function can be used to further improve the optimization effect, and the fitness expression is shown in equation (14).

$$Fitness = w_1 \times M + w_2 \times W + w_3 \times Z \quad (14)$$

In equation (14), M represents the objective function value. W represents stability indicators. Z represents the load capacity indicator. w_1, w_2, and w_3 represent the weights of M, W, and Z, respectively. This fitness function comprehensively considers the weighted sum of objective function values, stability indicators, and load-bearing capacity indicators, used to comprehensively evaluate the advantages and disadvantages of ship loading schemes.

4 Performance comparison of improved algorithms and analysis of optimization scheme effects

The study utilized SA to improve GA and constructed a corresponding ship rapid loading planning model. To verify the superiority of SA-GA, this chapter not only compared it with the comparative algorithm through simulation analysis, but also applied it to practical scenarios of ship rapid loading, and verified its practical application effect.

4.1 Performance comparison results analysis of optimized GA

Firstly, the performance of the proposed SA-GA was verified. The experiment was conducted in MATLAB and simulated by Simulink. The environment settings are shown below.

Table 2: Environment settings

Parameter variables	Parameter selection
Overall implementation platform	Simulink
Operating system	Windows11
Operating environment	MATLAB
PC side memory	8G
CPU main frequency	3.00Hz
Global procurement unit	GTX-1650
Central Processing Unit	i7 7820X
Data regression analysis system	SPSS26.0

This study selected the Traveling Salesman Problem (TSP) dataset as the comparative experimental dataset. The TSP dataset was constructed based on TSP, and the definition of TSP problem was to find the shortest path to access each city and return to the origin given the distance between a set of cities and each pair of cities. In the TSP dataset, the true values of each edge were determined by the TSP path provided by the Concord solver, and the TSP dataset used this time contains 5000 pieces of data. SA-GA combined the global search of GA and the local fine search of SA. In the SA part, the initial temperature was set to 1000, the temperature drop rate was set to 0.95, and the termination temperature was set to 1 to improve the ability of the algorithm to jump out of the local optimum. The population size was set to 100, the crossover rate to 0.7, and the variation rate to 0.01 in GA. The roulette selection method was used, with the termination condition of reaching 500 generations or meeting the preset accuracy. The selection of the above parameters was aimed at balancing search diversity and computational efficiency, ensuring that the algorithm performs sufficient search in the global domain and gradually focuses on the better solution, so as to accurately compare the performance of the three algorithms in solving the TSP. Firstly, the effectiveness of the improved algorithm was tested, with the shortest path as the optimization objective. The convergence curve of the SA-GA was obtained, and compared with GA and Wolf Pack Algorithm (WPA) algorithms, as shown in Figure 6.

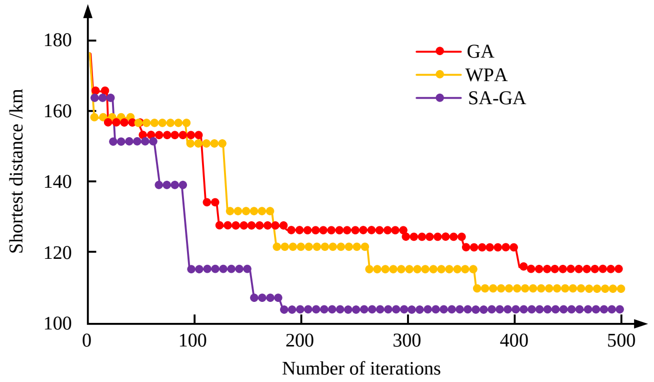

Figure 6: Convergence curves of the three algorithms under the shortest path goal

In Figure 6, the shortest path of the SA-GA after algorithm iteration was 104km. The shortest path after WPA algorithm iteration was 112km, and the shortest path after GA iteration was 118km. This result indicated that after multiple iterations of stable performance, the optimization performance of SA-GA was superior to WPA algorithm and GA. Subsequently, to further compare and analyze SA-GA's performance, comparative experiments were conducted with Ant Colony Optimization (ACO), Differential Evolution Algorithm (DE), and Particle Swarm Optimization (PSO). The TSP dataset was also used, and the loss results and fitting between the evaluation results and the actual results of the four algorithms are shown in Figure 7.

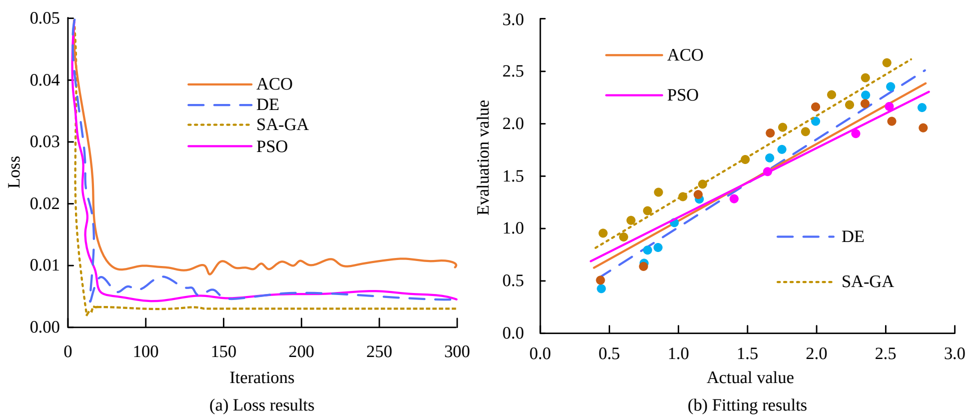

Figure 7: Loss results and fitting results of different algorithms

From Figure 7 (a), the loss curves of all four algorithms showed a decreasing trend as iteration increases, but the overall loss results of the loss curves of ACO, DE, and PSO were greater than those of the SA-GA proposed in the study. The SA-GA only exhibited small microwave fluctuations when the number of iterations was less than 1000, but gradually approached a loss value of 0.003 in the later stage, while the loss values of PSO algorithm, DE algorithm, and ACO algorithm were 0.005, 0.005, and 0.010. In Figure 7 (b), the predicted and measured values of the SA-GA for data evaluation were closer to the fitting curve, with a coefficient of 0.9632, which was greater than the 0.8821, 0.8632, and 0.8532 of PSO, DE, and ACO. The above results indicated that the SA-GA exhibited relatively stable performance. In addition, the study also compared the error and accuracy of four algorithms, as shown in Figure 8.

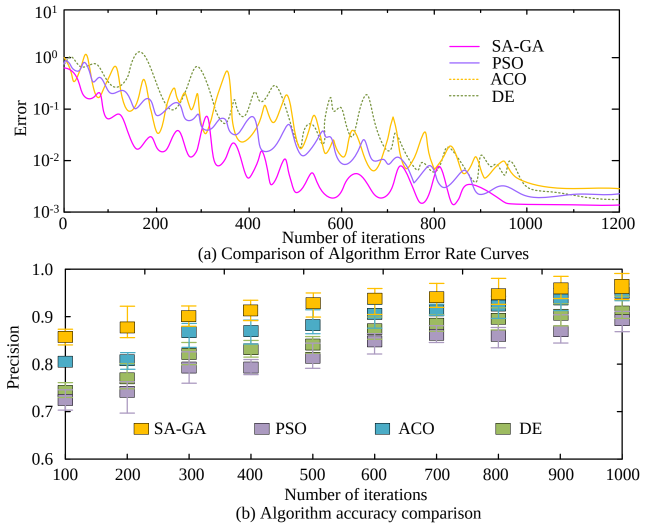

Figure 8: Comparison results of error and accuracy of the four algorithms

In Figure 8 (a), the errors of all four algorithms decreased with the increase of iteration times, with the lowest stable error value of SA-GA being 0.002, which was lower than 0.003 for DE, 0.004 for PSO, and 0.005 for ACO. As shown in Figure 8 (b), the accuracy of all four algorithms increased with the number of iterations, with the highest accuracy of SA-GA being 0.96, which was higher than DE's 0.91, PSO's 0.88, and ACO's 0.94. The above results indicated that from the dimensions of error and accuracy, the performance of the SA-GA proposed in the study was superior to similar algorithms. To comprehensively analyze the robustness of SA-GA, the other five benchmark algorithms, GA, WPA, ACO, DE and PSO, were compared in detail. Performance comparison indexes were primarily comprised of average computing time, standard deviation, sensitivity change, and statistical significance. The specific comparison results are presented in Table 3.

Table 3: Specific comparison results of indicators of different algorithms

Type of algorithm	Average calculation time (s)	Standard deviation	Performance change at +10% parameter (%)	Parameter -10% performance change (%)	P value compared to SA-GA
SA-GA	60.5	0.0005	+0.5	-0.4	/
GA	72.3	0.0008	+1.2	-1.0	0.030
WPA	68.9	0.0007	+0.9	-0.8	0.015
ACO	65.2	0.0009	+1.5	-1.3	0.012
DE	62.8	0.0006	+1.0	-0.9	0.025
PSO	64.1	0.0010	+1.7	-1.4	0.005

In Table 3, the average calculation time of SA-GA was relatively short, which was 60.5 seconds. The standard deviation was the smallest, which was only 0.0005, indicating its stable performance. In the sensitivity analysis with the parameter variation of ±10%, the performance of SA-GA changed the least, showing strong robustness. In addition, the performance indexes of SA-GA and five benchmark algorithms were tested by t statistics. It was concluded that the P-value of all algorithms is less than 0.05, which indicates that the performance indexes of SA-GA are significantly improved compared with other benchmark algorithms.

4.2 Actual planning effect analysis of optimizing GA

After verifying the superiority of the SA-GA, in order to analyze its practical application effect in ship rapid loading planning, the study applied it, along with the GA and ACO algorithm, to four different scenarios of ship rapid loading planning. Scenario 1 was an emergency evacuation scenario. Scenario 2 was a military action scenario. Scenario 3 was the departure of a luxury cruise ship. Scenario 4 was the scene of a scientific research investigation ship going to sea. The actual planning effectiveness of three algorithms was compared by their planning satisfaction rate, planning time, and expert ratings in four different scenarios. Figure 9 shows the planning satisfaction comparison results.

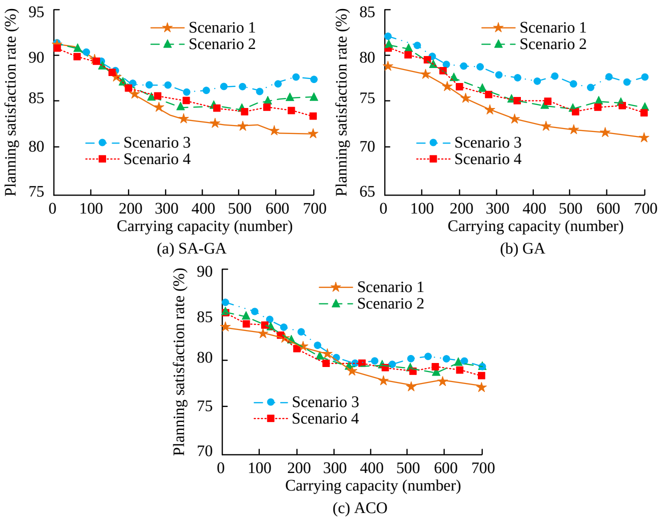

Figure 9: Planning satisfaction rate of three algorithms in four different scenarios

Figure 9 (a) shows the planning satisfaction results of the SA-GA in four different scenarios. As shown in Figure 9 (a), when the number of people was 700, the minimum and maximum planning satisfaction rates of the SA-GA in four scenarios were 82.3% and 87.2%, respectively. Figure 9 (b) shows the planning satisfaction results of the GA in four different scenarios. As shown in Figure 9 (b), when the number of people was 700, the minimum and maximum planning satisfaction rates of the GA in four scenarios were 71.1% and 79.0%, respectively. Figure 9 (c) shows the planning satisfaction results of the ACO algorithm in four different scenarios. As shown in Figure 9 (c), when the number of people was 700, the minimum and maximum planning satisfaction rates of the ACO algorithm in four scenarios were 77.5% and 79.8%, respectively. This indicated that SA-GA had good planning performance in different scenarios of ship rapid loading planning. The planning time results of the three algorithms in the first three scenarios are shown in Table 4.

Table 4: Planning time of the three algorithms in different scenarios (s)

Carrying capacity		100	200	300	400	500	600	700
SA-GA		8.3	9.1	9.8	10.4	11.0	11.6	12.1
GA	Scenario 1	15.2	17.1	19.5	22.2	25.3	28.6	31.2
ACO		13.5	15.8	18.1	20.3	22.8	25.1	27.6
SA-GA		8.5	9.3	10.5	10.9	11.5	12.3	12.9
GA	Scenario 2	15.8	17.5	19.6	22.4	25.5	28.9	31.8
ACO		13.9	16.1	18.8	21.5	23.7	25.8	27.9
SA-GA		8.6	9.1	9.8	10.4	11.0	11.6	12.1
GA	Scenario 3	15.2	17.1	19.5	22.2	25.3	28.6	31.2
ACO		13.5	15.8	18.1	20.3	22.8	25.1	27.6

From Table 4, in Scenario 1, when the number of passengers was 700, the planning time of the SA-GA was 12.1 seconds, significantly lower than the 31.2 seconds of the GA and the 27.6 seconds of the ACO algorithm. In Scenario 2 and Scenario 3, the planning time of the SA-GA was also significantly better than the other two comparative algorithms. In planning time dimension, the performance of SA-GA was also better than that of the comparison algorithm. Finally, the actual application effects of the three algorithms were compared through relevant expert scoring methods. The scoring results of the two algorithms are shown in Figure 10. The study selected 100 relevant experts and randomly divided them into 4 groups. The overall rating of the algorithm was based on the expert group's overall rating, with a maximum score of 100 points. Higher score meant higher evaluation.

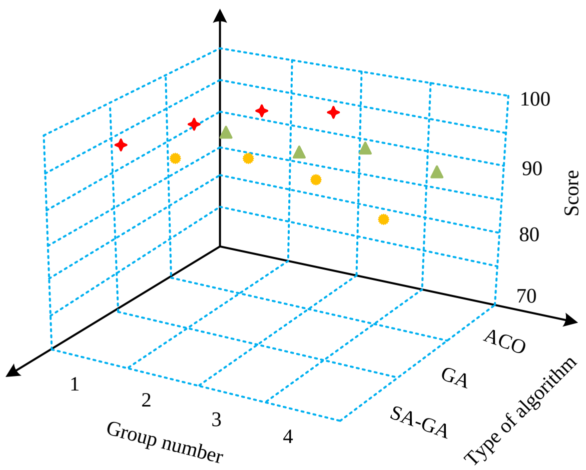

Figure 10: Expert rating results

In Figure 10, the relevant experts rated the practical application effectiveness of the SA-GA above 90 points, with an average score of 92.3 points, significantly higher than the 83.5 points of the GA and the 87.2 points of the ACO algorithm. This result indicated that from the perspective of expert evaluation, the performance of the SA-GA proposed in the study as better. Based on the comparison of the above dimensions, it could be found that the SA-GA had good performance in practical applications of ship rapid loading planning. Therefore, its application in practice could promote the development of the ship loading field. In order to further strengthen the influence of the research, the model was applied to the SA-GA in the rapid ship loading planning of a large port. Table 5 shows the application effect of the SA-GA in the rapid ship loading planning of a large port.

Table 5: Application effect of SA-GA in fast ship loading planning of a large port

Index	Traditional method	The SA-GA
Loading efficiency (ship/day)	20	25
Operating cost (10,000 yuan/month)	300	250
Planning time (hours)	10	8
Error rate (%)	5	2

In Table 5, compared with the traditional method, the SA-GA significantly improved the loading efficiency, reduces the operating cost, shorters the planning time and reduces the error rate in the rapid loading planning of ships. Among them, the carrying efficiency was increased from 20 vessels/day to 25 vessels/day, the operating cost was reduced from 3 million yuan to 2.5 million yuan, and the planning time was shortened from 10 hours to 8 hours. The above data further verified the effectiveness and superiority of the SA-GA in practical application.

5 Discussion

The experimental results indicated that the SA-GA has the advantage in solving the problem of ship rapid loading planning. Compared with traditional GA and other advanced optimization methods, the SA-GA showed significant improvement in convergence speed, accuracy and computational efficiency. First, in terms of convergence speed, SA-GA achieved faster convergence by combining the local search capability of SA and the global search capability of GA. Experimental results showed that the SA-GA reaches the shortest path in 183 iterations, which is significantly lower than 377 iterations of WPA and 415 iterations of GA. Its convergence speed was significantly better than that of traditional GA and contrast algorithms. This result was similar to the conclusion obtained by Zhang and Deng in the study of SA-GA [21]. The primary reason for the rapid convergence of the SA-GA is the incorporation of the Metropolis criterion within the SA algorithm. This criterion enables the algorithm to accept suboptimal solutions with a certain probability, thereby preventing the algorithm from becoming trapped in local optima and accelerating the search for global optima.

Secondly, in terms of accuracy, SA-GA also showed excellent performance. Through comparative experiments, it was found that the loss value of SA-GA when solving TSP problem is 0.003, which is significantly lower than that of PSO algorithm 0.005, DE algorithm 0.005 and ACO algorithm 0.010. This result was coincided with the research result of Qiu team in 2022 [22]. The above results demonstrated that the SA-GA can explore the solution space more effectively and find the solution closer to the global optimal. The outcome is mainly attributable to the fact that the SA-GA integrates the precision of the SA algorithm with the comprehensive search capability of the GA. Finally, in terms of computational efficiency, SA-GA also showed significant advantages. The experimental results indicated that the planning time of SA-GA is 12.1s, which is significantly lower than 31.2s of GA and 27.6s of ACO algorithm. The findings indicated that the SA-GA can facilitate the development of optimization schemes with greater efficiency, thereby enhancing the efficacy and responsiveness of decision-making processes.

In summary, the proposed SA-GA is superior to traditional GA and other advanced optimization methods in terms of convergence speed, accuracy and computational efficiency. This innovative solution provides a new contribution to the field of rapid ship loading planning and is expected to drive further development in this field.

6 Conclusion

With the continuous growth of global trade and the increasingly tight supply chain, the shipping industry is facing enormous pressure and challenges. In order to improve transportation efficiency and reduce costs, ship rapid loading planning has become a research hotspot in this field. However, the planning effectiveness of ship rapid loading planning is currently poor. To address this issue, a SA-GA hybrid algorithm that combines SA advantages and GA advantages has been proposed. Based on this algorithm, a ship rapid loading planning model has been proposed to improve the planning effectiveness. In algorithm comparison, it was found that the stability error value of SA-GA was 0.002, which was lower than 0.003 of DE, 0.004 of PSO, and 0.005 of ACO. In addition, it was found that the accuracy of SA-GA was 0.96, which was higher than DE's 0.91, PSO's 0.88, and ACO's 0.94. Afterwards, it was noted through expert evaluation of the algorithm's actual application performance that the average score of the SA-GA's actual application performance was 92.3 points, significantly higher than the 83.5 points of the GA and the 87.2 points of the ACO algorithm. This indicates that the SA-GA has good performance in practical applications of ship rapid loading planning. However, although the SA-GA is excellent in several aspects, there are some potential limitations. For instance, the efficacy of the algorithm is susceptible to alterations in the parameter settings, with disparate parameter combinations potentially yielding unstable outcomes. Moreover, the computational complexity of the SA-GA is likely to intensify in the context of ultra-large-scale ship loading, which could compromise its efficiency. Consequently, future research may wish to investigate avenues for optimizing the parameter configuration of the algorithm, with a view to enhancing its stability and adaptability. In addition, the development of parallel computing or distributed computing technologies should be considered to address the challenges posed by very large-scale ship carrying problems.

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