Optimization Technology of Civil Aircraft Stand Assignment Based on MSCOEA Model

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***Abstract*—The Chinese aviation transportation industry is constantly developing towards multiple objectives and constraints. The conventional optimization method for stand assignment of civil aviation aircraft has low efficiency and can no longer meet practical needs. Based on this, the paper firstly focuses on the problem of convergence and uniformity in multi-objective optimization, and uses the multi-strategy algorithm to optimize the multi-strategy algorithm of Multi-strategy competitive-cooperative co-evolutionary algorithm (MSCOEA). Then, for the problem of high time complexity in the traditional chromosome coding mode, the characteristics of quantum evolution algorithm can be reduced by MSCOEA algorithm. Front the results, the prediction accuracy of the research method was above 90% on both the training and validation sets. With the increase of iterations, the final accuracy was 96.8% and 97.53%, respectively. This algorithm achieved the same performance as some other comparative algorithms in most of the objectives. The optimal flight allocation rate reached 98.4%. The mean, optimal value, and variance of the number of flights allocated to remote stands were 5.75E+00, 4.00E+00, and 1.04E+00, respectively, which were superior to other comparative algorithms. The deigned stand assignment optimization method achieves efficient stand assignment, and improves the allocation efficiency of large and multi-objective stands.**

Keywords—Collaborative evolution; quantum algorithm; stand assignment; multi-objective optimization; population

I. INTRODUCTION

With the advancement of industrial technology, mathematical models related to optimal problems have become increasingly mature. Many practical optimization problems have been solved. However, how to efficiently solve such problems has always been a challenge that both the international community and the industry need to face together. In solving complex optimization problems, there are often problems such as multiple constraints, multiple decisions, and multiple objectives. It is difficult to achieve satisfactory results using conventional mathematical methods [1-2]. Cooperative Co-evolutionary Algorithm (CCEA) has been widely used to solve optimal problems [3-4]. Especially in the field of civil aviation transportation, solving complex optimization related problems is of great significance. With the continuous expansion of air cargo scale, the demand for every link in China's civil aviation industry chain is also increasing. Parking stands are a critical infrastructure for airlines, which are essential for ensuring the normal, safe, and efficient operation of civil aviation transportation systems. The conflict between the shortage of parking spaces and the increase in market demand has become a bottleneck problem restricting the civil aviation. Currently, there are two methods to address the shortage of parking spaces. One method is to expand the existing airport, that is, to build a new airport. Another effective way to alleviate the parking space resources is to efficiently allocate existing parking space resources to optimize the utilization rate of parking lot resources. This approach is both fast and cost-effective. Therefore, it has received high attention from the industry and academia [13]. Therefore, multi-strategy competitive coevolution algorithm (Multi strategy competitive co evolutionary algorithm, MSCOEA) is adopted, and then it is integrated with quantum evolution algorithm (Quantum Evolutionary Algorithm, QEA) to solve the problem of civil aviation shutdown shortage. This study consists of four parts. The first part is the literature review on the optimization of civil aircraft parking lot allocation; the second part is to construct the optimization method model of civil aircraft parking lot allocation based on MSCOEA algorithm; and the third part is to verify the validity and reliability of the model through relevant experiments; and the last part is to summarize the full text.

II. RELATED WORK

Pan et al. proposed an effective CEA for distributed assembly shop group scheduling problem to arrange multiple workpieces in multiple identical manufacturing units. The results showed that it had significant advantages over many meta-heuristic algorithms [5]. Similarly, for flow shop sequential scheduling with productivity measure, He et al. proposed a greedy CCEA for Multi-Objective Optimization (MOO) in flow shop group scheduling. The algorithm outperformed existing classical methods [6]. Regarding the cloud work scheduling problem in modern business and industrial fields, Qin et al. proposed a clustering CCEA for workflow scheduling in cloud environments. The algorithm significantly surpassed the baseline with a 95% confidence level [7]. Faced with satellite ranging scheduling, Xiong et al. proposed a CCEA based on elite archive strategy to provide a set of selectable schedules while maintaining the quality of the solution. This method outperformed comparative algorithms on effectiveness, diversity, and flexibility [8]. Faced with the limitations of most current architectural representation schemes, which cannot discover the limitations of more powerful liquid state machine architectures, Zhou et al. proposed a generative liquid state machine. The library structure of this state machine was evolved using a CCEA, and the weights of the algorithm were adjusted according to synaptic plasticity rules. This algorithm performed better than other methods on benchmark problems. The analysis indicated that the data parallel strategy was effective in accelerating the evaluation process [9]. Faced with problems such as short and fuzzy query length, and difficulty in extracting user intent from queries to establish a good query recommendation system, Barman et al. designed a CCEA-genetic algorithm for query recommendation. The algorithm adopted independent subpopulations to simultaneously solve sub problems. It searched for the complete Pareto optimal solution by gathering relevant members from two subpopulations [10].

Due to the dynamic characteristics of the vehicle network, the accuracy of traditional parking lot allocation methods is not high, which is confusing for both parking lot owners and vehicle owners [13]. Therefore, Hassija et al. built a new parking resource allocation method on the basis of virtual election to address the problems in parking resource allocation. Based on this method, users and parking lot owners easily reached a consensus on how to allocate parking spaces using the lowest bandwidth [14]. In response to the insufficient parking spaces in modern cities, Duan et al. designed a personalized parking guidance service, which described the relationship between the personalized parking service and drivers by establishing a two-layer programming model. The proposed stand assignment model was found to effectively balance the shared stand resources within the service area and minimize walking distance [15]. With the sustained growth of air traffic demand, stand space resources have become the main bottleneck restricting airport development. To comprehensively consider various stakeholders, Deng et al. established a three objective gate allocation model, which considered minimizing passenger walking distance, while optimizing to improve actual efficiency. The results showed that the model could solve passenger walking distance [16]. Regarding the fairness of allocation in various airlines, Jiang proposed the NSGA-II-LNS algorithm to model the airport boarding gate allocation problem as a MOO problem that minimized aircraft taxiing costs and passenger walking distance. This algorithm outperformed published algorithms on convergence and diversity of solutions [17]. In addition, acceptable computation time implies the actual potential of the research model. To address the increasing congestion pressure faced by air side ground transportation, Liu et al. designed an integrated model that simultaneously processed stand assignment and taxiway planning in a discrete spatiotemporal network. The flight pairs and connection times affected gate idle time and aircraft taxiing time [18].

In conclusion, although the current research on downtime allocation related problems has achieved some results, most of them use manual scheduling and supplemented by algorithm scheduling. However, this method lacks efficient real-time adjustment mechanism in the current parking lot allocation method in the complex and changeable operating environment of the airport, and it is difficult to deal with emergencies. At the same time, it is difficult to achieve a balanced distribution of flight types and airlines, resulting in unfair distribution of resources, which may cause competition and contradictions, and affect the fairness and efficiency of airport operation. In view of the above problems, the paper first discusses the convergence and uniformity of the multi-objective optimization problem, optimizes the characteristics of the cooperative coevolution algorithm with strong global search ability, and proposes the MSCOEA algorithm. Then, for the problem of high time complexity in traditional chromosome coding, the characteristics of quantum evolution algorithm can reduce the time complexity of the algorithm to propose a model for the optimization of parking lot allocation based on the improved MSCOEA algorithm. The contributions of this study are as follows: first, to improve the performance of the algorithm, introduce the MSCOEA algorithm and QEA, effectively improve the solving efficiency and accuracy of the parking space allocation problem, provide an effective means for large-scale and multi-target problems; the second, optimize the resource utilization, refine the multi-target optimization, realize the success rate of the highest bridge rate, and shorten the boarding distance, optimizing the utilization of airport resources, and improve the overall operation efficiency. These contributions have important implications for the issue of airport parking space allocation.

III. Methods and Materials

A. Construction of MSCOEA Model

To effectively balance convergence and uniformity in MOO problems, the MSCOEA model is proposed, which is an effective model for solving MOO problems. An adaptive random competition mechanism is built to address the difficulty in maintaining diversity in the CCEA population, enabling it to obtain more information in the next iteration process and improve the learning ability of the method. By introducing domain crossing and fully exploring the solution sets that are not dominant in the additional group, the information transmission during crossing is suppressed, and its local optimization performance is improved. Among them, in the adaptive random competition process, all individuals in each offspring group can combine with the optimal individuals in other offspring groups to obtain a complete solution result [19]. A method is proposed to use a cost function C_i to determine an individual's fitness value, in response to the time-consuming classical Pareto dominance algorithm, as shown in equation (1).

$$C_i = \min_{q \in I/i} c_{iq} \tag{1}$$

In equation (1), i represents an individual in the sub-population. I represents the approximate Pareto front. c_{iq} is described by equation (2).

$$c_{iq} = \max_{w} f_w^i / f_w^q \tag{2}$$

In equation (2), f_w^i represents a numerical vector of the objective function, which is consistent with solving i. For $C_i > 1$, individual i is not a dominant solution, but rather an advantageous solution. As C_i increases, the quality of individual i also increases. MSCOEA incentivizes the offspring population to search for areas that have not yet been found by evaluating the performance of the additional population, thereby evaluating population suitability. After obtaining the fitness $F_{i,j}$, the method further modified the additional population and determined the fitness extremum $AF_{\min}$ in the additional population. The method for determining whether a subpopulation lacks diversity is shown in equation (3).

$$\beta_{i,j} = \begin{cases} 0, if\ F_{i,j} < AF_{\min} \\ 1, otherwise \end{cases} \tag{3}$$

In equation (3), $\beta_{i,j}$ represents the flag position. After g iterations, the number $\eta_{g,i}$ of individuals with fitness greater than $AF_{\min}$ in the subpopulation i is shown in equation (4).

$$\eta_{g,i} = \sum_{j \in S_i} \beta_{i,j} \tag{4}$$

In equation (4), S_i represents the size of subpopulation i. When the fitness of all individuals in subpopulation i is greater than $AF_{\min}$, $\eta_{g,i} = |S_i|$. The growth ρ_i of the non-dominant solutions contributed by the subpopulation to the additional population is shown in equation (5).

$$\rho_i = \begin{cases} \rho_i + 1, if\ \eta_{g,i} < \eta_{g-1,i} \\ 0, otherwise \end{cases} \tag{5}$$

In equation (5), $\eta_{1,i} = 0$. If $\rho_i = N_{comp}$, then this offspring population will have certain differences and a competitive pathway will be established for the current population, with ρ_i set to 1. At the same time, by introducing the offspring population and randomly generated offspring population into the temporary population, and analyzing the fitness of each offspring population within the temporary population, the offspring population with the highest fitness is taken as the new offspring population. For the MOO problem of CCEA, the nearest neighbor crossover method is adopted to effectively mine the non dominant solutions in the additional population and restrict the information flow, thereby improving the global optimization performance. Finally, the flowchart of MSCOEA is shown in Figure 1.

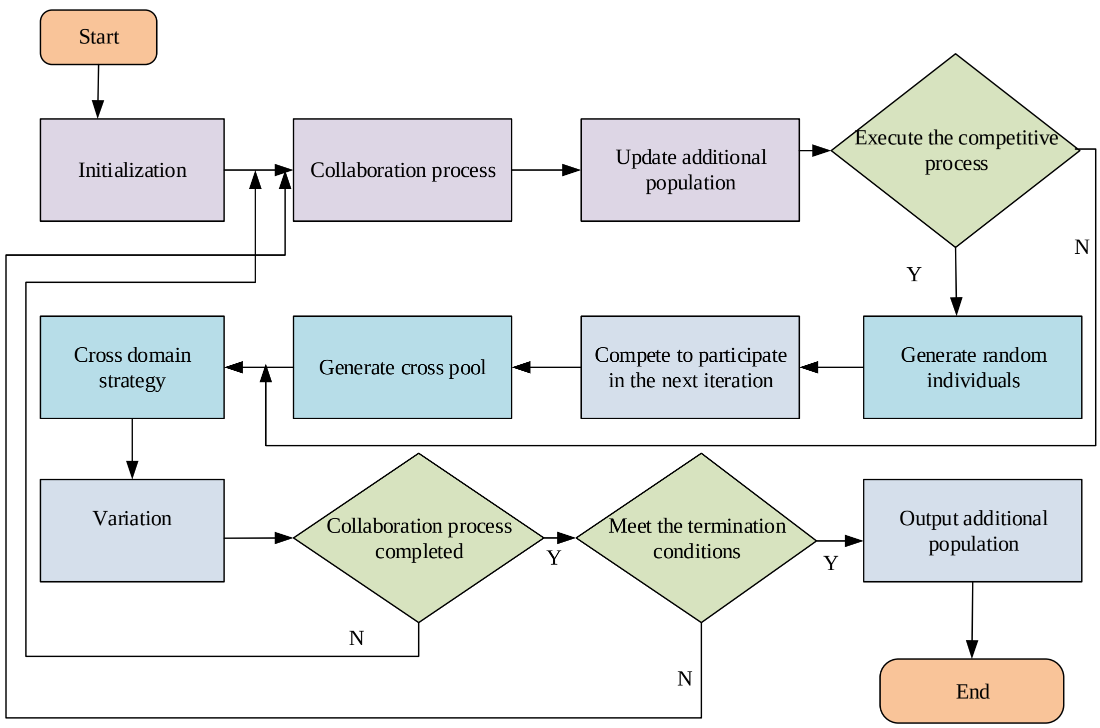


Fig. 1. Flow chart of MSCOEA.

B. Aircraft Stand Allocation Model Based on MSCOEA

After constructing the MSCOEA model, in order to reduce its time complexity, the study further improves the MSCOEA model by combining QEA. Based on this, an optimization model for aircraft stand assignment is proposed. Firstly, the rotation angle control method on the basis of Hamming adaptive is applied to obtain the rotation angle in QEA. The Hamming distance is represented by the number of corresponding coefficients between two solution elements, as shown in equation (6).

$$Hdis(S_1, S_2) = \sum_{i=1}^{m} (S_{1i}, S_{2i}) \tag{6}$$

In formula (6), S represents the shutdown location of the flight, m indicates the number of flights。In the final stage of this method, the greater the similarity between the two targets, the shorter the Hamming distance and angle of the targets, thereby improving the local optimization performance of the method. The rotation angle θ_{ig} is shown in equation (7).

$$\theta_{ig} = \frac{\exp\left(c \square Hdis\left(S_i, S_g\right)\right)}{\pi + \ln(m)} \tag{7}$$

In equation (7), c represents the adjustment coefficient, satisfying $0 \prec c \prec 1$. In order to avoid a decrease in its convergence rate, a probability-based method is adopted to determine whether to turn it to a random point, and the turning angle of that point is smaller than that of the point facing the best. At this point, the quantum gate can be found in equation (8).

$$\begin{pmatrix} \alpha_i' \\ \beta_i' \end{pmatrix} = \begin{pmatrix} \cos\left(s(\alpha_i,\beta_i)(\Delta\theta_b + \Delta\theta_r)\right) - \sin\left(s(\alpha_i,\beta_i)(\Delta\theta_b + \Delta\theta_r)\right) \\ \sin\left(s(\alpha_i,\beta_i)(\Delta\theta_b + \Delta\theta_r)\right) \cos\left(s(\alpha_i,\beta_i)(\Delta\theta_b + \Delta\theta_r)\right) \end{pmatrix} \begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} \quad (8)$$

In equation (8), θ_b signifies the rotation angle of the subgroup individuals towards the optimal individual. θ_r signifies the rotation angle of a subgroup individual towards a random individual. After integrating the QEA, the improved MSCOEA flowchart is shown in Figure 2.

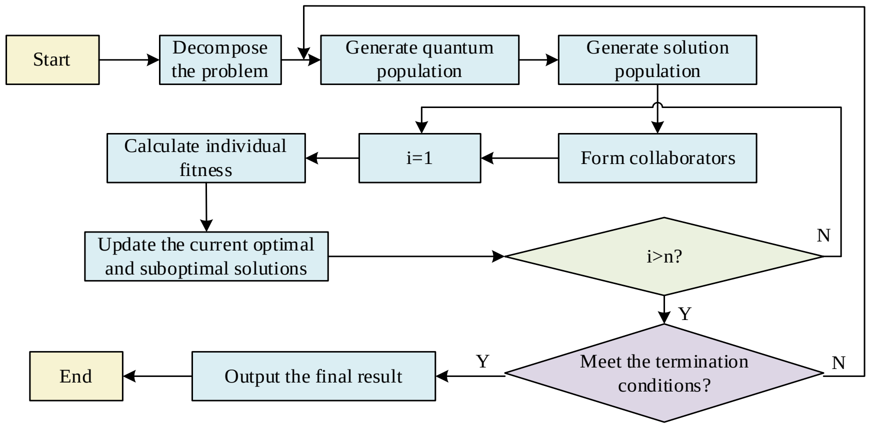


Fig. 2. MSCOEA process integrating QEA.

This model decomposes the problem into multiple sub problems, which are solved using the QEA method, and the sub groups work together to solve them. At the same time, representative individuals from each subpopulation form a complete solution set. The fitness of each subpopulation is calculated to achieve information exchange. To accelerate the convergence speed, the optimal individual from each subgroup is used to represent it. The offspring evolution is carried out through quantum gates. This study tests the algorithm performance using the knapsack problem, as shown in equation (9).

$$\max f(X) = \sum_{i=1}^{m} p_i x_i \quad (9)$$

In equation (9), x_i signifies the state of item i. When it is placed in the backpack, $x_i = 1$. Conversely, $x_i = 0$. p_i represents the profit of item x_i. Based on the proposed algorithm, this study aims to optimize the optimal parking position based on daily arrivals, taking into account both internal and safety factors, with a focus on passenger and airline revenue. The optimization objectives of this model include minimizing the total distance traveled by passengers, minimizing their stay time, minimizing the allocation of flights to distant locations, and maximizing the utilization of large seats. Considering the difficulty of solving MOO problems, the weighting method is taken to convert the MOO into a single objective function, as shown in equation (10).

$$F = \min\left(\lambda_1 F_1 + \lambda_2 F_2 + \lambda_3 F_3 + \lambda_4 F_4\right) \quad (10)$$

In equation (10), λ_1, λ_2, λ_3, and λ_4 stand for the four objective weights of minimizing the total distance traveled by passengers, minimizing their stay time, minimizing the allocation of flights to the apogee, and maximizing the utilization of large seats, respectively. F represents the objective function. In summary, the study integrates QEA with MSCOEA to construct a pre-allocation model for parking positions at civil airports, as shown in Figure 3.

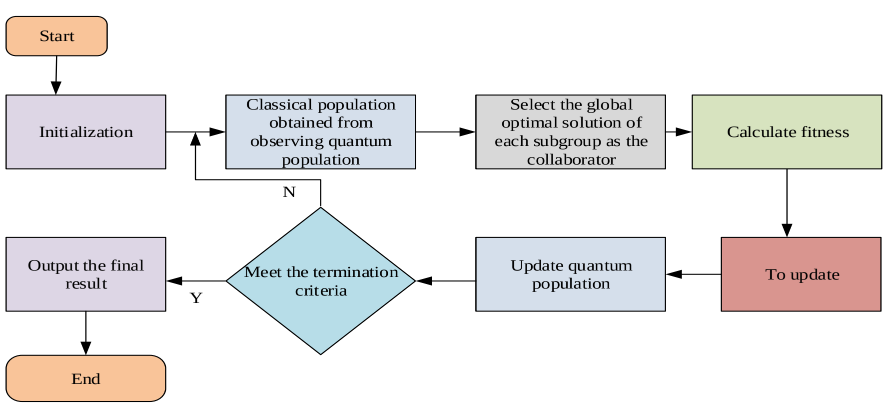


Fig. 3. Allocation method for parking positions at civil airports.

From Figure 3, this method first excludes flights that do not meet the constraints, then adds the remaining aircraft in the Important Person（VIP） aircraft group to the waiting aircraft set, and finally sorts these aircraft by parking position. For the assigned flight, it is inserted into the corresponding location of the docking point. If the constraints are satisfied, the next flight is assigned. If the constraint conditions are not satisfied, it is placed at the next docking point until all docking points have been tried once. If all VIP flight tasks cannot be completed after adjusting the solution set that has not reached the constraints, then the fitness of the solution is infinity.

IV. Results

A. Experimental Settings

To verify the effectiveness of the designed method, the comparative algorithms selected for this experiment are CCEA, Genetic Algorithm (GA), Reinforcement Learning (RL), Particle Swarm Optimization (PSO), Non-dominated Sorting Genetic Algorithm III (NSGAIII), Reference Vector Guided Evolutionary Algorithm (RVEA), Tabu Search (TS). The evaluation indicators for the quality of the solution results are Inverted Generational Distance (IGD), Pure Diversity (PD), and Pareto Set Proximity (PSP).MSCOEA The subpopulation size is 10, the evaluation number is 10000, the optimal adjustment coefficient is 1, then the individual is 0.5, the decomposition dimension is 2, the safety interval time is 8 minutes, the target weight value is 0.25, and the algorithm runs independently 20 times.The computer system used in the study was Intel(R)Core(TM)i7-7700CPU@3.6GHz with 8G RAM, Windows 10, and the algorithm was written in MATLAB 2018b, and the calculation time was 10s per time with 20 runs.The experimental environment and parameter settings are displayed in Table I.

B. MSCOEA Model Performance Testing

According to the relevant settings, after establishing the corresponding training and validation sets, the results are displayed in Figure 4.

In Figure 4, the loss of the research method in these two sets gradually decreased with the increase of iterations. When the last training ended, the loss in the training set reduced from 0.1800 to 0.1084, and the loss in the validation set reduced from 0.1362 to 0.0915. Its generalization ability continued to improve. The research model achieved a prediction accuracy of over 90% on both these two sets. As the iterations increased, the final accuracy was 96.8% and 97.53%, respectively. Taking MaF1 function as the research object, experiments are performed to study the effect of neighborhood crossover strategy on testing problems of different dimensions, as displayed in Figure 5.

From Figure 5 (a), in high-dimensional situations, the neighborhood crossover strategy resulted in poorer performance. This is in line with the expectations of the research. In low target dimensions, the search range is not large enough, and the neighborhood crossover strategy will lead to too high complexity, which will slow down the convergence rate of the method. In this way, in the case of a small search space, the neighborhood crossover strategy is constrained by information flow during traversal, which affects the global optimization of the entire algorithm. As shown in Figure 5 (b), the effect of neighborhood crossover strategy became increasingly significant as the dimensionality of the problem increased. The neighborhood crossover strategy has significant advantages in the solving process. The approximate Pareto front and approximate Pareto solution set obtained by the MSCOEA and the randomly selected comparison algorithm TS are shown in Figure 6.

From Figure 6, MSCOEA not only searched for solution sets in multiple decision spaces, but also had a similar number of non inferior solutions in each solution set. From the experimental results, MSCOEA performs better than TS in handling multi-modal and multi-objective test functions. The IGD of the solutions obtained by each algorithm for functions FON, MMF1, MMF3, and MMF4 is shown in Figure 7.

TABLE I. EXPERIMENTAL SETTINGS

Sum	Set up
Subpopulation size	10
Additional population A size	100 for FON,800 for MMF1, MMF3 and MMF4, 240 for MaF1 and MaF3
The number of evaluation	4 XD 104, D is the decision variable dimension
Encoder mode	Binary coding (length 20 per variable)
Choose the operator	Championship selection
Cross operator	Even cross
Cross probability	0.8
Variant operator	According to the variation
Probability of variation	1 / B, and B is the chromosome length
Variant pool size	Additional population size of 0.2
Scale of competition pool	Subpopulation size 2
Tool	Intel(R)Core (TM)i7-7700CPU@3.6GHz with 8G RAM
Operating system	Windows 10
Algorithm writing	MATLAB 2018b
Function	MMF1, FON, MaF1, MaF3, MMF3, MMF4

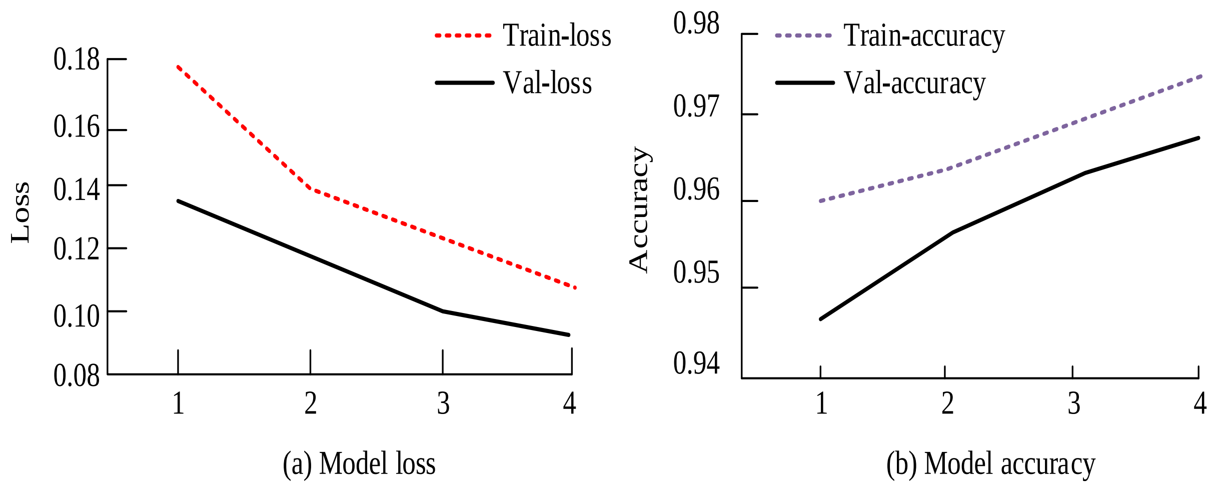


Fig. 4. Training results.

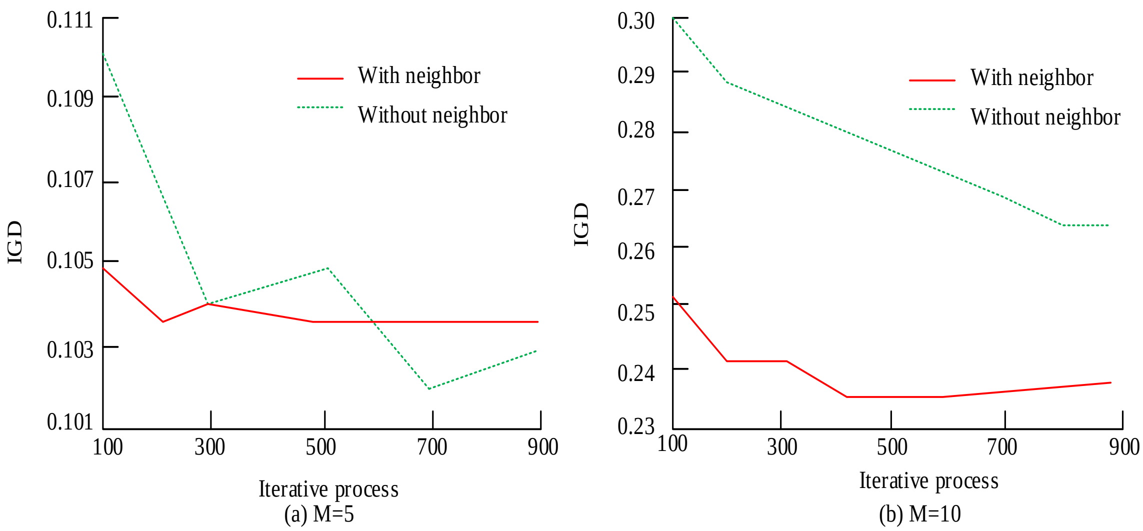


Fig. 5. Influence of domain mutation strategy on algorithm convergence process.

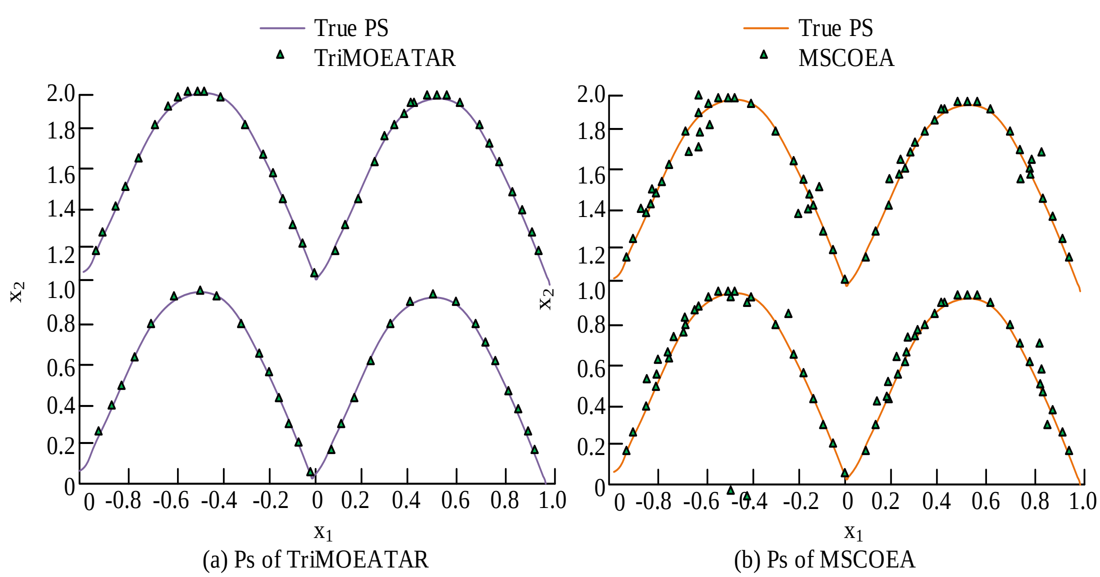
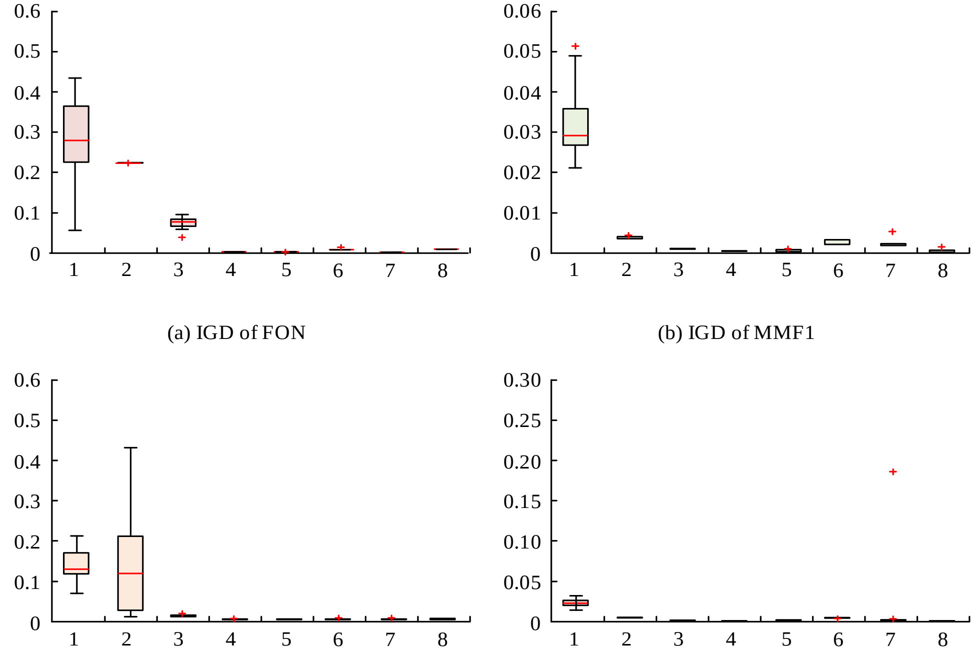


Fig. 6. Approximate Pareto fronts and approximate Pareto solution sets searched by TS and MSCOEA.



(a) IGD of FON (b) IGD of MMF1

(c) IGD of MMF3 (d) IGD of MMF4

Fig. 7. Results of each algorithm for function FON, MMF1, MMF3, MMF4.

From Figure 7, the performance of MSCOEA in solving single modal, low dimensional, and multi-index problems such as MMF1 and FON was superior to other comparative methods, indicating that MSCOEA can not only efficiently find and maintain overall consistency, but also has higher stability. The reason for this is largely due to the constraints of information flow when using neighborhood crossover strategy, which affects its overall optimization performance. However, the performance of MSCOEA surpasses that of basic CCEA. For the two types of multi-objective programming problems MMF3 and MMF4, MSCOEA can search for the actual Pareto front and the Pareto solutions. The difference between the optimal solutions obtained by MSCOEA when solving two types of Pareto optimal solutions is not significant, which provides a basis for decision makers to better choose the optimal solution. MSCOEA can not only solve Pareto frontier problems, but also solve distributed solutions on multiple Pareto sets, and the proportion of solutions on each Pareto set is similar. This is mainly due to the competitive mechanism that makes the offspring population more diverse, thereby making the decision-making space more complete throughout the entire evolutionary process. The performance test results of the algorithm for optimizing the objective functions of MaF1 and MaF3 are displayed in Table II.

TABLE II. IGD VALUES OF VARIOUS ALGORITHM TEST RESULTS WHEN M=10

Evaluation index value	**CCEA**	**GA**	**RL**	**PSO**		**NSGAMIII**	**RVEA**	**TS**	**Ours**
MaF1	Evaluation index value	3.19E+02	3.031E+00	4.54E+03	2.79E+01	2.90E+01	5.45E+02	4.28E+01	2.330E-01
	Quantity excellence	3.91E+02	3.18E+00	4.82E+03	2.85E+01	2.98E+01	688+01	4.83E+01	2.38IE01
	mean value	4.92E+01	3.360E+00	5.170E+00	2.90E+01	3.07E+04	8.48E+02	5.62E+01	2.45E+01
	Quantity difference	5.87E-01	7.000E-06	3.17E-04	5.000E-06	1.93E+05	6.05E+00	60686504	6.82E+06
MaF3	Evaluation index value	3.337E+01	1.157E+00	8.05E+07	2.625E+11	9.07E+03	7.65E+03	1.06E+01	L157E-00
	Quantity excellence	2.0600E+02	1.720E+00	2.692E+05	4.420E+11	2.14E+01	8.00E+05	1.10E+01	L328E-00
	mean value	4.495E+02	2.194E+00	5.155E+05	7.15E+11	3.60E+01	8.32E+01	1.17E+01	L561E-00
	Quantity difference	9.90E+03	3.880E-04	L399E+10	9.289E+21	6.17E+03	3.49E-03	9.86E+65	L219E-04

From Table II, MSCOEA has shown good convergence performance in both aspects, which is in line with the previous results on neighborhood crossover. Through this study, MSCOEA has good solving effects on these three types of MOO problems, which can improve the convergence speed and balance the compatibility of the solution set obtained. The final solution set can reflect the set of actual solutions. In single-mode multi-objective programming problems, the proposed method can comprehensively cover the Pareto frontier. In addition, the new method proposed in the study does not rapidly decrease in computational efficiency with the increase of the target space dimension when solving three types of single-mode high-dimensional MOO problems, and has good solving efficiency. The algorithm has good balance between convergence and uniformity, and has better stability.

C. *Test of Civil Aircraft Stand Allocation Model Based on MSCOEA*

To verify the proposed civil aviation aircraft, stand allocation model, a civil aviation airport is randomly taken as the research object. The flight data of the airport on a certain day are collected to construct the research database. The research data include 250 flights and 30 parking places. On this basis, 10% of the aircraft in each airport is regarded as VIP, and the parking seats of each airport is sorted in order. The safety interval is set to 8min. When the aircraft is pushed out, the aircraft adjacent to the seat shall not move within 5min. The weight of the indicator is 0.25. The subgroup is 2, and the maximum evaluation is about 200. The algorithm is executed 20 times separately. Firstly, QEA, QoS-aware Subcarrier Allocation (QSA), Phase-based Quantum Genetic Algorithm (POGA), research model and Quantum inspired Contest Evolution Algorithm (QCCEA) are selected to solve the knapsack problem, and 350 and 600 groups of data are set to examine the optimization problem, as displayed in Figure 8.

From Figure 8, with the increase of the problem scale, the efficiency of the research method also appeared. At 350 and 600, on the basis of Hamming adaptive rotation angle, the Random Rotation Direction Strategy (RRDS) effectively avoided local extremum and improved the global optimization ability. With the increase of the problem scale, its impact on the solution efficiency was increasingly significant. The convergence process of the three models is shown in Figure 9.

From Figure 9 (a) and (b), the research method had higher convergence efficiency than the other two methods in the case of 350 and 600. Although the results of QCCEA are better than QEA, it is always the slowest among the three methods. This is mainly because in CCEA, adding the cooperation mode can improve its convergence, but there are a lot of repeated optimization, which reduces its convergence rate. On this basis, the adaptive rotation angle and RRDS can not only effectively solve the above problems, but also avoid falling into local minima, so as to speed up the convergence rate and enhance the convergence performance. After verifying the knapsack problem, to further verify the civil aircraft stand allocation model, the proposed model is compared with QEA, OSA and POGA algorithms. The results are shown in Figure 10.

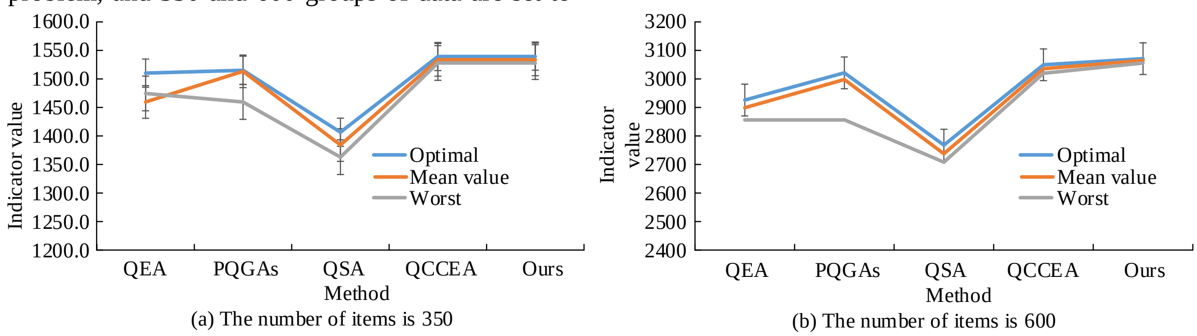


Fig. 8. Experimental results of knapsack problem.

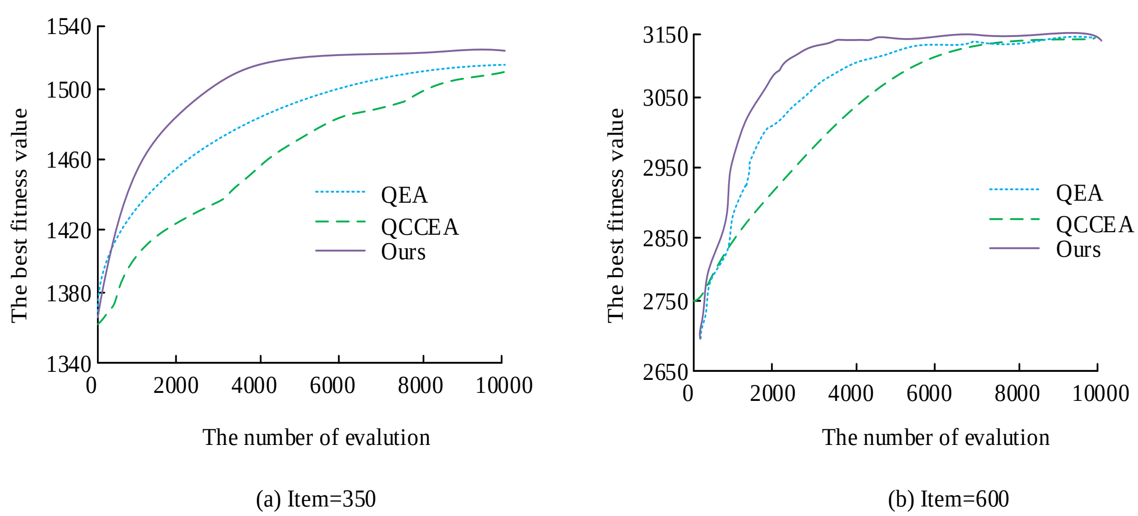
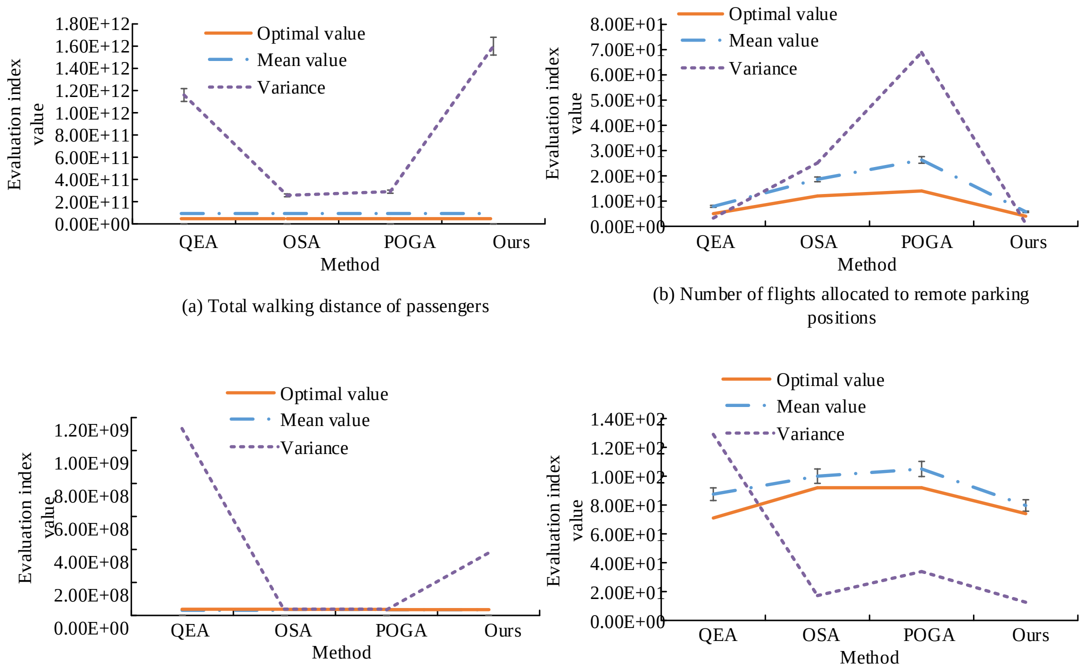


Fig. 9. Comparison of convergence results of various models.



(a) Total walking distance of passengers

(b) Number of flights allocated to remote parking positions

(c) Total idle time of parking positions

(d) Number of small and medium-sized flights parked at large stands

Fig. 10. Performance results of each algorithm on each optimization objective.

In general, the proposed research method achieved the same performance as other similar algorithms on most problems, which achieved the optimal allocation ratio of 98.4%, which surpassed the other three types of methods. In addition, the proposed model was applied to the optimal allocation of large-scale downtime resources, and its optimal value was 7.40 e+01. From Figure 10 (a) and (c), existing IPQEA and OSA methods had a large number of empty distances to be allocated, which not included the passenger travel distance. Therefore, the optimization effect of IPQEA and OSA methods in terms of passenger travel distance surpassed the other two methods. From Figure 10 (b), the average value of the research method on minimizing the number of flights allocated to the apogee was 5.75e+00, the optimal value was 4.00e+00, and the variance was 1.04e+00. In comparison to the other algorithms, the research method has better performance. From Figure 10 (d), the average optimization result of the research method in maximizing the utilization rate of large seats was 7.97e+01, and the optimization result on variance was 1.26e+01, which was better than other comparative algorithms. The designed algorithm has good robustness and reliability.

V. Discussion

In order to solve the problem of civil aviation parking lot allocation, the study is coevolution algorithm and QEA. In view of the shortcomings and shortcomings of the coevolution algorithm and QEA, the two algorithms are used for deep fusion to improve the optimization performance of the algorithm for complex optimization problems. Firstly, it studies the problem with the multi-objective optimization problem, optimizing the global search ability of the cooperative coevolution algorithm, and proposes the MSCOEA algorithm. In the performance test of the algorithm, the study found that the accuracy of the algorithm reached more than 90% and had better performance. In the process of solving functions FON, MMF 1, MMF 3 and MMF 4, it is found that MSCOEA solves mono low-dimensional multi-indexes such as MMF 1 and FON better than other comparison methods, indicating that MSCOEA can not only efficiently find and maintain the overall compatibility, but also has higher stability. This is because when using the neighborhood crossing strategy, it is constrained by the information flow, which affects its overall optimal performance. For MMF 3 and MMF 4, MSCOEA can not only complete the search for the actual Pareto frontier, but also complete the complete search for the Pareto solution of the decision space. Compared with the downtime optimization method proposed by Deng et al. [19] in ref, the difference between the optimal solutions obtained by MSCOEA when solving the two types of Pareto optimal solution is not obvious, which will provide a basis for the decision makers to better choose the optimal solution. This is mainly because the competition mechanism makes the offspring group more diverse, which makes the decision space in the whole evolutionary process more complete.

Then, the research for airport parking space allocation problem, with passenger walking distance, parking space idle time, allocated to the far number of flight and large station utilization to optimize the target airport parking space optimization model, and put forward the quantum cooperative collaborative evolution algorithm to establish multiple target airport parking space optimization model. The results show that the proposed method has high convergence efficiency, with better convergence compared with QEA, QSA, POGA and QCCEA in the cases of 350 and 600. Meanwhile, this result, compared with the collaborative optimization algorithm improvement strategy proposed by [20] in the literature, achieves the value of 7.97 E + 01,1.26 E + 01, with better robustness and reliability. This is because the quantum cooperative coevolution algorithm introduces the cooperative coevolution strategy, which improves the global search capability of the algorithm. As can be seen from the number of unassigned flights, the mean, optimal value and variance of the research method on the number of flights assigned to the remote flight position are 5.75E+00,4.00E+00,1.04E+00 respectively. This result is because the Haiming adaptive rotation angle strategy was designed to adjust the search step size and optimize the convergence speed and accuracy of the algorithm.

VI. Conclusion

With the rapid development of economy and society, the problem of shutdown allocation presents complex characteristics such as high-dimension, multi-objective and multi-constraint, which makes it difficult for traditional optimization algorithms to solve and solve low efficiency. In view of this problem, the problem of convergence and uniformity of multi-objective optimization, and the MSCOEA algorithm is proposed to improve the local search ability of the algorithm. The experimental results show that MSCOEA can effectively balance convergence and uniformity and provide stable performance for many types of multi-objective optimization problems. Secondly, for the problem of high time complexity in the traditional chromosome coding mode, the study of QEA algorithm can reduce the time complexity of the algorithm, put forward an optimization method model of civil aviation downlot allocation based on MSCOEA algorithm, and realize a new downlot allocation method. In order to verify the optimization ability of the research method, the backpack problem and the actual airport operation data were selected to verify the optimization performance of the algorithm. The experimental results show that MSQCCEA has good convergence speed and convergence accuracy, and the proposed downbit allocation optimization method can allocate downbits reasonably and effectively.

However, the algorithm proposed in this study still has two limitations. First, the convergence and stability of the algorithm are susceptible to factors such as population diversity, competitive strategy and quantum decoherence; second, the model adaptability and practical application are limited, such as airport layout, flight flow, passenger demand and so on are difficult to be fully quantified, leading to the limited accuracy and practicability of the model. In order to meet these challenges, future studies can adjust the competitive strategy parameters and introduce adaptive competitive strategies to improve the convergence and stability of the algorithm; meanwhile, through the configurable parameters and rules, the model can flexibly adapt to different airport layout and flight conditions, and improve the adaptability and practicability of the model.

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