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A Multi-Objective Grey Wolf Optimization Algorithm for Aircraft Landing Problem

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Abstract

Air traffic management is an important job and often faces various problems. One of the most common problems in this area is the issue of aircraft sequencing, which is a multi-dimensional problem due to the large number of flights and their different positional conditions. Previously proposed models were based on First Come, First Service (FCFS) have not considered the time factor, resulting in increased delay penalties. In this regard, this article proposes a model in which the time factor is one of the factors that is managed and additional costs due to delay will be eliminated. This paper proposed the Multi-Objective Grey Wolf Optimization (MOGWO) algorithm to evaluate three objective functions such as the airport runway efficiency, the apron and parking costs, and the fuel consumption costs. The proposed algorithm compared with well- known NSGA-II (non–dominated Sorting Genetic Algorithm). The obtain results represented that in the case of using all the data for the first, second and third-objective function, MOGWO performs better than NSGA-II. The brilliant results demonstrated the superiority of the proposed model. In this study, using the proposed model, the data set of Shahid Hasheminejad International Airport in Mashhad was analyzed.

Keywords: Aircraft Landing Problem (ALP), Grey wolf optimization algorithm, Multi-objective optimization.

1 | Introduction

Evolutionary algorithms and various intelligent methods in transportation planning and routing issues have been proposed in research due to the complexity of such problems that can be addressed to the problem of nurses' management in a hospital [1], vehicle routing [2] and the multi-criteria transportation problem [3]. One of the issues related to transportation planning is the issue of Aircraft Landing Problem (ALP), which is considered in this article.

Considering the large number of aircraft entering radar scope, managing of the landing schedule is challenging, it is also notified by international air transport associations.

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There are some priorities in the scheduling and these priorities can be changed based on some factors such as the time of entering the radar screen, the importance of the flight, the number of passengers and the fuel and consumption status [4]. The management and planning of aircraft landings is an NP-hard issue due to the constraints and dimensions. Some limitations in landing scheduling include: the number of aircraft under control, altitude of aircraft, the distance to the runway, type of aircraft, et al. One of the most important priorities is the sequence of entry into the radar scope, which is called First Come First Served (FCFS). Aircraft landing schedules are usually planned and scheduled according to FCFS [5]-[7].

Air traffic organizations have to be well - equipped to be able to manage the issue of rapidly increasing of the number of flights. As different aircraft enter the airport radar screen, air traffic controllers must determine the sequence of landing of aircraft close to the airport. There are many parameters to consider before ordering to land, including the number of arriving aircraft, the number of runways, the type of arriving aircraft, the minimum required separation between leading and trailing aircraft for avoiding wake vortex, the distance between two aircraft. The minimum required separation is essential from the point of view of aerodynamic issues, for avoiding aircraft accident. In an appropriate landing scheduling we minimize delays, reduce fuel costs and reduce passenger dissatisfaction which is the crucial. The fact is that the costs related to the fuel of the flight fleet constitute a significant percentage of the costs; hence, inappropriate scheduling of the landing can be cost significant for the airlines. As a result, most airports that perform better in terms of air traffic management are attracting more airline attention. On the other hand, by achieving good performance in managing air traffic, airport companies will be able to accommodate more aircraft in a fixed time period.

An important part of airport companies' revenue is from renting an aircraft parking space. The cost of parking spaces varies depending on its facilities such as Auxiliary Power Unit (APU) and jet way. Jet way is an enclosed, telescoping, movable ramp like bridge connecting an airport terminal and an aircraft, for using by passengers in boarding and disembarking. There are two types of parking lots in all airports of the world, which are parking lots with jet way and stand parking lots without jet way. But planes parked in remote stands (without jet way) need a bus lunch to pick up or drop off passengers. Of these two types of parking lots, the jet way parking lot has a higher price. The calculation of the amount of passenger transfer in this type of parking space is in the form of person-passenger, for which a fixed amount is received from the relevant airline for each passenger passing through it. This amount is much more than the price of bus lunch. Despite the higher price of the jet way parking lot, airlines prefer to use this type of passenger transfer station to satisfy their passengers. This type of stand also has an important safety advantage. By using this type of transfer channel, passengers will be safe from the dangers of being at the airport movement area. When concluding a contract between the airlines and the airports, airlines cannot determine the type of parking space, in fact, allocating the type of parking space for an aircraft is the responsibility of the airport controller at the time of landing. But with the accurate scheduling, more planes can be deployed to jet way parking lots, helping to increase airport revenue.

As it was also mentioned above, it is beneficial for the airports to be able to have suitable control on balancing of the two issues of aircraft traffic control (aircraft landing sequence) and the allocation of aircraft to jet ways. As soon as the planes land at the airport, a parking space should be allocated to each of them. This parking space must be empty at the time of landing and ready for service. ALP is one of the most important challenges at all airports. The goal of ALP is to minimize the time deviation from the original scheduled time for each flight, which reduces time and material costs. Each aircraft is supposed to land on a specific runway with a specific time-window.

Existing techniques do not measure time factors, which will result in very high delay penalty costs. So far, many techniques such as neural networks and genetic algorithms have been used to reduce this penalty. The main purpose of all these techniques is to eliminate congestion on airport runways and reduce flight delays. As an example Mokhtari et al. proposed a model to increase ALP efficiency using a multi-objective optimization function [8].

2 | Literature Review

Over the past few decades, air traffic operations have experienced prevalent and widespread growth. Airport runways are known as bottlenecks in the operating system. This feature resulted on increasing of the queue of aircraft landing and takeoff, which in turn increases the volume of air traffic, flight delays, fuel costs and environmental pollution [9]. On the other hand, the increase in the air transport demand increases the workload of the control tower. The workload is also extremely high during peak hours of air traffic when the capacity of the Terminal Control Area (TCA) is filling up. This problem would be existed, at least in large European airports, which face necessary infrastructure limitations [10]. One of the appropriate approaches to face this challenge could be improvement in the landing and takeoff system scheduling [11]. Ma et al. [12] proposed a Simulated Annealing (SA) approach with time analysis to solve the relevant problems. They performed computational analysis on the information of Charles de Gaulle Airport in Paris. Their goal was to solve the problems of the airport runway and reduce the flight delays [13].

Insaurralde and Blasch [14] in their proposed approach suggested a solution for anthologies next-generation avionics systems (ONAS). They used ONAS system for air communications analyses which include information related to air condition, flights and airspace. Hancerliogullari et al. [15] proposed a solution for scheduling arrival and departure flights at multi-runway airports using the ASP problem. Many other efforts have been made to solve the problem of sequencing aircraft in different dimensions. In most of the researches on the similar topics, arrival and departure flights are studied separately. In this study attempts have been made to provide solutions using methods based on data mining, mathematics, etc. For example, Beasley [16]-[17], Hu and Chen [18], Hu and Di Paolo [19] and Liu [20] solved this problem using metaheuristics such as genetic algorithm, ant colony and scatter search. Alligier and Gianazza [21] carried out similar studying using the machine learning model and a segment climbing algorithm. Kim [22] used deep learning architectures including stacked auto encoders, convolutional neural networks, and recursive neural networks as an architecture to predict the state of daily delay. Mirjalili et al. [23] introduced an approach in which the issue of aircraft landing and departing schedule were studied simultaneously on several runways. They minimized landing and flight departing delays by considering the limitation on the number of aircraft parking locations. One of the best integrated works on fuzzy controllers in air traffic is the approach introduced by El Hatri and Boumhidi [24]. In this work, aircrafts accidents were studied by using a fuzzy model. In one other research which is carried out by Lieder and Stolletz [10] the use of linear programming on flight schedule optimization, by dynamic programing, was studied. In another approach, Oza et al. [25] predicted the flight delays using specific data patterns from previous flight data. In this method archived data from large airports were used in existing flight information systems. In another study, Samà et al. [26] introduced an efficient approach to real-time aircraft routing and scheduling using methods based on linear optimization. Their model was performed on the real data from Roma Fiumicino Airport, the largest airport in Italy. In many researches on the flight scheduling optimization, mathematical models such as optimization, simulation, and queue-based models have been taken into account. One of the research works in this field is the approach introduced by Chen et al. [27].

In this approach in order to obtain an accurate prediction from the future air traffic for balancing the traffic demand and effective capacity, optimization method has been used for. From other side, considering the uncertainty of some information such as the weather condition, they provided a new effective computational algorithm for solving uncertainty in Air Traffic Flow Management (ATFM). The work done by Takeichi et al. [28], is noticeable among other research works done in the field of ATFM. Considering the weather condition, they used "machine learning" for estimating landing delay time and the number of flights that enter a control space at a time. In this model, by considering variables such as the type of aircraft, the arrival time at the destination and entering time to the control space and leaving the control space, the delay time on landing is predicted.

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As it was mentioned before, in ALP problems which are a "hard multi-constraint optimization" problem, considering the flight affecting parameters, finding an operative solution is really hard. Considering the limitation of the airports and efforts on decreasing of the delay related costs, finding an appropriate solution for air traffic management seemed to be unavoidable. In this article an effort has been put to optimize flight scheduling in Mashhad international airport. The novelty of this research work is using Grey Wolf Multi-Objective (GWMO) optimization which is more up-to-date compared to other optimization methods. A key feature of MOGWO is the leader-based strategy, which helps select alpha, beta and delta solutions as the leader of the archive hunting process which NSGA-II does not have this feature. Non-dominated solutions are stored with the help of an additional repository. With the help of adaptive parameters a and A, the ability to explore and extract is improved and a balance is established. The networking mechanism and leader selection maintain reservoir diversity during optimization. By using the roulette-wheel in selecting the leader, the local optimization in this algorithm is prevented from falling [23]. Dilip et al. [29] solved the problem of optimal power flow using the multi-objective grey wolf algorithm. They showed that the MOGWO algorithm had faster convergence and obtained better optimal beam points compared to NSGA-II. Ghorashi et al. [30] showed that MOGWO is better than MOPSO and NSGA-II in solving small and large size experimental problems in terms of diversity and convergence criteria. Also, this algorithm has been able to provide the best accurate approximation of correct beam lines. In this paper, ANOVA and Tukey experiments were used to evaluate the algorithms.

As it will be shown later, the results from MOGWO method are much better than the results obtained from the NSGAII method. Also, this study is the only flight scheduling optimization study on the Mashhad international airport flights.

3 | Proposed Model

The issue of aircraft landing scheduling has many limitations, known as the NP-hard issue. Finding answers for the optimal landing time intervals are challenging due to the large size inherent characteristics as well as the large number of constraints on the aircraft landing schedule. The importance of landing distance on front and back aircraft as well as the type of aircraft should be included in the solution provided for aircraft sorting and scheduling. Many studies have been done on optimal landing scheduling and provide algorithms and models to increase the capacity of the airport. In this study, an attempt has been made to study the problem of aircraft scheduling by using the multi-objective grey wolf algorithm. Before going into the detail on the study, first the conditions for obtaining the solution, requirements and parameters of the problem will be examined.

3.1 | Decision Making Variables

In the following, the decision making variables used in the proposed method are introduced. To formulate the problem, the equations presented in [8] have been used.

n: The number of aircraft to be scheduled.

SLT_i: The scheduled landing time of aircraft "i" calculated by trajectory synchronizer equipment after entering the aircraft into the radar range.

ELT_i: The expected or target landing time of aircraft i, based on the assigned time slot which is normally specified in flight plan.

$TELT_i$: Aircraft type i in size category based on three different types of aircraft in small, medium and large.

Δ_{ij}: The minimum time separation between aircraft i and j, if the landing of aircraft i is before aircraft j.

CAT_i: Airline cost per unit of time (except fuel factor) for landing of aircraft i after ELT_i .

CBT_i: Airline cost per unit of time (except fuel factor) for landing of aircraft i beforeELT_i.

FCD_i: Average required fuel burn cost per minute for landing aircraft i after ELT_i.

FCA_i: Average required fuel burn cost per minute for landing aircraft i before ELT_i.

Th: The time for a plane to circle for one loop when waiting its turn to land.

EAT_i: The earliest possible arrival time for aircraft i, subject to technical and operational restrictions.

LAT_i: The latest possible arrival time for aircraft i, which is usually determined from fuel limitation and maximum allowable delay.

ea_i: The allowed earliness for aircraft i to land before ELT_i, from the moment the wheels touch the ground to reach the parking lot (including across the taxiways).

da_i: The allowed lateness for aircraft i to land after ELT_i, from the moment the wheels touch the ground to reach the parking lot (including across the taxiways).

X_{ij}: Defined to be 1 if aircraft i land before (not necessarily immediately) aircraft j and otherwise 0.

e_i: The earliness for aircraft i, $e_i = max(0, (ELT_i - SLT_i))$.

d_i: The lateness for aircraft i, $d_i = max(0, (ELT_i - SLT_i))$.

3.2 | Objective Functions

Objective functions include criteria that we seek to optimize in scheduling. These criteria are as follows.

I. Maximizing airport runway efficiency: the goal is to maximize the number of aircraft that land on the runway by minimizing total landing times instead of maximizing the number of aircraft that land on the runway. The efficiency of the airport runway can be written as follows:

$$\text{Minimize} \sum_{i=1}^{n} \text{SLT}_i. \tag{1}$$

II. Minimizing the apron and parking costs and the other costs that are applied due to the additional stay of the aircraft at the airport, by minimizing the delay time and allowable earliness. This can be expressed as follows:

$$\text{Minimize} \sum_{i=1}^{n} \{|\text{SLT}_i - \text{ELT}_i| - \text{B}\}\, \text{A}. \tag{2}$$

In this formula, the A and B values are calculated as follows:

$$\text{A} \begin{cases} \text{CAT}_i, & \text{SLT}_i > \text{ELT}_i \\ 0, & \text{SLT}_i = \text{ELT}_i \\ \text{CBT}_i, & \text{SLT}_i < \text{ELT}_i \end{cases}. \tag{3}$$

$$\text{B} \begin{cases} \text{da}_i, & \text{SLT}_i > \text{ELT}_i \\ 0, & \text{SLT}_i = \text{ELT}_i \\ \text{ea}_i\,, & \text{SLT}_i < \text{ELT}_i \end{cases}. \tag{4}$$

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III. Minimizing fuel consumption cost and minimizing carbon dioxide pollution: Fuel consumption depends on various factors, including pilot flying skills, height of flight, wind speed and direction, type of aircraft, aircraft weight (including Passengers and cargo) and fuel in the tanks. This can be obtained by deduction of the early arrival time from the late arrival time:

$$\text{Minimize} \sum_{i=1}^{n} \{|SLT_i - ELT_i|\} C. \tag{5}$$

In this formula the C volume is calculated as follows:

$$C \begin{cases} FCD, & SLT_i > ELT_i \\ 0, & SLT_i = ELT_i \\ FCA, & SLT_i < ELT_i \end{cases}. \tag{6}$$

3.3 | Constraints

There are various operational constraints for ALP. Looking at the real world, the most practical ones for use in a band are mentioned. In general, all Scheduled Landing Times (SLT) should be determined and calculated based on the following constraints:

Limitations of runway in use: Each runway can only be used by one aircraft at a time. Thus plane i lands before plane j or vice versa:

$$X_{ij} + X_{ji} = 1, \qquad \forall_{ij} = 1,2, \dots, n. \tag{7}$$

Minimum required separation between leading and trailing aircraft: The following aircraft must be at a safe distance from leading aircraft to prevent wake turbulence created by leading aircraft in the air for avoiding aircraft accident:

$$(SLT_i - SLT_j) \geq \Delta_{ij}. \tag{8}$$

Time limit:

$$EAT_i + Th \leq SLT_i \leq LAT_i. \tag{9}$$

Scheduled time for each pair of aircraft (leading and trailing):

$$(ELT_i - ELT_j)(SLT_i - SLT_j) \geq 0. \tag{10}$$

Restrictions related to earliness or lateness:

$$0 \leq e_i \leq ELT_i - EAT_i. \tag{11}$$

$$0 \leq d_i \leq LAT_i - ELT_i. \tag{12}$$

5 | Scheduling Structure

The proposed method aims to provide multi-objective optimal scheduling using grey wolf algorithm optimizations. Scheduling by the grey wolf algorithm requires a structure that is base for all the calculations. Below the structure is introduced.

An array of length n is used to schedule a set containing n planes. Each cell in the array represents the expected landing time which is given in the ELT_i. To better illustrate this, suppose there is a set of 10 aircraft available for scheduling. In the sequence they enter the radar range of airport (the landing time) for this set of aircraft can be as *Table 1*.

Table 1. Expected landing times for 10 planes.

Num.	Landing Times
1	10:12
2	10:21
3	10:30
4	10:18
5	10:24
6	10:37
7	10:40
8	10:31
9	10:50
10	10:45

For example, in *Table 1*, the expected landing time of aircraft number 8 is scheduled for 10:31.

3.5.1 | Scheduling for Landing Using Multi-Objective Grey Wolf algorithm

The proposed model is on the base of converting single-objective grey wolf algorithm to multiple objectives, while a new component is added to the grey wolf algorithm. The added component is similar to the component used in the Multi-Objective Particle Swarm Algorithm (MOPSO). This is a part of an archive that is responsible for storing non-dominated answers. It should be noted that when there is more than one-objective function in the problem, it is not easy to prioritize the obtained answers.

The archive is a place to store and retrieve non-dominated answers that have been obtained so far (Pareto optimal solutions). During the algorithm iteration process, one answer is compared to the current members of the archive, and one of the following situations will occur:

I. The new member is dominated by at least one member of the archive. In this case, the new answer will not be allowed to be added to the archive.
II. The new member dominated one or more members of the archive. In this case, the dominated members are removed from the archive and the new member would enter the archive.
III. If neither the new member nor the members of the archive succeed in dominating the other, a new member will be added to the archive.
IV. If the archive is full, the member with the minimum crowding distance is removed to make room for the new member.

In this method different grey wolves are obtained and the impossibility of arranging grey wolves makes it difficult to identify alpha, beta and delta wolves.

Therefore, to determine these wolves that play a key role in the equations used in the grey wolf algorithm, these wolves need to be randomly selected from the archive. Before the flowchart of the proposed method using the multi-objective grey wolf algorithm is introduced, it is necessary to explain the created developments to increase the efficiency of the grey wolf method.

3.6 | Leader Selection Strategy

In the multi-objective grey wolf algorithm, due to the impossibility of determining the Leader of the wolves, the leader is selected randomly. But it can negatively affect the process of this algorithm. In the proposed method, in order to improve the performance of this process, a new technique generated

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based on the combination of grid and roulette-wheel [30] is used. As stated in [30], in the grey wolf algorithm, the top three answers are selected as the leader, which are the alpha, beta and delta wolf. The task of leaders is to guide other seekers to an area where they hope to find close-to-optimal answers. However, due to the existence of archives in the multi-objective search space, selecting a leader is not an easy task, and the mechanism for selecting a leader is needed to be developed.

In the proposed method, first the archive is graded, meaning that the archive is divided into equal parts in a dimension of the objectives to make the archive space grid-like. In this case, each section contains a certain number of non-dominated answers. After the archive is graded a leader is chosen to use the roulette-wheel. The leader selection mechanism selects one of the non-dominated answers as alpha, beta, and delta wolf among the least crowded sections in the archive. The choice by roulette -wheel will be as follows:

$$P_i = \frac{C}{N_i}. \tag{13}$$

In which C is a fixed value bigger than one, and N is the number of non-dominated answers in part i. In *Eq. (13)*, it is clear that sections with less congestion have a higher chance of being selected as a leader. It should be notified that the selected leaders Alpha, Beta and Delta cannot be the same. It means that Alpha, Beta and Delta are selected from non-dominated answers. These three wolves are different because they are the leader of the wolf group. In fact, this technique aims to get the wolves to less-sought areas; hence, it can be optimistic that the search space has been properly studied.

3.7 | How to Remove from Full Archive

When the archive is filled, some members of the archive must be removed. This is done by the valve operator. The valve component has the task of keeping the archive of answers as convergent as possible and creating enough space for new answers. In this method, from the target space, which is divided into several areas by the grid, the area with the highest density is selected and one of the answers is accidentally deleted to open the necessary space for the new answer.

3.8 | Selecting the Best Answer from the Archive

As stated in the previous section, the final output of the grey wolf algorithm is a set of answers. Each answer also has a degree of fitness that has not been dominated by the other answers, so it is not possible to simply select only one answer as the final answer from the archive. Therefore, using the method presented in [30], the closest answer to the optimal answer is determined. In this method, the distance of each of the answers in the archive with the ideal point (optimal solution position) is calculated and the point closest to the ideal point is returned as the answer. This technique is known as Utopia Point. The distance between ideal point and a non-dominated solution X_t could be calculated as $D = |X_{optimal} - X_t|$.

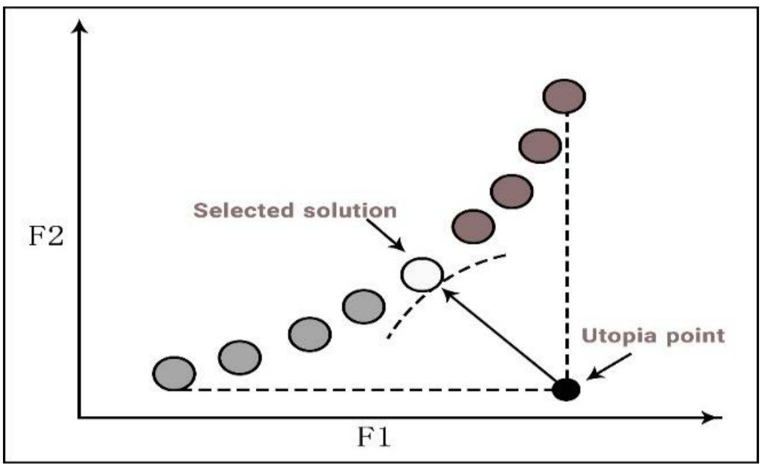

Fig. 1. Determination of the optimal point and the best answer from the archive.

The following is the algorithm of the proposed method, which is based on the multi-objective grey wolf algorithm. In this algorithm, the list of flights to be scheduled is entered into the system as input, while the output is flight scheduling time.

1. Start
2. Enter the flight information to be scheduled from data base → Current Flights.
3. Create the population of grey wolves with different ELT values according to Current Flights so that it meets the constraints.
4. Initialize the values of A, a and C.
5. Determine the target values for each of the search agents.
6. Find the non-dominated answers and put them in the archive.
7. Select X_α from the archive using the leader selection strategy.
8. Temporarily remove X_α from the archive to avoid choosing a leader similar to X_α.
9. Select X_β from the archive using the leader selection strategy.
10. Temporarily remove X_β from the archive to avoid choosing a leader similar to X_β.
11. Select X_δ from the archive using the leader selection strategy.
12. Return X_α , X_β and X_δ to the archive.
13. t = 1.
14. Perform the following steps if t is less than the maximum repetition number.
14.1. For every search agent:
14.1.1. Update SLT Search Agent.
14.1.2. Replace the new wolf if the new SLT meets the constraints.
14.2. Update the values of A, a and C.
14.3. Specify objective values for each search agent.
14.4. Find the non-determined answers.
14.5. Update the archive according to the non-dominated answers obtained.
14.6. If the archive is full, then,
14.6.1. Run the segmentation mechanism and delete one of the current members of the archive.
14.6.2. Add new answer to archive.
14.7. Otherwise, select X_α from the archive using the leader selection strategy.
14.8. Temporarily remove X_α from the archive to avoid choosing a leader similar to X_α.
14.9. Select X_β from the archive using the leader selection strategy.
14.10. Temporarily remove X_β from the archive to avoid choosing a leader similar to X_β.
14.11. Select X_δ from the archive using the leader selection strategy.
14.12. Return X_α , X_β and X_δ to the archive.
14.13. t = t + 1.
15. Return the final answer from the archive using the Utopia Point technique.

4 | Assessment Results

In this section, the results of the evaluation of the proposed method are studied. For this purpose, the implementation environment along with the initial parameters as well as the data set used for the evaluation is examined. The performance of the proposed method was studied by comparing of the results obtained from our proposed approach and the results extracted after implementing of the data in the NSGAII approach by [8] and [31].

4.1 | Initial Parameters

Following initial parameters are required to identify to be able to implement data in two different approaches. *Table 2* shows used initial parameters in this evaluation.

Table 2. Considered initial value for the parameters in two approaches.

Method and Parameter	MOGWO	NSGAII
The population size	10	10
The number of generation	10	10
Crossover rate	-	0.4

Mutation rate	-	0.04
Elitist selection	-	0.3
Number of grid segmentation	10	-
Archive size	20	-

4.2 | Testing Data Sets

The experiments in this study were based on the real data set. To perform the experiments, the recorded data set for the flights of Shahid Hasheminejad Airport in Mashhad were used. This data set, which includes flights from 03.05.2018 to 03.07.2018, contains some features that include date of flight, origin, destination, type of aircraft, flight altitude, aircraft weight, flight route, expected landing time, aircraft speed.

This data set ultimately includes 4368 flights and the features in these flights were used for the calculation in Section 3.2.1. In fact, before this information to be used, they were transformed into a format required by Section 3.2.1, and then they were used for the calculation.

4.3 | Assessment Results

This section presents the assessment results of the data obtained from Mashhad Hasheminejad airport using MOGWO and NSGAII methods based on objective functions. Assessments are on three objective functions introduced on the objective functions section. To perform the point-to-point assessment, all the data were classified in 10 groups. First group contained 10% of the data, and the second group contained 20% of the data, and the third group has the 30% of the data and so on. The tenth group contained 100% of the data. After classification of the data, both models were studied on classified groups of the data. First, both models were performed on the first group of the data and the results were recorded. Then both models were studied using the second set of data in group two which contained 20% of the data. And this was continued until we performed both models on the tenth group of the data which contained 100% of the data. As mentioned in 2-3 section, in all the evaluations based on the objective functions, the goal is minimizing. Hence, the approach that led to lower values has a better performance.

4.3.1 | Evaluation Based on the First-objective Function

MOGWO and NSGAII methods were implemented based on the first-objective function on the data obtained from Hasheminejad airport and the result of this implementation is given in *Fig. 2*.

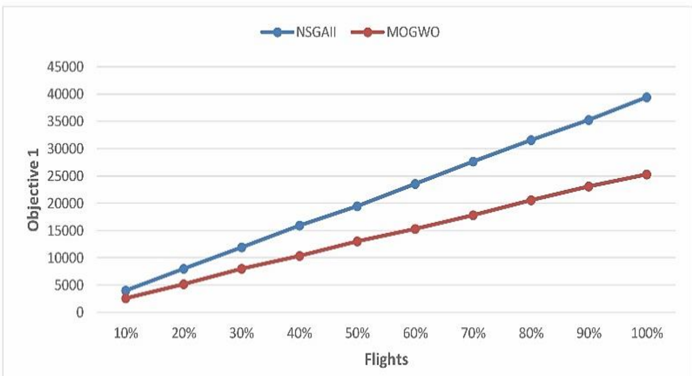

Fig. 2. Comparison of MOGWO and NSGAII methods on the first-objective function.

The results presented in *Fig. 2* for the first-objective function show the difference in the landing time when two different approaches, MOGWO and NSGAII, were implemented. It is clear that the proposed approach can provide a lower value of the first-objective function has a better performance. The results in *Fig. 2* shows the superiority of the proposed method in all the segmentation performed on the data set. *Fig. 2* also shows that with the enlargement of the data set, the difference of the values extracted from two used methods increases. Hence, the proposed method has a better performance than the NSGAII method.

4.3.2 | Evaluation Based on the Second- objective Function

MOGWO and NSGAII methods were implemented on the data set obtained from the Mashhad hasheminejad airport based on the second-objective function. *Fig. 3* shows the performance comparison of the proposed method and the NSGAII method based on the second-objective function.

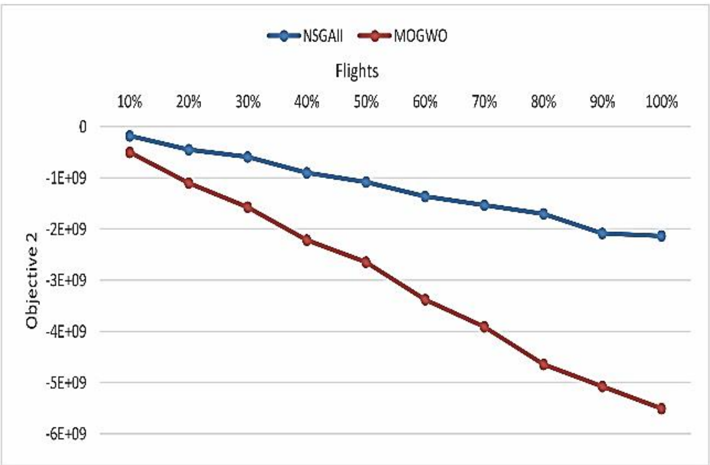

Fig. 3. Comparison of MOGWO and NSGAII performances implemented based on the second-objective function.

As it can be seen from *Fig. 3*, the performance of the proposed method is much better than the NSGAII method, and this conclusion is the same when both methods were implemented based on the first-objective function. In the 10% data set, the MOGWO method seems to have a small better performance compared to the NSGAII method. However, with the increase in the size of the data set, superiority of the proposed method increases.

4.3.3 | Evaluation Based on the Third- objective Function

As it was done in the last two sections, the performance evaluation of the NSGAII and MOGWO methods based on the third-objective function were implemented on the same data set. *Fig. 4* shows the results of this evaluation.

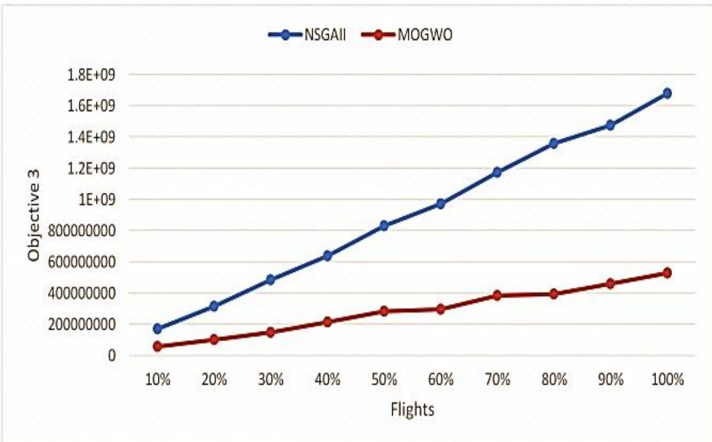

Fig. 4. Comparison of MOGWO and NSGAII methods based on the third -objective function.

As it can be seen from *Fig. 4*, the superiority of the proposed method to NAGAII based on the third-objective function is obvious, the same with the results when evaluation was performed base on the first and the second-objective functions.

5 | Conclusions and Future Work

This paper presents an approach to schedule flights to land at the airport. The proposed approach, using the multi-objective grey wolf algorithm, attempts to schedule flights in a way that includes the least difference between the calculated and scheduled time, as well as the lowest cost, including airport and fuel costs. For this purpose, we considered the multi-objective grey wolf algorithm with three-objective functions. In addition, in order to increase the efficiency of the proposed algorithm, we added improvements such as the leader selection strategy, how to remove from the archive, as well as selecting the best solution from the archive to the basic approach. In the proposed approach, we also presented the algorithm in a way that is consistent with the structure of the problem under study, so that in addition to consider the objective functions of the problem, the constraints on the problem are also observed. The assessment was performed on the real data set of flights from Mashhad Shahid Hasheminejad Airport in the period 03.05.2018 to 03.07.2018, including 4368 flights. In order to compare, the proposed approach is compared with the non-dominated Sorting Genetic Algorithm (NSGAII). The results were evaluated on triple-objective criteria and data set segmentation was in the range of 10% to 100%.). The obtain results show that in the case of using all the data for the first-objective function MOGWO and NSGA-II, the values 25000 and 40000 are obtained, respectively. For the second-objective function, MOGWO and NSGA-II, the values -5.5*e09 and -2*e09 are obtained, respectively. Finally, for the third-objective function, MOGWO and NSGA-II, the values 5.8*e08 and 1.7*e09 are obtained, respectively.

The results of the evaluations indicate that the proposed approach works better than the compared method. These results declare the proposed approach is superior to the method compared.

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