An Optimized Air Traffic Departure Sequence According to the Standard Instrument Departures

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***Abstract*—Sequencing efficiently the departure traffic remains among the critical parts of air traffic management these days. It not only reduces delays and congestion at hold points, but it also enhances airport operations, improves traffic planning, and increases capacity. This research paper proposes an approach, that employs a genetic algorithm (GA), to help air traffic controllers in organizing a sequence for the departure traffic based on the standard instrument departures (SIDs) configuration. A scenario with randomly assigned types, SIDs, and departure times was applied to a set of aircraft in a terminal area with a four-SID configuration to assess the performance of the suggested GA. Subsequently, a comparison with the standard method of First Come First Served (FCFS) was conducted. The testing data revealed promising results in terms of the total spent time to reach a specified altitude after takeoff.**

***Keywords*—Air traffic management; standard instrument departure; departure traffic sequencing; genetic algorithm; heuristic algorithm**

I. Introduction

Air traffic management (ATM) is a crucial system that manages aircraft's safe and efficient movement within the airspace and ground. It involves various technologies, procedures, and regulations to ensure the smooth operation of air traffic. It also plays a critical part in ensuring the safety and efficiency of air transportation worldwide. The present growth rate in air traffic is causing congestion at several airports throughout the globe. Furthermore, especially during the departure phase, the airport's existing infrastructure isn't always able to keep up with the increasing congestion. The optimization of air traffic flow in departure is essential for many reasons, including efficiency, safety, and environmental concerns.

A. Air Traffic Growth

Following the COVID-19 disease, air traffic movements have been increasing dramatically, which has pushed the congestion problem to the surface once more. [1] indicates that it will likely take 2.4 years for passenger demand to globally return to pre-COVID-19 levels (by late 2022). This recovery is undoubtedly one of the leading causes of delays in arrival and ground hold-ups for departure traffic. On the 8th of February 2023 in Montréal, using advanced big data analytics, the International Civil Aviation Organization (ICAO) predicts that air passenger demand in 2023 would quickly rebound to pre-pandemic levels on most routes by the first quarter, with a year-end increase of roughly 3% above 2019 [2].

The growth of air traffic is being driven by the increasing demand for air travel globally [3] due to population growth, economic expansion, and the rise of low-cost carriers, the latter of which has led to a growth of the budget airline industry that has increased demand for air travel.

B. Congestion and ATM Infrastructure

The amount of activity at airports grows as the number of flights increases, leading to congested runways, taxiways, and terminals. A well-planned air traffic control system is needed to mitigate increased workload and air traffic control delays [4]. The rate of aviation traffic growth may be too quick for air traffic control (ATC) infrastructure to keep up. It is crucial to tackle the problem of air traffic congestion to ensure that air travel can be done safely and efficiently. With the right solutions and efforts, the current congestion issue can be mitigated and long-term improvements put into place to ensure that the air travel system works effectively and efficiently [5]. To meet the increased requirements of air traffic controllers (ATCos), new technology must be adopted and implemented. Air Navigation Service Providers (ANSPs) must implement more efficient strategies for aircraft scheduling, operation, and ground control to minimize congestion. With accurate forecasting and real-time data analysis, ANSPs can optimize operations and reduce aircraft delays and ground holds [6].

C. Departure Traffic Optimization

The departure traffic optimization is an important aspect of efficient ATM. Departure optimization helps minimize flight delays and improve air transport scheduling efficiency. It involves decreasing aircraft queuing times at departure airports and improving safety by reducing the time an aircraft remains in taxiing or takeoff mode. This can be done through the use of real-time and predictive analytics to identify potential issues such as aircraft congestion or traffic delays from air traffic control before they become a problem [7].

The purpose of this work is to offer an approach that will help ATCos in sequencing departure traffic according to the SIDs. Firstly, a summary of previous research is provided. Following that, a brief overview of departure traffic regulations is given, along with a thorough description of the problem and a demonstration of the various techniques and algorithms used to solve it. The choice, concept, and design of the genetic algorithm are then covered in the methodology section along with references to previous publications. Subsequently, a modelization of the conflicts along with the suggested sequencing method with simulations is offered.

II. Overview of Precedent Works

A. Decision-making Tools for Air Traffic Control

Paper [8] introduced the Departure Planner (DP), a conceptual design of an automation aid system for air traffic controllers ATCos. This design can serve as the basis for the creation of decision-supporting tools, potentially working with already-in-place arrival flow automation systems, to enhance the efficiency of departure operations and optimize the runway time in busy airports. In [9] the authors commenced by outlining the algorithmic structure of the surface management system, a tool that helps air traffic controllers in scheduling and controlling arrival and departure traffic. Then, they suggested brand-new algorithmic improvements for the first tool to improve its efficiency in terms of conflict-free, ideal taxi routing, and flexible utilization of airport resources. Work [10] is a collaboration effort between the Massachusetts Institute of Technology and the German Aerospace Research Establishment. It covered the imbalance between capacity and demand and the need for automated decision-support tools to assist ATCos. It also offered a structure of the operations problem and further research foundation. Research [11] provided algorithmic bases of a decision assistance tool for ATCos which enhances the capacity and limits conflicts in airport operations. The suggested model is built using an iterative approach that combines optimization and simulation.

B. Mixed Integer Sequencing Techniques

The author in [12] handles the management of the departure queue zone by a first-in-first-out strategy using a mixed integer linear program. The proposed technique considers the spacing between subsequent departures and features an optional time-window-based prioritizing criteria. The work also offers changes for improved computational efficiency above the obtained reduction of the system delay. An enhanced rolling horizon technique was presented in [13], which separates an aircraft sequence into manageable fragments and tackles the aircraft sequence issue independently for each of these fragments. The improved algorithm was built by revising two Mixed Integer Linear Programming models. The suggested resolution used a tabu search heuristic algorithm with a quick calculation time. After the identification and research in detail of many operational functions such as runway configuration, runway assignment, takeoff sequencing, scheduling, ... etc. Work [14] offered an overview of optimization architecture and concentrated on the issue of scheduling taxiing and takeoff. The paper also discussed the numerical findings for the suggested integrated method using a mixed-integer mathematical program. A Mixed Integer Linear Programming (MILP) optimization model for the issues of airport taxiway trajectories and runway scheduling is discussed in [15]. The authors had very good results regarding the median taxi times and departure flow using the receding horizon algorithm with iterations in comparison with the First Come First Served method. To generate an ideal and reliable departure sequence under taxiing uncertainty, [16] discussed a method based on a mixed integer linear program. It schedules and releases aircraft from the stand to avoid waiting at the holding point and shorten the taxi time. the proposed model has shown good results while testing on operational data.

C. Diverse Algorithms used for Sequencing Departure Traffic

In [17], an innovative and collaborative method for establishing the order of departures was presented using game theory. In the negotiations for slot distribution, each aircraft was portrayed as a player. The proposed dynamic scenario was developed according to the collaborative decision manager system and Rubinstein protocol. Study [18] introduced a framework under Constrained Position Shifting (CPS) with evolving programming algorithms. This tool can quickly develop effective departure sequences that adhere to a variety of constraints such as the terminal air flow, arrival runway crossing, wake turbulence, etc. Work [19] focused on explicitly forming and developing departure procedures using the Petri net approach. It started by determining the essential departure-related components for the proposed model. Then, the authors used the cover-ability tree to check the process. Finally, the system has been tested to make sure of successful interaction between all air stakeholders with a special focus on the management of the capacity and demand challenges and air traffic jam reduction. Research [20] gives an in-depth review of the most recent advancements in the literature on stochastic modeling applications in aviation. The principal methods that are worth considering include stochastic integer programming, analytical queuing theory, robust optimization, and stochastic optimal control. These techniques are applied in a variety of aspects such as the anticipation of airport operating delays and the pre-tactical scheduling for aircraft departure times.

D. Other Sequencing Methods

The discussed approach in [21] outlined how to handle departing aircraft at an area or an airport gate within two-time windows. The idea behind this approach is to release the traffic from a gate at calculated times that are ideal for runway usage. In this work [22], a time-varying fluid queue is used to develop an aircraft departure model at a single runway. The duration an aircraft waits in the departure line can be computed using the suggested model, also efficient control techniques can be assessed so that aircraft spend the delay on their initial parking areas rather than runway holding points. Using validation criteria, the impact of the suggested model is examined in light of the unpredictability of real-world departure traffic. In paper [23] the authors took and adapted an existing functional Time-based flow management scheduling system for arrival traffic and then applied it to departure traffic. The paper also provided operational techniques that combine tactical departure scheduling with the spacing departure manager. It also tested the concept in simulations with two conditions "departure scheduling" and "arrival-sensitive departure scheduling". The authors in paper [24] offered a review of the actual spacing minima of traffic in departure. They also analyzed the currently used methods, evaluated the longitudinal spacing after takeoff, and proposed a notion of a single separation policy. A general unified technique for separating two aircraft, regardless of their post-departure trajectories. The paper discussed the possible operational gains. Work [25] presented an instantaneous tool based on a non-iterative approach to assist ATCos during traffic jams. It focused on reducing the runway line wait time while respecting spacing between aircraft after departure. The paper took into account the standard instrument departures, operation restrictions, and landing operations.

III. General Problem Statement

A. Departure Traffic Rules Overview

First and foremost, we shall provide some background information on SIDs and basic ATM rules for the departure traffic.

1) The Standard Instrument Departures (SIDs): They are standard Air Traffic Service (ATS) routes described in instrument departure procedures that an aircraft should follow after takeoff to join the en-route phase. They are designed to provide pilots with a standardized method of departing from an airport. They are published in the Chart Supplement and the Aeronautical Information Manuals. The procedures include information such as the orientation and angle of the procedure and minimum altitude requirements. The procedures are critical for maintaining consistent and safe airport operations.

2) Departure traffic spacing minima: Only one aircraft is cleared to enter and occupy the runway in service. The following aircraft has to wait a few minutes before taking off according to many factors such as:

- Wind
- Temperature
- Wake turbulence
- Preceding aircraft type and performance
- Potential catch-up
- The Followed SIDs, etc.

These are some spacing minima according to the Procedures for Air Navigation Services (PANS) - Air Traffic Management (Doc 4444) [26]:

Performance spacing minima:

- One minute of spacing is needed to ensure lateral separation when the aircraft followed courses deviate by 45 degrees at least just after takeoff.
- Two minutes are required When the preceding aircraft is 40kts (or more) faster than the following one and both aircraft will follow the same course.
- Five minutes separation is required if both departing aircraft are following the same route and the second one is expected to fly through the level of the first one.

When applying these spacings, ATC services should also take into account the wake turbulence spacing depending on the aircraft's weight.

Wake turbulence spacing minima: For departing aircraft which are taking off from the same runway the minimum ICAO time separation is 2 minutes in the following cases: a heavy behind a super, a light or medium behind a heavy, and a light behind a medium. Otherwise, a minimum of 3 minutes separation is required between a light or medium behind a super.

B. Problematic

Many factors can be the cause behind aircraft delays but technically the main two factors are the incompatibility of the Standard Instrument departures SIDs and aircraft performance. This research project is a follow-up of two prior publications that studied the topic of departure traffic scheduling from the parking area to the runway holding point.

1) Initial related works: In [27], using a tactical planning tool, the authors reduced the taxiing time of the departure traffic in the movement area. by allocating continuous and efficient trajectories to the holding point. Furthermore, by applying the Shortest Job First (SJF) algorithm, this tool allowed aircraft to maintain a steady speed for the longest feasible time during the taxiing phase. The second work [28] focused on enhancing the departing traffic sequence by developing an algorithm that considers the different aircraft categories, the taxiing, takeoff, and SID climb time. the suggested algorithm ordered the aircraft based on their estimates to arrive at the holding point. For simulation constraints, the work considered that all aircraft would follow the same SID after departure and the optimized scheduling was executed before reaching the holding point.

This paper will focus on sequencing departure traffic, which have different performances, following a four standard instrument departures (SIDs) configuration after take-off.

To solve such an optimization problem, various techniques can be used, such as mathematical programming, simulation, or heuristics. For example, mathematical programming can be used to formulate the problem as an optimization model and find the optimal solution by solving the corresponding mathematical equations. Simulation, on the other hand, involves creating a computer-based simulation of the air traffic system and evaluating different scenarios to identify the best solution.

2) Heuristic algorithms in departure traffic sequencing: Heuristics, such as greedy algorithms or meta-heuristics, can be used to find good solutions quickly without guaranteeing optimality. For instance, a greedy algorithm could be used to prioritize aircraft with the highest conflict coefficients and adjust the altitudes of previous aircraft accordingly. Alternatively, to swiftly search the space of potential solutions and identify a suitable one, meta-heuristics like simulated annealing or genetic algorithms could be of good use. For example, to have more accurate situation prediction, [29] presented a greedy algorithm pre-departure sequencing approach. The project began by outlining the existing sequencing strategy, including the requirements of spacing and runway usage. Then it proceeded to reduce the total takeoff operations delay passing through its different stages. In [30], the authors merged the fast-marching technique with the simulated annealing algorithm to produce 3D standard departure and arrival routes. The proposed work took into account the obstacles and separation minima between routes. The goal of [31] was to improve surface management and integrated departure performances. The authors provided a comparison between the conventional clearances and new ones using a mathematical tool based on a heuristic algorithm. The suggested technology aims for a fluid, instantaneous rescheduling that considers time constraints. Based on the particle swarm technique and the simulated annealing algorithm, the work [32] provided a sequencing mathematical algorithm for the departure traffic. The findings of the suggested algorithm were quite close to the general optimum value.

In summary, the scenario presented in the question involves a complex optimization problem related to air traffic control, which requires quantifying conflicts and resolving them by adjusting the altitudes of previous aircraft. Various techniques can be used to solve such problems, including mathematical programming, simulation, and heuristics.

IV. Methodology

A. Metaheuristic Optimization Examples

Among the most commonly used metaheuristic methods for optimization, we find:

- *Genetic Algorithms:* optimization algorithms founded on the idea of selection by nature. they use genetic parameters such as mutation, crossover, and selection to produce a population of possible solutions and gradually evolve towards better-quality solutions.
- *Simulated Annealing:* a method that simulates the process of cooling a molten metal. This method involves accepting less optimal solutions at a defined rate to avoid getting stuck in a local minimum. Simulated annealing It can be employed to resolve issues with combinatorial optimization.
- *Tabu Search:* an optimization method that uses a tabu list to prevent the algorithm from revisiting previously explored solutions. This method is particularly useful for solving combinatorial optimization problems.
- *Particle Swarm:* an optimizing technique based on the behavior of fish or birds in flocks. In this method, each particle represents a potential solution and travels within the search area to find the best solution.
- *Iterative Local Search:* a method that starts with an initial solution and explores neighboring solutions to find the optimal solution. This method can be effective for small or medium-sized combinatorial optimization problems.

These are just a few examples of the many metaheuristic methods that are available for optimization. These methods can be adapted and combined to solve complex optimization problems in different application domains. The challenge at hand and the features of the problem domain will determine which approach is best to use. To optimize the aircraft departure sequence following the Standard Instrument Departures, we adapted the genetic algorithm which is a heuristic method inspired by a natural selection process.

B. Genetic Algorithm Optimization and Process

The sequencing of departure times of aircraft is a crucial task in air traffic management, which aims to minimize delays and improve efficiency in airport operations. The problem consists of determining a sequence of departure times for a set of aircraft, such that the time intervals between consecutive departures are minimized while respecting certain constraints on the processing times and the maximum delay times. This problem is considered as NP-hard and it is challenging to figure it out optimally using exact methods. Therefore, metaheuristic optimization methods like genetic algorithms (GAs) have been suggested as a promising approach to finding almost perfect results efficiently. This work suggests a GA to address the issue of sequencing departure aircraft. The GA is an optimization technique dependent on a population that imitates the process of natural selection and genetic evolution and has been extensively utilized in several optimization issues. The GA operates by maintaining a population of potential solutions (i.e., chromosomes) and using genetic operators like mutation, crossover, and selection to repeatedly evolve the population. The population's fittest members are chosen to reproduce and create new offspring, while the least fit individuals are replaced with the new ones. Elitism is also implemented by preserving a certain proportion of the fittest individuals from the previous generation, by iteratively applying these genetic operators.

Genetic algorithm process

1) Define the chromosome: Each chromosome represents a possible sequence of aircraft departures. It is represented as a list of aircraft IDs in the order in which they will take off.
2) Define the fitness function: The fitness function rates each chromosome's quality (sequence of departures) based on the delay that it generates. In this case, the delay generated by each chromosome can be calculated by summing the delays of each individual (departing aircraft) using the table of generated delay (Di) values.
3) Generate the first population: It is chosen randomly by creating a set of chromosomes (sequences of aircraft departures) using the available aircraft SIDs.
4) Examine the chromosomes' fitness: Each chromosome in the population is assessed using the fitness function.
5) Select parents for the following generation: they are selected from the current population using a selection algorithm such as roulette wheel selection or tournament selection.
6) Create offspring using crossover and mutation: Offspring is created from the selected parents using crossover and mutation. Crossover involves selecting two parents and swapping parts of their chromosomes to create a new offspring. Mutation involves randomly modifying parts of a chromosome to create a new offspring.
7) Assess the offspring fitness: Each offspring in the population is assessed using the fitness function.
8) Select the fittest individuals for the next generation: The fittest individuals (chromosomes with the lowest delay) are selected for the next generation.
9) Repeat steps 5-8 until convergence: Steps 5-8 are repeated until the population converges to a set of optimal solutions as shown in Fig. 1 (sequences of departures with the lowest delay).

C. Genetic Algorithm Codes

GA pseudo-code

Algorithm 1 Genetic Algorithm pseudo-code

Define the problem parameters
Define the measurement of the population and how many generations are needed
Define the fitness function
function EVALUATEFITNESS(member)
    Evaluate the fitness of a member
end function
Define the mutation operator
Define the crossover operator
procedure CROSSOVER(member1, member2)
    Choose a random crossover point
    Create the offspring
end procedure
Initialize the population
for all members in the population **do**
    Evaluate the fitness of each member
end for
Run the evolution loop
for $generation = 1$ to $num\_generations$ **do**
    Choose two members from the population depending on their fitness
    Apply crossover with CROSSOVER(selected_member1, selected_member2)
    Apply mutation with
    Examine the fitness of the new members
    Change the least fit member in the population with the new offspring
    Print the best individual of generation $generation$
end for

The genetic algorithm can be customized by adjusting criteria such as population size, mutation, and crossover rates. The genetic algorithm can also be set up to speed up the search for the optimal solution.

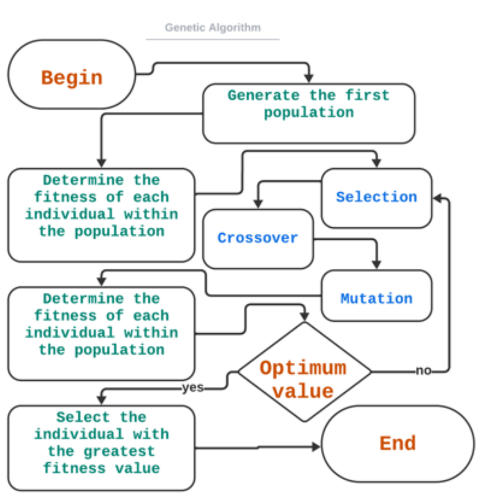

Fig. 1. Genetic algorithm chart.

GA detailed code

Algorithm 2 Genetic Algorithm code

// Set Initial Population //
Generate ϵ solutions;
Save them in M;
// Repeat until the convergence of M //
for $i = 1$ to δ **do**
    // Selection //
    $u = \epsilon \cdot \beta$;
    In M, choose the u best solutions;
    Save the result in $M1$;
    // Crossover //
    $u = (\epsilon - u)/2$;
    for $k = 1$ to u **do**
        (random);
        From M, choose two solutions Z_A and Z_B;
        Create Z_C and Z_D by crossover Z_A and Z_B;
        Save the result in $M2$;
    end for
    // Mutation //
    for $k = 1$ to u **do**
        From $M2$ choose Z_k;
        Generate Z_k^* by mutating each element of Z_k with rate γ;
        if Z_k^* not feasible **then**
            Repair Z_k^*;
        end if
        Update Z_k with Z_k^* in $M2$;
    end for
    // Updating //
    $M = M1 + M2$;
end for
// Sending back the optimal solution //
Send back Z, the optimal solution of M;

D. Previous Works using Genetic Algorithm

These are some works that handled aircraft sequencing using genetic algorithms: Paper [33] proposed a genetic algorithm that addresses the aircraft sequencing and scheduling (ASS) problem. The algorithm showed excellent instantaneous application possibilities for the ASS issue due to its uniform crossover operator and receding horizon technique. The detailed comparative study showed that the suggested uniform crossover operator is effective and efficient in discovering, inheriting, and safeguarding common sub-traffic sequences without surrendering the capacity to change chromosomes. In [34] they studied the departure scheduling problem for one runway fed up with two aircraft queues each one fed up with a single taxiway where the queue line metering is constant. The authors provided a greedy search method and compared its effectiveness to a genetic algorithm. As a result, and to reduce the spent time in the waiting queue under various traffic circumstances, It was found that a queue assignment algorithm was required to maintain an equitable distribution of traffic in the queues. The purpose of paper [35] was to intrude departure traffic into the arrival sequence using a fluid framework. To address the sequencing problem, the authors built a genetic algorithm considering the time-varying factors. To solve the departure sequencing problem, study [36] developed an enhanced genetic algorithm using the particle swarm technique with symbolic coding. The paper then provided a comparative study between simulations using a fundamental genetic algorithm and an adaptive one where the suggested approach performed exceptionally well.

To demonstrate the effectiveness of the suggested GA, we carried out tests on a problem instance with randomly generated departure times and processing times for a set of 10 aircraft. The problem instance was generated such that the aircraft's departure times were arbitrarily picked from a uniform distribution varying from 0 to 100, and the processing times were arbitrarily picked from a uniform distribution varying from 5 to 20. This paper will evaluate the effectiveness of the GA approach with the FCFS method for sequencing departures in air traffic management.

V. Modelization

The data provided involves the quantification of conflict generated by different trajectories and the resolution function for clearing aircraft for takeoff. Specifically, the scenario considers A_i as the identifier for each aircraft waiting for takeoff, T_i as the estimated time of departure, and S_i as the requested SID (Standard Instrument Departure) for each aircraft. Two consecutive aircraft, A_i and A_{i+1} , form a state $F(i)$. The problem at hand involves quantifying the conflict generated by a state of aircraft with the same performance following different SIDs. The conflict coefficient for a state F(i) is denoted as C_i and can be quantified by comparing the different trajectories following different SIDs. The data provided shows C_i values for different trajectories following the directions North (N), East (E), West (W), and South (S).

The resolution function R involves two variables: P_i, which denotes the altitude that must be cleared by the previous aircraft before the next aircraft can take off, and C_i, which is the conflict coefficient for the state $F(i)$. The function returns the altitude H_i that must be cleared by the previous aircraft to enable the next aircraft to take off safely allowing the approach organism to apply other spacing techniques in the next management phase.

The data provided in the question shows a table of values for P_i and C_i, where each value of P_i refers to a specific aircraft (1-5) and each value of C_i refers to a specific trajectory following different directions (N, E, W, S). Two consecutive aircraft $< A_i, A_{i+1} >$ form a state F(i) to make a state $F(i)$ compatible it is enough to act on the departure estimate T_i.

Quantification of the problematic factors

Conflict quantification generated by a state of aircraft with the same performance following different SIDs:

We consider C_i the conflict coefficient generated by the state $F(i)$ as illustrated in Table I:

TABLE I. Aircraft with the Same Performance Following Different SIDs

A_i/A_{i+1}	N	E	W	S
N	4	2	2	2
E	2	4	1	1
W	2	1	4	3
S	2	1	3	4

Conflict quantification generated by a state of aircraft with different performance following the same SID:

We consider P_i the performance of the aircraft A_i as shown in Table II:

TABLE II. Aircraft with Different Performances Following the Same SID

P_{i+1}/P_i	1	2	3	4	5
1	1	2	3	4	5
2	1	1	2	3	4
3	1	1	1	2	3
4	1	1	1	1	2
5	1	1	1	1	1

Let R be the resolution function of the variables P_i and C_i which returns H the altitude that must be cleared by the previous aircraft so that the next aircraft can be cleared for takeoff as summarized in Table III:

TABLE III. Cleared Altitude According to Aircraft Performance

P_{i+1}/P_i	1	2	3	4	5
1	3000	3500	4000	4200	4800
2	3500	4000	4400	4800	5300
3	4000	4500	5000	5300	5800
4	4500	5000	5500	5800	6500
5	4500	5500	6000	6500	7000

Then we calculated the generated delay D_i (of waiting departure aircraft) in minutes according to H_i (altitude of precedent departure aircraft) and P_i (performance of waiting departure aircraft) as detailed in Table IV.

TABLE IV. Generated Delay According to Aircraft Performance and Climbing Altitude

P_i/H_i	3000	3500	3800	4000	4300	4500	5000	5500	6000	6500	7000
1	1.2	1.4	1.6	1.8	2	2.2	2.4	2.6	2.8	3	3.8
2	1.5	1.8	2.1	2.4	2.7	3	3.2	3.4	3.6	3.8	4.4
3	1.8	2.4	2.7	3	3.2	3.4	3.6	3.9	4.2	4.4	4.8
4	2	2.5	3	3.3	3.6	3.9	4.1	4.3	4.5	4.8	5.1
5	2.4	2.8	3.2	3.6	3.9	4.2	4.5	4.7	4.9	5.1	5.4

VI. The Proposed Sequencing Method

To use the resolution function, we need to specify the values of P_i and C_i. For example, if the conflict coefficient for a state $F(i)$ is $C_i = (2, 4, 2, 1)$ for the trajectory following the directions (N, E, W, S), and the altitude that must be cleared by the previous aircraft for the current aircraft to take off safely is $P_i = (3500, 4000, 4400, 4800, 5300)$ for the current aircraft, then the resolution function R can be used to calculate the required altitude H as follows: $H = R(P_i, C_i)$.

The value of the resolution function is given in data in Table III, it takes into account the values of Pi and Ci to calculate the required altitude H.

Overall, the scenario presented involves a complex optimization problem related to air traffic control, where the goal is to minimize conflicts and ensure safe takeoff for all aircraft. The data provided shows how various factors such as trajectories, altitude, and performance can affect the conflict coefficient and the resolution function.

Based on the above assumptions and definitions in the previous sections the mathematical formula of the problem is stated as follows: $min \sum_{i=1}^{k} Di$ of a set of k aircraft. The classic sequencing algorithms (FCFS, SJF, ...) were not suitable for this traffic situation so we opted for a metaheuristic method with a genetic algorithm.

A. Simulations

We used the Python programming language to implement the GA algorithm and conducted the experiments on a personal computer with an Intel Core i7-8700 CPU and 16GB of RAM. We implemented both the GA and FCFS algorithms in Python and conducted the experiments on the same computer with the same hardware specifications.

The FCFS algorithm was implemented as follows:

1) Sort the aircraft in ascending order of their departure times.
2) Assign each aircraft the earliest possible departure time subject to the processing time and maximum delay time constraints.

The GA algorithm was applied in this order:

1) Set the chromosomal population with random departure time sequences for the set of aircraft.
2) Determine each chromosome's fitness by computing the total time interval between consecutive departures, subject to the processing time and maximum delay time constraints.
3) Redo this process till convergence or the highest number of generations is attained:
    a) Select a subset of the population's fittest chromosomes to serve as the reproduction's parents, using tournament selection.
    b) Perform crossover and mutation operations on the chosen parents to produce new offspring chromosomes.
    c) Assess the fitness of the offspring chromosomes and change the least fit individuals in the population with the new ones.
    d) Preserve a certain proportion of the fittest individuals from the previous generation using elitism.

B. Results

We carried out tests on a problem instance with randomly generated departure times and processing times for a set of 10 aircraft. Tables V and VI show the results of departure traffic sequencing using the FCFS and GA with:

- Std: Stand's distance to departure holding point.
- EOBT: Estimated off block time.
- T1: Time to get to the first taxiway.
- T2: Time to get to the sequencing taxiway.
- T3: Time to get the holding point.
- R: Regulation due to performance.
- Delay: Delay due to regulation.
- H 6000: Time to leave 6000 feet.
- SID: The followed Standard Instrument Departure.
- R2: Regulation due to the followed SID.
- H 6000: Time to leave 6000 feet before SID Regulation.
- S 6000: Time to leave 6000 feet after SID Regulation.

TABLE V. FCFS DEPARTURE SEQUENCING

Ai	Type	Std	EOBT	T1	T2	T3	R	Delay	H 6000	SID	R2	S 6000
1	5	10	1	51	110	171	121	0	200	N	0	200
2	3	7	3	24	67	101	136	57	320	S	0	320
3	2	5	5	15	45	70	151	93	400	W	45	445
4	1	3	7	10	23	43	166	129	440	s	35	475
5	5	9	9	54	109	173	181	57	640	W	33	673
6	4	8	11	43	88	141	196	92	800	N	15	815
7	3	6	13	31	66	107	211	128	920	W	20	940
8	2	4	15	23	44	77	226	164	1000	E	10	1010
9	1	1	17	18	21	49	241	201	1040	S	10	1050
10	1	2	19	21	22	53	256	214	1080	W	45	1125
Total time to leave Altitude 6000 using FCFS												7053

TABLE VI. GA DEPARTURE SEQUENCING

Ai	Type	Std	EOBT	T1	T2	T3	R	Delay	H 6000	SID	R2	S 6000
4	1	10	1	11	30	51	51	0	40	N	15	55
3	2	9	3	21	49	80	80	0	120	S	0	120
2	1	8	5	13	28	51	95	44	160	W	25	185
1	3	7	7	28	67	105	110	5	280	E	0	280
9	2	6	9	21	46	77	125	48	360	W	0	360
8	3	5	11	26	65	101	140	39	480	E	0	480
7	5	4	13	33	104	147	155	8	680	W	0	680
6	4	3	15	27	83	120	170	50	840	N	30	870
5	5	2	17	27	102	139	185	46	1040	S	15	1055
10	5	1	19	24	101	135	200	65	1240	E	0	1240
Total time to leave Altitude 6000 using GA												5325

According to Tables V and VI the results show that the GA algorithm saves 24,5% of the total time for the set of 10 aircraft to reach altitude 6000ft.

VII. CONCLUSION

In this study, we compared the performance of the GA with the FCFS rule for sequencing the departure aircraft in air traffic management. We conducted experiments on a problem instance with randomly generated departure times and processing times for a set of 10 aircraft. The findings show that the GA surpasses the FCFS method with approximately 25% of the total time. The Genetic algorithm was faster in terms of run time in comparison with the FCFS method and can be also considered as a viable strategy for resolving the sequencing issue of departure aircraft in air traffic management. Further work can be carried out in changing the followed SID according to the terminal Area leaving point.

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