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A strategic flight conflict avoidance approach based on a memetic algorithm

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KEYWORDS

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Abstract Conflict avoidance (CA) plays a crucial role in guaranteeing the airspace safety. The current approaches, mostly focusing on a short-term situation which eliminates conflicts via local adjustment, cannot provide a global solution. Recently, long-term conflict avoidance approaches, which are proposed to provide solutions via strategically planning traffic flow from a global view, have attracted more attentions. With consideration of the situation in China, there are thousands of flights per day and the air route network is large and complex, which makes the long-term problem to be a large-scale combinatorial optimization problem with complex constraints. To minimize the risk of premature convergence being faced by current approaches and obtain higher quality solutions, in this work, we present an effective strategic framework based on a memetic algorithm (MA), which can markedly improve search capability via a combination of population-based global search and local improvements made by individuals. In addition, a specially designed local search operator and an adaptive local search frequency strategy are proposed to improve the solution quality. Furthermore, a fast genetic algorithm (GA) is presented as the global optimization method. Empirical studies using real traffic data of the Chinese air route network and daily flight plans show that our approach outperformed the existing approaches including the GA based approach and the cooperative coevolution based approach as well as some well-known memetic algorithm based approaches.

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1. Introduction

Airspace has become more and more crowded because of the rapid increase of Chinese air traffic. As the density of flights in airspace jumps to a high level, it is difficult to keep safe separation among flights. Consequently, the probability of flight conflicts could increase, which threatens airspace operational safety. Moreover, it has resulted in other problems, such as delays, fuel waste, and pollution, which cost the airline

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industry billions of dollars every year. Conflict avoidance (CA), which provides effective solutions for flights to eliminate conflicts, is a key technique to ensure safety among aircraft. It has drawn much attention of researchers during the last several decades.³

The current approaches are mainly focused on short-term situations which need to solve conflicts happening in very short time.^{4,5} In the last decade, many approaches have emerged,^{6,7} which can be mainly categorized into: rule-based methods,³ game theory methods,^{4,8} field methods,⁹ geometric methods,⁵ numerical optimization methods,^{1,10–13} and multi-agent methods.^{14–16}

Short-term approaches require the fastest respond to handle emergencies on the way, which will be within several minutes or even shorter. Hence, local trajectories adjustments are usually implemented, such as instant velocity change and/or instant heading angle change. ^{1,3} However, the reactive and passive way to provide solutions in real time cannot consider the overall situation, and cannot give a feasible global solution. ¹⁴

On the contrary, long-term approaches can take advantage of full knowledge to plan traffic flow strategically and provide solutions from a global view. ¹⁷ Therefore, strategic conflict avoidance (SCA) approaches via optimizing all flight plans to reduce conflicts have become a research tendency.

SCA is a large-scale combinatorial optimization problem with complicated constraints, which is hard to be handled by classical approaches. Some researchers introduced evolutionary algorithms (EAs) to manage it.

Durand used a genetic algorithm (GA) to solve it. Considering the problem is too large and complex, a sliding forecast time window was introduced to reduce the dimension of the problem to get feasible solutions. 18 However, it cannot get a global optimum solution, and it may overstock amount of flights in later time windows which causes high difficulty for the GA-based approach to solve. Recently, cooperative coevolution was successfully applied to deal with the problem.¹⁹ It used a divide-and-conquer strategy to decompose the largescale problem into several sub-problems which can be solved by adopting an EA for each one. However, the searching space of the sub-problems is still huge, and the variables and the constraints are tightly coupled, which cause the cooperative coevolution (CC) with a random grouping strategy to get into local optimum easily.²⁰ The two global optimization approaches both suffer from premature convergence in the SCA problem because of their limited search capabilities in a huge solution space with large amounts of variables and constraints.

Memetic algorithms (MAs), one of the recently growing areas in EA research, are population-based meta-heuristic search methods inspired by Darwinian's principles of natural evolution and Dawkins' notion of a meme defined as a unit of cultural evolution that is capable of local refinements. They can be regarded as a bridge between a population-based global search and the local improvement made by each of the individuals. They have shown to speed up the search process, attaining higher quality solutions on complex design problems compared with their conventional counterparts. ²³

In this work, with the aim to minimize the risk of premature convergence and yet to get high quality solutions, we propose an effective strategic conflict avoidance framework based on a MA. In addition, a specially designed local search operator and an adaptive local search frequency strategy are proposed

to improve the solution quality. Furthermore, a fast GA is presented as the global optimization method. Empirical studies using the real traffic data of the Chinese air route network and daily flight plans show that our approach outperforms the existing approaches including the GA based approach and the cooperative coevolution based approach as well as some well-known memetic algorithm based approaches.

2. Problem formulation

Taking Chinese air route network in Fig. 1 for example, suppose that there are s air routes $(A_1, A_2, ..., A_s)$ with l waypoints $(W_1, W_2, ..., W_l)$ in the air route network involved in the problem, and there are n flights $(F_1, F_2, ..., F_n)$ with specific flight plans. Many conflicts may occur in the air route network because of separations broken among flights at some waypoints. In addition, suppose that there are only two flight levels on one air route segment, and the flights with opposite directions would fly on the two levels, respectively. Therefore, a conflict between two flights on the opposite directions along the same segment will be avoided while it will not along different segments.

Fig. 2 describes the conflict vividly. Aircraft *i* and *j* are separately flying from Xilinhot airport to Ulanhot airport and from Hailar airport to Tongliao airport. Black points denote waypoints in the routes. From the picture, we can see that

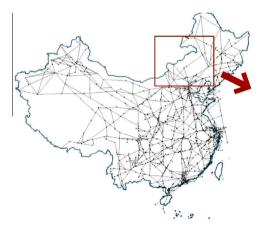


Fig. 1 Air waypoint network of China.

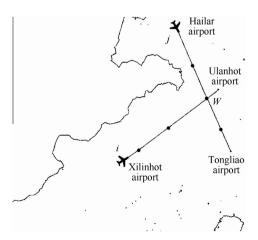


Fig. 2 Conflict description.

the two flights may meet at waypoint W. The conflicts occurring at the intersection of routes are more complicated and dangerous which we discuss mainly in this work. The conflicts happening in segments of routes are assumed to be solved by the flights involved themselves, and meanwhile through self-adjustment, the time of these flights to the intersection of routes is assumed to be not changed by the conflict resolution maneuvers. Define the map $P: N \times T \to 2D \times 2D$ as the position of an aircraft at some time. Then a conflict is defined as follows: $\exists t_w$, s.t.

$$||P_i(t_w) - P_j(t_w)||_2 < \omega, i \neq j$$

$$\tag{1}$$

where ω is the minimum safe separation. Conflicts can be detected by the nominal method.⁵

We adopt the ground delay method to avoid conflicts at waypoints which is an effective, economical, and safe method via delaying flights on the ground before departure.

With consideration of reducing cost for airlines, the objective here is to eliminate conflicts and reduce flight delays. ¹⁹ The objective function is defined by

Maximum
$$F = \frac{1 - \frac{1}{n} \sum_{i=1}^{n} \frac{\delta_i}{\delta_{\text{max}}}}{1 + N_{\text{C}}}$$
 (2)

Subject to

$$||P_i(t_{w_k}) - P_j(t_{w_k})||_2 \geqslant \varepsilon, \forall t_{w_k}, w_k \in A_{i'} \cap A_{j'}, i \neq j$$
(3)

$$\delta_i \in [0, \delta_{\text{max}}/t_{\text{s}}], i \in [1, n] \tag{4}$$

$$i, j \in [1, n], i', j' \in [1, s], i', j', i, j, \delta_i \in \mathbf{N}^+$$
 (5)

where δ_i represents the departure delay of flight i, $\delta_{\rm max}$ is the allowable maximum delay, and $N_{\rm C}$ is the total conflict number of the flights. The objective function shows that the less the conflicts are, the better, and the less the flights' average delay is, the better. Eq. (3) is the separation constraints for all flights at any waypoint. Eq. (4) means the delay of any flight is limited to a maximum value which can avoid that some flights are

postponed for too long. t_s is the time step for time sampling. Eq. (5) is the integer constraint.

It can be demonstrated that SCA is a large-scale combination optimization problem. Supposing that there are 1000 flights, $\delta_{\rm max}$ is set to 90 min, and the time step is 0.5 min, then each decision variable δ will have 180 values. In addition, the Chinese air waypoint network has 1100 waypoints and 2286 air route segments. Many air routes have crossing points. Hence, the search space will be huge. Moreover, the objective function is nonlinear, and the variables and constraints are tightly coupled because of conflict avoidance.

3. Optimization framework

To avoid premature convergence and get high quality solutions, we propose an SCA approach based on MA (SCAMA) which can take advantage of both the global optimization and local search to improve the search capability and obtain high quality solutions.²⁴ In addition, a local search operator and an effective local search frequency strategy are specially designed for the problem. Furthermore, a fast GA is present as the global optimization method. The framework is described in Fig. 3.

3.1. Local search

As described in the introduction, MA is a marriage between EA and local search heuristics, which is crucial to the success of the search and optimization processes by maintaining a balance between exploration and exploitation. Local search methods can effectively improve search capability and solution quality via locally meticulously searching global solutions. There are two critical issues in the approach: (1) local search operator; (2) local search frequency strategy. In this work, a local search operator and an effective local search frequency strategy are specially designed.

BEGIN

Initialize the population. gen=0.

//Main loop:

WHILE gen<maxgen

Evaluate all individuals in the population.

Calculate the number of individuals undergoing local search using a local search frequency strategy

//local search

For the selected individual in the population

- Apply local search operators.
- Proceed with local improvement and replace the genotype in the population with the improved solution.

End For

//global optimization

Proceed the SCR approach based on the fast GA.

Evaluate all individuals in the population and update the best solution.

gen=gen+1.

END WHILE

Obtain the best solution

Fig. 3 The framework of SCAMA.

3.1.1. Local search operator

The local search operator is used to locally improve individuals which are placed back into the population to compete for reproductive opportunities. It decides the effect of local search directly. Here, an effective local search operator based on gene fitness is specially designed. It takes advantage of the conflicts among flights and makes the gene with more conflicts and less delays to have a high probability to mutate. Hence, the conflicts can be eliminated directly, and the delays can be improved.

The individual i of the population can be denoted as

$$ind_i = (\delta_{i1}, \delta_{i2}, \dots, \delta_{in}), 1 \leqslant i \leqslant p_s \tag{6}$$

where p_s is the size of the population. We introduce gene fitness g_f defined below for each individual to describe the local search operator conveniently.

$$g_{f_i} = (g_{f_{i1}}, g_{f_{i2}}, \dots, g_{f_{in}}) \tag{7}$$

where

$$g_{f_{ij}} = \frac{1 - \delta_{ij} / \delta_{\text{max}}}{1 + \text{nc}_{ii}}, 1 \leqslant j \leqslant n$$
(8)

where nc_{ij} is the number of conflicts of flight j when ind_i is the final solution.

For every chosen member in the population to execute local search, every gene will be redefined if its fitness is less than a given parameter ε .

3.1.2. Local search frequency strategy

As mentioned above, local search can speed up convergence rate. However, population diversity degrades gradually. Hence, on one hand, exhaustive local search frequency may cause premature convergence and ineffective search, which would waste a lot of computational time. On the other hand, insufficient local search cannot obtain better solutions. Therefore, a local search frequency strategy is particular important to reduce this risk.

To control the local search frequency during an MA search, we propose a dynamic adaptive strategy based on Shannon's information entropy. The basic idea of our strategy is almost the same as the diversity-based dynamic adaptive strategy in Ref. ²³. In addition, some characteristics of the SCA problem are fully taken advantage of, such as the number of conflicts, to improve the strategy's performance.

The diversity of the population can be measured by various means. One simple approach is based on Shannon's information entropy, 21 which represents an overall measure for describing the state of the dynamical system represented by the population. The number of conflicts of individual i is defined by

$$c_i = \sum_{i=1}^n c_{ij} \tag{9}$$

where c_{ij} means the number of conflicts of flight j in individual i.

Then the subsets $G_1, G_2, ..., G_Q$ are defined to represent groups of individuals with the same number of conflicts from the population. The ratio of the number of individuals in a partition G_j to the entire population can therefore be written as follows

$$p_{j} = \frac{|G_{j}|}{\sum_{i=1}^{Q} |G_{i}|} \tag{10}$$

where $|G_j|$ means the cardinality of the set G_j .

Based on partitioning of individuals according to the number of conflicts, one approach to describe the state of the dynamical system is based on Shannon's information entropy E as follows²¹

$$E = -\sum_{j=1}^{Q} p_j \lg p_j \tag{11}$$

In order to reduce parameters adjustment, the dynamic adaptive local search frequency strategy β can be defined by

$$\beta(\text{gen}) = \frac{E(\text{gen})}{E(0)} \tag{12}$$

where E(0) and E(gen) are the population entropy measures at the generations 0 and gen, respectively.

During the evolution, there are two special individuals which need to undergo local search. One is the individual with the best fitness value which is the current best solution and needs to undergo local search to obtain higher solution quality. The other one is the individual with the worst fitness value which may have the highest potential to get a higher quality solution. The number of other randomly selected individuals is written as follows:

$$\varphi(\text{gen}) = \begin{cases} \text{popsize} & \text{gen} = 0\\ \min[\varphi(0) * \text{floor}(\beta(\text{gen})) - 2, \text{popsize}] & \text{gen} > 0 \end{cases}$$

$$\tag{13}$$

We can conclude from Eq. (13) that the larger E(gen) is, the more the number of individuals undergoing local search will be.

3.2. Global optimization

The global optimization method is another critical issue in the MA framework. In this study, the fast GA is proposed as the global optimization method.¹⁹ It is especially effective to eliminate conflicts.

The optimization operators are demonstrated as follows.

3.2.1. Selection

The classic method, tournament selection, is adopted in this study.

3.2.2. Adaptive crossover operator

The crossover operator specially designed for SCR has a great advantage, i.e., it can find feasible solutions quickly at the beginning of the optimization.

Suppose that A and B are chosen as parents in the population. As shown in Fig. 4, if $g_{f_{A1}} > g_{f_{A2}}$, the two children inherit A_1 accordingly, and if $g_{f_{B1}} > g_{f_{A1}}$, they inherit B_1 . Otherwise, the children are obtained by the combination of parents with a probability α . The crossover is operated with a probability p_c .

3.2.3. Adaptive mutate operator

It can be concluded from Fig. 4 that if $g_{f_j} < \varepsilon$, the gene j mutates with a probability $p_{\rm m}$.

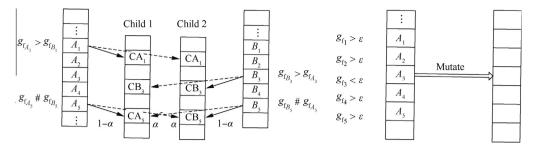


Fig. 4 Adaptive crossover operator and mutate operator.

4. Experimental studies

In this work, the real data of the Chinese airway network and flight plans of a day are adopted. The air route network is shown in Fig. 1, which includes more than 1100 waypoints with thousands of flight plans on it.

In addition, the takeoff and landing parts of trajectories are truncated around airports within a given radius (usually 10 NM (1 NM = 1.852 km)) as the traffic is considered to be handled with specific procedures by the TMA control services in these zones. Then, the flights are almost in the cruise phase. Therefore, the velocity of flights can be considered to be a constant value for simplicity, and here it is supposed to be 800 km/h.

The minimum safe time interval $\tau = 60$ s. δ_{max} is set to be 90 min, the value interval of δ is 0.25 min, and $\omega = 5$ NM.

The algorithms were implemented in a Visual Studio 2008 programming environment on a server with an E5620 2.4 GHz CPU and 12 GB RAM. For each algorithm, the results were collected and analyzed on the basis of 15 independent runs.

The parameters applied in all experiments are presented in Table 1.

4.1. Comparing SCAMA with existing methods

The experiment aims to evaluate the efficacy of the proposed SCAMA by comparing it with some existing algorithms, which are a classical method based on improved GA and an excellent approach based on cooperative co-evolution with a random grouping (CCRG) strategy which is designed to randomly and equally divide decision variables into several sub-groups and uses an EA to optimize each sub-group.²⁰

In order to better describe the differences between the algorithms' performances, we consider two situations, 1100 flights (the busiest 1 h) and 2400 flights (the busiest 3 h).

The results calculated based on 15 independent runs were analyzed statistically in terms of their best value (Best), average value (Average), standard deviation (Std), average delay (Ad), and average value of conflicts (Ac) for each method, and the results are shown in Table 2.

Table 1 Parameters of the experiments. Parameters Description Value Popsize Population size 80 800 Maxgen Max generation Crossover probability 0.35 $p_{\rm c}$ Mutate probability 0.4 $p_{\rm m}$

In Table 2, we can see that SCAMA has the best performance in almost all domains, and GA performed worst. For 1100 flights, the three methods all have good solutions. Obviously, as the scale grows, CCRG keeps showing a robust performance and has significantly improved the solution more than others. It has the best average value. The most important thing is that the average value of conflicts and delay got by CCRG are much lower than those got by others, e.g., even when n = 2400, there is no conflict and the average delay is 4.18 min which is much better than those of others.

Evolutionary curves of the compared algorithms as n is set to 1100 and 2400 are depicted in Fig. 5. In Fig. 5, the values in each generation are averaged over 15 runs. It provides a clearer demonstration of their performances. As we can see, GA has the worst performance. There is small difference between CCRG and SCAMA for 1100 flights. However, as the number of flights increases, compared to the other algorithms, SCAMA obtains the best solution and finds the feasible solution with the least number of conflicts and average delay most rapidly. Because the SCA problem has a large searching space which also increases exponentially, GA has difficulties in finding optimal solutions as the scale increases, so it performs poorly gradually. CCRG, using the decompose-and-conquer strategy, performs better than GA. However, tight interaction exists among flights for conflict avoidance. Therefore, as the scale increases, the performance of CCRG deteriorates gradually. However, SCAMA adopts global search and local improvement, which can minimize the risk of premature convergence and improve solutions' quality.

For 1100 flights, SCAMA almost obtains the best solution at 45 generations, which takes about 8 min. For 2400 flights, it takes SCAMA 150 min to get the best solution. We can conclude that, as the scale increases, the time consumption grows sharply. On one hand, our method can be used several hours or even days ago before real operations. On the other hand, advanced parallel computing technology can effectively shorten the time consumption. Therefore, our method could be useful for real applications.

In general, aircraft have different categories, such as the light aircraft, the medium aircraft, and the heavy aircraft. These aircraft have different velocities and safe separations between each other, which may seriously influence the results of these methods. Next, we will test our method at the situation with aircraft fleet mix. All flights are allocated one of the three aircraft categories randomly, and the velocities of the three categories are set to be 600, 700, and 800 km/h. Table 3 shows the safe separations between different aircraft.

In Table 4, we can see that SCAMA also has the best performance in almost all domains. Especially, for 1100 and 2400 flights, SCAMA can obtain the least average delay and the

Table 2 Comparison of GA, CCRG, and SCAMA.							
n	Algorithm	Best	Average	Std	Ad	Ac	
1100	GA CCRG SCAMA	0.857528 0.934176 0.969255	0.716537 0.930213 0.968551	$0.0047 2.59 \times 10^{-8} 1.98 \times 10^{-8}$	7.8163667 4.2736895 2.830455	0.4 0 0	
2400	GA CCRG SCAMA	0.856304 0.928368 0.937299	0.100861 0.732537 0.904938	0.1757 0.0463 0.00038	14.347430 6.5725796 4.1753905	8.2 0.842 0	

1.0	1.0
0.8	0.8 CRG SCAMA
S 0.6	0.6 Sitings
E 0.4	E 0.4 €
0.2 GA CCRG SCAMA	0.2
0 100 200 300 400 500 600 700 800 90	0 100 200 300 400 500 600 700 800 900
Generation	Generation 400 200 300 400 700 800 900
(a) <i>n</i> =1100	(b) <i>n</i> =2400

Fig. 5 Evolutionary process of the mean best value found for GA, CCRG, and SCAMA with n = 1100 and n = 2400.

Table 3 Safe separations between different aircrafts.					
Safe separation (NM)	Light	Medium	Heavy		
Light	4	3	3		
Medium	5	5	5		
Heavy	6	5	5		

lowest number of conflicts. In Fig. 6, the trend of the evolutionary curves is almost the same as that in Fig. 5. SCAMA can always obtain the highest quality solution quickly. Therefore, we can conclude that, to the problem we discussed in this work, the category of aircraft cannot influence the performance of our method.

4.2. Comparing our local search operator with others

By now, the first set of experiments has justified the superiority of SCAMA over existing methods. The next experiment is designed to further investigate whether the proposed local search operator contributes to the success of SCAMA.

The local search operator is a key issue in the MA-based framework. 21–24 There are several popular local search operators which are common and not specially designed for specific problems by now, i.e., *k*-gene mutation and *k*-gene exchange between chromosomes. 25,26. These algorithms share exactly the same settings as SCAMA in the experiment, including the diversity-based dynamic adaptive local search frequency, except the local search operators. They are briefly described below:

(1) SCAMA-M: this SCAMA adopts *k*-gene mutation as its local search operator.

- (2) SCAMA-E: this SCAMA adopts *k*-gene exchange between chromosomes as its local search operator.
- (3) SCAMA: SCAMA adopts the local search operator based on gene fitness.

Table 5 presents the results obtained by the three compared methods in terms of the best result, average result, standard deviation, and the number of conflicts. k cannot be too big or too small generally, so it is set to $5\%^*n$ in which n is the number of flights. We can conclude that SCAMA is much superior to SCAMA-M and SCAMA-E in average value, standard deviation, the number of conflicts, and delay as the scale grows, e.g., when n = 2400, SCAMA-M and SCAMA-E both have almost 4 conflicts, whereas SCAMA does not have any. In addition, the delays of SCAMA-M and SCAMA-E are almost twice as much as that of SCAMA.

Furthermore, like the first experiment, the evolutionary curves of the compared algorithms are depicted in Fig. 7. SCAMA shows its dramatic superiority in the convergence rate and quality of solutions. It can be concluded that the common and blind local search operators such as k-gene mutation and k-gene exchange between chromosomes cannot deal with the SCA problem efficiently. The reason perhaps is that the two local search operators which randomly change k genes cannot directly solve conflicts between flights. However, the local search operator based on gene fitness takes advantage of the conflicts among flights and makes the gene with more conflicts and less delays to have a high probability to mutate. Hence, the conflicts can be eliminated directly, and the delays can be reduced. It is experimentally validated that the local search operator based on gene fitness can find solutions with least conflicts and delays quickly, and obtain the optimal solution effectively.

Table 4 Comparison of GA, CCRG, and SCAMA with aircraft fleet mix.							
n	Algorithm	Best	Average	Std	Ad	Ac	
1100	GA CCRG SCAMA	0.845257 0.929463 0.970637	0.706376 0.929683 0.970425	$0.0052 \\ 2.47 \times 10^{-8} \\ 1.62 \times 10^{-8}$	7.8247695 4.6832457 2.5790365	0.573 0 0	
2400	GA CCRG SCAMA	0.847248 0.930637 0.947378	0.113604 0.742678 0.914267	0.20737 0.03690 0.00024	16.852587 6.2480047 4.0945376	8.752 0.793 0	

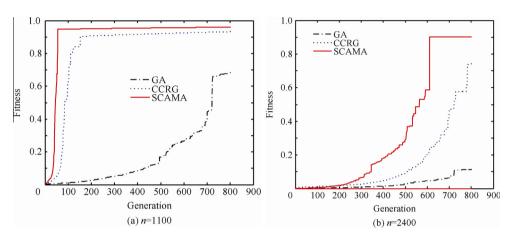


Fig. 6 Evolutionary process of the mean best value found for GA, CCRG, and SCAMA with n = 1100 and n = 2400 at the situation with aircraft fleet mix.

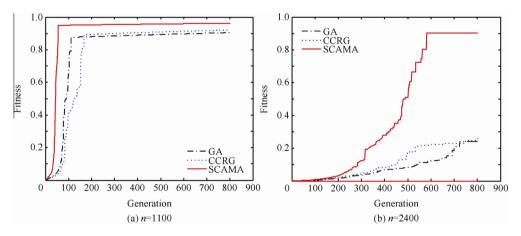


Fig. 7 Evolutionary process of the mean best value found for SCAMA-M, SCAMA-E, and SCAMA with n = 1100 and n = 2400.

4.3. Comparing the dynamic adaptive local search frequency strategies with others

SCAMA has been compared to existing methods and some MA-based algorithms with different local search operators. However, it is still unclear how the local search frequency strategy works. To investigate this issue, we have compared SCAMA with two other MA-based algorithms with frequently-used local search frequency strategies. These algorithms share the same local search operator and other

settings except for the local search frequency strategy. They are briefly described below:

- (1) SCAMA-G: the local search frequency is modeled as Gaussian distribution which can ensure high search efficiency at the initial stages of the search and less search frequency at the later stages.²¹
- (2) SCAMA-A: all individuals undergo the local search operator,²⁷ which means the search frequency is always 100%.

Table 5 Comparison of SCAMA-M, SCAMA-E, and SCAMA.							
n	Algorithm	Best	Average	Std	Ad	Ac	
1100	SCAMA-M SCAMA-E SCAMA	0.904738 0.902694 0.969255	0.883694 0.891422 0.968551	$0.00037 \\ 0.00015 \\ 1.98 \times 10^{-8}$	6.413631 4.283641 2.830455	0.065 0.057 0	
2400	SCAMA-M SCAMA-E SCAMA	0.863568 0.863647 0.937299	0.248861 0.257357 0.904938	0.0934 0.0913 0.00038	8.2317488 7.9436486 4.1753905	3.93 3.71 0	

Table 6 Comparison of SCAMA-G, SCAMA-A, and SCAMA.							
n	Algorithm	Best	Average	Std	Ad	Ac	
1100	SCAMA-G SCAMA-A SCAMA	0.951452 0.952382 0.969255	0.935806 0.951690 0.968551	5.37×10^{-6} 1.83×10^{-8} 1.98×10^{-8}	3.182576 2.924795 2.830455	0 0 0	
2400	SCAMA-G SCAMA-A SCAMA	0.925378 0.924684 0.937299	0.763573 0.742684 0.904938	0.00973 0.00724 0.00038	6.6475322 6.9357636 4.1753905	0.36 0.32 0	

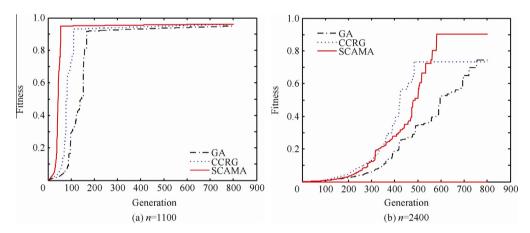


Fig. 8 Evolutionary process of the mean best value found for SCAMA-G, SCAMA-A, and SCAMA with n = 1100 and n = 2400.

The results are summarized in Table 6. It is obvious that SCAMA still performs better than the other two. Fig. 8 also provides the evolutionary curves of the compared algorithms. It provides a clearer demonstration of their performance. As we can see, there is little difference among the three algorithms for 1100 flights. However, SCAMA has the best performance, and SCAMA-G performs worse than SCAMA-A. Perhaps it is not enough for SCAMA-G to improve searching capability efficiently via randomly proceeding the local search operator on subsets of individuals. As the scale of flights grows, compared with others, SCAMA still has not caused any conflict and has the least delay. SCAMA-A converges rapidly. However, SCAMA-G performs better than SCAMA-A at last. Perhaps it is because that when the scale of the problem increases, the strategy of all individuals proceeding local search can help the algorithm to find better solutions quickly, ^{30,31} but easily fall into prematurity because of excessive exploitation in a large and complex space. In addition, at the later stages of the search, SCAMA-G can avoid excessive exploitation by selecting fewer individuals to undergo local search.

5. Conclusions

- (1) A strategic conflict avoidance approach based on a memetic algorithm is developed in this paper to deal with the long-term conflict avoidance.
- (2) A local search operator and an adaptive local search frequency strategy are specially designed to improve the solution quality. Furthermore, the fast GA is adopted as the global optimization method.
- (3) Empirical studies using real data of Chinese air route network and daily flight plans show that our approach outperformed the existing approaches including the genetic algorithm based approach and the cooperative coevolution based approach as well as some well-known memetic algorithm based approaches. Next, we will try to optimize the path and delay of flights simultaneously.

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