Arrival Aircraft Optimal Sequencing based on Teaching-Learning-based Optimization Algorithm with Immunity

To cite this article: Yang Li et al 2018 IOP Conf. Ser.: Earth Environ. Sci. 189 062003

You may also like

- Research on the Problem of Sorting Parallel Runway Aircraft in Terminal Area Based on Genetic Algorithm
  Na Lu, Jing Zhang and Ling Zhong

- A Decade of SCUBA-2: A Comprehensive Guide to Calibrating 450 m and 850 m Continuum Data at the JCMT
  Steve Mairs, Jessica T. Dempsey, Graham S. Bell et al.

- Analysis of load variation on chicken slaughterhouse waste water treatment using GAS-SBR
  I Septiana, L Siami, T Tazkiaturrizki et al.
Arrival Aircraft Optimal Sequencing based on Teaching-Learning-based Optimization Algorithm with Immunity

LI Yang, NIE Dang-Min, WEN Xiang-Xi, GAO Yang-yang
(School of Air Control and Navigation, Air Force Engineering University, Xi’an 710051, China)
Email: liyangisvip@163.com

Abstract. Sequencing and scheduling of arrival aircrafts is of great significance for ensuring flight safety and reducing flight costs. A multi-constrained approach aircraft optimization ranking model with minimum delay time as an objective function was established. Based on the “Teaching-Learning Based Optimization” (TLBO), the algorithm was discretized, combined with the "antibody injection" and "immune modification" of the Immune Algorithm (IA). The improved algorithm was used to simulate the aircraft sequencing optimization model and compared with the traditional FCFS method. The simulation results show that compared with the FCFS method, the improved TLBO algorithm can significantly reduce the total aircraft delay, effectively mitigate the delay of aircraft arrival, and can be used to solve the problem of aircraft optimization.

1. Introduction
Arrival aircraft sequencing and scheduling is based on certain rules and standards, to be approached to form an aircraft approach queue with a certain sequence. According to the ranking results of the aircraft, the aircraft is allocated appropriate entry timings and landing time, to achieve the safe and orderly operation of arrival aircraft.

At present, the commanding of the commander for approaching aircraft is mainly based on experience, using the first-come first-serve (FCFS) strategy to determine the landing sequence for entering aircraft. This strategy is easy to operate and the features are fair and equitable. With the rapid economic development in recent years, air traffic continues to grow, and the shortcomings of traditional commanding methods are becoming more and more significant. The problems of aircraft delays and airspace congestion have become increasingly worse. The sequencing and scheduling of arrival aircrafts has become one of the hot issues in current research.

The core of the Arrival Sequencing is to maintain the safety interval between aircrafts, and to reorder and deploy the approaching aircraft according to certain constraints, in order to achieve the purpose of increasing runway capacity, reducing delays, and reducing the workload of controllers. As a heuristic algorithm, intelligent algorithms have been rapidly developed in recent years and are widely used to solve the problem of aircraft model optimization sequencing and deployment. In 2015, Chen Jin-liang[1] and others used the improved artificial fish swarm algorithm to establish a multi-runway airport approach sequencing model with the minimum total cost of flight as the objective function, which effectively mitigated flight delays and reduced flight costs. Ma Ying-wei [2] and others proposed an improved strategy for the shortcomings of the traditional particle swarm algorithm and
solved the problem of flight landing scheduling. In 2016, Ma Weiping \[3\] and others used the global search capability of ant colony algorithm, combined with CPS to ensure the operability and fairness of the scheduling, effectively reducing the total delay time of landing flights in a relatively short period of time. Zhang Wei-jie \[4\] and others proposed an improved genetic algorithm that introduced a cross-mask to reduce the total cost of queue delays for aircrafts.

These algorithms could be applied to solve the problem of optimal sequencing of approach aircraft, and had achieved good results, but the algorithm itself has certain limitations, such as the need to set a certain control parameters. The choice of parameters for the search ability of the algorithm will have great influence. Teaching-Learning Based Optimization (TLBO) is a new population intelligence optimization algorithm proposed by Rao \[5\] in 2010. The algorithm is implemented by simulating the teacher's teaching process and the student's learning process. The algorithm, cancelling the control parameter like other intelligent algorithms, receiving extensive attention, because it is simple, has faster convergence speed, and has strong convergence ability. In this paper, we improve the algorithm, increase the process of discretization, and combine the "antbody injection" and "immune modification" of immune algorithm to propose an Immune Teaching-Learning Based Optimization (ITLBO) for the purpose that it can be applied to approaching aircraft. After discretization, the program of scheduling problem was verified the effectiveness by the simulation experiments.

2. Arrival aircraft ranking model

Assuming that the airport has only one runway and only considers the landing queue, the incoming aircraft can land the airport from several different routes. All aircraft can be queued according to the arrival time and re-ordered. Assuming that the aircraft to be sorted in the approach section has \( N \) aircrafts, defined as the set \( F \), \( F=\{F_1,F_2,\ldots,F_N\} \). The estimated and schedule time of arrival are respectively defined as \( \text{ETA}_i \) and \( \text{STA}_i \).

Aircraft types can be divided into three types: heavy (H), medium (M), and light (L). Arrival aircraft are usually based on time, and aircraft wake spacing is an important reference factor. The definition of the \( i \)th aircraft type is denoted by \( p(i) \). When the \( i \)th aircraft and the \( j \)th aircraft are respectively the front and rear aircraft of this route, the wake interval between the two aircraft is \( d[p(i), p(j)] \). As shown in Table 1, the revised ICAO radar wake separation criteria based on the time dimension is used, where the columns indicate the front plane and the rows indicate the rear plane.

| The rear plane | Heavy (H) | Medium (M) | Light (L) |
|----------------|-----------|------------|-----------|
| Heavy (H)      | 113       | 135        | 170       |
| Medium (M)     | 89        | 89         | 110       |
| Light (L)      | 83        | 83         | 94        |

According to the aircraft arrival sequence and radar wake separation criteria, the actual arrival time of the aircraft can be obtained.

\[
\begin{align*}
\text{STA}_i & = \text{ETA}_i \\
\text{STA}_{i+1} & = \max \left\{ \text{ETA}_{i+1}, \text{STA}_i + d[p(i), p(i+1)] \right\} \quad i=1, 2, \ldots, n-1
\end{align*}
\]

The delay time of the \( i \)th aircraft is expressed as \( D(i) \).

\[
D(i) = \text{STA}_i - \text{ETA}_i
\]

The goal of optimization is to minimize average aircraft delays, expressed as \( \bar{D} \).

\[
\bar{D} = \min \left\{ \frac{1}{n} \sum_{i=1}^{n} \{ D(i), 0 \} \right\}
\]
Restrictions:
(a) During the sequencing process of the aircraft, the aircrafts must maintain a minimum safety interval. The standard of this interval mainly depends on the landing sequence of the aircraft and the wake standard of the front and rear aircraft.

\[ STA_{i+1} - STA_i \geq d \left[ p(i), p(i+1) \right] \] (4)

(b) During the sequencing process of the aircraft, if the re-arranged sequence seriously deviates from the FCFS sequence, the commander's control load will increase, and at the same time it will not be conducive to the safe operation of the aircraft. Therefore, it is necessary to set the maximum positional deviation of the aircraft. Assuming there are a total of five aircraft, the maximum position constraint is 1, and the aircraft is located on the second FCFS rank, and its possible positions of change are 1, 2 and 3. Considering the commander's workload and operational restrictions, the maximum position constraint value is generally defined as 1 or 2.

3. Immune Teaching-Learning Based Optimization

3.1. Basic TLBO algorithm

The optimization algorithm based on teaching and learning is to simulate the learning style of the class. The improvement of the level of students in the class requires the teacher's "teaching" to guide. At the same time, the students need to "learn" each other to promote the absorption of knowledge. Among them, teachers and students are equivalent to individuals in evolutionary algorithms, and teachers are one of the best individuals in terms of fitness. A certain subject learned by each student is equivalent to a decision variable. The student's grade is the function fitness value, and the classroom is the best individual for the fitness value. The specific definition is as follows:

(a) Class. In the TLBO algorithm, the set of all points in the search space becomes a class.
(b) Students. One point in the class \( X_j = (x^1, x^2, \ldots, x^d) \) is called a student.
(c) Teacher. \( X_{best} \), the student with the best academic performance in the class, called it a teacher, and said it with \( X_{teacher} \).

The TLBO algorithm steps are as follows:

(1) Initialization of the class. Each student in the class is randomly generated in the search space.

\[ x^i_j = x^j + rand(0, 1) \times (x_{teacher}^j - x^j) \quad j = 1, 2, \ldots, NP; i = 1, 2, \ldots, d \] (5)

(2) "Teaching" stage. During the TLBO "teaching" stage, each student \( X_i (j = 1, 2, \ldots, NP) \) in the class learns on the basis of the difference between \( X_{teacher} \) and the student mean \( X_{mean} \).

\[
\begin{align*}
X^i_{new} &= X^i_{old} + X_{difference} \\
X_{difference} &= r(i) \times \left( X_{teacher} - TF_i \times X_{mean} \right) \\
TF_i &= \text{round} \left( \left[ 1 + \text{rand}(0, 1) \right] \right) \\
X_{mean} &= \frac{1}{NP} \sum_{i=1}^{NP} X^i
\end{align*}
\] (6)

The learning step size is \( r(i) = \text{rand}(0,1) \); \( X_{difference} \) is the difference between each student and teacher.

Update the students after the teaching is completed. For each student, obtain the corresponding function fitness value, and compare the score after learning with the score before learning. The program is as follows:

\[
\begin{align*}
\text{if} & \quad f \left( X^i_{new} \right) > f \left( X^i_{old} \right) \\
X^i_{old} &= X^i_{new}
\end{align*}
\] (7)
End

(3) "Learning" stage. Through the mutual learning between students, there is an optimized solution set. The "learning" stage is for students to learn from each other in a small-scale search space, but it will soon move closer to the global best, enhancing the global search ability of the algorithm and effectively maintaining the diversity of the population. Each student randomly selects another student as a learning object in the class, analysed and compared each other to update. It adopts the formula:

\[
X_{new}^i = \begin{cases} 
X_{old}^i + r(i) \cdot (X^i - X^j) & f(X^j) < f(X^i) \\
X_{old}^i + r(i) \cdot (X^j - X^i) & \text{else}
\end{cases}
\] (8)

After the completion of the mutual learning stage, the renewal rule of the "teaching stage" was used to update the students.

(4) If the end condition is satisfied, the result is output. Otherwise, it returns to the teaching stage to continue optimization.

3.2. Algorithm improvement

The traditional TLBO algorithm can’t be directly applied to the optimization problem of aircraft sequencing. It needs to improve the algorithm as follows:

(1) Discretization. The basic TLBO is mainly aimed at solving the continuous problem. The problem of aircraft sequencing optimization belongs to the discrete complexity problem. Therefore, it is necessary to improve the TLBO algorithm to solve such discrete optimization problems. Therefore, the method adopted in this paper is to discretize the students, that is, to recompile \( X_i \), so as to generate new students and perform evaluation on new students.

Assuming that the first student randomly generated \( X_1 = (1.26, 1.03, 2.25, 4.63, 6.96, 6.21) \). The random numbers generated by the student are sequenced in ascending order, and the ranked index is used as a new random number to generate new students. For example, \( X_1 \) generates a new student \( Y_1 = (2, 1, 3, 4, 6, 5) \).

(2) Immune Teaching-Learning Based Optimization (ITLBO)

The immune algorithm simulates the process of biological immunization and it is a heuristic random search algorithm that combines deterministic and random selection, has the capabilities of "exploration" and "mining". During the aircraft sequencing process, there is a maximum position constraint conversion problem (CPS) and the maximum position offset of the aircraft needs to be set. This article intends to introduce the antibody injection theory of immune algorithm and improve the "teaching and learning" algorithm to improve its convergence speed and robustness.

(a) Antibody injection in initialization stage.

In the process of initializing the class, there are too many possible solutions that do not satisfy the constraints in the randomly generated sequence, which affects the convergence speed of the entire class, resulting in a low efficiency of the algorithm. Therefore, the introduction of immune algorithm antibody injection strategy, in the initialization class stage, for the random generation of students in advance injection of antibodies, adding the maximum position constraint conversion (CPS), making the random generation sequence closer to the best sequence, thereby enhancing the convergence of the algorithm.

If the maximum position constraint of the sequencing process is, the imaginable position of the \( i \)th aircraft is “\( i-a \)”, “\( i-a+l \)”, ..., “\( i+a \)”. Students in the class randomly generated in the search space. Search space can be set as follows:

\[
x_{j}^{i} = (i - a) + \text{rand}(0, 1) \times 2a, j = 1, 2, \ldots NP, i = 1, 2, \ldots n
\] (9)

(b) Teaching Process Immunity

In the “teaching” stage and the mutual learning stage, students’ updates will be conducted and new students will be created. The newly-generated students may have the situation of “non-conforming trainees”, that is, they cannot be used as feasible solutions of the original model. In this case, the
vaccine amendments in the immune algorithm need to be introduced to correct the new trainees and eliminate the negative impact of the new trainees. In the "teaching" process, the newly generated student $x^j$ has been discretized and obtained the student $y^j$. If it is satisfied for $\|y^j-i\| \leq a$, $y^j$ is a feasible solution of the original model. Otherwise, $y^j$ is a "failed student".

4. The Simulation analysis
Using 15 aircraft at a certain airport as a sample to conduct an experiment. Aircraft information is as follows. In order to test the feasibility and effectiveness of the proposed algorithm, the first-come-first-serve sorting method and the IATLBO algorithm were used in arrival aircraft sequencing. The number of iterations was set to 100, the number of trainees was 20, and CPS is 1. The simulation results are shown in Table 2.

| Initial Sequence | Type | ETA | FCFS | ITLBO |
|------------------|------|-----|------|-------|
|                  |      |     | STA  | D(i)  | ETA  | STA  | D(i)  |
| 1                | L    | 30  | 30   | 0     | 1     | L    | 0     | 30    |
| 2                | L    | 84  | 119  | 35    | 2     | L    | 35    | 119   |
| 3                | L    | 112 | 208  | 96    | 3     | L    | 96    | 208   |
| 4                | H    | 175 | 297  | 122   | 5     | L    | 122   | 386   |
| 5                | L    | 203 | 432  | 229   | 4     | H    | 229   | 297   |
| 6                | L    | 265 | 521  | 256   | 7     | H    | 256   | 545   |
| 7                | H    | 301 | 610  | 309   | 6     | L    | 309   | 410   |
| 8                | L    | 354 | 699  | 345   | 8     | L    | 345   | 634   |
| 9                | L    | 399 | 788  | 389   | 9     | L    | 389   | 723   |
| 10               | L    | 448 | 877  | 429   | 10    | L    | 429   | 812   |
| 11               | L    | 502 | 966  | 464   | 12    | H    | 464   | 1036  |
| 12               | H    | 543 | 1055 | 512   | 11    | L    | 512   | 901   |
| 13               | S    | 713 | 1190 | 477   | 13    | S    | 477   | 1146  |
| 14               | L    | 796 | 1279 | 483   | 15    | S    | 483   | 1323  |
| 15               | S    | 906 | 1389 | 483   | 14    | L    | 483   | 1240  |
| Total delay time |     |     | 4629 |       |       |       |       | 3979  |

The final delay time for aircraft of the FCFS method is 4629s. The delay time for the arrival aircrafts sequencing by the ITLBO algorithm is 3797s. The improved ITLBO algorithm can effectively sequence the arrival aircraft and reduce the total delay time by 650s.

5. Conclusion
Simulations show that the improved ITLBO algorithm can be applied to the optimized sequencing model of approach aircraft, and has a smaller delay compared with the traditional first-come-first-serving method, which can accelerate the landing time of the aircraft and reduce the flight cost.

References
[1] ZHANG Wei-jie, LONG Hua, HU Ting, SHAO Yu-bin. Improved genetic algorithm applied to overdue aircraft arrival sequencing[J]. Information Technology, 2016, 6: 78-83.
[2] MA Ying-jun, SUN Xiao-na, ZHAO Dong-fang. Research of flight landing scheduling problem based on improvement partial swarm optimization[J]. Application Researching of Computers, 2015, 32 (7): 2035-2038.
[3] MA Wei-dong, YANG Wen-juan, XU Bo. Research on Application of Ant Colony Algorithm Based on Displacement Constraints in Flight Landing Scheduling Problem[J]. Journal of Industrial Engineering Management, 2016, 30(1): 191-196.
[4] CHEN Jin-liang, WANG Shao-peng, ZHANG Jian-feng, WANG Peng. Research on Air Traffic Flow Approach Scheduling Management[J]. Computer Simulation, 2015,32(10): 108-112.

[5] Rao R V, Savsani V J. Teaching -learning based optimization: A novel method for constrained mechanical design optimization problems [J]. Computer Aided Design, 2011,43(3):303-315.