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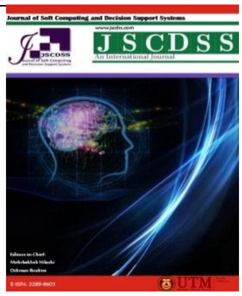

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A New Intelligent Approach to Aircrafts Take-off/Landing Planning at Congested Single Runway Airports

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Abstract

Nowadays, air transportation has gained a significant growth due to its advantages in transporting goods and passengers. The rapid growth of this activity and some limitations in different parts of aviation operation often cause traffic congestion the mismanagement and proper planning of which can lead to a lot of flight delays; accompanied by different problems. In order to appropriately systematize air traffic congestion various researches have been done during the recent two decades the major part of which is dealing with planning of aircrafts taking-off and landing. Thus, in the current study; and for the first time, the two algorithms Biogeography-Based Optimization (BBO) and Particle Swarm Optimization with Constriction Coefficient (CPSO) deal with a feasible planning of aircrafts take-off /landing, taking modern conditions and limitations into account. Simulations prove that adding rich and effective knowledge to optimization process can, to a large extent, undue and redundant outcomes; and increase convergence rate of the above algorithms. This can be followed by over 50% of total flight delays compared with First-Come/First-Serve (FCFS) plan. Besides, comparing the results of applying the two new optimization algorithms showed that BBO can be more effective than CPSO because of its better research domain.

Keywords: Take-off/landing, Total flight delays, ROT, CPSO, BBO

1. INTRODUCTION

In recent decades, because of various advantages of air trips including comfort, cost reduction, high speed and great safety, requests for air transportation services have increasingly grown. The imbalance between this growth and the air traffic capacity in routes, sectors, terminal areas and airports has brought about air traffic congestion (Yifei & Kai, 2010). Unless air and ground traffic congestion in airports is properly controlled, it can lead to diverse negative results including lots of flight delays, passengers' dissatisfaction, decrease of airlines' profitability , increase in operational errors on the part of traffic control personnel (controllers), increase of fuel consumption of aircrafts, and increase of ecological pollutants.

These problems made those in charge of and specialists in aviation industry search for appropriate practical solutions to introduce optimal control on air traffic in different domains. One most important domain of these is systematizing traffic in air routes and airports. The initial approaches to control traffic congestion and decrease of flight interference in air routes included the presentation of new air routes (Zhang et al., 2011; Yuan & Min, 2010). Not being economical of the new routes regarding distance and consumed fuel of aircrafts, as well as the high cost of constructing and maintaining of navigation and radar sites for them had some researchers use simulators and flight planning systems so as to decrease traffic congestion and remove probable flight interference. Another domain that could specifically impact on traffic congestion in the air routes and terminal control area (TCA) was systematizing traffic congestion in the arrival/departure operation of flights.

Although, initially, some tentative solutions including the construction of new runways or airports were presented in this respect, they were faced with a lot of economical and geographical limitations. Thus, as the computer science developed, planning systems came into use. In spite of being useful, the systems were not able to reach the optimal or nearly optimal solutions. Such problems and the non-linear and non-convex nature of the NP-hard problem of aircraft landing planning (ALP) led to the usage of different heuristic and meta-heuristic algorithms by many researchers of the field in the two recent years (Amrahov & Ibrahim Alsalihe, 2011; Hancerliogullari et al., 2013).

Cheng et al. (1999) presented four genetic search methods for 12 aircrafts and 3 parallel runways. Then, Beasley et al. (2000) presented a general description of the model, goals, and mathematical formulation of the landing planning for one or more runways. Later, Hansen (2004) used four genetic search methods for thornier problems. He examined and simulated the genetic search methods for 12 aircrafts with 3 runways (with /without the limitation of the landing of one type of aircraft on a runway), 15 aircrafts with 3 runways, and 20 aircrafts with 5 runways. Pinol and Beasley (2006) introduced scatter search (SS) and bionomic algorithms for two linear and non-linear goals of ALP. Examining and simulating the researchers' methods presented for different cases like 500 aircrafts and 5 runways showed that for non-linear goals, the bionomic algorithm has a better performance than the SS algorithm, but for linear goals, the SS algorithm performs better. Tang et al. (2008), Kumar et al. (2008), and Jia et al. (2008) presented MONSDE algorithm, ART1 algorithm, and CSA-RHC algorithm, respectively. The inspiration for the second algorithm came from the Adaptive Resonance Theory and in the third algorithm two techniques named EGSS and IFD were used for speeding the convergence trend of the algorithm and the effective guidance of the optimization operation. Then, Hu and Paolo (2009) presented an effective genetic algorithm with a uniform crossover for the ALP. Simulations showed that the suggested method can significantly decrease the total flight delays compared to the presented method by Hansen (2004). After that, Salehipour et al. (2009) presented the meta-heuristic algorithm named Variable Neighborhood Descent (VND) for the ALP in whose method, two time units were determined for the minimum safe separation between successive landings by different aircrafts in each runway. Zhan et al. (2010) presented the RHC-ACS-ASS algorithm for sequencing and scheduling of landings in a runway and compared their simulation results with GA-RHC and BRGA methods (Hu & Chen, 2005; Hu & Paolo, 2008). The diverse optimization methods like some methods based on the algorithms of Ant Colony Optimization (ACO), Cellular Automata Optimization (CAO), and GLS with a threshold accepting mechanism were presented for the ALP problem (Bencheikh et al., 2011; Wang et al., 2011; Yu et al., 2011; Liu, 2011). Then, Tavakkoli-Moghaddam et al. (2012) used fuzzy programming to sequence the landings by aircrafts.

Since the control of traffic congestion in airports is not limited only to the landing of aircrafts, some researchers have tried the use of feasible techniques to plan the departure of aircrafts, as well. Among significant efforts in this regard, the approach based on an improved genetic algorithm by Wang et al., (2009) can be mentioned. Therefore, since the optimization algorithms and methods can play a significant role in achieving an effective solution to the planning of flights and minimizing delays, in the present paper a new problem with real conditions has been defined to examine the optimal control of aircraft taking-off/landing. This has been done applying a profound knowledge to the optimization operation based on BBO algorithm. The approach can somehow lead to the elimination of non-optimal solutions which are taken for granted and to the emergence of a limited space for finding the optimal solutions. Such a practical and effective planning, in which aviation safety standards are observed too, can be used as an appropriate supplemental means in air traffic control centers (ATCs). Among the most important included standards in the intelligent planning, the consideration of minimum safe separation between successive arrivals and departures and of runway occupancy time (ROT) can be mentioned.

The current paper continues in the following manner: in the second section, base notions and mathematical formulations are stated; in the third section, a brief description of BBO algorithm is offered; in the fourth section, the suggested intelligent approach is defined; then, in the fifth section, the suggested intelligent approach is simulated and the obtained results are compared with the ones of FCFS; and at the end, in the sixth section, the conclusion is drawn.

2. The Explanation of Base Notions and Problem Formulation

In order to have high efficiency and profit in air routes, following the determined flight plans is crucial. In recent years, considering the increasing competition among airlines, one of the most important goals strived for by those in charge of air transportation is arranging the flights with minimum delays. In other words, aircrafts, in the dynamic targeted networks of air transportation, after landing in their destination airports and spending little time in the entrance and exit of the airports and receiving required ground services, present their services in other flight routes according to the predetermined flight plans. The strategy enables airlines and companies to offer their services by fewer aircrafts in more flight routes. However, in most of congested airports throughout the world, the limitation of runway capacity and great number of flights in arrivals and departures, cause flight delays, which are sometimes too long. The goal of optimizing traffic congestion in the take-off/landing operation is a proper systematizing of air traffic before landing operation and of ground traffic before the departure of taxi aircrafts in a way that total delays in arrivals and departures would be minimized. The operation makes an organizational order in the TCA and significantly decreases the holding delay maneuvers. Since the notions of TCA, minimum safe separation, and ROT play an important role in an effective planning, these practical notions are first explained briefly, and, then, their mathematical explanation is stated.

2.1. TCA

TCA shows a specific area from the controlled air space around a large airport with heavy traffic, which is used to arrange landing aircrafts from different flight routes. The area usually centers on a cylindrical configuration on the geographical coordinates of the airport.

2.2. Minimum safe separation

To keep an aerodynamic resistance by aircrafts caused by turbulences of wake vortices and jet wash in successive takes-off/landings, a minimum space for safe separation between different types of aircrafts should be allocated. One of the greatest dangers that these turbulences, whose impacts can remain for about three minutes too, have is rolling and yawing of aircrafts from their predetermined routes. The dangers increase when a small aircraft follows a heavy one and the small aircraft may move with a roll more than 30 degrees. The initial turbulence of wake vortices can also be determined by parameters like weight, speed, configuration, wingspan, and angle of attack.

2.3. Runway occupancy time

In the operation of take-off/landing in every airport, considering the time of runway occupancy for each flight is necessary. Many factors impact on ROT the most important of which are the way of take-off/landing, runway length, aircraft type, and the angular velocity of aircraft departing from the runway. According to the definition, landing ROT is the spent time on a runway from the time when the aircraft's wheels hit the runway to the time when the runway is cleared off from the aircraft and the take-off ROT is the spent time on a runway from the time when the permission of taking the runway is given to the aircraft to the time when the aircraft passes the opposite threshold of runway.

2.4. Mathematical description of the problem

Nowadays, in some congested airports throughout the world, just one runway is used for take-off/landing operation because of some limitations. In such airports, high traffic congestion, the time interference of planned arrivals/departures, and the observance of limitations on minimum safe separation between different aircrafts often cause a high load of work for the controller. Moreover, factors like the consideration of ROT for each aircraft also increase the controller's work posing many challenges for him in dealing with the optimal control of the traffic congestion. The problems led to the use of flight planning systems in the traffic control centers of the airports in this respect. The major problem of these systems was that the results of planning were not optimal and, sometimes, they were not even nearly optimal either. Therefore, in the present section, while defining the following variables using a practical point of view, a mathematical analysis of aircraft take-off/landing planning is dealt with; using the following terminology:

N_A: the number of aircrafts that are to land in a congested airport,

N_D: the number of aircrafts that are to departure a congested airport,

PLT_i: the approximate planned landing time for the aircrafts $i\,(i=1,2,...,N_A)$,

ALT_i: the allocated time (resulted from planning) to the landing of aircrafts, $i\,(i=1,2,...,N_A)$,

Δ_i: the delay of aircraft i due to traffic congestion and the observance of minimum safe separation $(i=1,2,...,N_A)$,

PDT_j: the approximate planned take-off time for the aircraft $j\,(j=1,2,...,N_D)$,

ADT_j: the allocated time (resulted from planning) to the leaving of aircraft $j\,(j=1,2,...,N_D)$,

δ_j: the delay of aircraft $j\,(j=1,2,...,N_D)$,

Sep_L: the minimum safe separation time between successive landings,

Sep_T: the minimum safe separation time between successive takes-off,

Sep_{LTL}: the minimum safe separation time between takes-off/landings,

ROT: the time of runway occupancy by each aircraft,

AT_1: the first allocated time to a flight due to planning.

Based on the above-mentioned definitions, the allocated time for each take-off/landing is calculable through the Eq. (1) and Eq. (3):

$$PDT_j \le ADT_j \le PDT_j + \delta_j \qquad j=1,2,\dots,N_D \tag{1}$$

$$\delta_j = \begin{cases} ADT_j - PDT_j & that\ PDT_j \langle ADT_j \\ 0 & Otherwise \end{cases} \tag{2}$$

$$PLT_i \le ALT_i \le PLT_i + \Delta_i \qquad i=1,2,\dots,N_A \tag{3}$$

$$\Delta_i = \begin{cases} ALT_i - PLT_i & that\ PLT_i \langle ALT_i \\ 0 & Otherwise \end{cases} \tag{4}$$

Thus, if in the planning, the flight ADT is equal to PDT or the flight ALT is equal to PLT, the flight delay after planning for that flight will be zero meaning that the optimal scheduling for that flight has been achieved.

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Another important point is that based on Eq. (5), in the planning operation, to a flight with minimum predetermined time no delay is attributable.

$$AT_1 = PLT_i \quad if \quad \begin{array}{l} PLT_i < PLT_{i+1} \\ ;PDT_j < PDT_{j+1} \\ ;PDT_j > PLT_i \end{array} \tag{5}$$

Thus, based on Eq. (5), if $PDT_j < PLT_i$, then $AT_1 = PDT_j$.

Besides, for planning and scheduling of aircrafts takes-off/landings, safety and practical limitations should be considered, which are definable through Eq. (6) to Eq. (9) as follows:

$$ALT_{i+1} \geq ALT_i + Sep_L \tag{6}$$

$$ADT_{j+1} \geq ADT_j + Sep_T \tag{7}$$

$$ALT_i \geq ADT_j + Sep_{LTL} + ROT \tag{8}$$

$$ADT_j \geq ALT_i + Sep_{LTL} + ROT \tag{9}$$

On the other hand, based on previously done researches, and since due to the time separation between successive takes-off/landings, flights take their time to simply leave the runway, in Eq. (6) and Eq. (7) the ROT has not been used (Zhan et al., 2010; Hu & Paolo, 2008).

Along with these mathematical descriptions, in order to achieve the most basic goal of planning (i.e. minimizing total flight delays); the objective function Eq. (10) must be used.

$$objective\,function = min(\sum_{i=1}^{N_A} \Delta_i + \sum_{j=1}^{N_D} \delta_j) \tag{10}$$

3. BBO and CPSO Algorithms

3.1. BBO algorithm

The optimization algorithm, which was based on biogeography and inspired by the theory of geographical distribution of biological organisms, and the notions of migration and mutation in different species and animals, was first presented by Dan Simon (2008). The biogeography theory and the related mathematical models deal with how species migrate from one habitat to another and how new species emerge. Obviously, the higher the habitat suitability index (HSI), the more the population and rivals and so the habitat would be more crowded. Such habitats with a large population have a low rate of immigration, but a high rate of emigration. Factors and features like vegetation density, rainfall, diversity of plant species, and temperature have significant impacts on the HIS (Hadidi & Nazari, 2013). The factors are called suitability index variability (SIV). Communicating information and features from better (more crowded) habitats to worse ones (less crowded) is done through the migration operator. Therefore, weak habitats/solutions earn many of their good features through good ones and their SIV is raised.

HSI in BBO is like fitness in meta-exploration optimization algorithms. In this population-based algorithm, the operators of migration and mutation lead to appropriate changes in the production trend of future generations. Each habitat (solution) in BBO has immigration (λ) and emigration (μ) rate, the amount of which is calculable through Eq. (11) and Eq. (12) (Kumar et al., 2013; Jain & Singh, 2013):

$$\lambda_k = I(1 - \frac{k}{n}) \tag{11}$$

$$\mu_k = E(\frac{k}{n}) \tag{12}$$

where I and E have the highest immigration and emigration rates, k is the number of species for the case k and n is the maximum number of species. A good solution has high HSI, less λ and more μ. In Fig. 1, the relationship between the emigration rate, the immigration rate, and the number of species in a habitat has been shown (Annamalai & Govinthasamy, 2013).

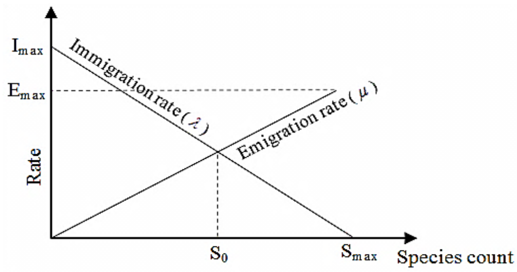

Fig. 1. The relationship between λ and μ, and the number of species in a habitat.

Apart from the implicitly mentioned notion of migration, another important notion used in BBO is mutation. The SIV mutation in BBO can be considered as sudden apparently accidental events like sickness, flood, and natural disasters which may change the HSI amount of a habitat. The mutation operator can lead to the improvement of above-mentioned solutions with high HSI and to the increase of the algorithm exploration capability and the diversity of population. The mutation rate is determined by the probability of available species in the habitat and to calculate the mutation rate m, Eq. (13) can be used (Jain & Singh, 2013):

$$m(S) = m_{max}(\frac{1 - P_s}{P_{max}}) \\ P_{max} = arg\,max\,P_s \tag{13}$$

where m_{max} is the greatest mutation rate defined by the user and P_s is the probability of having exactly S species in the habitat (S=1,…, n). Generally, a standard BBO algorithm consists of the different following steps:

Step 1, initial allocation of amounts to the parameters: determining the size of population (number of habitats), SIVs, mutation coefficient, the maximum emigration and immigration rates.

Step 2, random presentation of initial solutions (habitats).

Step 3, calculation of HSI, λ and μ for each habitat.

An International Journal JSCDSS
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Step 4, the improvement of non-elite habitats using λ and μ, and the calculation of HSI and migration operator for them.

Step 5, the correction of the population using the migration operator.

Step 6, saving the best results of elitism.

Step 7, returning to step 3 until reaching the stop conditions (the stop condition can be achieving an appropriate solution or passing a given number of iterations).

3.2. CPSO algorithm

PSO algorithm is based on collective consciousness, which was first presented by James Kennedy and Russell Eberhart (1995) who drew their inspiration from birds' and fish' social behavior and dynamic movement (Mohammadi-Ivatloo et al., 2012). In this researching method of finding the collective flight pattern of birds a group of them, which act as an answer to the problem, are dispersed in a search space and their aim is the spot where their food is. In this collective movement to find the food every bird acts as a "particle" among a group of "particles". The fitness function assesses the aptness of each particle with respect to its proximity to the aim in the search space. Each particle is mobile and continues its movement in the search space, following the best other particles. In PSO the displacement of the dispersed particles in the search space is affected by their own and their own neighbors' experience and knowledge. Therefore, the aptness and position of other particles influence on the searching process of each particle. The simulation result of such a social (collective) behavior is a searching procedure in which different particles are led towards better and more apt positions. The particles learn something from each other and, on the basis of this learning, approach their best neighbors. Thus, PSO is based on the principle that at every moment each particle chooses its position in the search space regarding the best position it has so far been at and the best neighboring position.

These affairs can be taken into account for a standard PSO algorithm under the following six steps:

Step 1, initial outcome of velocity and positions: initial outcome of a group of particles with random velocity and position in the N dimension space of the problem using a uniformly probable distributive function.

Step 2, assessment of the particles' aptness: e.g. minimization and maximization range of an objective function in an optimization problem.

Step 3, comparing each particle's aptness with personal best (*pbest*).

Step 4, comparing each particle's aptness with global best (*gbest*). This is to find the best particle among all.

Step 5, updating the velocity and position of each particle (Eq. (14) and Eq. (15)):

$$V^i_{k+1} = V^i_k + C_1 r_1 (p^i_k - x^i_k) + C_2 r_2 (p^g_k - x^i_k) \tag{14}$$

$$x^i_{k+1} = V^i_{k+1} + x^i_k \tag{15}$$

where (i= 1, 2, …, N) illustrates particles population, x^i_k shows the position, v^i_k represents the velocity, and P^i_k the best experienced position of each particle; and P^g_k is the best attained position among the whole particles. To indicate each particle's velocity change to *pbest* and *gbest* positive velocity constants C_1 and C_2, which are respectively self-learning coefficient and social learning coefficient are employed. The symbols r_1 and r_2 are random (independent) numbers whose value oscillates between "0" and "1" (Izakian & Pedrycz, 2012).

Step 6, returning to stage 2 until the availability of stopping condition: stopping condition can be attained after passing of a specific number of iterations or achieving an appropriate response.

After introducing the initial version of PSO algorithm, in order for the improvement of searching in the search space, arriving at more qualitative answers, and controlling of the algorithm's convergence speed Clerk and Kennedy presented CPSO algorithm through changing and expanding of the standard version of PSO, using Constriction Coefficient as a result of theoretical dynamic constriction analysis. Through changing Eq. (14), which illustrates updating of each particle's velocity in the standard PSO and applying the factor "χ" to guarantee convergence in the algorithm, it is possible to attain a CPSO algorithm (Sahu et al., 2012; Bharat et al., 2012). By using CPSO the oscillation range of the particles decreases and this gradually causes convergence of the algorithm. Therefore, in CPSO the velocity and position of each particle are pinpointed through Eq. (16) and Eq. (17):

$$V^i_{k+1} = \chi\,[V^i_k + C_1 r_1 (p^i_k - x^i_k) + C_2 r_2 (p^g_k - x^i_k)] \tag{16}$$

$$x^i_{k+1} = V^i_{k+1} + x^i_k \tag{17}$$

where "χ" or "constriction coefficient", as a coefficient under the impact of C_1 and C_2 is defined in Eq. (18):

$$\begin{cases} \chi = \dfrac{2}{\phi - 2 + \sqrt{\phi^2 - 4\phi}} \quad , \quad \phi = C_1 + C_2 \;\; ; \;\; \phi \rangle 4 \\ C_1 = C_2 \approx 2.05 \qquad , \quad \chi = 0.7298 \end{cases} \tag{18}$$

4. The Suggested Intelligent Approach

In flight intelligent planning, the allocation of optimal times for arrivals and departures and the determination of the priority of aircraft take-off/landing must be in a way that, while observing the standards and multiple limitations of the aviation safety, total flight delays would be appropriately minimized (Lieder et al., 2014). The suggested intelligent process for controlling traffic congestion is in a way that at first, using the intelligent

An International Journal JSCDSS
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algorithm, a randomly chosen amount is added to the flight arrival/departure predetermined times and then the arrangement of flights changes according to the new times of take-off/landings in an ascending manner. In the next step, the predetermined times for aircraft arrivals/departures and the types of aircrafts are summoned. Then, the standards and multiple limitations of aviation safety and ROT are studied based on the presented Eq. (6) to Eq. (9) in the second section. The limitations of planning have been considered according to Table 1 for Sep_L and Sep_T while for Sep_{LTL}, the fixed amount of 60 seconds, and for the ROT, the fixed amount of 70 seconds (for all aircrafts) have been used (Wang et al., 2011).

Table 1
The minimum safe separation time between successive takes-off/landings.

Landing	Trailing Traffic			
	Type	1	2	3
Leading Traffic	1	130	180	240
	2	130	130	200
	3	130	130	130
Take-off	Trailing Traffic			
Leading Traffic	1	120	120	180
	2	120	120	120
	3	120	120	120

If the predetermined flight time does not change after applying these limitations, it will be considered as the allocated time and the flight delay will be zero. However, if the planning is in a way that the limitations of the problem and the runway occupancy time have not been observed in the scheduling, the takes-off/landings of some aircrafts will have delays based on the amounts of these limitations. After that, out of the very total probable delays, and Eq. (19), the fitness of each scheduling process is determined.

$$fitness = \sum_{i=1}^{N_A} (ALT_i - PLT_i) + \sum_{j=1}^{N_D} (ADT_j - PDT_j) \quad (19)$$

After determining the fitness of a flight schedule and expiring of some specific iteration steps the intelligent algorithm will be after finding the best answer to the problem.

5. The Results of Simulation

For simulating the problem, MATLAB software was used and the traffic data included 22 arrivals and 18 departures. The type of aircrafts is based on ICAO standards consisting of three kinds; *Light (L)*, *Medium (M)*, *Heavy (H)*. The limitations of the problem are presented in Table 1 and ROT and Sep_{LTL} amounts in the previous section (Wang et al., 2011). The information on the traffic data including flight numbers, aircraft types, and the scheduled times of aircraft arrivals and departures are presented in Table 2. The other important information in Table 2 is related to the results of systematizing the traffic congestion based on the scheduled FCFS.

According to this method, first, flights are arranged in an ascending manner based on the scheduled times of arrivals and departures. Then, the limitations of minimum safe separation and ROT are examined for each scheduling and some flights face delays due to not observing the very limitations. The scheduled FCFS, while being useful, is not often optimal or even nearly optimal. Thus, the present paper maintains that for a better comparison of the suggested intelligent approach simulations are done by means of two new and different algorithms for scheduling air transportation. In the intelligent planning of BBO algorithm the number of population size was taken 50, maximum number of iteration as 200, and probability of mutation as 0.3. Regarding CPSO algorithm the population size of the particles was taken 50, maximum number of iteration as 200; and C_1 and C_2 equal to 2.05.

The best result of the suggested intelligent approach using the two algorithms BBO and CPSO, as illustrated in Table 2, indicates that total flight delays significantly decrease in spite of modern multiple limitations. Analyzing the total details in Table 2 approves the scheduling activities. For example, according to the intelligent approach using BBO algorithm Sep_{LTL} between the 1st and 23rd flights which are respectively arrival and departure flights must be calculated 130 seconds, since this limitation is properly considered regarding the delay in the second flight.

The decrease of more than 50 percent in the total flight delays compared to FCFS shows, above all, the proficiency and suitability of the suggested approach in achieving an optimal solution to the problem applying a rich and effective knowledge to optimization process. Besides, attaining fewer total flight delays for BBO compared to CPSO indicates that BBO algorithm, due to better and comprehensive search in the searching space can act as a more effective optimization means in intelligent scheduling of aircrafts take-off/landing. Fig. 2 presents a sample of the best convergence between the two algorithms BBO and CPSO in the following:

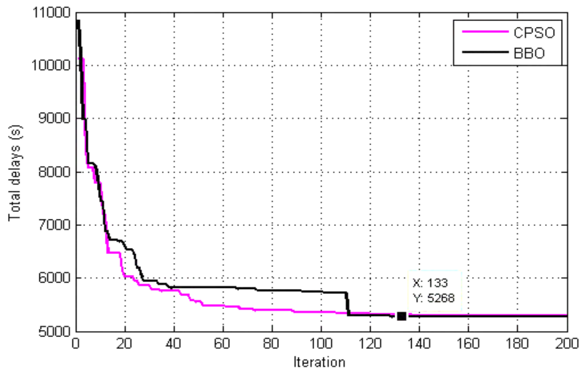

Fig. 2. A convergence sample between the two algorithms BBO and CPSO in scheduling take-off/landing of 40 aircrafts.

An International Journal JSCDSS
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Table 2
A comparison of the best results of the suggested approach with the results of FCFS.

Data				FCFS			CPSO [a]			BBO [a]		
No.	TP	A/D	PLT /PDT	No.	ALT /ADT	delay	No.	ALT /ADT	delay	No.	ALT /ADT	delay
1	3	A	6	1	6	0	1	6	0	1	6	0
2	1	A	159	23	136	51	23	136	51	23	136	51
3	2	A	263	2	266	107	2	266	107	3	266	3
4	2	A	442	3	446	183	24	396	93	2	396	237
5	1	A	643	24	576	273	3	526	263	25	526	39
6	3	A	845	4	706	264	4	656	214	24	646	343
7	2	A	1123	25	836	349	5	786	143	4	776	334
8	1	A	1309	5	966	323	27	916	73	5	906	263
9	2	A	1526	27	1096	253	25	1036	549	27	1036	193
10	2	A	1735	6	1226	381	6	1166	321	6	1166	321
11	1	A	2018	7	1356	233	7	1296	173	7	1296	173
12	1	A	2351	29	1486	311	8	1426	117	8	1426	117
13	3	A	2476	8	1616	307	29	1556	381	29	1556	381
14	2	A	2822	9	1796	270	9	1686	160	9	1686	160
15	1	A	2938	10	1926	191	10	1816	81	10	1816	81
16	2	A	5318	31	2056	105	31	1951	0	31	1951	0
17	3	A	3335	11	2186	168	11	2081	63	11	2081	63
18	1	A	3478	28	2316	163	28	2211	58	28	2211	58
19	2	A	3763	32	2436	117	32	2331	12	32	2331	12
20	3	A	3022	12	2566	215	12	2461	110	12	2461	110
21	1	A	4219	13	2806	330	33	2591	23	33	2591	23
22	1	A	4597	33	2936	368	13	2721	245	13	2721	245
23	3	D	85	14	3066	244	14	2851	29	14	2851	29
24	1	D	303	15	3196	258	15	2981	43	15	2981	43
25	3	D	487	20	3436	414	34	3161	0	34	3161	0
26	2	D	3638	34	3566	405	20	3291	269	20	3291	269
27	3	D	843	17	3696	361	17	3421	86	17	3421	86
28	1	D	2153	18	3826	348	18	3551	73	18	3551	73
29	2	D	1175	35	3956	378	35	3681	103	35	3681	103
30	3	D	4928	26	4076	438	26	3801	163	26	3801	163
31	1	D	1951	19	4206	443	36	3921	72	36	3921	72
32	2	D	2319	36	4336	487	37	4041	81	37	4041	81
33	3	D	2568	37	4456	496	38	4161	69	38	4161	69
34	2	D	3161	38	4576	484	19	4291	528	19	4291	528
35	1	D	3578	21	4706	487	40	4421	94	21	4421	202
36	3	D	3849	40	4836	509	21	4551	332	40	4551	224
37	1	D	3960	22	4966	369	22	4681	84	22	4681	84
38	2	D	4092	30	5096	168	30	4928	0	30	4928	0
39	1	D	5013	39	5216	203	39	5048	35	39	5048	35
40	3	D	4327	16	5346	28	16	5318	0	16	5318	0
Total delays (s)				11482 s			5298 s			5268 s		
Computational time (s)				-			39.62 s			27.92 s		

Note: "No. : Flight number TP: Aircraft type A/D: Arrival/Departure"
[a] The proposed approach (running on an Intel Core i5 2.66 GHz CPU laptop computer with 4 GB RAM).

Then, after performing 10 times of the intelligent programs of the two algorithms the following results were obtained, as observed in Table 3 below.

Table 3
Results of 10 times performing of the programs.

Method	Total delays (s)			Computational time (s)		
	Worst	*Best*	*Mean*	*Worst*	*Best*	*Mean*
CPSO	5738	5298	5369.1	34.71	9.67	24.68
BBO	5358	5268	5299.5	29.64	7.48	20.76

In Fig. 3 and Fig. 4 the manner of convergence between CPSO and BBO in performing 5 times of the program is illustrated.

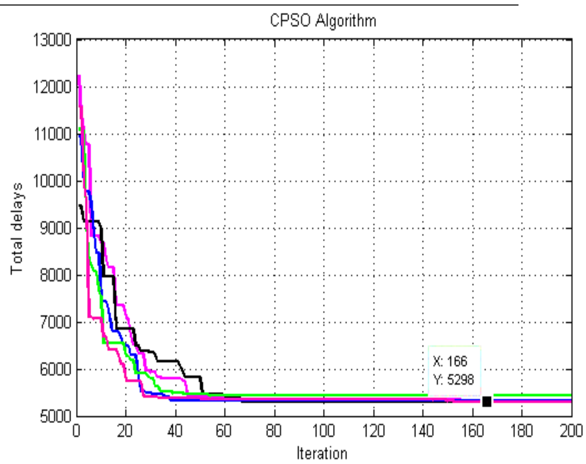

Fig. 3. A sample of CPSO convergence in 5 times intelligent planning.

An International Journal
JSCDSS
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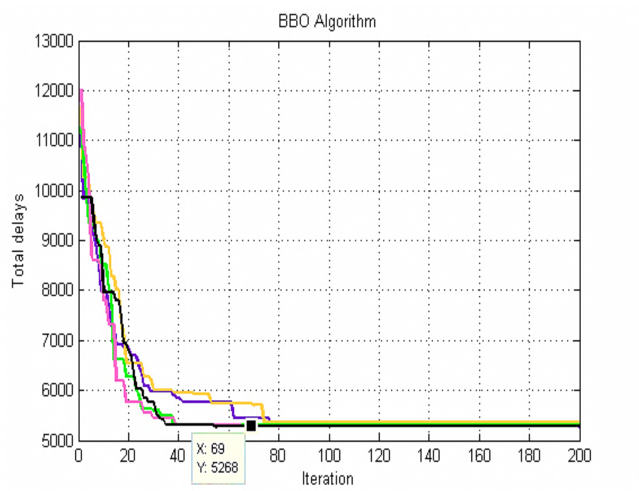

Fig. 4. A sample of BBO convergence in 5 times intelligent planning.

6. Conclusion

In the present study, for the first time, the optimal control of aircraft take-off/landing was examined while considering new practical limitations. This was achieved using a new approach, defining a new fitness function, applying rich effective knowledge to the optimization operation (to increase the speed of optimization operation, to delete the obvious non-optimal solutions, and to find the optimal solutions in the limited searching space created).

For showing the quality of the suggested intelligent approach, simulations were performed using BBO and CPSO algorithms and the obtained results were compared to those of FCFS. The results of simulation showed that the presented BBO-based intelligent approach (adding a random time length to estimated arrival/departure time of flights and doing the other steps of planning according to section 4) can decrease flight delays more than 50 percent compared to FCFS. Moreover, comparing the results of applying the two new optimization algorithms showed that BBO can be more effective than CPSO because of its comprehensive exploring domain. Thus, the present intelligent planning which has a little computational time and in which different practical limitations are taken into account in an effective way can act as an appropriate auxiliary means in ATCs; and have a significant role in decreasing of controllers' workload.

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