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A Non-Dominated Sorting Genetic Algorithm Approach for Optimization of Multi-Objective Airport Gate Assignment Problem

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Abstract

Gate assignment problems (GAP) are one of the most substantial issues in airport operation. The ever-increasing demand producing high occupancy rates of gates, the potential financial loss from imbalances between supply and demand in congested airports, and the limited scope for expanding facilities present challenges that require an advanced methodology for optimal supply allocation. In principle, tackling GAP involves seeking to maintain an airport's maximum capacity through the best possible allocation of resources (gates). There are a wide range of dependent and independent resources and limitations involved in the problem, adding to the complexity of GAP from both theoretical and practical perspectives. In this study, GAP is extended and mathematically formulated as a three-objective problem, taking into account all resources and restrictions, which can be directly linked to airport authorities' multiple criteria decision-making processes. The preliminary goal of multi-objective formulation is to consider a wider scope, in which a higher number of objectives are simultaneously optimized, and thus to increase the practical efficiency of the final solution. The problem is solved by applying the second version of Non-dominated Sorting Genetic Algorithm (NSGA-II) as a parallel evolutionary optimization algorithm. Results illustrate that the proposed mathematical model could address most of the major criteria in the decision-making process in airport management in terms of passenger walking distances, robustness, and traditional costs. Moreover, the proposed solution approach shows promise in finding acceptable and plausible solutions compared with other multi-objective algorithms (BAT, PSO, ACO, and ABC).

The flight-to-gate assignment problem has gained attention in recent years, particularly in the context of the need to address capacity shortcomings at the airports, resulting from the global increase in air travel. The growth in the size of fleets and the volume of commercial services together with lower fares offered by low-cost carriers have boosted global demand for air travel in recent years. According to statistical reports, air travel demand, in both domestic and international scheduled flights, grew from 2.628 billion passengers in 2010 to 3.464 billion passengers in 2015 (growth of 31%) and continued to 3.696 billion in 2016 (a growth of 0.06%) (*1*). As demand for air travel has continued this apparently inexorable growth over the last decade, problems associated with limited airport capacity have been revealed. In fact, the need for accurate operational and management functions has become even more acute as has the need to maximize operational efficiency maximization and achieve align resources more effectively to the traffic.

Gate scheduling and assignment is a key activity in airport operations and air transportation systems (ATS). A wide range of resource modules need to be taken into account. These are generally divided into three major categories: airlines, air traffic management (ATM), and airport resources (*2*). In the struggle to optimize the use of resources, each single problem, such as aircraft assignment, crew scheduling, runway sequencing, airspace capacity, and so forth, has a huge number of highly interdependent restrictions and limitations (for example, number of flights, available terminal space, baggage claims),

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where many conflicting objectives have to be considered. This interdependency between resources makes resource optimization a major challenge for airports and raises difficult issues in decision-making procedures which affect airport performance.

From a theoretical perspective, the Gate Assignment Problem (GAP) at airport terminals refers to the task of assigning a given set of flights to a set of available terminal gates (which are limited in number) in a way that both meets the operational requirements as well as passengers' convenience, and minimizes the operating costs of airports and airlines.

In this context, a "gate" is not only a facility through which passengers pass to board and alight from aircraft, but it is the location at which an aircraft is serviced and prepared for its next flight. Such station operations account for a small proportion of an airline's costs, but they have a major impact on the flight schedules and on the levels of passenger satisfaction achieved (*3*).

A set of strict rules and constraints should be adhered to when seeking to achieve a well-constructed schedule (*4*):

- one gate can only process one aircraft at any time
- service requirements
- space restrictions with respect to adjacent gates
- minimizing the ground time of the aircraft
- ensuring minimum time between aircraft

Regarding the NP-hard characteristic of the GAP problem (*5*), seeking to increase services amid growing constraints will only make the problem more intractable. Issues such as the number of flights, the availability of gates, times spent at gates, hold-ups with taxiing, and so forth, all have the potential to exacerbate the problem (*6*, *7*).

The intention of this paper is to address a greater number of objectives in tackling the GAP problem by presenting a three-objective mathematical model. A modified well-known meta-heuristic evolutionary algorithm is also proposed to provide a simultaneous solution technique for finding a series of feasible solutions to the problem which still allows operational requirements to be met.

Literature Review

Airport supply allocation has been a hot topic in aviation research for a long time (*8–13*), and the techniques adopted to address the issue have evolved from simple mathematical formulations to sophisticated hybrid algorithms. The ultimate aim of this ongoing improvement is to prepare a sophisticated yet simple-to-use methodology that can be applied through commercial optimization software in airport applications.

Technically speaking, the airport gate assignment problem is modeled with either unit-weighted or evolutionary methods, reflecting the competing objectives that need to addressed. The objectives are usually described as minimizing the total passenger walking distance (or, in the same way, connection times), the number of ungated flights, and towing procedures. In this regard, current GAP literature can be viewed and classified either based on the objectives and constraints being taken into account, or based on the varieties of techniques proposed as solutions.

Passenger satisfaction, usually defined as the minimization of the total walking distance, is probably the most popular objective considered in the literature (*14–27*). By nature, the total passenger walking distance is based on the passenger transfer volume between every pair of aircrafts and the distance between every pair of gates. Therefore, the problem of assigning gates to arriving and departing flights at an airport is a Quadratic Assignment Problem (QAP) (*7*). Minimizing walking distances directly affects airline/airport customer satisfaction and also decreases the odds of passengers missing flights. Different methods such as branch-and-bound algorithms, integer programming, linear programming, expert systems, heuristic methods, tabu search algorithms, and various hybrid methods have been employed (*3*).

The idea of ungated flights, considered as a way of minimizing the number of flights assigned to remote terminal gates (apron stands), or equivalently, maximizing the number of flights assigned to fixed gates is recognized as the second most prevalent objective in the literature (*14*, *16*, *17*, *23*, *27*). This issue is discussed predominantly in the context of avoiding mismatches between flight sizes and gate types, as well as satisfying safety requirements in (*27*).

Besides the two main objectives above, some effort has focused on taking cost into account. In fact, minimizing cost is modeled as an objective (*22*, *28*, *29*). Yu and Lau (2014) and Yu et al. (2016) (*22*, *29*), look as minimizing cost in terms of the personnel cost resulting from towing aircraft, conflict cost from the robustness of the schedule, and the cost of passenger transfers. Delays from ramp conflicts are studied in Kim et al. (*30*). Cost was a factor in penalizing the assignment of two flights to the same gate, as examined by Neuman and Atkin (2013) (*28*).

A wide variety of constraints have been considered in the literature. Fundamentally, the GAP has two basic constraints: first, one gate can only accommodate one single aircraft at a time (restricted gate), and second, two flights cannot be assigned to the same gate if they overlap in time (single gate per activity) (*4*). Other issues are:

- airlines' gate preferences
- adjacent gates cannot handle certain types of aircraft simultaneously (shadow restrictions)
- pushback restrictions (integrating gate allocation with the ground movement to limit the number of aircraft that are expected to block each other while maneuvering in the area close to the gates)
- calculating the idle time of each gate before each flight
- guaranteeing that each arrival and departure has one and only one gate assignment

Recent research on the topic has focused on multi-objective solution techniques:

A hybrid heuristics algorithm guided by Simulated Annealing (SA) heuristics accompanying greedy heuristics and tabu search heuristics was applied by Drexl and Nikulin (2008) (*19*). Their proposed integer program worked with multiple objectives including quadratic and quadratic constraints and quadratic assignment formulation solved by Pareto simulated annealing to obtain a representative approximation for the Pareto front. Although computational experiments have produced good results, relatively limited data was used to test the proposed algorithm.

Characteristics of stochastic and heuristic approaches were combined in a hybrid model to generate an assignment order for the all planes corresponding to assignment priority in Genç et al. (*31*). A proposed Single Leap Big Bang Big Crunch (SL-BBBC) evolutionary model worked effectively with both test and real world data waiving the need for detailed constraints or cost calculation.

Yu and Lau (*22*) proposed a hybrid meta-heuristic algorithm which applied the genetic algorithm (GA) capability of exploration as a population-based artificial intelligence method, and the exploitation capability of large neighborhood search (LNS) methods to each individual in the population. Comparison of results between CPLEX and GALNS revealed that the proposed method can deal better with realistically large problems in terms of their size and computation time. Results from Kaliszewski et al. (*32*) also demonstrated inappropriate application of CPLEX in large problems compared with an Evolutionary Multi-objective Optimization (EMO) algorithm.

A multi-island parallel evolution framework (PEA) with a left-right probability migration topology was applied by Guan el al. (*33*) to solve a multi-objective large-scale flight assignment with consideration of the reduction in airspace congestion and flight delay using real traffic data from the China air route network and daily flight plans. Comparing the results from the proposed approach to some well-known multi-objective evolutionary algorithms based on decomposition demonstrated the better solution quality of the PEA.

A probabilistic tabu search was proposed by Aktel et al. (*34*) and the results were compared with SA algorithm performance considering different problem sizes. This method is also applied in (*30*) to minimize taxi time/delay as well as passenger transit time. Based on different airport terminal layouts, the results are then compared with a genetic algorithm and a quadratic integer program (QIP). Using greedy algorithm as a benchmark showed different performances based on problem size. In Deng et al. (*35*), an improved adaptive particle swarm optimization (DOADAPO) algorithm was used to solve multi-objective GAP. Verifying the results by test data and comparing with twelve basic algorithms showed an improved performance by DOADAPO in slow convergence, search precision, and local optimality. However, the proposed method had time complexity in solving the problem.

In a comprehensive methodological study published by Zhang and Klabjan (*36*), diving and variable rolling horizon algorithms are used to minimize total flight delays, the number of gate reassignment operations, and missed passenger connections, all examples of frequent airport operation disruptions.

Although multi-objective evolutionary methods have shown superior capability as a solution technique for GAP in recent efforts, they have not received sufficient attention in the literature.

Problem Definition and Model Structure

The primary purpose of flight-gate assignment is to assign aircrafts to appropriate gates (terminal gates) in a way that meets both operational and safety requirements while minimizing inconvenience to passengers. As discussed in previous sections, the gate assignment problem is multi-objective in nature. A multi-objective mathematical modeling approach, with an appropriate solving method, usually results in a trade-off between several conflicting objectives. Solving the multi-objective problem will consequently result in a compromise between several goals that can positively influence passenger satisfaction and save extra money for airport authority/operator and airlines.

The proposed GPA framework in this paper focuses on two of the most popular objectives: minimizing passenger walking distances and minimizing taxi conflicts. Existing overlap times between consecutive flights assigned to the same gate represents the conflict duration and is used to measure the robustness of a gate assignment plan. High robustness is achieved when the expected conflict duration is low among aircraft (*37*). Considering that aircraft movements will cause additional costs and inconvenience to the landside facilities, staff, and other aircraft, the tow frequency also needs to be minimized. In this research, the reducing cost imposed by towing aircraft and assigning flights to remote (or unfavorable) gates is also considered as the third objective. The proposed model is expected to address all three objectives simultaneously.

Considered objective functions are as follows:

- The first term in the model (*38*) includes the objective of minimizing the total passenger walking distance, which could be divided into the distance a passenger walks 1) to departure gates, 2) to baggage reclaim areas and 3) between connecting flights (for those flights with connections in the flight plan).

$$min \sum_{i=1}^{N}\sum_{k=1}^{M} F_{o,i}.W_{o,k}.Y_{i,k} + \sum_{i=1}^{N}\sum_{k=1}^{M}\sum_{bc=1}^{B} F_{i,bc}.WBC_{i,bc}.Y_{i,k} + \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{K=1}^{M}\sum_{l=1}^{M} F_{i,j}.W_{k,l}.Y_{i,k}.Y_{j,l}$$

The following notations are used in the first model:

N: number of flights arriving at and/or departing from the airport

M: number of gates, including remote gates

B: number of baggage claims

$F_{o,i}$: number of passengers from check-in area to flight i

$F_{i,bc}$: number of passengers from flight i to the baggage claim area

$F_{i,j}$: number of passenger transferring from flight i to flight j

$W_{o,k}$: walking distance between check-in area and gate k

$WBC_{i,bc}$: walking distance between gate i and baggage reclaim area

$W_{k,l}$: walking distance between gate k and gate l

$Y_{i,k}$: a binary value representing the association of flight i to gate k

$Y_{j,l}$: a binary value representing the association of flight j to gate l

- The second term is intended to address the objective of minimizing taxiway conflicts (push-back blocking, taxi blocking) and measures the assignment robustness as it prevents rescheduling of the original assignment.

$$min \sum_{i=1}^{N}\sum_{j=1}^{N} \frac{y_{i,j}}{a_i + d_j + 2b}$$

The following notations are used in the second model:

$y_{i,j} = 1$ if $Y_{i,k} = Y_{j,k}$, 0 otherwise

a_i: arrival time of flight i

d_j: departure time of flight j, $di > a_i \forall_i$

b: buffer time (to enlarge the interval between any two adjacent aircraft assigned to the same gate, which is set to 30 min)

- The third term includes the objective of minimizing costs from towing and assignments to unfavorable gates.

$$min \sum_{i=1}^{N}\sum_{k=1}^{M} C_{t(i)}.C_{ufg(i)}.Y_{i,k}$$

The following notations are used in the third model:

$C_{t(i)}$: The actual cost of towing an aircraft

$C_{ufg(i)}$: The actual cost of being assigned an unfavorable gate

$Y_{i,k}$: a binary value representing the association of gate k to flight i

This optimization problem is subject to the following constraints:

1) Restricted gates: assures that every flight must be assigned to exactly one gate including the apron (remote gate).

$$\sum_{k=1}^{M} Y_{i,k} = 1, 1 \le i \le n$$

n: total number of flights, i.e. $n = |N|$

2) Activity overlap restriction: prohibits schedule overlapping of two flights assigned to the same gate.

$$Y_{i,k}.Y_{j,k}(d_j - a_i)(d_i - a_j) \le 0$$
$$1 \le i,j \le n, k \ne RG$$

Remote Gate (RG) represents the apron gate where flights arrive when no terminal gates are available.

3) Dummy variables: each gate can only be occupied with one aircraft.

$$Y_{i,k} \in \{0,1\}, 1 \le i \le N, 1 \le k \le M$$
$$Y_{j,l} \in \{0,1\}, 1 \le j \le N, 1 \le l \le M$$

4) Mismatch restriction: avoid mismatch between flights and gates.

$$(AT_i - GT_k)Y_{i,k} \le 0, i \in N, k \in M$$

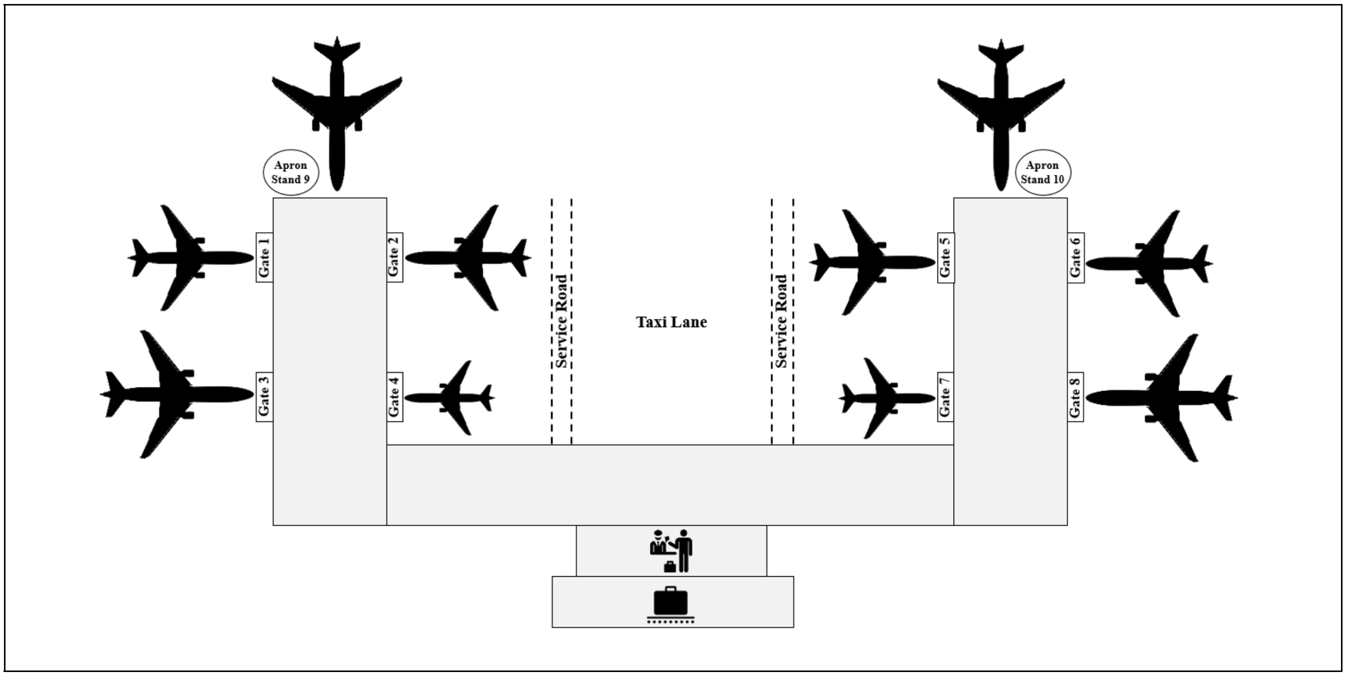

Figure 1. Pier terminal configuration.

AT_i: parameter indicating the aircraft's type of flight i. $AT_i = 1$ if flight i is a large aircraft, else $AT_i = 0$.

GT_k: parameter indicating the type of gate k. $GT_k = 1$ if gate k is a large one, else $GT_k = 0$.

Problem Implementation

It is obvious that different terminal layouts have different impacts on the cost-efficiency of daily airport operations. In our study, one terminal with a pier concourse configuration is considered, the terminal is assumed to have eight gates with two remote/apron stands, as illustrated in Figure 1.

It is difficult to gain access to real world data for GAP. Basically, the data should contain a wide variety of information such as; type of aircraft, type of flight (origin/destination), gate preference (provided by airline/airport), number of passengers who check in at the airport and those whose final destination is the airport, the move from the passenger terminal to a gate or vice versa. Moreover, passengers who have connections at the airport go from one gate to another. Airlines regard these data as private and so do not publish them. As a result, fewer studies use real world data and so do not contain all the passenger information mentioned above. Certain assumptions are made and missing data generated by statistical analysis of the information provided or randomly simulated based on the understanding of the problem (*28*, *39*, 40).

In this study, we investigated the problem using three simulated datasets including sets of 20, 40, and 100 flights assigning to a set of 10 available gates to numerically test the proposed model and solution approach for a defined terminal layout. Inputs include: flight arrival times, corresponding transfer flights, aircraft/gate sizes (small, medium, large) and corresponding capacities, costs associated with mishandling assignments, towing costs, gate-to-gate distances, and gate-to-check-in/baggage reclaim distances.

Arrival flights with corresponding arrive time (minute), aircraft size and transfer flights for the set of 20 aircrafts is illustrated below:

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
s	m	l	m	m	l	m	l	s	l	s	m	l	m	m	l	m	l	s	l
0	10	15	20	30	35	40	45	50	60	125	135	140	145	155	160	165	170	175	185
*	*	*	*	*	1	2	3	4	*	*	*	*	*	*	6	7	8	9	*

Considered gate to gate walking distance (Wk,l) is as follows:

	1	2	3	4	5	6	7	8	9	10
1	0	6	8	10	36	45	31	40	5	43
2	6	0	10	8	28	36	23	31	5	43
3	8	10	0	6	31	40	26	35	13	38
4	10	8	6	0	23	31	18	26	13	38
5	36	28	31	23	0	6	8	10	40	5
6	45	36	40	31	6	0	10	8	48	5
7	31	23	26	18	8	10	0	6	35	13
8	40	31	35	26	10	8	6	0	43	13
9	5	5	13	13	40	48	35	43	0	51
10	43	43	38	38	5	5	13	13	51	0

In our simulated datasets, three types of aircraft, those with a capacity of 100, 200, and 300 passengers are considered and listed as small, medium, and large, respectively. In this example *Fo,i* and *Fi,bc* are assumed to be equal. In terms of determining transfer passengers, we considered 10% of the capacity of the small aircraft, 15% of the capacity of the medium aircraft, and 20% of the capacity of the large aircraft, i.e. 10, 30, 60 passengers (*Fi,j*). Aircraft numbers 6 to 9 have connections with aircraft 1 to 4, and aircraft 16 to 19 have connections with aircraft 6 to 9 in this example. This trend is followed to simulate the other considered sequence of aircraft. All departure times (*di*) are considered to be 1 hour after the arrival time.

Solving Approach

NSGA-II Algorithm

The comprehensive literature review on the GAP revealed that several methods, algorithms and heuristics, and hybrid methods could be used to solve the gate assignment problem. In particular, a Genetic algorithm (GA) has been widely used to solve ATM, airline and airport operation problems such as GAP (*3*, *24*, *41*), and Aircraft Landing Problems (ALP) (*42–44*), fleet/crew scheduling (*45*, *46*), and so forth.

Multi-objective evolutionary algorithms (MOEAs) have attracted the attention of many researchers in the last 20 years, and it is still a challenging topic in the field of optimization research. Following the broad and successful applications of GAs in solving optimization problems in numerous domains, a non-dominated sorting genetic algorithm (NSGA-II) is employed in this study to produce a Pareto optimal set, in which the three aforementioned objectives can be considered simultaneously, resulting in higher levels of flexibility for decision makers.

The Non-dominated Sorting Genetic Algorithm (NSGA) was one of the first such evolutionary algorithms introduced for multi-objective optimization problems (*47*). However, over the years the following shortcomings in its application have been revealed as mentioned in Deb et al. (2002) (*48*):

- High computational complexity of non-dominated sorting

The currently used non-dominated sorting algorithm has a computational complexity of $O\ (MN^2)$, where "M" is the number of objective functions and "N" represents the population size, while, NSGA has a computational complexity of $O\ (MN^3)$. This complexity comes from the non-dominated sorting procedure in each and every generation.

- Lack of elitism

The elitism can speed up the performance of the GA significantly (*47*). The elitism feature of NSGA-II is keeping the best individuals from the parent and child population, so the best individual in terms of objective function values have never been lost once they are found.

- Need to specify the sharing parameter

The crowding distance mechanism in NSGA-II has satisfied diversity in the population. As a result, it no longer requires the specification of a sharing parameter.

The operational function of NSGA-II could be elaborated as follows. At the beginning, the population is initialized as usual GA. With respect to the values of objective functions, the initialized population is consequently sorted based on non-domination into each front. The first front is totally non-dominant set in the current population while the second front is being dominated by

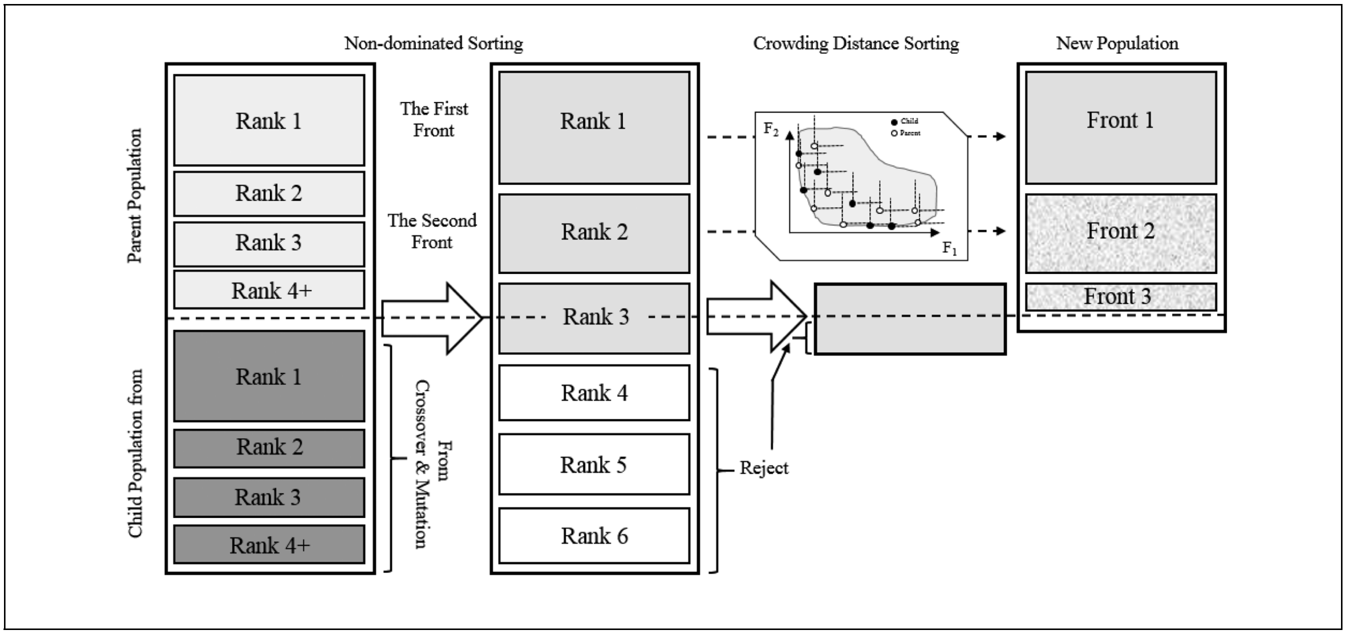

Figure 2. Elitism process conducted in each NSGA-II iteration.

the individuals in the first front only and other fronts are determined in the same way. The crowding distance indicates how close an individual is to its neighbors. Large average crowding distances suggest better diversity in the population. An individual selected in the rank is lesser than the others or, if the crowding distance is greater than the others, this is the main difference between the conventional GA and NSGA-II which is actually the elitism feature previously discussed. Parents are selected from the population by using a roulette-wheel selection based on the rank and crowding distance. The selected population generates offspring from crossover and mutation operators. The population then consists of the current population and the current offspring is sorted again based on non-domination and only the best individuals are selected based on the rank and crowding distances. Once the number of the calculated generation P is larger than the critical number $Pset$, the search will be terminated. The final purpose of this procedure is to get the Pareto-optimal front, that is, the curve with Rank = 1 (*49*).

In general, in NSGA-II, total tasks are conducted in the sections of population production, crossover and mutation as merging and then non-dominated sorting is performed based on the rank and crowding distance; and finally additional parts are truncated. The steps and elitism process conducted in each iteration of the NSGA-II algorithm is shown in Figure 2.

The implementation of the proposed NSGA-II approach for the multi-objective optimization of GAP problem is discussed below.

Implementing NSGA-II Operators and Related Parameters for GAP

Here, some modifications have been done on the algorithm operators explained as follows.

- Selection method

Pairs of parent chromosomes are selected from the current population according to the selection probability and the roulette-wheel (which is also known as "fitness proportionate selection") approach is then applied to generate the offspring.

- Crossover

Arithmetic crossover is applied in this study. Its operator linearly combines two parent vectors $x^1 = \left(x_1^1, x_2^1, \ldots, x_n^1\right)$ and $x^2 = \left(x_1^2, x_2^2, \ldots, x_n^2\right)$ selected by applying the roulette-wheel selection method to produce two new offspring $y^1 = \left(y_1^1, y_2^1, \ldots, y_n^1\right)$ and $y^2 = \left(y_1^2, y_2^2, \ldots, y_n^2\right)$. For our integer decision variables, it is coded as:

$$y_i^1 = \left(\alpha * x_i^1\right) + \left((1-\alpha) * x_i^2\right)$$
$$y_i^2 = \left(\alpha * x_i^2 + ((1-\alpha) * x_i^1\right)$$

Where α is a random weighting factor chosen before each crossover operation generates as:

$$\alpha = rand\left(\left[x^1\right]\right)$$

- Mutation

A continuous mutation method was applied in which a member is selected using the roulette-wheel selection method and then a new offspring generated as follows:

$$y = 0.1 unifrnd\left(-1, 1, \left(\left[x^1\right]\right)\right)*(upperbound - lowerbound)$$

- Algorithm parameters

Before generating the initial population, we initialized the population size together with other algorithm parameters. In this study, we came up with the maximum number of algorithm iterations for a series of 20, 40, and 100 flights with 10 available gates as 40, 60, and 120 respectively. The number of initial populations are set to 20, 40, and 100. The percentage of the population taking part in crossover is equal to 0.6 and the index of mutation is equal to 0.4.

The parallel computing of the objective function with three different objectives simultaneously will be explained here: the flights are first sorted according to their arrival times and the gates are sorted according to their corresponding number and size. Then, for each new flight, we start by testing if the first gate can receive the considered flight in comparison with each pair of flight and gate, so if a flight cannot be assigned to gate "1" for instance, the next gate being checked would be "2". The process is repeated for all the flights and gates. Meanwhile, the walking distance between flights and baggage reclaim, flights and check-in area, and between gates for those flights which have connections, are taken into account based on aircraft size which represents the number of passengers and the percentage that are transfer passengers. The flights are also evaluated and sorted in the same way as in the previous approach, based on corresponding towing and mishandling costs. Then, we use the previous heuristics with a random sorting of gates. Thus, new possible solutions can be reached at each new sorting of gates.

Results

Using MATLAB R2016a software, we checked the performance of the proposed method with a simulated dataset including sequences of 20, 40, and 100 aircraft arriving in a three time intervals; 0 to 185, 0–385, and 0–1,140 minutes respectively to be assigned to one of 10 gates on a specific terminal layout. In our datasets, 40% of each sequence of 10 aircrafts is considered to have connections with other flights, in the way that flights 6, 7, 8, and 9 have connections with flights 1, 2, 3, and 4 and it is repeated for subsequent sequences of every 10 flights. However, our model is not size-dependent.

Figure 3 is the Gantt chart which illustrates the gate assignments obtained for different sets of aircraft.

As can be seen in Figure 3, the first arrival flight in the sequence of 20 aircraft is assigned to gate 4. Checking the aircraft type and gate type illustrates that both are the same size, small. This can be generalized to all flight sizes as none of the constraints are violated in our model. Considering connection flights associated with aircraft size, aircraft 6 has connection with aircraft 1, meanwhile, aircraft 16 has connection with 6. Among the available size-matched options which are all large gates including 3, 8, 9, and 10, flight 6 is assigned to gate 3. The walking distances between gate 4 and gates 3, 8, 9, and 10 are 6, 26, 13, and 38, so flight 6 is assigned to nearest possible gate. The second connection, aircraft 16, has the same size-matched options and it is assigned to gate 9. Following the same pattern for the second connection, the distances between gate 3 and the available options are 35, 13, and 38 for gates 8, 9, and 10 respectively, so gate 9 has the shortest distance with gate 3. All other gate assignments can be investigated in a similar way for different aircraft sequences being considered.

To investigate the ability of the proposed method in finding the non-dominated Pareto fronts, some other well-known multi-objective optimization algorithms, including Multi-objective Bat (MOBAT), Particle Swarm Optimization (MOPSO), Ant Colony Optimization (MOACO), and Artificial Bee Clooney (MOABC) are considered for comparison purposes.

Considering the amount of time spent, it is important to keep the non-dominated set as diverse as possible. To evaluate the distribution and spread of the non-dominated fronts generated by NSGA-II and four other meta-heuristic algorithms, three major metrics are considered as follows (*50*):

- Elapsed/computational time
- Diversity
- Spacing

The amount of time required to come up with the solution is measured by elapsed time. Diversity measures how well the true Pareto front is covered by the approximation set by summing up Euclidean distances of each solution from other solutions. Spacing measures how evenly the solutions obtained distribute themselves in the search space. This metric is obtained from distance standard deviation of each solution to the nearest solution in which the lower amount indicates that the obtained solutions are better organized. Moreover, the higher number of obtained Pareto frontiers indicates a better search and more feasible search space.

The comparison of the results is summarized in Table 1.

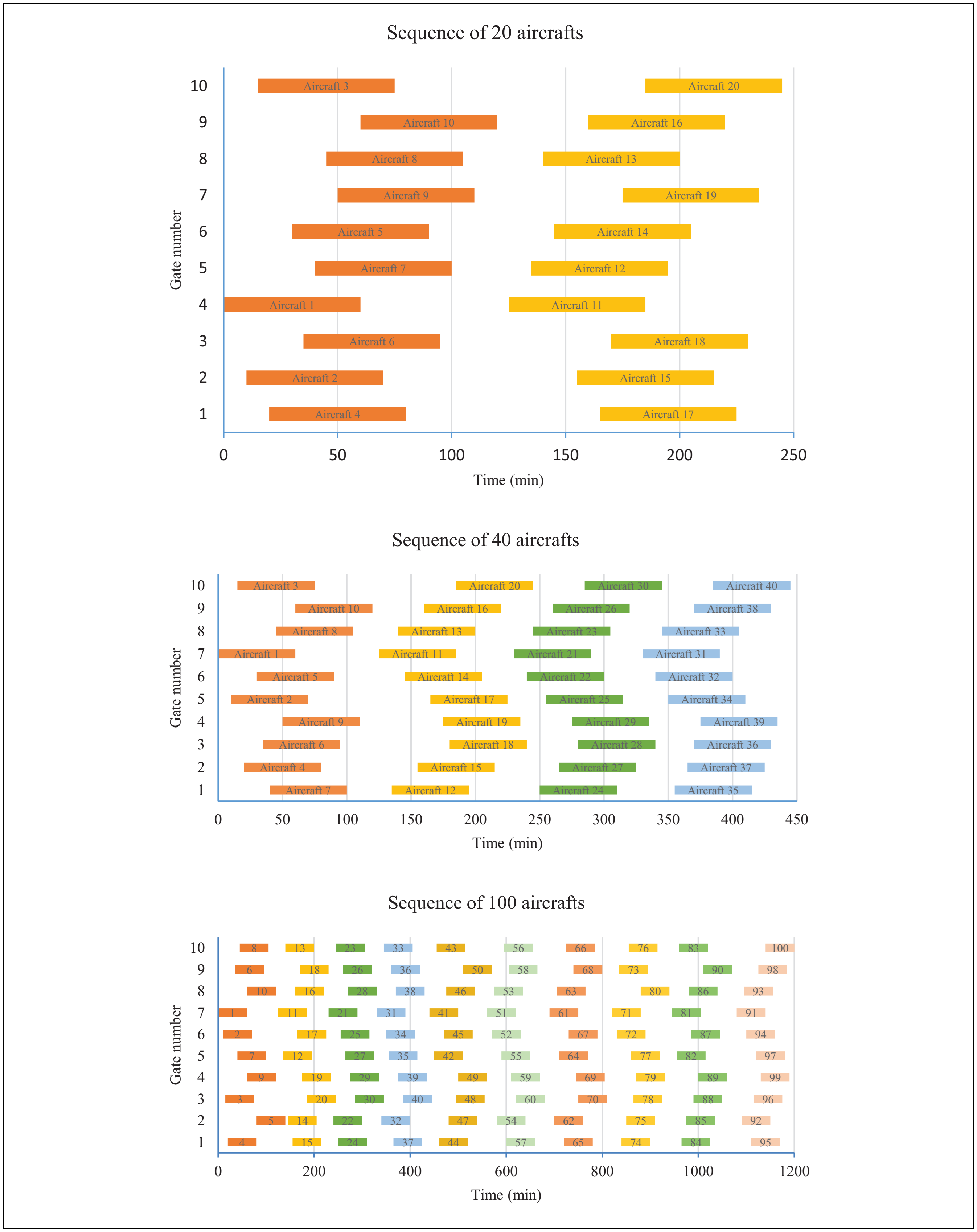

Figure 3. Gate assignment model result for different sequences of aircraft.

Table 1. Heuristics Computational Results

Algorithms	Number of flights	Number of iterations	Initial populations	Number of obtained solutions	F1 members	Diversity	Spacing	Elapsed time (seconds)
Non-dominated sorting genetic algorithm (NSGA-II)	20	40	20	4	20	94868	1.33	2.61
Multi-objective BAT (MOBAT)				4	20	54772	1.33	2.86
Multi-objective particle swarm optimization (MOPSO)				3	20	54772	1	2.65
Multi-objective ant colony optimization (MOACO)				6	6	94868	1.6	517.17
Multi-objective artificial bee colony (MOABC)				2	2	54772	0	2.48
Non-dominated sorting genetic algorithm (NSGA-II)	40	60	40	7	40	144910	1.33	17.18
Multi-objective BAT (MOBAT)				7	40	54773	1.66	17.72
Multi-objective particle swarm optimization (MOPSO)				4	40	77460	1.33	17.69
Multi-objective ant colony optimization (MOACO)				11	11	284600	1.6	149.14
Multi-objective artificial bee colony (MOABC)				6	6	122470	1.2	16.07
Non-dominated sorting genetic algorithm (NSGA-II)	100	120	100	24	100	561250	1.65	356.23
Multi-objective BAT (MOBAT)				13	100	444970	1.04	349.7
Multi-objective particle swarm optimization (MOPSO)				19	21	268330	1.77	340.04
Multi-objective ant colony optimization (MOACO)				8	8	279280	0.95	908.29
Multi-objective artificial bee colony (MOABC)				6	6	225830	0.93	331.88

Results from Table 1 illustrate that NSGA-II gives acceptable computational time with good diversity and spacing to explore better solutions. All other approaches are lacking in certain areas. For instance, MOACO has the highest amount of computational time, while MOPSO gives low diversity and high spacing in large size problems. MOABC has a lower number of obtained results in all problem sizes. However, MOBAT has the potential to compete with NSGA-II in large sample size scenarios.

Conclusions

This paper has presented a modified NSGA-II to solve the flight-gate assignment problem in which the consideration is given to minimizing: total walking distance (representing passenger satisfaction); taxi conflicts (which demonstrate assignment robustness to keep the airport schedule well maintained); and airport/airline traditional costs. To the best of authors' knowledge and according to a well-elaborated literature review, most of the studies reviewed have overlooked one or some of the major concerns, applicable variables, and objectives in one model structure and therefore do not capture the true multi-criteria nature of the gate assignment problem. In addition, considering the NP-hard nature of the GAP problem, the authors believe that a meta-heuristic approach is a more appropriate candidate as it can solve the problem efficiently. The results of a recent study illustrate the computational inefficiency of a set of exact algorithms for practical implementation (*29*).

The proposed model was further tested under different simulated datasets that were created based on a sample airport layout. However, our model can simply be generalized to other terminal configurations. The model run results demonstrated good capabilities of NSGA-II in solving the model with no constraint violation. It means that the algorithm is capable of finding a series of acceptable feasible solutions in a practical amount of time. In the case of multi-objective optimization, providing decision makers with a list of feasible solutions is a substantial step in selecting the final optimal solution from the Pareto frontier, usually based on policy-related considerations.

Further research may include a real-life dataset for a specific hub airport layout to test the model efficiency. Other potential solution techniques such as hybrid meta-heuristics can also be investigated to get the higher accuracy solutions and validate the efficiency and effectiveness of the proposed algorithm. Moreover, common types of decision analysis methods can be applied to find an appropriate solution from the Pareto frontiers obtained, which supports its practical usability for future decision-making tools.

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