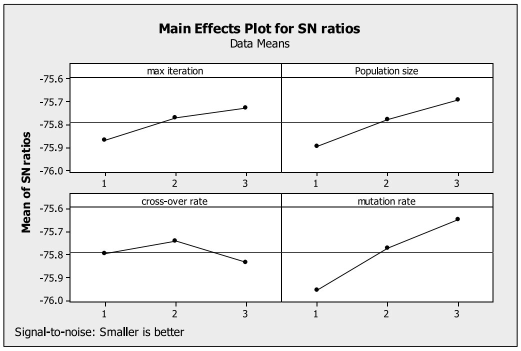

Figure 4. Mean S/N ratio plot for each level of factors in GA.

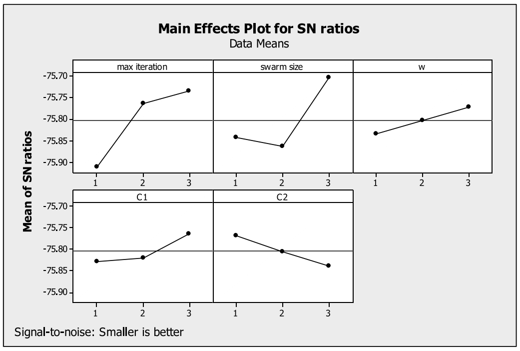

Figure 5. Mean S/N ratio plot for each level of factors in PSO.

6. COMPUTATIONAL RESULTS

In this paper, a set of problem instances extracted by Kasirzadeh et al. (2017) is used to validate the suggested model and evaluate the efficiency of proposed algorithms. 12 instances with different sizes are used to validate the model. Table 1 shows the details of these problems, as well as computational results. In this table, the 2nd to 4th columns indicate the characteristics of each problem, including the number of available flights, the number of planning horizon time, and the number of available crew. Columns 5 and 6 indicate the number of covered flights from the available set of flights, and the number of crew members used amongst the existing crew members. According to the results, metaheuristic algorithms were able to find the global solutions for small-sized problems. By increasing the problem size, the computational time of the exact approach increased considerably, so the software was stopped after a predetermined time (24 hours), and the solutions were recorded as local solutions. In these problems, both metaheuristic algorithms obtained the acceptable solutions (within 9% gap) significantly faster than GAMS. This shows the efficiency of the algorithms. Eventually, for large-sized problems, only the solutions obtained by the proposed algorithms are recorded. It should be noted that the comparison of the algorithms reveals that the PSO algorithm is a bit less time consuming and achieved better solutions compared to GA (Figures 6 and 7). The solutions are achieved on the laptop with the specifications of corei7, 2.4GHz, and 4GB of RAM.

Table1. computational results.

Instance	Problem data					GAMS			PSO				GA			
	No. of flights	No. of days	No. of crew members	No. of covered flights	No. of used crew members	GAMS solution	GASM CPU time	Status	Best solution	Ave. solution	Ave. CPU time	GAP%	Best solution	Ave. solution	Ave. CPU time	GAP%
1	35	2	15	35	10	3050	6	Optimal	3050	3070	7	0.00	3050	3070	7	0.00
2	38	2	15	38	11	3390	40	Optimal	3390	3501	20	0.00	3390	3690	29	0.00
3	50	2	20	50	14	4280	33	Optimal	4280	4300	35	0.00	4280	4340	37	0.00
4	26	3	15	26	8	2520	13	Optimal	2520	2520	6	0.00	2520	2540	10	0.00
5	31	3	15	31	10	3230	420	Optimal	3230	3230	42	0.00	3300	3396	51	2.17
6	31	3	15	31	9	2870	10	Optimal	2870	2870	11	0.00	2870	2901	15	0.00
7	26	3	15	26	9	2880	23	Optimal	2880	2880	7	0.00	2880	2922	10	0.00
8	70	4	30	70	19	5800	21 hour and 10 min,32 sec	Optimal	6170	6310	19min and 32sec	6.38	6330	6425	23min and 2 sec	9.14
9	76	4	30	76	23	7080	24 hour	Local	7240	7354	15min and 19 sec	2.26	7310	7421	17min and 48 sec	3.25
10	57	5	30	57	21	5270	24 hour	Local	5450	5596	25min and 29 sec	3.42	5510	5798	26min and 38 sec	4.55
11	93	6	40	-	-	-	-	-	15423	16012	30 min and 32 sec	-	16190	17011	32 min and 4 sec	-
12	134	6	50	-	-	-	-	-	14960	15569	34 min and 4 sec	-	15645	16901	38 min and 51 sec	-

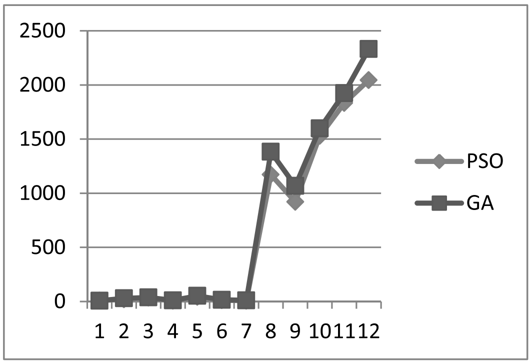

Figure 6. Comparison of problem-solving time between PSO and GA.

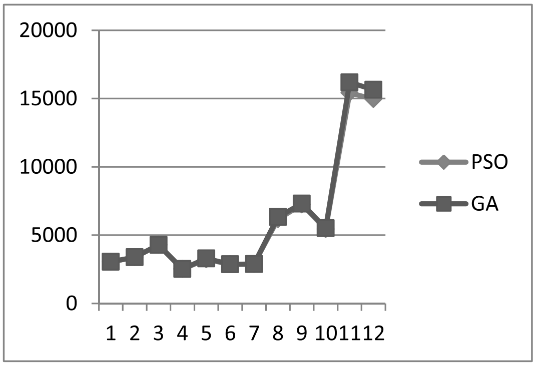

Figure 7. Comparison of the achieved solutions between PSO and GA.

7. DISCUSSION

In this section, the performance of the proposed integrated mathematical model for CSP is evaluated. First, two separate mathematical formulations for the CPP and CRP are presented. Then, two models are solved based on the sequential order so that the CPP outputs are assumed as CRP inputs, and the final results are achieved by solving the CRP model. At the end, the achieved results can be compared with integrated ones in terms of objective functions and CPU time.

CPP formulation:

For the CPP formulation, the following modifications in CSP integrated model are required. New Sets, indices, and constraints for this problem are as follows:

Sets and indices

P : Set of all pairings

p : Index of pairing (p $\in P$)

O : Set of all home base

o : Index of home base (o $\in O$)

Constraints

$$\sum_{j \in O} s_{pjd} \geq -M * \left(1 - y_{pdf}\right) + 1 \quad \forall\, p \in P, f \in F, f = 1 \tag{38}$$

$$w_{pjd} \geq s_{pjd''} - M * \left(1 - y_{pdf}\right) - M * \Big(\sum_{\substack{d'=d+1 \\ d' \in D}} \sum_{\substack{f'=f+1 \\ f' \in F}} y_{pd'f'}\Big) - M * (1 - y_{pd''f''})$$

$$\forall p \in P, j \in O, d \in D, f, f'' \in F: f \leq d, f'' \leq d'', \qquad f'' = 1 \tag{39}$$

An index of i is replaced with p in the formulations presented in Section 4, and the new index of o is also introduced. The constraints (6), (7), and (16) are removed from the model, and the new constraints (38) and (39) are added. The new constraints ensure that each pairing must start from and end at the same home base. Finally, the crew cost item in the objective function is also removed.

CRP formulation:

Sets, indices, parameters, and decision variables for the problem of CRP are as follows.

Sets and indices

I: Set of all crew members

i: Index of crew member ($i \in I$)

P : Set of all pairings

p : Index of pairing (p $\in P$)

o_p: Home base of pairing p

Parameter

r_i : cost of using crew i.

Decision variables

u_{ip} : If pairing p is assigned to crew member i, 1 otherwise 0

Constraints and objective function

$$\sum_{i \in o_p} u_{ip} = 1 \quad \forall p \in P \tag{40}$$

$$\sum_{p \in o_i} u_{ip} \leq 1 \quad \forall i \in i \tag{41}$$

$$min \sum_{i \in I} \sum_{\mathrm{p} \in P} u_{ip} * r_i \tag{42}$$

Constraint (40) states that each selective pairing must be assigned to only one of the crew members with the same home base. Constraint (41) ensures that each crew member can handle at most one selective pairing. The objective function (42) tends to minimize the total cost of the system including crew cost assignment.

Finally, the results of the proposed combined model are compared with the results obtained when the two models are considered separately through some test problems (Table 2). As can be seen, in contrast to the sequential models, the integrated one generates accurate and appropriate work schedules for the existing crew members, leading to 14.39% average cost reduction in only 7.27% CPU time increase. The archived results show the superiority of the integrated model in comparison to the sequential order ones.

Table 2. Comparison between the integrated model and sequential order ones.

Instance	Integrated model		Sequential order models		Related percentage of deviation (RPD) objective%	Related percentage of deviation (RPD) CPU time%
	Objective function	CPU time(se)	Objective function	CPU time(sec)		
1	4280	33	4731	31	10.54	6.45
2	3050	6	3391	6	11.18	0.00
3	3230	420	3791	399	17.37	5.26
4	3390	40	3732	38	10.09	5.26
5	2520	13	2822	12	11.98	8.33
6	2870	10	3254	9	13.38	11.11
7	2880	23	3234	21	12.29	9.52
8	5800	76232	7442	67938	28.31	12.21
				Average	14.39	7.27

CONCLUSION

Crew scheduling problem has always been one of the researchers' interests; however, due to the complex nature of this problem, it has always been solved in two separate steps, namely, crew pairing and crew rostering problems. It should be noted that few investigations have been concerned on integrating these two steps. In this study, a new integrated mathematical model of the two above steps was introduced considering the rules of aviation. Due to the Np-hardness of the problem, it was not possible to achieve an optimal solution for large-sized problem over a reasonable amount of time. Therefore, two solution approaches, namely, particle swarm optimization (PSO) and genetic algorithm (GA), were implemented. In the case of the small-sized problems, it was concluded that both of the algorithms were able to achieve an optimal solution. By increasing the problem size, the software computational time was highly increased; consequently, metaheuristic algorithms were used for large-sized problem and could achieve the acceptable solution in a reasonable time. When it comes to the comparison of the algorithms in terms of optimality of the solutions and computing time, PSO outperformed GA, which in turn indicates its successful performance. Moreover, the results of the proposed combined model were compared with the results obtained when the two models are considered separately through some test problems. In comparison to the sequential order models, the proposed integrated model in this study generated more accurate and appropriate work schedules for the existing crew members, leading to about 14.39% average cost reduction in only 7.27% CPU time increase. It is suggested that researchers investigate the problem by considering the possibility of having more than one flight from a specific origin to a specific destination daily. Consideration of other aviation laws relating to duties and vacations is also suggested.

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