Particle swarm optimization for airlines fleet assignment

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ABSTRACT

Airline fleet assignment is the process of assigning aircraft types to scheduled flight legs in order to minimize operating cost and achieve maximize revenue, while satisfying a set of constraints. This paper formulates the fleet assignment problem for airlines that optimization goal is to minimize the total assignment cost. Particle swarm optimization (PSO) proposed to solve this model. The model successfully applied to Egyptair airline dataset using the particle swarm optimization and mixed integer programming. The proposed method compared with mixed integer programming and current Egyptair assignment methodology. The results showed that the particle swarm optimization is the best method for the Egyptair fleet assignment process. The solution quality is better than mixed integer programming and Egyptair assignment methodology where we saw a daily cost reduction with a percentage of 14.6% and 19.3% respectively.

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1. INTRODUCTION

The fleet assignment problem (FAP) is the process of assigning each type of aircraft with different capacities to scheduled flights based on equipment functions and availability, operational costs, and potential revenue. The fleeting decision of an airline will greatly affect its revenue: assigning aircraft smaller than those needed to flight will result in customer loss due to insufficient capacity; allocating larger aircrafts will cause the seats to be unsold and possibly higher operating costs [1].

Egyptair is the largest airline company in Egypt; it has about 300 daily flights around the world and owns about 58 aircraft with different types. Egyptair has a major challenge in determining the optimum fleet type for all flight. Egyptair airlines assign a fixed type of aircraft for each flight leg according to its daily flight schedule because of the lack of intelligent model for fleet assignment that automate the assignment process.

Attempts to solve the problem of fleet assignment have used various optimization methods. Mixed-integer linear programming proposed for the formulation of the uniform fleet assignment problem and the results showed that using the heuristic mixed-integer programming method could produce good quality solutions [2]. Ant colony algorithm used to solve the fleet assignment problem by a focus on the optimal fleet assignment. The ant colony algorithm shows that dynamic demand consideration provides significantly outcomes including a decrease of operating expense with the rise in income [3]. Several recent studies [4-8] have suggested a solution for combining two or more sub problems. They combine airline fleet assignment with crew rostering, routing decisions, schedule design and maintenance. A nonlinear mixed integer-programming model and two heuristic methods to locate a cruise time control for the first time in an integrated model for aircraft fleeting [9]. Metaheuristic method that uses the variable neighborhood search (VNS) approach used to solve both fleet sizing problem and fleet assignment problem at the same time [10]. Deterministic linear programming (DLP) used for the historical development to overbooking and the consideration of flexible products as well as further applications [11]. The multi-criteria method used to solve the fleet assignment problem by minimizing the emission cost or maximizing the profit as an objective function [12]. Some of researchers use data of 22 aircraft types from 15 major US airlines to prototype the financial and operating data as an optimize aircraft selection [13]. Other researchers suggests that load factor, aircraft utilization, and aircraft size had influence over determining the operating cost of an airline [14]. On the other hand, in [15] show that the intelligent transportation solution for advanced fleet assignment can improve an airline's market benefit and increase customer satisfaction as well. The research analyzes a new airline stochastic fleet assignment problem with arbitrary passenger requirements in risk aversion. It showed a two-stage stochastic mixed-integer programming model for risk aversion. It starts with tactic level decisions: assigning aircraft families to flight legs. In the second stage, an algorithm used to assign aircraft types to flight legs. A parallel master-slave genetic algorithm (PMS-GA) used for solving the integrated flight schedule design and fleet assignment problem with demand recapture [16]. Nowadays, Artificial intelligence techniques have an effective role in enhancing companies, governments and in community development. Artificial intelligence techniques try to simulate human behavior. Compared with existing conventional techniques, they supply a better, faster, and more accurate solution to optimization problems. Artificial intelligence techniques usually use multiple solutions to obtain the best solution [17].

In this paper, we formulate the fleet assignment problem for airlines. We propose one the artificial intelligence optimization techniques, which is particle swarm optimization (PSO) to solve the fleet assignment model for Egyptair airlines by using actual dataset. The formulating and solving the FAP will contribute in optimizing the aircraft assignment process for Egyptair airlines that minimizing the overall operating costs required for operating the different fleet types and maximizing the company profitability. In addition, this paper compares the performance and objective function value for PSO results with the mixed integer programming (MIP) method and Egyptair current assignment methodology.

2. RESEARCH METHOD

2.1. Fleet assignment problem formulation

The fleet assignment process is usually depending on the airline's flight network and it formed as a mixed integer program [18]. Two main trends were used when constructing networks: the use of arcs to represent connections (connected networks), and the use of arcs to represent flight segments (time-space networks). In essence, these two constructions are similar because they both ensure that the model adheres to the following main constraints:

- Cover constraints: to ensure that each flight leg is assigned to exactly one fleet type
- Balance constraints: for continuity of aircraft flow
- Availability constraints: to ensure that total assigned aircraft limits the available

For each fleet type there exist three types of connection arcs in the network, the first arc is the ground arc that represent the aircraft staying in the same station(airport) for a period of time. The second arc is flight arc that represent the flight leg. The third arc is wrap-around arc, which connects the last event of the day with the first event of the next day to ensure the continuity of the daily fleet assignment. The following model proposed by Hane *et al.* [19].

$$\begin{gathered}
\text{Objective function: } \boldsymbol{Minimize} \quad \textstyle\sum_{l\epsilon L} \sum_{f\epsilon F} \boldsymbol{G_{fl} Z_{fl}} \\
\boldsymbol{Subject\ to} \\
\boldsymbol{Cover}: \sum_{f\epsilon F} \boldsymbol{Z_{fl} = 1} \quad \forall\, \boldsymbol{l\epsilon L}, \\
\boldsymbol{Balance}: \textstyle\sum_{o\epsilon S} \boldsymbol{Z_{fost}} + \boldsymbol{g_{fst^{-}t}} - \sum_{d\epsilon S} \boldsymbol{Z_{fsdt}} - \boldsymbol{g_{ftt^{+}}} = \boldsymbol{0} \quad \forall \{\boldsymbol{fst}\}\boldsymbol{\epsilon N}, \\
\boldsymbol{Avalability}: \textstyle\sum_{l\epsilon O(F)} \boldsymbol{Z_{fl}} + \sum_{s\epsilon S} \boldsymbol{g_{fst_n t_1}} \leq \boldsymbol{A_f} \,\forall\, \boldsymbol{f\epsilon F},\ \boldsymbol{Z\ binary}, \boldsymbol{g} \geq \boldsymbol{0}
\end{gathered} \tag{1}$$

where;

S: set of stations in the network, indexed by $s, o, or\ d$

F: set of fleet types, indexed by f

L: set of flight legs scheduled, indexed by l or $\{odt\}$, where $o, d\ \epsilon S$ and t denotes the time when the flight

N: set of nodes in the network, indexed by $\{fst\}$, where $f\epsilon F$, $s\epsilon S$, and t denotes the event time

$O(f)$:set of arcs for fleet type, f that cross the aircraft count time-line, $f\epsilon F, l\epsilon L$
The aircraft count time-line is the starting point for representing a series of events taking place in the network. The first node set after this timeline is represented as$\{fst_1\}$, $f\epsilon F$, $s\epsilon S$, and the last node set of the day is represented as $\{fst_n\}$, $f\epsilon F$, $s\epsilon S$.
G_{fl}:cost of assigning fleet type f to leg l, $f\epsilon F,\ l\epsilon L$
$A_{f:}$number of available aircraft for fleet type $f, f\epsilon F$
$Z_{fl} = 1\ if\ fleet\ f\ assigned\ to\ leg\ l, 0\ otherwise$
$g_{fstt'}$: flow of aircraft on the ground arc from node $\{fst\}\epsilon N$ to node $\{fst'\}\epsilon N$ at station $s\epsilon S$ in fleet
t^-, t^+: the time preceding and succeeding t, respectively, in the time-line

2.2. PSO

PSO is an algorithm proposed by Kennedy and Eberhart [20]. The PSO population, called cloud (or swarm), is composed by particles that are candidate solutions to the problem. Drawing an analogy with the flocks of birds, each particle acts as a bird from the flock looking for food. A swarm particles system begins the process of optimization with a population of random solutions, and searches for the optimal solution by updating the potential solutions through the iterations, the particles “fly” over the searching area looking for better solutions [21]. The PSO solutions cooperate among themselves and look for what called an optimal solution [22]. The velocity V_k^t and position X_k^t for a particle k updated as following in (2, 3);

$$V_k^t = w\, V_k^{t-1} + c_1 r_1 (pbest_k - X_k^{t-1}) + \quad c_2 r_2 (gbest - X_k^{t-1}) \qquad (2)$$

$$X_k^t \;=\; X_k^{t-1} + \; V_k^t \qquad (3)$$

where $pbest_k$ the personal best position found by the particle k and $gbest$ the global best position of the swarm. w The inertia factor that forces the particle to move in the same direction of the previous iteration. c_1 the cognitive factor that indicates the self-confidence of the particle. c_2 The social factor that forces the particle to follow the same way of the best particle of the swarm. r_1, r_2 are random numbers between [0, 1]. To prevent the particle from driving too far away, we can adopt a velocity bound to keep it in the interval of V_{min} and V_{max}, which are system parameters. All particles try to improve the performance of PSO by updating their velocity and position according to personal best and global best, and changing other parameters in different acceptable areas [23, 24].

2.3. PSO representation for fleet assignment optimization

In this section, we describe the representation of a PSO for solving airlines fleet assignment problem. The PSO classical approach needs some adjustments in order to be apply to optimization problems, such as redefining the particle in a discrete model, and adapting velocity operators [25]. Kennedy and Eberhart [26] encoded a particle k as a binary matrix and velocity defined as probability matrix in which the values can change from zero to one as the following:

$$X_k^t = \begin{bmatrix} x_{k,11}^t & x_{k,12}^t \cdots & x_{k,1n}^t \\ x_{k,21}^t & x_{k,22}^t & x_{k,2n}^t \\ \cdots & \cdots & \cdots \\ x_{k,m1}^t & x_{k,m2}^t & x_{k,mn}^t \end{bmatrix},\ x_{k,ij}^t \epsilon\, [0,1] \quad , \quad V_k^t = \begin{bmatrix} v_{k,11}^t & v_{k,12}^t \cdots & v_{k,1n}^t \\ v_{k,21}^t & v_{k,22}^t & v_{k,2n}^t \\ \cdots & \cdots & \cdots \\ v_{k,m1}^t & v_{k,m2}^t & v_{k,mn}^t \end{bmatrix},\ v_{k,ij}^t \epsilon\, \mathcal{R}$$

The representation of the fleet assignment will be achieved by using the binary representation of PSO described above by consider the rows in the particle matrix as the fleet type and columns as flights. The matrix X_k^t represents a particle k made of m×n bits, which considered a position solution to the problem. When $x_{k,ij}^t = 1$, this means that fleet type i will be assigned to flight j, $x_{k,ij}^t = 0$ otherwise. The particle movement was defined based on the probability of a position choosing one of two possible status, considering that the velocity is restricted to the interval [0; 1]. According to the authors’ example, if $v_{k,ij}^t$ = 0.20, then there is a 20% chance that the bit $x_{k,ij}^t$ will become 1, and 80% chance that it will become 0. Table 1 and Table 2 describes an example for the representation of particle position and velocity used for solving the fleet assignment problem.

To keep the particle velocity values limited to interval [0,1]. In (4) used to normalize the particle velocity.

$$N(V_k^t) = \frac{1}{1+\exp(-V_k^t)} \tag{4}$$

Then the particle position updated by adding the normalized particle velocity as in (4), so in (3) updated as the following:

$$X_k^t = X_k^{t-1} + N(V_k^t) \tag{5}$$

As seen in (1), the objective function used to evaluate the particle k to determine the optimal particle position, which is the fleet assignment solution. It calculated by summing the assignment cost $G(i,j)$ requird to assign fleet type i to flight j multiplied by particle position values $x_{k,ij}^t$ for particle k at iteration t as in (6).

$$C(X_k^t) = \sum_{i,j} G(i,j).x_{k,ij}^t \tag{6}$$

Table 1. Representation of the particle position

	Flights					
Fleet	0	1	0	0	1	0
Types	0	0	1	0	0	1
	1	0	0	0	0	0
	0	0	0	1	0	0

Table 2. Representation of the particle velocity

	Flights					
Fleet Type	0.10	0.99	0.19	0.15	0.99	0.27
	0.09	0.23	0.99	0.23	0.14	0.80
	0.97	0.20	0.17	0.15	0.13	0.33
	0.12	0.17	0.18	0.75	0.26	0.29

2.4. Fleet assignment solution algorithm

As we saw in section 2.3 and how represent the particle position, velocity and objective function for PSO to solve the fleet assignment problem. In addition, we formulate the problem in section 2.1 (1). Now we ready implement the solution algorithm [27]. Table 3 display the proposed algorithm for the solution of fleet assignment using PSO.

Table 3. Fleet assignment solution algorithm using PSO technique

Input: number of stations st, number of flights n, number of fleet types m, ground aircraft at each station g_f ($matrix\ of\ size\ m * st$), maximum capacity for each fleet type A_f($matrix\ of\ size\ m * 1$), available aircraft for each fleet type A_v ($matrix\ of\ size\ m * 1$), operating cost for each fleet type with different flights G ($matrix\ of\ size\ m * n$), PSO parameters (swarmSize, number of iterations itr, w, c_1, c_2 , r_1 , r_2, V_{min} , V_{max})
Output: optimal particle position that satisfy minimum operating cost and meets all constraints as mentioned in equation 1 (the output is a matrix of size m*n)
Start

1. t =0
2. $gbest \longrightarrow$ binary matrix will all ones of size m*n
3. **for** k=0 to swarmsize-1 do (Initialize the particles with random positions and velocities)
  3.1. $X_k^0 \longrightarrow$ a random binary solution (matrix size of m*n)
  3.2. $V_k^0 \longrightarrow$ a random velocity $\epsilon[V_{min}, V_{max}]$ (matrix size of m*n)
  3.3. $pbest_k \longrightarrow X_k^0$
4. **end for**
5. $C(gbest) = \sum_{i,j} G(i,j).gbest_{i,j}$ (total assignment cost for particle $gbest$, where $gbest_{i,j}$ is is global best position values at iteration number 0)
6. **for** k=0 to swarmsize-1 do
  6.1. $C(X_k^0) = \sum_{i,j} G(i,j).x_{i,j}^0$ (total assignment cost for particle position X_k^0 where $x_{i,j}^0$ is the particle position values at iteration number 0)
  6.2. **If** $C(X_k^0) < C(gbest)$ **then**
    6.2.1. $gbest \longrightarrow X_k^0$
    6.2.2. $C(gbest) = C(X_k^0)$
  6.3. **End if**
7. **End for**
8. **while** $t < itr$ **do**
  8.1. **for** k=0 to swarmSize-1 **do**
    8.1.1. $C(X_k^t) = \sum_{i,j} G(i,j).x_{i,j}^t$ (total assignment cost for particle position X_k^t ,where $x_{i,j}^t$ is the particle position values at iteration number t)
    8.1.2. $C(pbest_k) = \sum_{i,j} G(i,j).pbest_{i,j}$ (total assignment cost for best position, where $pbest_{i,j}$ is the particle best positon values at iteration number t)
    8.1.3. **if** C(X_k^t) < C($pbest_k$) **then**
      8.1.3.1. $pbest_k \longrightarrow X_k^t$

8.1.4. **end if**
8.1.5. **if** C(X_k^t) < $C(gbest)$ **then**
8.1.5.1. $gbest \longrightarrow X_k^t$
8.1.6. **end if**
8.1.7. $V_k^{t+1} = w\,V_k^t + c_1 r_1(pbest_k - X_k^t) + \; c_2 r_2(gbest - X_k^t)$
8.1.8. $N(V_k^{t+1}) = \frac{1}{1+\exp(-V_k^{t+1})}$
8.1.9. $X_k^{t+1} \; = \; X_k^t + \; N(V_k^{t+1})$
8.1.10. $X_k^{t+1} \;\epsilon\; \{0,1\}$
8.1.11. check constraints as in equation 1
8.1.11.1. **if** X_k^{t+1} apply constriants **then**
8.1.11.1.1. update X_k^{t+1} values to follow constriants
8.1.11.2. end if
8.2. end for
8.3. t=t+1
9. end whileEnd

2.4. Data acquisition

Datasets collected from Egyptair airlines company for two years from 1/7/2017 until 30/6/2019. The data extracted from Egyptair accounting and costing system. The data attributes are Flight date, flight number, origin, and destination, assigned aircraft type, operating cost, number of KM flown, number of available seats, and number of passengers. For simplicity of fleet assignment implementation, we choose seven stations from Egyptair network. That is Cairo international airport (CAI) as the hub station and the spokes are Kuwait (KWI), New York (JFK), Frankfurt (FAR), London (LHR), Jeddah (JED) and Riyadh (RUH). The data set has 20671 of rows and nine columns for the specified seven stations above. Egyptair airlines have nine different category of aircraft types fly over the word. The fleet types are A320-232, A321-231, A330-200, A330-300, B737-800, B737-800NEW, B777-200, B777-300, and B787-900. Egyptair have 4, 2, 5, 4, 20, 9, 2, 6, and 6 from each type respectively. The specified seven stations have about 30 flights per day. Table 4 represent the sample of data for flights schedule in a day, in addation contains the corresponding assigned fleet type and its operating cost. The table contains the number of passengers and the distance flown.

Table 4. Sample of collected dataset for a day

Flight No.	Origin	Destination	Assigned Aircraft	Operating cost (USD)	number of KM flown	Number of available seats	Number of passengers
MS0610	CAI	KWI	B737-800	5316	1601	144	85
MS0611	KWI	CAI	B737-800	10728	1601	144	107
MS0612	CAI	KWI	B737-800	5803	1601	144	119
MS0613	KWI	CAI	B737-800	9785	1601	144	108
MS0620	CAI	KWI	B737-800	5614	1216	144	127
MS0621	KWI	CAI	B737-800	9465	1216	144	139
MS0647	CAI	RUH	B737-800	3879	1216	144	82
MS0648	RUH	CAI	B737-800	8792	1216	144	132
MS0649	CAI	RUH	A330-200	15018	1216	268	180
MS0650	RUH	CAI	A330-200	18616	1216	268	262
MS0651	CAI	RUH	B737-800	5930	1216	144	117
MS0652	RUH	CAI	A330-200	18096	1216	268	257
MS0661	CAI	JED	B737-800	5124	1216	144	80
MS0662	JED	CAI	B737-800	8989	1216	144	125
MS0663	CAI	JED	A330-300	16838	1216	301	185
MS0664	JED	CAI	A330-300	20377	1216	301	287
MS0665	CAI	JED	B777-300	53550	3531	346	329
MS0666	JED	CAI	B777-300	63648	3531	346	263
MS0671	CAI	JED	B737-800 NEW	26860	3531	154	139
MS0672	JED	CAI	B737-800 NEW	22982	3531	154	125
MS0673	CAI	JED	B737-800 NEW	17645	2921	154	128
MS0674	JED	CAI	B737-800 NEW	20709	2921	154	98
MS0777	CAI	LHR	B777-300	150710	9010	346	319
MS0778	LHR	CAI	B777-300	183501	9010	346	311
MS0779	CAI	LHR	B777-300	28836	1601	346	227
MS0780	LHR	CAI	B777-300	36397	1601	346	272
MS0785	CAI	FRA	B737-800	2224	1216	144	120
MS0786	FRA	CAI	B737-800	6279	1216	144	125
MS0985	CAI	JFK	B737-800	6313	1216	144	120
MS0986	JFK	CAI	B737-800	2496	1216	144	122

3. RESULTS AND DISCUSSION

The proposed PSO algorithm described in section 2.4 for the solution of fleet assignment problem developed by authors using Python programming language. The developed model implemented and tested using Egyptair dataset specified in section 2.5. The developed model reads the dataset from an excel sheet. It extracts all required inputs and makes a suitable representation for the data to get the optimal solution for fleet assignment problem. On the other hand, we develop another model to solve the fleet assignment problem using other optimization technique, which is mixed integer programing (MIP). The developed model based on MIP solver implemented by google. We implement and test the model on the same dataset for Egyptair airlines. To measure the effectiveness and validity of PSO algorithm, results compared with other, MIP and current Egyptair assignment methodology. The criteria of performance considered were the quality of solutions (optimal total assignment cost). The percentage of improvement in total assignment cost computed as the following equation for the different methods [28]:

$$\left(1-\frac{Total\ asignment\ cost\ using\ the\ one\ method}{Total\ assignment\ cost\ using\ the\ other\ method}\right)\times 100 \quad (7)$$

We use the following parameter values when using PSO. The inertia weight w=0.5, cognitive and social factors c_1=c_2 = 1, swarm size=1000, the number of iterations=10000 and particle velocity bounds between 0 and 1.

For simplicity, we will display the PSO and MIP results for the specified stations mentioned in section 2.5 with detailed results for one day (01/01/2019). Table 5 displays the fleet assignment solution for scheduled flights for one day using PSO and MIP. The results compared to Egyptair assignment methodology. The results display that there are cost reduction when using MIP than Egyptair methodology by 5.5% or saving daily cost 43,814$. If we use PSO, we have cost reduction by 19.3% than using Egyptair assignment methodology or we save daily cost 152,585$. On the other hand when compare PSO with MIP technique, we find 14.6% improvement or save daily cost 108,771$. For other assignment, Table 6 displays the assignment cost comparison for Egyptair assignment methodology, MIP and PSO for seven days (1/2/2019, 1/3/2019, 1/4/2019, 1/5/2019, 1/6/2019, 1/7/2019 and 1/8/2019).

Table 5. Egyptair fleet assignment solution and cost comparison for Egyptiar methodology, PSO and MIP for day 1/1/20109

Flight NO.	Origin	Destination	Assigned fleet type by using Egyptair method	Assigned Fleet By using MIP	Assigned Fleet by using PSO
MS0610	CAI	KWI	B737-800	B737-800	B787-900
MS0611	KWI	CAI	B737-800	B737-800 NEW	B737-800
MS0612	CAI	KWI	B737-800	B737-800	B777-300
MS0613	KWI	CAI	B737-800	B737-800	A330-300
MS0620	CAI	KWI	B737-800	B737-800	A330-300
MS0621	KWI	CAI	B737-800	B737-800	B777-200
MS0647	CAI	RUH	B737-800	B737-800 NEW	B777-300
MS0648	RUH	CAI	B737-800	B737-800	B787-900
MS0649	CAI	RUH	A330-200	B737-800	B777-300
MS0650	RUH	CAI	A330-200	B737-800	A330-200
MS0651	CAI	RUH	B737-800	B737-800	B777-300
MS0652	RUH	CAI	A330-200	B737-800	A330-300
MS0661	CAI	JED	B737-800	B737-800	A320-232
MS0662	JED	CAI	B737-800	B737-800	A320-232
MS0663	CAI	JED	A330-300	B737-800	B777-300
MS0664	JED	CAI	A330-300	B737-800	A321-231
MS0665	CAI	JED	B777-300	B737-800	B737-800
MS0666	JED	CAI	B777-300	B737-800	B737-800
MS0671	CAI	JED	B737-800 NEW	B737-800 NEW	B737-800
MS0672	JED	CAI	B737-800 NEW	B737-800	B737-800
MS0673	CAI	JED	B737-800 NEW	B737-800	A330-200
MS0674	JED	CAI	B737-800 NEW	B737-800	B737-800
MS0777	CAI	LHR	B777-300	B737-800 NEW	B737-800
MS0778	LHR	CAI	B777-300	B737-800 NEW	B737-800
MS0779	CAI	LHR	B777-300	B737-800 NEW	B787-900
MS0780	LHR	CAI	B777-300	B737-800 NEW	B787-900
MS0785	CAI	FRA	B737-800	B737-800 NEW	B787-900
MS0786	FRA	CAI	B737-800	B737-800 NEW	B787-900
MS0985	CAI	JFK	B737-800	B737-800	B737-800
MS0986	JFK	CAI	B737-800	A330-200	B777-200
Total assignment Cost (USD)			790,520	746,706	637,935
Cost Improvement (%)				5.5% than Egyptair methodology	19.3% than Egyptair methodology14.6% than MIP method

The results in Table 6 displays the effect on the assignment cost for the three methods. We choose these days to display a different number of flight schedule for the referred seven stations. Table 6 displays the total assignment cost per day for each methodology. We note that there are cost reduction for these days 314,907$ when using MIP than Egyptair methodology. The cost reduction increases when using PSO we find 1,202,908$ for seven days than using Egyptair methodology. When comparing PSO with MIP for the same period, we found a cost reduction of 888,001$. Figure 1 displays the assignment cost comparison for the three techniques. The effect of the developed model is to obtain the optimal fleet assignment and automate the process of fleet assignment for Egyptair airlines instead of using fixed aircraft type for each flight leg. The model uses an intelligent method to solve the problem. The solution to the problem has a great effect on company revenue by decreasing the operating costs required for covering the scheduled flights with different aircraft types. We found that the PSO technique is the best technique for solving the fleet assignment for Egyptair airlines.

Table 6. Egyptair assignment cost comparison for company methodology, MIP and PSO

Method	Assignment Cost/Day							
	1/2/2019	1/3/2019	1/4/2019	1/5/2019	1/6/2019	1/7/2019	1/8/2019	Total assignment_cost
Egyptair assignment methodology	768,751	983,683	1,025,752	984,773	1,464,852	832,752	1,005,532	7,066,095
MIP	725,000	901,252	1,002,375	898,026	1,390,455	830,860	1,003,220	6,751,188
PSO	670,327	780,780	899,744	780,845	1,200,405	640,560	890,526	5,863,187

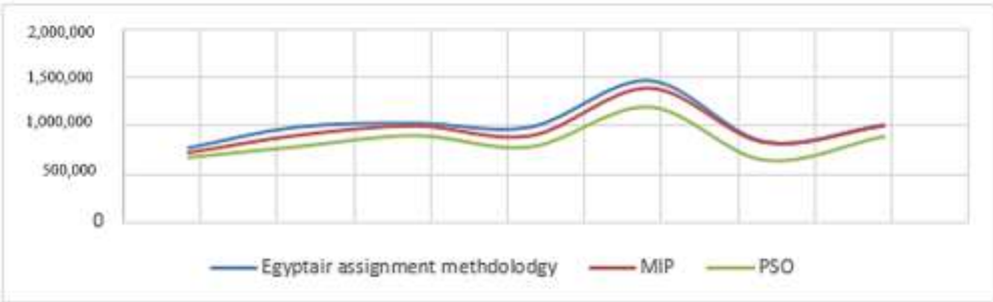

Figure 1. Egyptair assignment cost comparison for three techniques in seven days

4. CONCLUSION AND FUTURE WORK

Air transportation is the fastest long-distance transportation method. People prefer to use air transportation during holidays, business trips and almost all travel needs. Airlines faced with difficult and comprehensive issues such as fleet assignment, airline scheduling, and crew scheduling. Operating costs is the highest costs for airline companies that play a basic parameter in fleet assignment decision. The effective assignment of fleet types to flight segments is critical to airline planning. This paper formulated the fleet assignment problem for airlines that optimization goal is to minimize the total assignment cost. The problem solved by using one of the artificial intelligence optimization techniques, which is particle swarm optimization. To implement the model, we developed a python model for solving the fleet assignment problem using PSO and MIP methods. The model is tested and validated on Egyptair airlines actual dataset. The performance of PSO algorithm evaluated in comparison with MIP and Egyptair assignment methodology. The results showed that the PSO algorithm is the best solution. Where we see a daily cost reduction with percentage of 14.6% and 19.3% than MIP and Egyptair methodology respectively. To get more insights from results and its effects on Egyptair airlines. We test the program on flights for seven days. We solved the fleet assignment for Egyptair by available fleet types. We note that there are cost reduction for these days 314,907$ when using MIP than Egyptair methodology. The cost reduction increases when using PSO we find 1,202,908$ during seven days than using Egyptair methodology. A natural extension to this work would be applying another representation of particles for PSO as position permutations and compare it with the obtained results using the binary representation.

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