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SHORT COMMUNICATION

Arrival Sequencing and Scheduling using an Evolutionary Approach in a 4D Environment

Daniel Alberto Pamplona*[1,2] | Claudio Jorge Pinto Alves[2]

[1]Department of Civil Engineering, University of Calgary, Alberta, Canada
[2]Department of Air Transportation, Aeronautics Institute of Technology, Sao Paulo, Brazil

Correspondence
*Daniel Alberto Pamplona, Department of Civil Engineering, 2500 University Drive NW, Calgary, AB, T2N 1N4. Email: pamplonadefesa@gmail.com

Abstract

The aim of this article is to use an Evolutionary Algorithm (EA) to solve the Aircraft Landing Problem (ALP) in an Air Traffic Flow Management (ATFM) environment. The ALP addresses the function of generating optimal or near-optimal landing sequences and time intervals between arrivals to provide runway capacity increase and reduce air delay. Problems of the ALP type in a dynamic environment such as Air Traffic Control (ATC) are considered Non-Polynomial (NP) complete. We simulated three different models. In the first model, the algorithm was applied when there was a schedule conflict between aircraft and separation measures where used to ensure safety. On the second and third models,we scheduled the flights in hourly batches. In the third model, a Maximum Constrained Shift (MCS) restriction was introduced to simulate more realistic conditions. To test the effectiveness of our study, we used actual data from Guarulhos International Airport. Results showed a capacity gain of 12 aircraft and a delay decrease of five percent when compared to the airport current sequencing operations. Introducing this technique represents a shift from the current arrival sequence model to a Trajectory-Based Operations (TBO) model, balancing air traffic demand with airspace capacity to ensure the most efficient use of the airspace system.

KEYWORDS:
Air Traffic Flow Management; Evolutionary Algorithm; Arrival Management; Intelligent Systems

1 | INTRODUCTION

Air delay is an existing problem in most airports around the world, bringing an increase in costs to the airlines and discomfort to the passengers. Flights in Europe, due to airspace inefficiencies and capacity bottlenecks, are delayed 10 minutes on average per flight[4]. One reason for air delay is the concentration that some airports face because of the air demand with long-haul and regional traffic, creating global hubs. The air traffic growth is concentrated with a few global cities. In Latin America, since 2007, 10 airports accounted for 45% of the air traffic operations [1].

The airspace capacity is defined as the maximum number of aircraft per unit of time that can be safely accommodated in the airspace given controller workload, pilot workload and airspace constraints. When the demand for airspace is exceeded, capacity bottlenecks arises and causes delay [3]. Most congestion problems are fixed on the day of operations tactically using demand management measures. One of the most common measures applied in the Air Traffic Flow Management (ATFM) programs is to delay the flights on the ground (ground delay) to temporally spread the demand [5]. When the aircraft is airborne, other measure is to implement Flow Sequencing Programs, suggesting alternative routes to decrease the number of aircraft holding procedures.The adherence to its flight schedule is of primary importance in the efficient operation and profitability of an airline [6].

The aim of this article is to use an Evolutionary Algorithm (EA) to solve the problem of Aircraft Landing Problem (ALP). To test the effectiveness of the proposed model, we used actual data from Guarulhos International Airport (SBGR), the busiest airport by passenger and aircraft traffic in Brazil. We simulated three different models. In the first model, the algorithm was applied when there was a schedule conflict between aircraft and separation measures where applied to ensure safety. On the second and third model, scheduled the flights in hourly batches. In the third model, a Maximum Constrained Shift (MCS) was used to simulate more realistic conditions. This present study is part of a broad research line on Air Traffic Flow Management, specifically for building a traffic manager adviser (TMA). The TMA seeks to rearrange the arriving aircraft in an airport to the available runways aiming to minimize delays and satisfy safety constraints, particularly the wake-vortex safety separation. Decision support systems (DSSs) based on optimization algorithms may help to exploit at most the capacity available in the terminal maneuvering area (TMA) during operations [3].

The remainder of this paper is organized as follows. In Section II, the arrival sequencing and scheduling problem and genetic algorithm are discussed. Section III presents the framework and optimization model. In Section IV the outcomes are presented and analyzed. Section V shows conclusions about the study.

2 | LITERATURE REVIEW

2.1 | The Arrival Sequencing and Scheduling Problem

To think about air congestion mitigation measures is an exercise of managing the aircraft flow in a determined space. Air Traffic Flow Management (ATFM) is a function of Air Traffic Management (ATM) that aims to balance the demand for air traffic in space and/or ensure the most efficient use of the airspace system [7]. Because of the constant air traffic growth in the last decades, especially in high-density airports, congestion is always present, leading to lower operational efficiency and more flight delays. Seeking to increase efficiency in the ATC system, a major reform is taking place in the world such as NextGen in the United

States, SESAR in Europe and SIRIUS in Brazil. One measure adopted in landing approaches to ensure flight safety and air traffic management on arrival is the redistribution of aircraft arrivals to ease air congestion. This procedure is called Aircraft Landing Problem (ALP)[8].

ALP is based on two premises. First, safety regulations state that any two co-latitudinal aircraft must maintain a **minimum horizontal separation**, which is a function of the types and of the relative positions of the two aircraft; Second, the **landing speed** of a type of aircraft is generally different from that of another type of aircraft. Because of the variability of the above parameters, the Landing Time Interval (LTI), which is the minimum permissible time interval between two successive landings, is a variable quantity. Problems of the ALP type in a dynamic environment such as air traffic are considered NP-complete because they require an exponential time to be solved[9].

The ALP is a discrete optimization problem and can be formulated as a permutation-based optimization problem[8].The problem is governed by the following features[6]: a) For each n arrival flights, an Estimated Time of Arrival (ETA) to each of m runways is available; b) All flights scheduled to land on a runway must observe specific separation rules based on the aircraft types between the leading aircraft and the trailing aircraft. Three aircraft are specified: Heavy (H), Large (L), and Small (S). The separations are given in terms of time separation determined at the runway threshold. A special case is when an airport only allows certain types of aircraft on specified runways; and c) When a flight is scheduled to a runway, the delay as result of the schedule is defined as the difference between the Scheduled Time of Arrival (STA) and the earliest ETA among the runways for that flight.

In the last decades, many researchers have sought to solve the ALP. Several approaches were taken to its resolution, using various types of mathematical models. Considering the objective functions of optimization, Hu and Di Paolo[10]; Hu and Chen[9]; Hu and Chen[11] sought to minimize the total delay in flight. Beasley, Krishnamoorthy, Sharaiha and Abramson[12]; Beasley, Sonander and Havelock[13]; and Beasley, Krishnamoorthy, Sharaiha and Abramson[14] used extra costs (extra costs generated by early or late arrival). Hu and Chen[9]; Hu and Chen[10]; and Lei, Jun and Yanbo[15] used the time required for all landings.

ALP is still one of the core problems in the research of ATC[8]. Delahaye, Alliot, Schoenauer and Farges[20] show three utilization of Genetic Algorithm (GAs) to Traffic Flow Management (TFM): (a) optimization of air space sectoring, (b) traffic assignment, and (c) en-route conflict resolution. GAs are appropriate to TFM problems because of their robustness on non-convex, non-linear, or non-analytic domains[21].

2.2 | Genetic Algorithm

A genetic algorithm (GA) is a search variant in a stochastic beam in which the successor state is generated by combining two related conditions that emerge. The analogy of the natural selection of mating and reproduction found in nature is used[24]. Genetic algorithms are a search method based on the principles of natural selection and genetics. In a GA, the decision variables in a search problem are encoded in finite-length strings containing alphabets of a certain cardinally [25].

The strings that are candidates for the solution of the search problem are called the chromosomes. The alphabets are called genes. The values of the genes are called alleles [25]. GA has its beginning with a set of k individuals, which can also be called the states, are generated probabilistically. This set is called the population. Each individual will be represented by a sequence of a finite alphabet, being represented by the binary numbers 0 and 1, for computational reasons. Each population is represented by the binary numbers 0 and 1, for computational reasons, and is ordered by the objective function of the problem to be solved. The terminology used in GA is the fitness function [24]. The objective function, a mathematical model or a computer simulation, has the purpose of being the parameter used to compare the presented solutions, thus allowing the implementation of natural selection (distinguish good solutions from others).

A major factor of GA is the notion of population. Candidates for the solution will emerge from the population. Population size, which is a parameter specified by the problem modeler, is one of the important factors affecting scalability, which can be defined as the ability of a system to deal with a growing portion of the demands to be performed and the performance of a GA [25].

In the present study, it was used the roulette wheel as a method of selection. In the present study, the one-point recombination operator will be used. The basis of the method is that two individuals are selected according to selection techniques, and their offspring result from recombination of the parents with a crossover probability (cp). The one-point recombination operator is one of the most commonly used methods. A crossover site is selected at random over the string length, and the alleles on one side of the site are exchanged between the individuals [25].

Mutational operators are designed to add adversity to the population and ensure that it is possible to explore the entire sample space in search of the best solution. Generally, low probabilities are used. In the present study, a mutation probability of 0.1 was used. For replacement, once the new offspring solution is created through the use of crossover and mutation techniques, it is necessary to introduce them into the parents' sampling spectrum. In the present study, the delete-all technique was used. In this technique, all members of the current population are replaced with the same number of chromosomes that have just been created. Since GA is an efficient algorithm for non-constrained optimization, the penalty technique is used in this problem. Through this method, a constrained optimization problem is transformed into an unconstrained problem by penalizing the infeasible solution [24].

3 | FRAMEWORK AND STUDIED MODELS

3.1 | Studied models

First Come, First Served (FCFS) is a cornerstone of Air Traffic Control. In accordance of FAA[26], FCFS is the algorithm used for operational priority. In the FCFS algorithm, a queue is formed from which elements are extracted in a first-in, first-out manner. Adapting to the air traffic control reality, as the aircraft approaches an airport for landing, a queue is formed and the aircraft are sequenced. Usually, radar vectors and Standard Terminal Arrival (STAR) Procedures are used to form this queue independently of the aircraft category and other characteristics. Because of pair-wise separations between aircraft, measures of decreasing speed or performing holding procedures are requested by the ATC. The main consequence is an increase in airborne time and inefficiency.

Although FCFS scheduling establishes a fair order based on predicted landing time, it ignores other useful information which can efficiently use the capacity of the airport, reduce airborne delays and/or improve the service to airlines[9]. Evidence shows that FCFS is not the best strategy to maximize the use of existing airport capacity and to reduce the average delay costs. The problem is that FCFS policy mostly depends on the work experience of the controllers to make sorting of flight. For the approach flight, controllers need to make a reasonable allocation of their runways and taxiways to make them land smoothly and reach the apron safely[27]. For air traffic controllers, a simple way to solve the ALP is to schedule the arriving aircraft by the FCFS algorithm and the predicted landing time maintaining the safety pair-wise separation between aircraft[28].

Our GA models were implemented in all arrival flights in a single day at SBGR and comprehended 354 flights as shown in Figure 1.

Some periods of the day are more congested than others. The Minimum Safe Separation (MSS) was used as a constraint in all models. The main purpose of these separations is to maintain a safe distance between aircraft due to the wake vortex. In terms of flight safety, the problem that may exist is excessive scrolling and yawing caused to the tracking aircraft, and may sometimes exceed the controllability of the aircraft. The most serious scenario is when the aircraft in a takeoff or landing approach, flying at low altitude, is subjected to the rolling and yaw forces, losing control of the airplane and causing accidents, which is aggravated by flying at low speed. The recovery of an extreme event will be inherent in the altitude, maneuverability, and power of the aircraft. In the present study, it was considered that all aircraft would be separated in pairs by seconds as described in Table 1.

The aircraft were divided into three categories:

- **Heavy**: all types of aircraft with a maximum take-off weight of 136,000 kg or more.
- **Medium**: all types of aircraft with a maximum take-off weight of less than 136,000 kg and over 7,000 kg.
- **Light**: all types of aircraft with the maximum take-off of 7,000 kg or less.

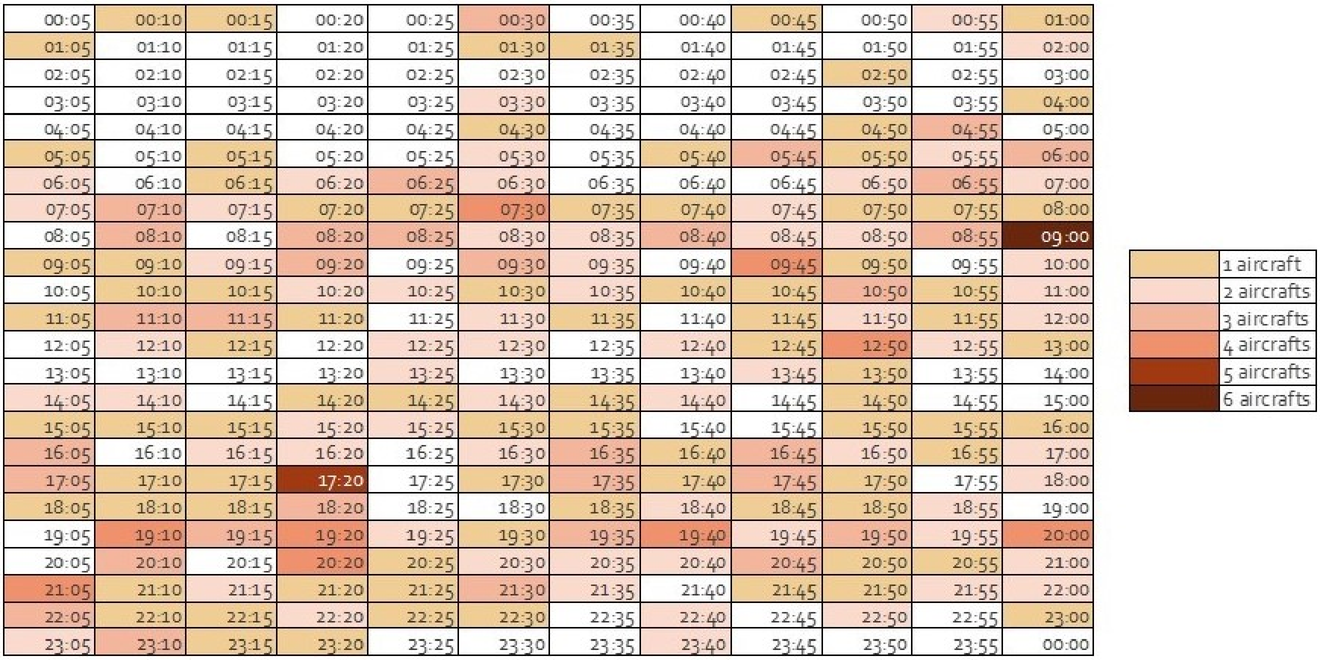

FIGURE 1 Landing schedule for SBGR.

TABLE 1 Minimum Safe Separation for different pairs of aircraft types

	Trailing Aircraft		
Leading Aircraft	Heavy	Medium	Light
Heavy	94	114	167
Medium	74	74	138
Light	74	74	98

We formulated our problem as a static case where all landing aircraft must be sequenced when all information is known in advance[3]. Most literature formulated ALP as a static case where the data of all arriving flights is thought to be known ahead of time and scheduling of every one of these flights will be conducted.[14,13,12,18,29,30,31,32,33,34,35]

3.1.1 | First Model

In the first model, we aimed to minimize the air delay subject with the wake-vortex separation. The first objective function it was used in the present study was:

Minimize:

$$\sum_{i=1}^{N} DT_i = \sum_{i=1}^{N} (ETA_i - STA_i), \tag{1}$$

Subject to:

$$ETA_i - ETA_j \geq MSS_{ij} \tag{2}$$

where:

DT_i: Delay Time of $aircraft_i$;

ETA_i: Estimated Arrival Time of $aircraft_i$;

STA_i: Scheduled Arrival Time of $aircraft_i$;

MSS_{ij}:Minimum Safe Separation of $aircraft_i$ and $aircraft_j$.

3.1.2 | Second and Third Models

In the second and third models all flights were rescheduled in batches. Each batch comprehended a one-hour period, scheduling the arrival aircraft within approximately 40 to 200 nautical miles from the airport. For example, one hour bank is composed of the aircraft are in the radar range for landing in the next hour. As proposed by Hansen[6] a flight vector identifies the flights in the current aircraft bank. For example, in the first hour of the day (0100), the flight bank is composed of 12 aircraft. For confidential reason, the airline and the respective flight numbers were removed. A vector also describes the associated aircraft types, under their wake-vortex classification. Another vector identifies the Estimated Time of Arrival (ETA) for the flights in seconds on the current aircraft bank.

- FLIGHT BANK 0100 = ['AC_01', 'AC_02', 'AC_03', 'AC_04', 'AC_05', 'AC_06', 'AC_07', 'AC_08', 'AC_09', 'AC_10', 'AC_011', 'AC_12',].
- AIRCRAFT TYPE 0100 = [M, M, H, M, H, H, M, M, H, H, M,H].
- ETA 0100 = [3600, 3600, 3900, 3900, 4100, 4200, 4200, 4600, 4600, 5000, 5800].

The second model presented no constrained shift. Due to practical reasons where an aircraft cannot keep longer periods waiting for landing or cannot advance for so long in the scheduled landing time, a new restriction has been added (Third Model) that introduces a Maximum Constrained Shift (MCS) for aircraft landing. Because of aircraft and approach limitations, each aircraft will present a maximum position shifting of five aircraft when compared to the original scheduled order to land.

We added the following restriction to the third model:

$$MCS_i = IP_i - FP_i,\ 0 \leq\ 5 \tag{3}$$

where:

MCS_i: Maximum Constrained Shift of $aircraft_i$;

IP_i: Initial Position of $aircraft_i$;

FP_i: Final Position of $aircraft_i$.

Figure 2 shows the application of the complete model in the studied problem. The proposed optimization was implemented in the Guarulhos International Airport (SBGR/ICAO). It is the largest airport in Brazil, with an annual movement estimated of 40 million passengers per year. SBGR has two runways, and it was considered that runway 09R will be used only for landing. Actual data provided by the Brazilian Aviation Agency (ANAC) through the Transport Time Schedule (HOTRAN) was used in the implementation process of the algorithm.

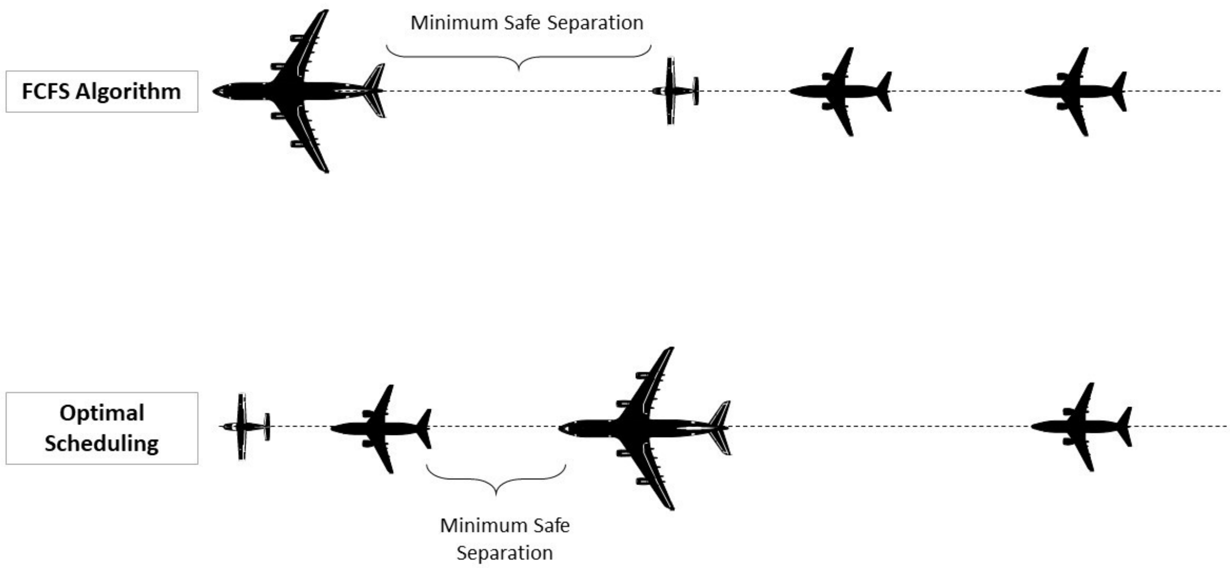

FIGURE 2 Optimal Scheduling.

4 | RESULTS

The main purpose of our study was to effectively diminish flight delay in the Final Approach Procedure segment of a flight. A 4D-compliant framework was used where the aircraft must meet the three axes (latitude, longitude, and altitude) plus fly-by at a determined time an aeronautical fix.

Since the models are based on the wake-vortex separation (Equation 2) for better rearrangement, due to the aircraft mix presented at Guarulhos Airport, some schedule conflicts (Model 1) and batches (Model 2 and 3) were not selected. Model 1 presented 110 scheduled conflicts and only 25 were selected for model application. From the 24 batches presented on Model 2 and 3, seven batches were not selected due to a homogeneous fleet presented. The aircraft mix is directly linked to the airlines and the presented demand and their business model.

All the simulations were conducted with a Intel Core i7 5500U CPU 2.4GHz.

Even with the low rate of Model 1 usage (23%) for the resolution of time conflicts, Model 1 presented a decrease of 4% on air traffic delay. Considering the most common aircraft pairs (Medium-Medium) presented at the airport and its time separation Table 1 , it represents a capacity gain of 11 operations in a single day.

Table 2 shows the results for the second and third model. The columns represent the objective function sum in each batch for the First Come First Service Model, Model 2 and Model 3.

TABLE 2 Results for FCFS, Model 2 and Model 3

∑ Obj. Function	FCFS	GA_II	GA_III
batch 0	638	**598**	**598**
batch 1	282	**242**	**242**
batch 2	188	**158**	**158**
batch 3	114	**74**	114
batch 6	1558	**1468**	1710
batch 7	1730	**1680**	1710
batch 8	2062	**1972**	2002
batch 9	1918	**1858**	1888
batch 10	1334	**1304**	1324
batch 12	1458	**1418**	1458
batch 16	1686	**1616**	1626
batch 17	1830	**1730**	1760
batch 19	2318	**2268**	2318
batch 20	1898	**1848**	1878
batch 21	1626	**1586**	1616
batch 23	786	**746**	776

Batches 4, 5, 11, 13, 14, 15, 18 and 22 were not optimized due aircraft mix homogeneity. FCFS denotes First Come First Service. GA_II denotes the Genetic Algorithm used in the Second Model. GA_III denotes the Genetic Algorithm used in the Third Model. Best performance in bold

The main objective was to minimize the runway total operation time. We noticed that depending on the sequence size and aircraft mix the objective function tend to decrease. It represents an increase in the runway capacity. Model 2 increased the daily capacity in 12 aircraft. When MCS measures were applied (Model 3), the capacity was increased in 6 aircraft.

The objective of the study was to solve the ALP in a fast and secure (feasible solutions) way. The GA algorithm provided fast and good solutions, adapting to the Air Traffic Control reality where there is a constant need for fast responses (bellow one second). The best results appeared when the congestion levels increased. Genetic Search algorithms proved to be reliable to the TMA task of scheduling aircraft for arriving banks of aircraft. It provided a real-time controller support.

5 | CONCLUSION

Delay is a reality in the busiest airports around the world. One of the reasons for its appearance is when the demand of an airspace is exceeded. The main consequence of this inefficiency is the increase in the airlines costs and discomfort for the passengers.

Most the congestion problems are fixed on the day of operations in a tactical manner, during operations through tactical actions. The aim of this article is to use an Evolutionary Algorithm (EA) for arriving flow management to solve the Aircraft Landing Problem.

The results showed the importance of the FCFS algorithm and the necessity of operational constraints in the model to minimize delay. The model and the GA algorithm proved to be quick and efficient.

However, some limitations can be pointed out in the present study. The present model does not consider, if there will be space for the parking of aircraft at the airport, only considering the use of the runway. Likewise, the costs of delays differ according to the aircraft model. Finally, in the model, a priority level for sequencing is not used that uses the airport concentration of a certain airline. This is a next step to extend the studied model.

6 | CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

References

1. Little A. *Mega-Aviation Cities Project*. Cornell University Press . 2013.

2. Krozel J, Mitchell J, Polishchuk V, Prete J. Capacity estimation for airspaces with convective weather constraints. In: ; 2007: 6451.

3. D'Ariano A, Pacciarelli D, Pistelli M, Pranzo M. Real-time scheduling of aircraft arrivals and departures in a terminal maneuvering area. *Networks* 2015; 65(3): 212–227.

4. Burghouwt G, Lieshout R, Boonekamp T, Spijker vV. *Economic benefits of European airspace modernization*. SEO Amsterdam Economics . 2016.

5. Ivanov N, Netjasov F, Jovanović R, Starita S, Strauss A. Air Traffic Flow Management slot allocation to minimize propagated delay and improve airport slot adherence. *Transportation Research Part A: Policy and Practice* 2017; 95: 183–197.

6. Hansen JV. Genetic search methods in air traffic control. *Computers & Operations Research* 2004; 31(3): 445–459.

7. ICAO . *Doc 9971 Manual on Collaborative Air Traffic Flow Management* . 2014.

8. Ji XP, Cao XB, Du WB, Tang K. An evolutionary approach for dynamic single-runway arrival sequencing and scheduling problem. *Soft Computing* 2017; 21(23): 7021–7037.

9. Hu XB, Chen WH. Genetic algorithm based on receding horizon control for arrival sequencing and scheduling. *Engineering Applications of Artificial Intelligence* 2005; 18(5): 633–642.

10. Hu XB, Di Paolo E. Binary-representation-based genetic algorithm for aircraft arrival sequencing and scheduling. *IEEE Transactions on Intelligent Transportation Systems* 2008; 9(2): 301–310.

11. Hu XB, Chen WH. Receding horizon control for aircraft arrival sequencing and scheduling. *IEEE Transactions on Intelligent Transportation Systems* 2005; 6(2): 189–197.

12. Beasley JE, Krishnamoorthy M, Sharaiha YM, Abramson D. Displacement problem and dynamically scheduling aircraft landings. *Journal of the operational research society* 2004; 55(1): 54–64.

13. Beasley JE, Sonander J, Havelock P. Scheduling aircraft landings at London Heathrow using a population heuristic. *Journal of the operational Research Society* 2001; 52(5): 483–493.

14. Beasley JE, Krishnamoorthy M, Sharaiha YM, Abramson D. Scheduling aircraft landings—the static case. *Transportation science* 2000; 34(2): 180–197.

15. Lei Z, Jun Z, Yanbo Z. Affinity propagation clustering classification method for aircraft in arrival and departure sequencing. In: IEEE. ; 2009: 7–D.

16. Ribeiro VF, Pamplona DA, Fregnani JAT, Oliveira dÍR, Weigang L. Modeling the swarm optimization to build effective Continuous Descent Arrival sequences. In: IEEE. ; 2016: 760–765.

17. Dear RG. The dynamic scheduling of aircraft in the near terminal area. tech. rep., Cambridge, Mass.: Flight Transportation Laboratory, Massachusetts Institute . . . ; 1976.

18. Psaraftis HN. A dynamic programming approach for sequencing groups of identical jobs. *Operations Research* 1980; 28(6): 1347–1359.

19. Venkatakrishnan C, Barnett A, Odoni AR. Landings at Logan Airport: Describing and increasing airport capacity. *Transportation Science* 1993; 27(3): 211–227.

20. Delahaye D, Alliot JM, Schoenauer M, Farges JL. Genetic algorithms for partitioning air space. In: IEEE. ; 1994: 291–297.

21. Cheng V, Crawford L, Menon P. Air traffic control using genetic search techniques. In: . 1. IEEE. ; 1999: 249–254.

22. Mitchell M. *An introduction to genetic algorithms*. MIT press . 1998.

23. Banzhaf W, Nordin P, Keller RE, Francone FD. *Genetic programming: an introduction*. 1. Morgan Kaufmann San Francisco . 1998.

24. Russell SJ, Norvig P. *Artificial intelligence: a modern approach*. Pearson Education Limited, . 2016.

25. Sastry K, Goldberg D, Kendall G. Genetic algorithms. In: Springer. 2005 (pp. 97–125).

26. FAA . *JO 7110.65W Air Traffic Organization Policy* . 2015.

27. Zhou H, Jiang X. Multirunway optimization schedule of airport based on improved genetic algorithm by dynamical time window. *Mathematical Problems in Engineering* 2015; 2015.

28. Ji XP, Cao XB, Tang K. Sequence searching and evaluation: a unified approach for aircraft arrival sequencing and scheduling problems. *Memetic Computing* 2016; 8(2): 109–123.

29. Balakrishnan H, Chandran B. Scheduling aircraft landings under constrained position shifting. In: ; 2006: 6320.

30. Bianco L, Ricciardelli S, Rinaldi G, Sassano A. Scheduling tasks with sequence-dependent processing times. *Naval Research Logistics (NRL)* 1988; 35(2): 177–184.

31. Bianco L, Dell'Olmo P, Giordani S. Scheduling models and algorithms for TMA traffic management. In: Springer. 1997 (pp. 139–167).

32. Carr GC, Erzberger H, Neuman F. Delay exchanges in arrival sequencing and scheduling. *Journal of Aircraft* 1999; 36(5): 785–791.

33. Carr GC, Erzberger H, Neuman F. Fast-time study of airline-influenced arrival sequencing and scheduling. *Journal of Guidance, Control, and Dynamics* 2000; 23(3): 526–531.

34. Guo Y, Cao X, Zhang J. Constraint handling based multiobjective evolutionary algorithm for aircraft landing scheduling. *International Journal of Innovative Computing, Information and Control* 2009; 5(8): 2229–2238.

35. Yu SP, Cao XB, Zhang J. A real-time schedule method for Aircraft Landing Scheduling problem based on Cellular Automation. *Applied Soft Computing* 2011; 11(4): 3485–3493.

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