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A Revised Formulation for the Airline Fleet Assignment Problem

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Abstract

The Fleet Assignment Problem (FAP) deals with assigning aircraft types to the scheduled flights based on fleet capabilities, aircraft availabilities, flight requirements, and operational costs. Due to high operating costs, the large number of flights scheduled each day, and the dependency of the following processes in the airline scheduling processes on FAP output, solving the FAP has always been a challenging task for the airlines. In this work, a revised integer linear programming model is proposed for solving the daily FAP. The model has an objective function of minimizing the operating cost of assigning a fleet type to a specific flight. In addition, the proposed model of the daily FAP aims to satisfy the following constraints: flight cover, aircraft type balance, fleet size, flight traffic (demand), flight flying altitude, and runway length requirements. The proposed model was successfully applied on a real-world dataset related to a national airline and solved using Gurobi software. Furthermore, sensitivity analysis has been performed to show the effect of changing different FAP parameters on the obtained results.

Keywords
Airline scheduling, Fleet assignment problem, Integer linear programming, Optimization.

1 Introduction
1.1 Background
Air transport is crucial to the economic growth and development of any country, it facilitates the integration of the global economy and provides vital connectivity both nationally and internationally. Airline scheduling is the backbone of any airline's operation as it deals with everything related to flights, such as destinations, departure and arrival times, and working days. In addition, it includes assigning aircraft for each flight, along with developing cabin crew and maintenance schedules for each aircraft. The airline scheduling process provides a plan of the usage pattern of the airline's aircraft and their resources, such as cabin crew and pilots, to meet the forecasted demand. The schedule planning is usually for one season only, which spans from six to nine months (Camilleri, 2018).

More formally, the airline scheduling process helps in reaching the optimal situation that achieves the objectives of the airline, such as maximizing profits, minimizing costs, reducing the number of aircrafts used, and improving the performance of airlines. This process typically involves many complexities, including complex flight network, different aircraft types, limited number of gates, air traffic control restrictions, environmental regulations, stringent safety requirements, multiple crew work rules, complex payment structures, competitive dynamic environments in which passenger demands are uncertain, and complex pricing strategies (Bazargan, 2010).

The aforementioned challenges have encouraged researchers to develop and apply models and/or algorithms to assist in the decision-making process. The airline scheduling process has been typically divided into several sequential planning steps or sub-problems to facilitate dealing with the decisions related to the whole process, such that the output of one sub-problem serves as input for the next. The first of these planning steps is the "flight schedule generation" step. It is one of the most crucial steps since it has a significant impact on the number of passengers through specifying the timing, the number, and the capacity of flights. Besides, this step affects every following planning step (Grosche, 2009). Then, there is the "aircraft scheduling" step, which includes two subproblems, fleet assignment and aircraft routing. The final step in the airline scheduling process is "crew scheduling". Since the crew costs are high, airlines try to assign the appropriate crew members to each flight in a way to reduce their expenses (Ozdemir et al., 2012). It should be noted that the focus of this paper is on the fleet assignment problem, which is related to determining the suitable aircraft type for each flight.

The Fleet Assignment Problem (FAP) is an essential planning step in the airline scheduling process. It affects the revenue of the airline industry. More specifically, it is the problem of assigning the appropriate aircraft types to the flights. Many factors influence this assignment, such as flight demand, capacity of the aircraft, length of the runway, flight flying attitude, fleet size, flow balance, and operating cost.

1.2 Objectives

According to the International Civil Aviation Organization (ICAO), 44% of an airline's total operating costs lies on aircraft operating expenses alone (International Civil Aviation Organization, 2017). In addition, Eller and Moreira (2014) found that the type and characteristics of aircraft is one of the major factors affecting airline's costs. Camilleri (2018) mentioned that airlines' costs generally include direct and indirect operating costs. Many of these costs are dependent on the aircraft type. Since the number of airline passengers is rapidly increasing, more flights are needed to cope with this increase. Moreover, assigning small aircrafts to high demand flights will lead to losing passengers. So, to avoid passenger loss and reduce operating costs, effectively assigning fleet types for flights is crucial in the airline scheduling process.

The objective of this work is to help airlines solve the problem of fleet assignment by building a mathematical model that: 1) supports decision-making and 2) has the potential of saving time, money, and effort in determining the best aircraft type for each planned flight in the schedule. Since each type of aircraft has its own cost, assigning the appropriate aircraft can reduce the overall operating cost. More specifically, the proposed model is an integer linear programming model including a variety of constraints, such as the runway length, the flight altitude, fleet seat capacity, flight cover, and flow balance constraints, to provide a more practical representation of reality.

This paper is structured as follows; Section two presents a brief review on papers handling the fleet assignment problem. The section after that illustrates the elements of the proposed mathematical model. Section four shows the application of the proposed model using a real-world dataset and the sensitivity analysis conducted to show the effect of changing different parameters on the obtained results. The last section concludes the presented work and provides recommendations for future work.

2. Literature Review

The Fleet Assignment Problem (FAP) is the first sub-problem of the second step of an airline scheduling process. This phase is concerned with the fleet type, not a particular aircraft, and it also affects the later steps in the airline scheduling process. In this section, a review of different papers tackling FAP is briefly presented. More specifically, this section illustrates the objective function(s), constraints, and how the FAP was represented for the reviewed papers.

Different objective functions were used to solve the FAP. Perhaps the most common objective functions considered were the ones minimizing different type of costs, such as minimizing the operating costs alone (Mancel and Mora-Camino, 2006), both the operating and spill costs[1] (Hane et al., 1995; Ozdemir et al., 2012; Sherali et al., 2006), or the fleet assignment cost (Allung Blegur et al., 2014; Ozdemir et al., 2012). Other objective functions were also considered, such as the ones minimizing the total number of aircrafts used (Allung Blegur et al., 2014; Su et al., 2019),

[1] Spill cost is the revenue of lost passengers due to insufficient aircraft capacity, assigning small aircraft to flights with high demand leads to passenger spills.

maximizing the flight operation profit (Barnhart et al., 2009; Liu et al., 2023; Sherali et al., 2006; Su et al., 2019), and maximizing the total income from flights (Li and Tan, 2013).

The constraints also play a key role in the mathematical model. Their contribution makes the model more realistic by including practical limitations. Some basic constraints were utilized in most models, such as flight cover and aircraft balance constraints. The flight cover constraint ensures that every flight is assigned to only one type of aircraft; while the aircraft balance constraint balances the number of aircraft for every fleet type at each airport at different times (nodes) over the day, by taking into account all the incoming and outgoing flights A fleet size constraint was also used in some models (Allung Blegur et al., 2014; Barnhart et al., 2009; Hane et al., 1995; Liu et al., 2023; Mancel and Mora-Camino, 2006; Ozdemir et al., 2012; Sherali et al., 2006). This constraint makes sure that the number of aircraft of certain type does not exceed the available number of that type.

Additional constraints were also utilized by researchers in this area. For example, a schedule balance constraint was used by Sherali et al. (2006). This constraint ensures that the same number of aircraft of each type remains at each station every night, so that the same assignment can be repeated daily. As another example, take-off and landing runway length constraints were added by Allung Blegur et al. (2014) to ensure that an aircraft can only be assigned to airports having runways longer than the minimum runway length the aircraft needs to take off or land. Flight area, flight model code, and fleet seat capacity constraints were also proposed by Li and Tan (2013) to ensure that the mathematical model assigns the suitable aircraft model according to the suitability of aircraft model to fly in an area with a certain terrain type, the required aircraft model for the flight, and the flight traffic, respectively. In addition, Su et al. (2019) introduced a constraint to limit the number of fleet types taking off or landing at an airport. Finally, Liu et al. (2023) included a constraint to ensure that the amount of fuel purchased is not less than the amount of fuel required by the aircraft.

It is important to determine how the FAP will be formulated based on the underlying network representation. Many researchers formulated their models based a time-space network representation (Allung Blegur et al., 2014; Barnhart et al., 2009; Hane et al., 1995; Liu et al., 2023; Mancel and Mora-Camino, 2006; Ozdemir et al., 2012; Su et al., 2019). Sherali et al. (2006), however, presented two formulations based on a time-space network representation and a connection network representation.

Based on the reviewed literature, the following can be concluded. Firstly, minimizing the operating cost of assigned aircraft type is the most common objective function. Secondly, the reviewed models used a wide range of constraints, such as runway length, flight flying area, the fleet seat capacity, and aircraft count constraints. Thirdly, most of the papers used time-space network to represent the assignment problem. Finally, the integer linear programming model was the common mathematical model type due to the nature of the problem, and the daily assignment was the common planning horizon.

2 The Proposed Mathematical Model

2.1 Problem Description

As previously mentioned, an integer linear programming model is proposed to solve the daily Fleet Assignment Problem (FAP). The proposed model aims to minimize the operating costs. It assigns the appropriate aircraft type to the flights, while satisfying the flight cover, flow balance, fleet size, fleet seat capacity, flight flying altitude, and runway length constraints. It should be noted that these constraints were not included together in any of the reviewed models in the related literature. In addition, this model is formulated based on the time-space network representation.

2.2 Model Assumptions

The following assumptions are considered in building the proposed model:

- Operating costs for each flight are fixed.
- Passenger-spill costs are not considered.
- Flight distance between the same origin-destination flights is fixed.
- The round-trip flights between two airports use the same fleet type.
- Each node represents a specific time during the day at a specific airport, at which a flight leaves from or arrives at an airport. The number of aircraft at any node changes with respect to an instant before that node. Figure 1 illustrates the use of nodes to present two flights between two airports as an example. Each node represents the timing of departure/arrival of flight from/to the airport.

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Figure 1. Nodes Illustration

2.3 Model Elements

In this section, the sets, parameters, and decision variables of the developed model are defined. Then, the model's objective function and constraints are presented.

2.3.1 Sets

F = Set of flights
L = Set of fleet types
E = Set of airports
N = Number of nodes in the network
M = Sets of last nodes (representing all nodes in the network with aircraft grounded overnight at all airports)

2.3.2 Parameters

$$c_{fl} = Operating\ cost\ of\ assigning\ fleet\ type\ l\ to\ flight\ f$$
$$A_l = Number\ of\ available\ aircraft\ of\ fleet\ type\ l$$
$$S_{nfe} = \begin{cases} 1, & if\ flight\ f\ is\ arriving\ at\ node\ n\ in\ airport\ e \\ -1, & if\ flight\ f\ is\ departing\ from\ node\ n\ in\ airport\ e \end{cases}$$
$$P_l = Passenger\ seat\ capacity\ of\ fleet\ type\ l$$
$$T_f = Average\ traffic\ of\ flight\ f\ (number\ of\ passengers\ in\ flight\ f)$$
$$d_l = Suitable\ flying\ altitude\ of\ fleet\ type\ l$$
$$k_f = Minimum\ flying\ altitude\ required\ by\ flight\ f$$
$$o_f = Origin\ airport\ runway\ length\ related\ to\ flight\ f$$
$$v_f = Destination\ airport\ runway\ length\ related\ to\ flight\ f$$
$$r_l = Minimum\ airport\ runway\ length\ requirement\ for\ fleet\ type\ l\ to\ take\ off$$
$$q_l = Minimum\ airport\ runway\ length\ requirement\ for\ fleet\ type\ l\ to\ land$$

2.3.3 Decision Variables

$$x_{fl} = \begin{cases} 1 & \text{if flight } f \text{ is assigned to fleet type } l \\ 0 & \text{otherwise} \end{cases}$$
$$G_{enl} = Integer\ variable\ representing\ number\ of\ aircraft\ of\ fleet\ type\ l\ on\ ground\ at\ node\ n\ at\ airport\ e$$

2.3.4 Objective Function

The objective function, equation (1), seeks to minimize the total operating costs of assigning the various fleet types to all the flights in the schedule.

$$\min \sum_{l\in L} \sum_{f\in F} c_{fl} x_{fl} \tag{1}$$

2.3.5 Constraints

$$\sum_{l\in L} x_{fl} = 1, \quad \forall f \in F \tag{2}$$
$$G_{e(n-1)l} + \sum_{f\epsilon F} S_{fne}\, x_{fl} = G_{enl}, \quad \forall\, e\, \epsilon\, E, \forall\, n \in N\ and\ \forall\, l \in L \tag{3}$$
$$\sum_{n\epsilon M} \sum_{e\epsilon E} G_{enl} \le A_l, \quad \forall\, l \in L \tag{4}$$
$$\sum_{l\in L} x_{fl}\, P_l \ge T_f, \quad \forall\, f \in F \tag{5}$$
$$\sum_{l\in L} x_{fl}\, d_l \ge k_f, \quad \forall\, f \in F \tag{6}$$
$$\sum_{l\in L} x_{fl}\, r_l \le o_f, \quad \forall\, f \in F \tag{7}$$

$$\sum_{l \in L} x_{fl}\, q_l \leq v_f \;, \qquad \forall f \in F \tag{8}$$

$$x_{fl} \epsilon \{0,1\} \;, \qquad \forall f \epsilon F \; and \; \forall l \epsilon L \tag{9}$$

$$G_{enl} \epsilon Z^{+} \;, \qquad \forall n \epsilon N, \forall l \epsilon L \; and \; \forall e \epsilon E \tag{10}$$

Constraints (2) are the flight cover constraints to ensure that each flight is flown by one type of fleet. Constraints (3) are the aircraft type balance constraints. The number of aircraft for any fleet type at any node is the number of aircraft of that fleet type just before that node (represented by $G_{e(n-1)l}$) plus the arrivals (represented by S_{fne} taking a value +1) minus the departures (represented by taking S_{fne} a value of -1). Constraints (4) represent the fleet size for different fleet types. The number of aircrafts of fleet type l at the last node n should not exceed the available number of aircraft of that fleet type. Constraints (5) ensure that the assigned fleet type meets the flight traffic (demand) requirements. Constraints (6) ensure that the assigned fleet type satisfies the required allowed flight flying altitude. Constraints (7 and 8) are the runway length requirements. In constraints (7), a fleet type can only be assigned to airports that have runways longer than the minimum length of runway required by the fleet type to take off. Whereas in constraints (8), a fleet type can only be assigned to airports that have runways longer than the minimum length of runway required by the fleet type to land. Constraints (9) and (10) represent the nature of decision variables, where Z+ is the set of positive integer numbers.

3 Practical Application

3.1 Case Study Description

A hypothetical case is applied to illustrate how the proposed model solves the daily Fleet Assignment Problem (FAP). In this case, a national airline that serves 20 international flights to/from five stations is considered. The Cairo international airport (CAI) is the hub station for this case, and the substations are Kuwait (KWI), Frankfurt (FRA), London-Heathrow (LHR), and Jeddah (JED) airports. The airline has five fleet types available, which are B737-800, A330-300, B777-300, B737-800 NEW and A330-200. The airline has 10, 2, 3, 3, and 2 aircraft from each fleet type, respectively. The airline needs to assign the available fleet types to these international flights to minimize the total operating costs, while considering the flight cover, aircraft balance, fleet size, fleet seat capacity, flight flying altitude, and runway length constraints.

The data related to each fleet type, such as the number of aircraft, cruising altitude, number of available seats, required landing runway length, required takeoff runway length, and the Cost of Available Seat Kilometer (CASK), are presented in Table 1, whereas the data related to the airport, such as its code and the airport's runway length are illustrated in Table 2. In addition, the flights' data, such as the flight code, flight origin and destination, departure and arrival times, number of passengers (demand), flight flying attitude, and number of kilometers flown, are shown in Table 3. The input data was obtained from Abouzeid et al. (2021) and a flight tracking website. Finally, it should be noted that the operating cost of a flight is calculated from the following equation:

$$OC = CASK \times D \times N, where$$

OC: Operating cost of a flight, CASK: Cost available per seat per kilometer, D: Distance of flight (kilometer), and N: Number of seats in aircraft.

Table 1. Required data for every fleet type.

No	Aircraft Type	No. of Aircrafts	Cruising Altitude (m)	Number of Available Seats	Landing Length (m)	Takeoff Length (m)	CASK ($)
1	B737-800	10	12,496	144	2,012	2,499	0.047
2	A330-300	2	12,500	301	1,750	2,500	0.098
3	B777-300	3	11,000	346	2,500	3,000	0.113
4	B737-800 NEW	3	10,668	154	2,016	2,510	0.050
5	A330-200	2	10,700	268	1,750	2,220	0.087

Table 2. Data available for each airport

No	Airport Code	Airport	Runway Length (m)
1	CAI	Cairo International Airport in Egypt	3,999
2	KWI	Kuwait International Airport in Kuwait	3,500
3	JED	Terminal 1 King Abdulaziz International Airport in Saudi Arabia	4,000
4	LHR	London-Heathrow Airport in England	3,902
5	FRA	Frankfurt Airport in Germany	4,000

Table 3. Scheduled flights' data

No	Flight Code	Origin	Departure Time	Destination	Arrival Time	Number of Passengers	Flight Flying Altitude (m)	Kilometers Flown
1	MS0610	CAI	9:50 am	KWI	12:46 pm	85	11,880	1,604
2	MS0611	KWI	1:45 pm	CAI	3:35 pm	107	12,180	1,728
3	MS0612	CAI	11:50 pm	KWI	3:15 am	119	11,280	1,604
4	MS0613	KWI	4:15 am	CAI	6:05 am	108	10,980	1,728
5	MS0620	CAI	3:00 pm	KWI	6:30 pm	127	11,040	1,604
6	MS0621	KWI	7:30 pm	CAI	9:15 pm	139	10,980	1,728
7	MS0661	CAI	7:20 am	JED	10:30 am	80	10,050	1,293
8	MS0662	JED	11:30 am	CAI	12:40 pm	125	10,350	1,230
9	MS0663	CAI	11:40 pm	JED	2:42 am	185	11,280	1,293
10	MS0664	JED	3:30 am	CAI	4:35 am	287	12,180	1,230
11	MS0665	CAI	2:05 am	JED	5:10 am	300	11,280	1,293
12	MS0666	JED	6:10 am	CAI	7:15 am	263	12,192	1,230
13	MS0671	CAI	2:25 pm	JED	5:30 pm	139	11,580	1,293

No	Flight Code	Origin	Departure Time	Destination	Arrival Time	Number of Passengers	Flight Flying Altitude (m)	Kilometers Flown
14	MS0672	JED	6:30 pm	CAI	7:35 pm	125	9,750	1,230
15	MS0673	CAI	1:25 pm	JED	4:35 pm	128	12,450	1,293
16	MS0674	JED	05:00am	CAI	6:10 am	98	10,350	1,230
17	MS0777	CAI	9:10 am	LHR	1:35 pm	319	10,980	3,537
18	MS0778	LHR	3:00 pm	CAI	8:40 pm	311	11,000	3,535
19	MS0785	CAI	9:55 am	FRA	2:10 pm	120	11,580	3,039
20	MS0786	FRA	3:25 pm	CAI	7:20 pm	125	11,280	2,941

3.2 Results and Discussion

The software Gurobi was used on a device with an Intel(R) Celeron(R) B800 processor, 4,096 MB RAM, and Windows 2010 operating system, to solve the FAP problem. Table 4 shows the fleet type assigned to each flight after running the model on Gurobi. The total operating cost for all flights is $584,701.

Table 4. Model results

No.	Flight Code	Origin	Departure Time	Destination	Arrival Time	Assigned Fleet type
1	MS0610	CAI	9:50 am	KWI	12:46 pm	B737-800
2	MS0611	KWI	1:45 pm	CAI	3:35 pm	B737-800
3	MS0612	CAI	11:50 pm	KWI	3:15 am	B737-800
4	MS0613	KWI	4:15 am	CAI	6:05 am	B737-800
5	MS0620	CAI	3:00 pm	KWI	6:30 pm	B737-800
6	MS0621	KWI	7:30 pm	CAI	9:15 pm	B737-800
7	MS0661	CAI	7:20 am	JED	10:30 am	B737-800
8	MS0662	JED	11:30 am	CAI	12:40 pm	B737-800
9	MS0663	CAI	11:40 pm	JED	2:42 am	A330-300
10	MS0664	JED	3:30 am	CAI	4:35 am	A330-300
11	MS0665	CAI	2:05 am	JED	5:10 am	A330-300
12	MS0666	JED	6:10 am	CAI	7:15 am	A330-300
13	MS0671	CAI	2:25 pm	JED	5:30 pm	B737-800
14	MS0672	JED	6:30 pm	CAI	7:35 pm	B737-800
15	MS0673	CAI	1:25 pm	JED	4:35 pm	B737-800
16	MS0674	JED	5:00 am	CAI	6:10 am	B737-800
17	MS0777	CAI	9:10 am	LHR	1:35 pm	B777-300
18	MS0778	LHR	3:00 pm	CAI	8:40 pm	B777-300
19	MS0785	CAI	9:55 am	FRA	2:10 pm	B737-800
20	MS0786	FRA	3:25 pm	CAI	7:20 pm	B737-800

The second output obtained from Gurobi is the value of G, which represents the number of aircraft of a certain fleet type at every node at every airport. For example, at LHR airport, there is one aircraft of fleet type 3 at Node 1. The G values ensure that the used aircraft do not exceed the available number of aircraft of each fleet type. For the sake of brevity, the details of the obtained G values are not shown here.

Sensitivity analysis was also conducted to study the effect of changes in problem parameters on the model results. Since airlines are subject to changes in flights' demand and timings, two scenarios were tested to reflect the change in number of passengers (flight demand) and in flights' timings. Firstly, to study the effect of changing the number of passengers on fleet types assigned to flights and on the total operating costs, the number of passengers for six flights was changed. The flights with changes in number of passengers are presented in Table 5.

Table 5. Flights with changes in number of passengers

No.	Flight Code	Origin	Departure Time	Destination	Arrival Time	Number of Passengers	Flight Flying Altitude (m)	Kilometers Flown
5	MS0620	CAI	3:00 pm	KWI	6:30 pm	282	11,040	1,604
6	MS0621	KWI	7:30 pm	CAI	9:15 pm	290	10,980	1,728
7	MS0661	CAI	7:20 am	JED	10:30 am	148	10,050	1,293
8	MS0662	JED	11:30 am	CAI	12:40 pm	152	10,350	1,230
19	MS0785	CAI	9:55 am	FRA	2:10 pm	160	11,580	3,039
20	MS0786	FRA	3:25 pm	CAI	7:20 pm	175	11,280	2,941

After solving the model, the following were noticed:

(1) The total operating costs changed from \$584,701 to \$798,715 (increased by 36.6%) as a result of the new assignment of fleet types to the flights. Specifically, the values of operating costs of changed flights are higher as they have higher CASK values.

(2) The fleet type assigned to flights 5, 6, 7, 8, 19, and 20 has changed to be A330-300, A330-300, B737-800 NEW, B737-800 NEW, A330-300, and A330-300 respectively (instead of B737-800). Such an assignment is due to the change in the number of passengers, which necessitates a new fleet type to be appointed that suits the new demand required for the flight.

Secondly, the changes in flights' times were evaluated along with the change in the number of passengers on some flights. The departure times of flights 1, 19 and 20 were changed, such that flights 1, 17, and 19 depart at the same time. In addition, the arrival times of flights 1, 19 and 20 were also changed, such that flights 18 and 20 will arrive at the same time. Finally, the number of passengers of two flights 17 and 18 was changed as well. All these changes are presented in boldface in Table 6.

Table 6. Modified dataset according to changes in flight times and number of passengers

No	Flight Code	Origin	Departure Time	Destination	Arrival Time	Number of Passengers	Flight Flying Altitude (m)	Kilometers Flown
1	MS0610	CAI	**9:10 am**	KWI	**12:06 pm**	85	11,880	1,604
17	MS0777	CAI	9:10 am	LHR	1:35 pm	**138**	10,980	3,537
18	MS0778	LHR	3:00 pm	CAI	8:40 pm	**140**	11,000	3,535
19	MS0785	CAI	**9:10 am**	FRA	**1:25 pm**	120	11,580	3,039
20	MS0786	FRA	**4:45 pm**	CAI	**8:40 pm**	125	11,280	2,941

After solving the model with the previously mentioned changes, the following was observed:

(1) The total operating costs changed from \$584,701 to \$356,063 (decreased by 39.1%) due to the changes in flights' timings and demand.

(2) The fleet type assigned to flights 17 and 18 has changed from B777-300 to B737-800 due to the decreased number of passengers on these flights.

(3) The required number of aircraft of some fleet types has changed due to changes in flights' timings. For example, six aircrafts are now needed of the first fleet type. In addition, the number of nodes has changed too, they now became 17 nodes, instead of 20.

The model results and the sensitivity analysis showed the applicability of the proposed model in solving the daily FAP under different situations. Studying different scenarios would help airlines in optimizing the total operating costs and determining the number of aircraft that should be available of each fleet type to cope with the changes in number of passengers and flights' timings. Knowing the optimum assignment (and number) of aircraft required in different situations, airlines should be able to save money.

4 Conclusion

The Fleet Assignment Problem (FAP) has a major effect on airline operating costs and satisfying passengers' demand; therefore, optimizing FAP is crucial. FAP is the problem of assigning the right fleet type to each flight in the airline schedule. More specifically, it aims to assign as many flights as possible in the schedule to one or more fleet types, while optimizing an objective function and meeting various operational constraints. In FAP, airlines typically operate several different fleet types. Each fleet type has different characteristics and costs. In this paper, a mathematical model is developed to solve the daily FAP, where it is formulated as an integer linear programming model. The model's objective function is to minimize the total operating costs. A set of constraints are included in the model, such as flight cover, aircraft type balance, fleet size, flight traffic (demand), flight flying altitude, and runway length requirements. The applicability of the proposed model has been demonstrated by a real-world dataset related to a national airline, which was solved using Gurobi optimization software. In addition, a sensitivity analysis has been conducted to evaluate the effect of changes in problem parameters on the model results, where two scenarios were evaluated. In the first scenario, changing the number of passengers is assessed. While in the second scenario, flights' timings of some flights have been changed, along with changing the number of passengers of some flights. In these scenarios, the total operating costs and the assigned fleet types for some flights have changed. The total operating cost increased by 36.6% in the first scenario and decreased by 39.1% in the second scenario. Also, the required number of aircraft of some fleet type has changed in the second scenario.

As further work, the following is proposed. Taking the fleet maintenance time into consideration and, hence, not all aircraft would be available all the time. Furthermore, including more than one objective function such as minimizing the costs and maximizing the utilization of aircraft. Finally, utilizing a metaheuristic approach to solve the model in a suitable computational time, especially for large datasets.

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