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Two-stage stochastic robust programming based on MOPSSCA for flight crew scheduling problem

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Abstract: The main purpose of providing the mathematical model is to achieve the optimal flight schedule, optimal fleet allocation, optimal aircraft routing, and crew scheduling to reduce the total costs of flights and the amount of fuel consumed in all flights. Due to the uncertainty of the flight of the planes at the appointed time and the presence of numerous delays, modelling in different scenarios was presented based on the probability of the event. The calculation results of solving the numerical example with the epsilon method of the limit showed that the change in the flight schedule of the planes and the presence of delay in it leads to an increase in the flight costs and, as a result, leads to an increase in the amount of fuel consumed. In this article, a new hybrid algorithm named MOPSSCA was introduced, which has achieved near-optimal solutions with a maximum error of 2%. [Submitted: 12 December 2023; Accepted: 29 July 2024]

Keywords: flight crew scheduling; two-stage stochastic robust programming; MOPSSCA; crew scheduling; flight routing.

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Biographical notes: Parvaneh Zeraati Foukolaei is a Research Assistant Professor at the Department of management, Azad University, Jouybar branch. She is Faculty member of the management department of Azad University, Jouybar branch. She has got all his Bachelor, Master, and PhD degrees in the field of Management. But she has passed with different trends in business, finance and production and operations.

1 Introduction

Flight crew scheduling (FCS) is one of the most important and challenging issues in the airline industry. In this issue, things like crew, flights, repair and maintenance, inventory, purchase of equipment and crew training need to be planned, which have faced many problems in the aviation industry. Each planning problem has its own considerations, complexities, set of time horizons and goals (Kenan et al., 2018). During the last half century, due to the rapid expansion of some major airlines and the increase in the number of passengers who use air transportation for their travel, in all areas of planning. There has been a significant increase in airlines in transportation planning (Yan and Tseng, 2002). This effect is felt more in the FCS stage in airline planning. Although FCS continues to pose new challenges to the operations research community, in many cases great strides have been made in solving these problems optimally. The goal of the FCS problem is to create a set of minimum cost crew pairs that cover all flight schedules (Katsigiannis and Zografos, 2021). Every flight needs at least one pilot with other crew such as first officer, flight attendant, etc. According to the rules and regulations of the airlines, the flight crew must have enough rest after each trip every day and between consecutive days, and without taking this issue into account, they will not be able to travel again. Also, each pilot can have a limited number of flights per day. Considering such restrictions along with the increase in the number of passengers and the urgent need for multiple flights leads to the complexity of the issue. So that unscheduled flights can lead to an increase in costs as well as the amount of fuel consumed, which is challenging from an environmental point of view in addition to economic problems (Zhao et al., 2019; Dai et al., 2021).

FCS consists of four issues: flight schedule, fleet allocation, flight routing, and crew scheduling. The integration of four categories of problems has led to the fact that today meta-heuristic algorithms and different solution methods are used to optimise FCS problems. In these problems, the schedule should be in such a way as to minimise the total costs of consecutive flights and comply with the crew scheduling rules and regulations. In the first stage of flight planning, airlines look for flights among the candidate flights that increase the company's revenue and then reduce operational costs (Deveci and Demirel, 2018). The input information for this stage of scheduling includes the identification of the number of flight origins and destinations based on demand and operating costs related to the existing fleets in the company, as well as their number and composition. The results obtained from the first stage of scheduling are used in the fleet allocation stage. The input information in this stage includes the number and type of fleet as well as the flight schedule specified in the first stage. The purpose of this section is to allocate the fleet to the flights planned from the previous stage. The next stage includes the routing of the planes according to the limitations of their maintenance and repairs. This stage forms a part of the model presented in this research, whose input information includes the number and type of aircraft, operational costs of each type of aircraft, and limitations related to aircraft maintenance and repairs. This stage of scheduling determines which aircraft should be used for each flight chain (a set of consecutive flights) in order to minimise the operational costs of the aircraft in addition to complying with the maintenance and repair restrictions and generally increase the profit of the airline company increase (Wei and Vaze, 2018).

Various researches show that the amount of carbon dioxide (CO_2) released from air movements is 550 billion tons per year, which is 2.5% of the total carbon dioxide produced by humans. Each airplane passenger produces about 140 grams of carbon dioxide per kilometre, while this figure is 100 grams per kilometre for each car passenger. Of course, the indirect emission of greenhouse gases in the stages of making devices, refining, and transporting oil is more in cars than in airplanes, despite this, even considering the carbon dioxide produced in these sectors, it can be seen that the amount of emission greenhouse gases per airplane passenger are 16% more per kilometre compared to each passenger in a car. The importance of this issue on fuel costs and the amount of greenhouse gas emissions is a strong reason for the importance of airplane flight timing. Any non-optimal route can increase the emission of greenhouse gases and increase the cost of fuel.

Therefore, in this paper, with regard to the challenging problem of FCS, a new model of flight scheduling has been modelled in which, due to the existence of multiple delays in the flight of airplanes, uncertainty is included in the form of scenarios. Therefore, the important decisions that the model of the article is looking for are the optimal flight routing in such a way that the crew returns to their city (origin) after flying from the origin and making consecutive flights. Otherwise, the airline will be fined. Also, the assignment of the crew to the flight, the assignment of the air fleet is among other decisions that we are looking for in this paper. Also, due to proving that the problem is NP-hard, a hybrid algorithm consisting of two MOPSO and MOSCA called MOPSSCA has been introduced, in which, in addition to local search with the MOSCA, movement speed in different dimensions has also been considered. Therefore, the mathematical model seeks to optimise two objective functions of minimising the total flight costs and minimising the amount of fuel consumed.

The structure of the paper is as follows, in the second part, the literature review related to FCS is done and the research gap is identified at the end of the literature review. In the third part, using two-stage stochastic robust programming (TSSRP) and in different scenarios, a FCS model is designed. In the fourth part, MOPSSCA and the initial solution of the problem are introduced. In the fifth section, the analysis of the problem and the comparison between the methods used in solving the problem are discussed. Finally, in the sixth section, conclusions and suggestions for future research have been discussed.

2 Literature review

In this section, various articles have been reviewed in four sections: flight scheduling (FC), flight assignment (FA), flight routing (FR) and crew scheduling (CS).

2.1 Flight scheduling

Kasirzadeh et al. (2017) reviewed the literature on the FCS problem, presented solution algorithms and also introduced new solution methods. They also presented a new model of the FCS problem for the USA. Wen et al. (2020) modelled an FCS problem where departure/landing time deviation was considered as the main feature of the model. In order to solve the problem, a heuristic algorithm was presented, based on the experiments, it was observed that operating costs are reduced by 9.7% compared to traditional models. Chin (2021) used optimisation techniques to improve the FCS process. He started with a basic integer program formulation and developed OBFs based on maximising the training requirements completed and assigning the fewest qualified pilots to each pilot seat. Wen et al. (2022) studied the relationship between manpower availability and FCS strategies. Dixit (2022) conducted a study based on the management and planning of AIRINDIA airlines to investigate some of the known problems and their solutions. In this program, he fixed the shortcomings of airline planning, which aimed to increase the productivity of crew members through the crew allocation model, and reduce the time spent on non-critical operations, leading to an increase in airline profits.

Jangizehi et al. (2023) proposed a fuzzy analytical network process (FANP) method to provide a correct decision during the disruption of the flight schedules. The results show that the most important factors that make disruption of flight schedules are arrival delays and technical failure of the airline fleet. Shambour and Abu-Hashem (2023) used DEA, HSA, GA, FPA, and BWO algorithms to solve FCS problem in the King Abdulaziz International Airport's pilgrimage station in the Kingdom of Saudi Arabia. Du et al. (2023) developed a data-driven method to model and solve the FCS problem. The results show that the RF-based ETA prediction method could improve scheduling performance.

2.2 Flight assignment

Shao et al. (2017) presented a mathematical model for the integrated problems of fleet assignment, flight routing and FCS considering travel demand. Androutsopoulos et al. (2020) modelled and solved a bi objective FCS problem. They used a local search algorithm to implement the model in a Greek regional airport. The computational results show that the proposed algorithm is reasonably accurate and has the ability to approximate the entire efficient frontier of the problem. Wen et al. (2021) investigated the FCS problem and features of these models with different aspects by considering COVID-19 and blockchain technology. Baradaran and Hosseinian (2021) proposed a multi-objective mathematical model for the FCS problem, which includes the OBFs of maximising the number of scheduled vacation days given the flight crew's declared days and minimising the penalty costs associated with violations of minimum and maximum working hours. Due to the NP-hard of the model, they used MODE and NSGA II, which were compared based on several multi-objective performance metrics. Nozari et al. (2023) presented an integrated model for assigning crew and aircraft to flights in order to achieve a fair FCS, whose OBF is to minimise the difference between the crew's working time on the aircraft. PSO was used as the solution approach and to validate the solution approach.

2.3 Flight routing

Cordeau et al. (2001) considered flight routing and FCS problem simultaneously and presented a model and solution approach. The objective function (OBF) of this model was to minimise the time between departure/landing of the flights. Gürkan et al. (2016) presented an integrated model for FCS, fleet allocation and flight routing considering aircraft speed. They showed that considering this factor in the routing of flights can lead to more efficient use of airplanes and reduce the number of airplanes needed to perform flights. Hu et al. (2017) presented a multi-objective model for flight routing. The OBF of this model included minimising the total deviations from the original flight schedule and minimising the maximum delay time. Garg et al. (2024) presented an integrated model of FCS and flight routing for a low-cost carrier in emerging markets. They solved this large-scale integer programming problem using Lagrangian relaxation and Benders approaches.

2.4 Crew scheduling

Liu et al. (2010) presented a mixed integer linear programming (MILP) model to minimise the number of delayed flights considering a one-day time horizon. They used the GA to solve the problem and showed that the use of this algorithm has a higher efficiency than similar algorithms. Rodič and Baggia (2017) solved a FCS problem using heuristics and simulation algorithms. In this method, the algorithms first calculate the manpower and equipment requirements based on the flight plan and the stored exploratory criteria. Workforce requirements are then optimised using task time shifting and task reassignment, which smooth out the workforce demand peaks, and finally the simulation model is used to validate the generated schedule. Antunes et al. (2019) presented a robust model of the FCS problem that reduces costs by creating a schedule for the crew. They stated that the use of a robust method can produce solutions that significantly reduce delay and disruption costs with a slight increase in planned costs. Zeighami et al. (2020) modelled and solved a FCS problem in which there was a constraint of crew and pilot unavailability on some days of the month. They used a Lagrangian decomposition approach to solve the problem. The proposed approach greatly reduces scheduling costs compared to traditional methods. Orhan (2022) presented a bi-objective FCS model, in order to minimise the number of flight crews and minimise costs. The results showed that the bi-objective model can provide significant cost benefits for airlines. Computational experiments have been performed on a set of real data. Ouyang and Zhu (2023) proposed a new heuristic solver based on the parallel GA and an innovative crew scheduling algorithm, which improves traditional crew scheduling by integrating CPP and CRP into a single problem. Compared with the GA, CPLEX and Gurobi, the new method shows high optimisation efficiency, with a time reduction of 16.57–85.82%.

In Table 1, the most important features of the FCS problem are discussed.

Table 1 The important features of the FCS problem

Author	*OBFs*	*Decision variables*	*Environment model*	*Uncertainty parameters*	*Control method*	*Solution method*
Stojković et al. (2002)	MC	FC-FA-FR-CS	D	-	-	CPLEX
Lee et al. (2007)	MC	FC-FR-CS	D	-	-	MOGA
Liang and Li (2014)	MC	FC-FR	D			ACO-GA
Kenan et al. (2018)	MC	FC-FA	U	Demand	TSSP	SSA
Zeighami et al. (2020)	MC	FC-FR	D	-	-	Lagrangian decomposition
Nafstad et al. (2021)	MC	FC-FR	D	-	-	DCG
Salem et al. (2022)	MC	FC-FR	D	-	-	Dijkstara's algorithm
Cecen (2022)	MF	FC-CS	U	Flight duration time	SP	TS
Li et al. (2022)	MT	FC-FR	D	-	-	GA
Liu et al. (2023)	MF-MO	FA-CS	U	Demand-fuel price	TSSP	SSA

Table 1 The important features of the FCS problem (continued)

Author	*OBFs*	*Decision variables*	*Environment model*	*Uncertainty parameters*	*Control method*	*Solution method*
Zhou et al. (2023)	MC-MS	FR-CS	D	-	-	BBPSO
Crego et al. (2023)	MC	FR-CS	D	-	-	GA
Gui et al. (2023)	MF	FC-FR	D	-	-	Cplex
This paper	*MC-MF*	*FC-FA-FR-CS*	*U*	*Departure/ landing time-allocation cost*	*TSSRP*	*MOPSSCA MOPSO-MOSCA*

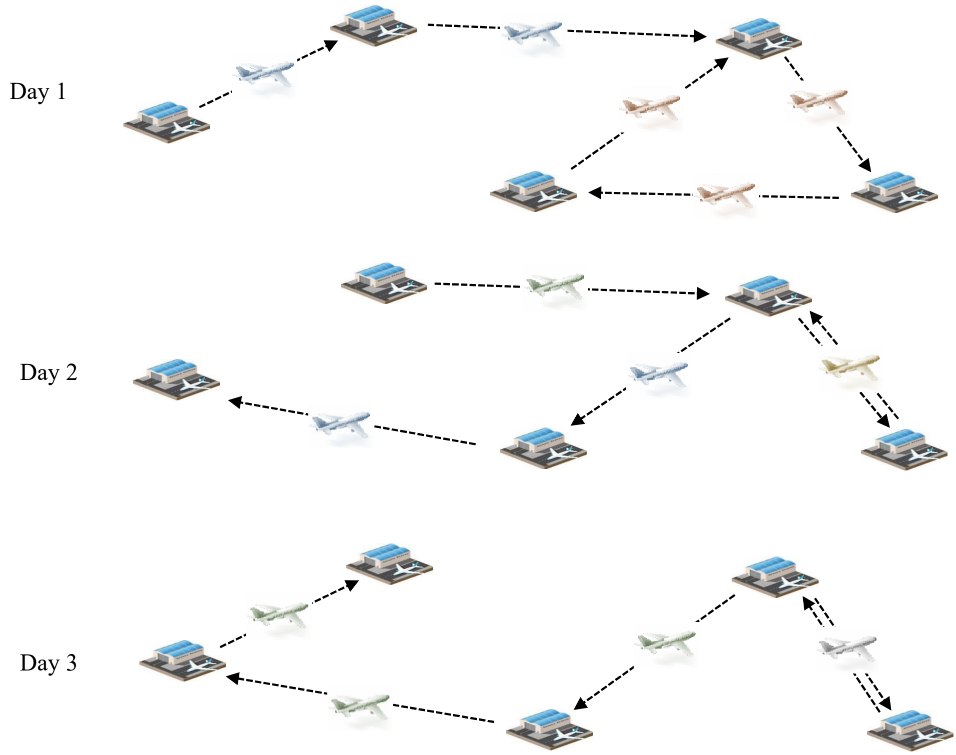
MC: minimising the costs	FC: flight scheduling
MF: minimising the fuel consumption	FA: flight assignment
MT: minimising the total flight delay	FR: flight routing
MO: minimising the carbon dioxide emissions	CS: crew scheduling
D: deterministic	MS: maximum crew satisfaction
U: uncertainty	TSSP: two-stage stochastic programming
TSSRP: two-stage stochastic robust programming	SP: stochastic programming

By examining the literature review, it can be said that so far, many researches have been conducted in the field of FCS. Using the models available in the literature, this paper presents a new model of FCS, in which, in addition to complying with all rules and regulations related to crew rest, it optimises the two OBFs of total costs and the amount of fuel consumed. The importance of greenhouse gas emissions and fuel costs have been neglected in many FCS problems, and uncertainty in flight timing has not been considered. While this issue has a direct impact on the company's profitability, environmental protection and sustainability. The use of combined methods to control possible parameters has not been considered in the articles. Therefore, this article aims to investigate this research gap. Also considering the deviation from the flight time which is controlled using the TSSRP method. Finally, a population-based algorithm called MOPSSCA is developed to solve the problem.

3 Problem definition and modelling

In this part, the modelling of a FCS problem is discussed. In this problem, there is a set of airports and airplanes that should transport passengers based on the schedule. The existence of flight rules and regulations in each trip has created a set of flight restrictions, which has led to FCS optimisation being considered as an NP-hard problem. Based on this, according to Figure 1, the problem of FCS can be understood as follows:

Figure 1 FCS in different periods (see online version for colours)



Several flight schedules are specified during the planning horizon, and for each flight, flight personnel including pilots, co-pilots and flight attendants are assigned. The flight plan is such that it must already exist in the plane's passengers and flight personnel in order for the flight operation to take place. There are restrictions on the rest of the flight personnel after each trip and a certain minimum time is defined for it. Also, there is the FCS problem in such a way that they try to return to their place of residence after the trip on the same day. Based on this, the modelling of the FCS problem with two objective functions of minimising flight costs and minimising the amount of fuel consumed is presented based on the following assumptions:

- Between any two consecutive flights corresponding to one pilot day, there should be a minimum time interval suitable for the pilot to rest and move.
- Between two consecutive flights of two consecutive days of a pilot, we should have a minimum time interval suitable for the pilot to rest.
- The pilot should start his flight schedule from his place of residence and at the end of the working period, he should be at his place of residence.
- Each flight must be entrusted to at least one pilot. Assigning more than one case of each flight to the pilots means that the pilots use that flight as a passenger to transfer to reach their destination to carry out the flight schedule.
- The flight schedule is already known.

- The number of pilots and their place of residence is also known.
- The daily flight hours of each pilot have a specific ceiling.
- The daily working hours of each pilot is also limited.
- The overall flight hours of each pilot in the working period or the planning horizon also have a specific ceiling.

Considering the high cost of fuel as well as the transportation of air flights, the exact determination of the cost of flights is possible and these costs affect the profitability of each airline company. In a situation where the cost of fuel increases, the timing of the airplane flight becomes a very important issue, because every flight on a non-optimal route; in addition to creating disorder in the flight, the size of the fleets increases, it also increases the costs of the airline company. Therefore, different possibilities are considered for the cost of the flight. On the other hand, the flight and landing time of the plane is also the most important issue in the scheduling of the entire transportation fleet. These two sensitive parameters, in turn, can increase the costs of flying and waiting. Therefore, these two parameters are considered as two possible parameters that are controlled by the two-stage stochastic programming method to determine the best scenario for flight scheduling. On the other hand, in order to justify the problem, the robust optimisation method has been used to control the cost parameter.

According to the stated assumptions as well as the minimisation of the two objective functions of the total flight planning costs and the minimisation of the fuel amount, the following symbols are defined for modelling:

Sets

I Set of pilots $i \in \{1, 2, \dots, I\}$.

J Set of airports (location) $j, j', j'' \in \{1, 2, \dots, J\}$.

o_i Pilot's residence i.

D Set of days $d, d', f \in \{1, 2, \dots, D\}$.

N Set of flight permutations $n \in \{1, 2, \dots, N\}$.

S Set of scenarios $s \in \{1, 2, \dots, S\}$.

Parameters

$l_{jj'ds}$ The landing time of flight of airport $j \in J$ to airport $j' \in J$ corresponding to the day $d \in D$ in scenario $s \in S$.

$d_{jj'ds}$ The departure time of flight of airport $j \in J$ to airport $j' \in J$ corresponding to the day $d \in D$ in scenario $s \in S$.

φ If there are two consecutive flights in one day in the work schedule of a pilot, there should be the minimum possible time between these flights φ for the pilot to rest and move.

ψ If there are two consecutive flights, one on the same day and the other on the other day, in the work schedule of a pilot, there should be the minimum possible time for the ψ pilot to rest between these flights.

ρ Maximum flight time in one day.

τ Maximum flight time in the planned horizon.

σ Maximum total minutes in a day form the first flight of that day to the last flight of that day.

$m_{jj'ds}$ The cost for assigning multiple flights of airport $j \in J$ to airport $j' \in J$ per day $d \in D$ and in scenario $s \in S$ to the pilots and is imposed on the airline company.

h Penalty cost (is considered due to the pilot not returning to this place of residence at the end of the day).

$c_{jj'}$ Fuel consumption for the flight of airport $j \in J$ to airport $j' \in J$ is imposed on the airline company.

p_s The probability of scenario $s \in S$.

ρ_m Flight cost change factor (uncertainty rate in robust model).

M Positive big number.

Decision variables

$X_{ijj'dns}$ 1; if the flight of airport $j \in J$ to airport $j' \in J$ is assigned to pilot $i \in I$ in scenario $s \in S$ during the day $d \in D$ and the permutation.

0; otherwise.

Y_{idfs} 1; if the pilot $i \in I$ start $f \in D^{\text{th}}$ his working on day $d \in D$ in scenario $s \in S$.

0; otherwise. $f \leq d$.

S_{ijds} 1; if the start of the work program related to pilot $i \in I$ is on day $d \in D$ of airport $j \in J$ and in scenario $s \in S$.

0; otherwise.

W_{ijds} If the completion of the work schedule related to pilot is $i \in I$ in day $d \in D$ of airport $j \in J$ and in scenario $s \in S$.

0; otherwise.

$\eta^m_{jj'ds}$ Robust penalty coefficient of the model.

δ_s The maximum cost of robust model in scenario $s \in S$.

$$Min\ OBF1 = \sum_{s \in S} p_s \delta_s \tag{1}$$

$$Min\ OBF2 = \sum_{s \in S} p_s \left[\sum_{d \in D} \sum_{j' \in J} \sum_{j \in J} \left(\sum_{n \in N} \sum_{i \in I} X_{ijj'dns} - 1 \right) c_{jj'} \right] \tag{2}$$

s.t.

$$\sum_{n\in N}\sum_{i\in I} X_{ijj'dns} \geq 1, \ \forall j, j', d, s \tag{3}$$

$$\sum_{n\in N} X_{ijj'dns} \leq 1, \ \forall i, j, j', d, s \tag{4}$$

$$\sum_{d\in D}\sum_{j'\in J}\sum_{j\in J} X_{ijj'dns} \leq 1, \ \forall i, n, s \tag{5}$$

$$-\left\{\varphi + l_{jj'ds}\right\}\left(2 - X_{ij'j''d,n+1,s} - X_{ijj'dns}\right) \leq \varphi \leq d_{j'j''ds} - l_{jj'ds}, \ \forall i, n, j, j', j'', d, s \tag{6}$$

$$\begin{gathered}-\left\{\psi + l_{jj'ds}\right\}\left(2 - X_{ij'j''d+1,n+1,s} - X_{ijj'dns}\right) \leq \psi \leq 1{,}440 + d_{j'j'',d+1,s} - l_{jj'ds}, \\ \forall i, n, j, j', j'', d, s\end{gathered} \tag{7}$$

$$S_{ijds} \geq -M\left(1 - Y_{idfs}\right) + 1, \ \forall f = 1, i, j = o_i, s \tag{8}$$

$$W_{ijds} \geq 1 - M\left(1 - Y_{idfs}\right) - M\left(\sum_{d'=d+1}\sum_{f'=f+1} Y_{id'f's}\right), \ \forall i, f \leq d, j = o_i \tag{9}$$

$$\begin{gathered}W_{ijds} - M\left(2 - Y_{idfs} - Y_{id',f+1,s}\right) \leq S_{ijd's} \leq W_{ijds} + M\left(2 - Y_{idfs} - Y_{id',f+1,s}\right), \\ \forall i, j, d, d', f, s\end{gathered} \tag{10}$$

$$S_{ijds} + \sum_{n\in N}\sum_{j'\in J} X_{ij'jdns} = \sum_{n\in N}\sum_{j'\in J} X_{ijj'dns} + W_{ijds}, \ \forall i, j, d, s \tag{11}$$

$$-M\left(1 - \sum_{f\in D} Y_{idfs}\right) \leq \sum_{n\in N}\sum_{j'\in J}\sum_{j\in J} X_{ijj'dns} \leq \left(\sum_{f\in D} Y_{idfs}\right), \ \forall i, d, s \tag{12}$$

$$\sum_{j\in J} S_{ijds} = \sum_{f\in D} Y_{idfs}, \ \forall i, d, s \tag{13}$$

$$\sum_{j\in J} W_{ijds} = \sum_{f\in D} Y_{idfs}, \ \forall i, d, s \tag{14}$$

$$\sum_{f\in D} Y_{idfs} \leq 1, \ \forall i, d, s \tag{15}$$

$$\sum_{d\in D} Y_{idfs} \leq 1, \ \forall i, f, s \tag{16}$$

$$\sum_{d\in D}\sum_{f\in D} Y_{idfs} \geq 1, \ \forall i, s \tag{17}$$

$$Y_{idfs} = 0, \ \forall i, d < f, s \tag{18}$$

$$\sum_{n\in N}\sum_{j'\in J} X_{ijj'dns} \geq S_{ijds}, \ \forall i, j, d, s \tag{19}$$

$$1 - M\left(2 - Y_{idfs} - X_{ijj'd,n+1,s}\right) \le \sum_{j'' \in J} X_{ij''jdns} \le 1 + M\left(2 - Y_{idfs} - X_{ijj'd,n+1,s}\right), \quad \forall i, j, j', d, n, s, f = 1 \tag{20}$$

$$1 - M\left(3 - Y_{id',f+1,s} - Y_{idfs} - X_{ijj'd',n+1,s}\right) \le \sum_{j'' \in J} X_{ij''jd'ns} \le 1 + M\left(3 - Y_{id',f+1,s} - Y_{idfs} - X_{ijj'd',n+1,s}\right), \quad \forall i, j, j', s, n, f, d' > d \tag{21}$$

$$1 - M\left(1 - Y_{id,f+1,s}\right) \le \sum_{\substack{d' \\ d' < d}} Y_{id'fs} \le 1 + M\left(1 - Y_{id,f+1,s}\right), \ \forall i, s, f + 1 \le d \tag{22}$$

$$\sum_{n \in N} \sum_{j' \in J} \sum_{j \in J} \left(l_{jj'ds} - d_{jj'ds}\right) \cdot X_{ijj'dns} \le \rho, \ \forall i, d, s \tag{23}$$

$$\sum_{n \in N} \sum_{d \in D} \sum_{j' \in J} \sum_{j \in J} \left(l_{jj'ds} - d_{jj'ds}\right) \cdot X_{ijj'dns} \le \tau, \ \forall i, s \tag{24}$$

$$\sum_{n \in N} \sum_{j' \in J} \sum_{j \in J} \left(l_{jj'ds} - d_{jj'ds}\right) \cdot X_{ijj'dns} + \sum_{n \in N} \sum_{j \in J} \sum_{j' \in J} \sum_{j'' \in J} \left(l_{jj'ds} - d_{jj'ds}\right) \cdot X_{ijj'dns} \cdot X_{ij'j''d,n+1,s} \le \sigma, \ \forall i, d, s \tag{25}$$

$$\left[\sum_{d \in D} \sum_{j' \in J} \sum_{j \in J} \left(\left(\sum_{n \in N} \sum_{i \in I} X_{ijj'dns} - 1 \right) m_{jj'ds} + \eta^m_{jj'ds} \right) + \sum_{d \in D} \sum_{j \ne o_i \in J} \sum_{i \in I} h W_{ijds} \right] \le \delta_s, \ \forall s \tag{26}$$

$$\rho_m \left(\sum_{n \in N} \sum_{i \in I} X_{ijj'dns} - 1 \right) m_{jj'ds} \le \eta^m_{jj'ds}, \ \forall j', j'', d, s \tag{27}$$

$$\rho_m \left(\sum_{n \in N} \sum_{i \in I} X_{ijj'dns} - 1 \right) m_{jj'ds} \ge -\eta^m_{jj'ds}, \ \forall j', j'', d, s \tag{28}$$

$$X_{ijj'dns}, Y_{idfs}, S_{ijds}, W_{ijds} \in \{0, 1\}; \ \eta^m_{jj'ds} \ge 0 \tag{29}$$

Equation (1) minimises the maximum cost of robust model. Equation (2) minimises the fuel consumption of consecutive airplane flights on consecutive days. Equation (3) guarantees that the flight $jj' \in J$ per day must be entrusted $d \in D$ to at least one of the qualified pilots for the flight. In fact, this flight is entrusted to one of the pilots and if it is included in the work schedule of other pilots, these pilots use that flight as passengers to reach their desired place in the work schedule. Equation (4) states that the flight $jj' \in J$ per day can $d \in D$ be placed at most in one of the positions related to the pilot $i \in I$. Equation (5) guarantees that at most one flight can be placed in each permutation related to each pilot among the flights. Equation (6) guarantees that if two consecutive flights $j'j'' \in J$ and $jj' \in J$ on day $jj' \in J$ in two consecutive permutations are assigned to pilot $i \in I$ in scenario $s \in S$ ($X_{ij'j''d,n+1,s} = 1$ and $X_{ijj'dns} = 1$), therefore, between the landing time of flight $jj' \in J$ and the departure of flight $j'j'' \in J$ to have the minimum possible time (φ) for the pilot to rest and move. Equation (7) guarantees that if two consecutive flights $j'j'' \in J$

and $jj' \in J$ on day $d \in D$ in two consecutive permutations are assigned to pilot $i \in I$ in scenario $s \in S$ ($X_{ij'j''d+1,n+1,s} = 1$ and $X_{ijj'd,ns} = 1$), so it should be between the landing time of flight $jj' \in J$ and the departure of flight $j'j'' \in J$ is the minimum possible time (ψ) for the pilot to rest. Equation (8) states that if pilot $i \in I$ performs his first work day in scenario $s \in S$ ($Y_{id1s} = 1$), then this pilot should start his work schedule from his place of residence (o_i) start that day $(S_{io_ids} = 1)$. Equation (9) states that if for pilot $i \in I$, the working day $f \in D$ is on day d ($Y_{idfs} = 1$) and after that the working day is not defined $\left(\sum_{d'=d+1}\sum_{f'=f+1} Y_{id'f's} = 0\right)$, so this day ($d \in D$) is the last working day for the pilot in question and there should be a flight at the end of the day to the pilot's place of residence (o_i) to take place $(W_{io_ids} = 1)$. Equation (10) guarantees that if the pilot $i \in I$, does his f^{th} working day in scenario $s \in S$ ($Y_{idfs} = 1$) and $f + 1^{\text{th}}$ working day in the scenario $s \in S$ ($Y_{id',f+1,s} = 1$), therefore, from the place where he finished his work on the day $d \in D$ in the location $j \in J$. He should start his work schedule from there on day $d' \in D$ ($s_{ijd's} = W_{ijds}$). Equation (11) is the balance equation and specifies a series of flights that are created in one consecutive day for a pilot's work schedule. Equation (12) guarantees that if pilot $i \in I$ has no work schedule on day $d \in D$ $\left(\sum_f Y_{idfs} = 0\right)$, therefore no flight should be considered in this pilot's work schedule for this day $\left(\sum_{j'}\sum_j X_{ijj'dns} = 0\right)$, and otherwise a flight on this day is considered for the pilot $\left(\sum_{j'}\sum_j X_{ijj'dns} \geq 1\right)$. Equations (13) and (14) guarantee that if day $d \in D$ for pilot $i \in I$ in scenario $s \in S$ is a working day $\left(\sum_f Y_{idfs} = 1\right)$, then there is only one place from where the pilot can plan his flight. It starts on that day $\left(\sum_j S_{ijds} = 1\right)$ and there is only one place where the pilot completes his flight schedule on that day $\left(\sum_j W_{ijds} = 1\right)$. Equation (15) states that each day of the planning horizon can be considered as a working day at most once. Equation (16) states that the f^{th} working day for pilot $i \in I$ can be at most one of the days in the planned horizon. Equation (17) guarantees that every pilot must have a working day at least on one of the days of the planning horizon. Equation (18) guarantees that the working day index $f \in D$ must be smaller than to the day index $d \in D$. Equation (19) states that if $S_{ijds} = 1$ in a day, then there must be a flight from $j \in J$ to other places in the working schedule of the pilot. Equation (20) guarantees that if on the first working day ($f = 1$) there is a flight from $j \in J$ to $j' \in J$ in the permutation ($n + 1$), then in the previous permutation ($n \in N$) there must be a flight to $j \in J$ in the desired pilot's work plan. Equation (21) states that on a working day other than the first day ($f + 1$), if there is a flight from $j \in J$ to $j' \in J$ in the permutation ($n + 1$), therefore, in the previous permutation ($n \in N$) there must be a flight to $j \in J$ in the working schedule of the intended pilot on the same working day ($f + 1$) or the previous working day ($f \in D$). Equation (22) guarantees that if working day ($f + 1$) in the pilot's work schedule takes place on day ($d \in D$) from the planning horizon ($Y_{id,f+1,s} = 1$), therefore working day ($f \in D$)is also before that on day $d' \in D$ should be $\left(\sum_{\substack{d' \\ d'<d}} Y_{id'fs} = 1\right)$. Equation (23) limits the amount of flight time per day for each pilot to the maximum value of ρ. Equation (24)

limits the amount of flight time in the planning horizon for each pilot to the maximum value of τ. Equation (25) limits the working time from the start of the first flight in a day to the last flight in that day to the maximum value of σ. Equation (26) shows the total costs of the consecutive flight and the pilot not returning to his residence on the day of the flight in each scenario. Equations (27) and (28) show the maximum changes of the main decision variables of the problem in the robust model (Ben-Tal et al., 2009). Equation (29) shows the type of the decision variables.

4 Initial solution and MOPSSCA

Many researchers have tried to solve the FCS problem with exact and heuristic methods (Yaakoubi et al., 2021; Wen et al., 2021; Gopalakrishnan and Johnson, 2005; Klabjan et al., 2002). Therefore, in the literature, FCS is known as an NP-hard problem. As a result, researchers have tried to provide effective meta-heuristic algorithms to solve the FCS problem. In this section, a hybrid MOPSO and MOSCA called MOPSSCA is presented and the operators of the hybrid algorithm are described.

The most important part in implementing the proposed algorithm is designing the initial solution. Figure 2 shows the initial solution of the problem. In this paper, this solution is a row vector whose columns are equal to the number of available flights. These columns are sorted in descending order based on the number of flight pairs. In other words, the first columns show flights with fewer pairs and the last columns show flights with more pairs. Each column is filled with a random key number. Random keys were first introduced by Bean (1994). Flight selection starts from the beginning of this vector and continues until the end. After a flight is selected, the pair that contains that flight is determined through the chromosome. In fact, the random number in this solution is multiplied by the number of pairs related to the selected flight and the desired pairing is determined. The above method is repeated for other choices. During flight selection, if a flight has already been selected by the pair(s), it is ignored. The selection process continues until no flight is selected (Saemi et al., 2022).

Figure 2 Initial solution for FCS problem (see online version for colours)

Flight 1	*Flight 2*	*Flight 3*		...		*Flight n-2*	*Flight n-1*	*Flight n*
0.17	*0.64*	*0.38*	...	...	...	*0.84*	*0.32*	*0.24*

Flight 1	*Flight n*	*Flight n-1*	...	...	...	*Flight 3*	*Flight 2*	*Flight n-2*
0.17	*0.24*	*0.32*	...	...	...	*0.38*	*0.64*	*0.84*

Population-based optimisation techniques start the optimisation process with a set of random solutions. This random set is repeatedly evaluated by an objective function and improved by a set of rules that are the core of the optimisation technique. Because population-based optimisation techniques randomly seek to optimise optimisation problems, there is no guarantee of finding a solution in a single run. However, with a sufficient number of random solutions and optimisation steps (iterations), the probability of finding the global optimum increases. Regardless of the differences between algorithms in the field of population-based optimisation, it is common to divide the optimisation process into two phases: exploration versus exploitation (Mirjalili et al., 2020).

In the first step, the optimisation algorithm combines random solutions to find promising regions of the search space. In the exploitation phase, however, gradual changes in the stochastic solutions occur, and the stochastic changes are significantly less than in the exploration phases. In the proposed algorithm, in addition to the equations related to the search for the solution based on the sin and cos equations, the movement and speed of each solution are also effective. In this paper, the following position update equations are proposed for both stages:

$$X_i^{t+1} = X_i^t + r_1 \cdot \sin(r_2) \cdot \left| r_3 P_i^t - X_i^t \right| \tag{30}$$

$$X_i^{t+1} = X_i^t + r_1 \cdot \cos(r_2) \cdot \left| r_3 P_i^t - X_i^t \right| \tag{31}$$

$$\begin{cases} V_i^{t+1} = V_i^t + c_1 r_1 \left(pbest_i - X_i^t \right) + c_2 r_2 \left(gbest_i - X_i^t \right) \\ X_i^{t+1} = X_i^t + V_i^{t+1} \end{cases} \tag{32}$$

where x_i^t is the position of the current solution in the i^{th} dimension (size) in the t^{th} iteration and r_1, r_2, r_3 are random numbers and P_i^t is the position of the destination point in the i^{th} dimension and | | refers to absolute value. Also, V_i^{t+1} the velocity of dimension *i* in the new iteration *t*, V_i^t the velocity of dimension *i* in the current iteration *t*, X_i^{t+1} the current position of dimension $t + 1$, X_i^t the position of the particle in the new iteration, $pbest_i$ is the best position that dimension *i* has taken so far, and $gbest_i$ is the best position of the best dimension (the best position that all solutions have taken so far). c_1 and c_2 are cognitive and social parameters, respectively. These three equations are combined for use as follows:

$$\begin{cases} X_i^{t+1} = X_i^t + r_1 \cdot \sin(r_2) \cdot \left| r_3 P_i^t - X_i^t \right| & r_4 < 0.3 \\ X_i^{t+1} = X_i^t + r_1 \cdot \cos(r_2) \cdot \left| r_3 P_i^t - X_i^t \right| & 0.3 \le r_4 < 0.6 \\ \begin{cases} V_i^{t+1} = V_i^t + c_1 r_1 \left(pbest_i - X_i^t \right) + c_2 r_2 \left(gbest_i - X_i^t \right) \\ X_i^{t+1} = X_i^t + V_i^{t+1} \end{cases} & r_4 \ge 0.6 \end{cases} \tag{33}$$

where r_4 is random number between [0, 1]. As the above equations show, there are four main parameters in MOPSSCA r_1, r_2, r_3 and r_4. The parameter r_1 refers to the position of the next region (or the direction of movement), which can be in the space between the solution and the destination or outside it. The parameter r_2 defines how far the movement should be towards the destination or away from it. The r_3 parameter gives you a random weight for the destination to emphasise randomness ($r_3 > 1$) or low importance ($r_3 < 1$) in determining the distance. Finally, the parameter r_4 varies equally between the components of equation (33).

An algorithm should be able to balance exploration and exploitation to find promising regions of the search space and eventually converge to the global optimum. In order to balance exploration and exploitation, the amplitude of sine and cosine in equation (33) is adaptively changed using the following equation:

$$\begin{cases} X_i^{t+1} = X_i^t + a - t\dfrac{a}{Max\ it} \cdot \sin([0, 2\pi]) \cdot \left| r_3 P_i^t - X_i^t \right| & r_4 < 0.3 \\ X_i^{t+1} = X_i^t + a - t\dfrac{a}{Max\ it} \cdot \cos([0, 2\pi]) \cdot \left| r_3 P_i^t - X_i^t \right| & 0.3 \le r_4 < 0.6 \\ \begin{cases} V_i^{t+1} = wV_i^t + c_1 a - t\dfrac{a}{Max\ it}\left(pbest_i - X_i^t \right) \\ \qquad +c_2[0, 2\pi]\left(gbest_i - X_i^t \right) \\ X_i^{t+1} = X_i^t + V_i^{t+1} \end{cases} & r_4 \ge 0.6 \end{cases} \tag{34}$$

where t is the current iteration, *Max it* is the maximum number of iterations, and a is a constant. In the MOPSSCA, the search for new solutions is based on the combination of the operators of the MOSCA and MOPSO, and due to the bi-objective of the FCS problem, a set of effective solutions is obtained in each iteration.

5 Analysis of the results

In this section of the paper, the analysis of different numerical examples is discussed. First, a numerical example is designed in a small size and using the epsilon constraint method (EPC), the problem is solved and the Pareto front is analysed. Next, in order to solve numerical examples in a large size, the parameters of the heuristic algorithms have been tuned and numerical comparisons have been made of the indices of these algorithms.

5.1 Analysis of numerical example in small size

Before solving sample problems in larger scales, a sample problem with three airports, three pilots for two consecutive days and in two scenarios has been considered. Also, the parameters of the problem are considered based on the uniform distribution as described in Table 2. Also, the flight schedule is presented in Table 3.

Table 2 The value of the parameters

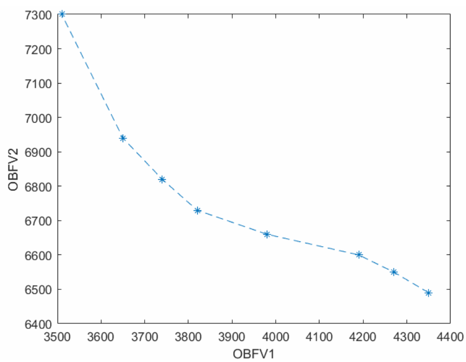
Parameter	*Approximate interval*	*Parameter*	*Approximate interval*
$l_{jj'ds}$	$\sim U[0, 60]$ min	τ	600 min
$d_{jj'ds}$	$\sim U[45, 120]$ min	σ	1,500 min
φ	20 min	$m_{jj'ds}$	$\sim U[800, 1{,}200]\$$
ψ	300 min	h	\$300
ρ	400 min	$c_{jj'}$	$\sim U[700, 1{,}000]$ Lit/km
τ	600 min		

Table 3 The flight schedule

Airport	*Day 1*			*Day 2*		
	1	*2*	*3*	*1*	*2*	*3*
1	-	flight		-	2 flights	flight
2	flight	-	flight	flight	-	flight
3	2 flights	-	-	-	flight	-

According to the data presented in Table 3 and also considering the probability of occurrence of 50% for each scenario, the set of efficient solutions obtained from solving the problem with the EPC is shown in Figure 3.

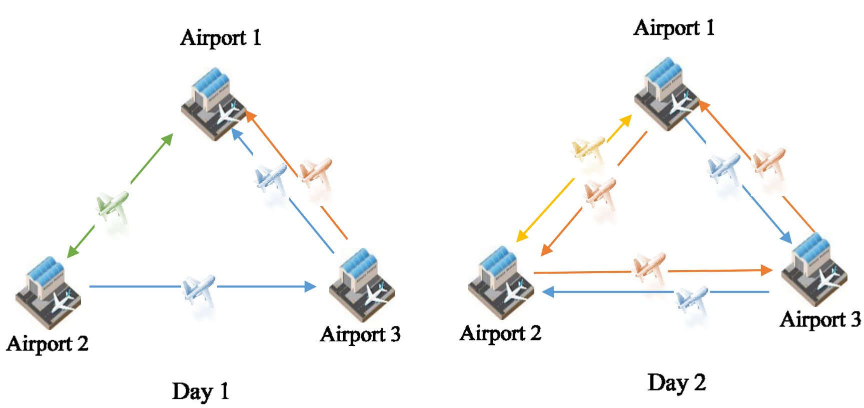
Figure 3 Efficient solutions and Pareto front obtained (see online version for colours)



OBF2	*OBF1*	*Efficient solution*
4,350	6,490	1
4,270	6,550	2
4,190	6,600	3
3,980	6,660	4
3,820	6,730	5
3,740	6,820	6
3,650	6,940	7
3,510	7,300	8

According to the above results, it can be seen that by reducing the amount of fuel consumption due to the change in the flight schedule of the plane on different days, the total costs increase. Based on the EPC in solving the sample problem, eight different efficient solutions have been obtained, which the flight schedule in the first efficient solution is shown in Figure 4.

Figure 4 FCS for the first efficient solution to the problem (see online version for colours)



5.2 Sensitivity analysis

The ability of the TSSRP to control the uncertainties is evaluated using expected value of perfect information (EVPI) and value of stochastic solution (VSS). The EVPI measure is determined as the difference between random solutions and wait-and-see (WS) solutions and shows how valuable it is to know the future with complete certainty. For this purpose, the landing/ departure time has been studied, and the $EVPI = WS - SP$ in Table 3 is shown. In Table 4, the value of EVPI when landing and departure time is considered as an uncertainty parameter is presented. To calculate the value of EVPI, first, the stochastic problem is solved for each scenario separately. According to the optimal solution and the probabilities of each scenario, weighted averages are calculated for all solutions, which represent the WS solution. EVPI is then calculated as the difference between the WS solutions and the SP random solutions.

Table 4 EVPI value in uncertain conditions of parameters

Uncertainty parameter	*SP*		*WS*		*EVPI*	
	OBF1	*OBF2*	*OBF1*	*OBF2*	*OBF1*	*OBF2*
Landing time	4,355	6,512	4,369	6,624	14	112
Departure time	4,370	6,530	4,391	6,693	21	163

The results of Table 4 show that the uncertainty in the departure time compared to the landing time has a greater impact on the flight crew's timing. Therefore, managers should bear more costs in order to achieve high accuracy of the network. Also, to measure the advantages of using the TSSRP over the deterministic approach, VSS is calculated and is defined as the absolute difference between the EEV solutions and the SP solutions. In this case, the higher the value of VSS shows that the random programming approach has a higher ability to deal with uncertainty in the network. To calculate expected value (EEV), instead of uncertainty parameters, the average of the expected data is used in the model to represent the deterministic state of the network. Therefore, Table 5 shows the value of VSS when landing and departure time are considered as uncertainty parameters.

Table 5 VSS value in uncertain conditions of parameters

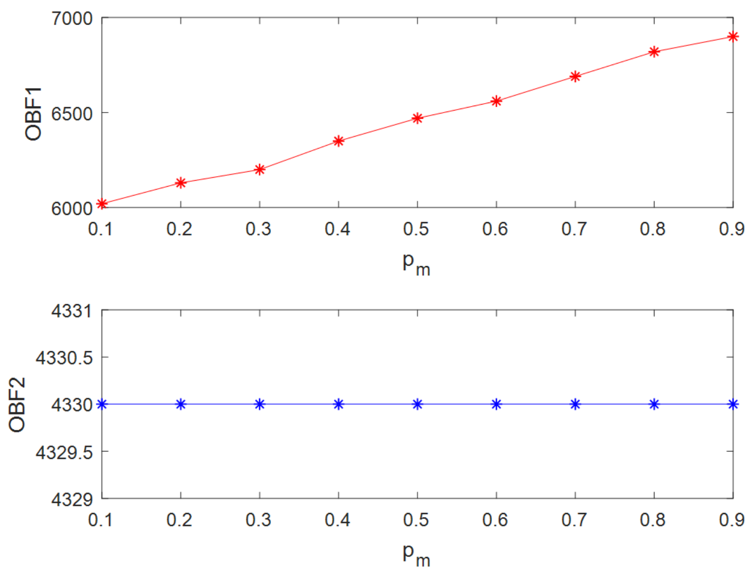
Uncertainty parameter	*SP*		*EEV*		*VSS*	
	OBF1	*OBF2*	*OBF1*	*OBF2*	*OBF1*	*OBF2*
Landing/departure time	4,381	6,535	4,423	6,693	42	158

Based on the results of Table 5, it can be seen that the value of VSS for OBFs in the EPC is a positive value, which indicates that the use of a TSSRP has a higher reliability to deal with the uncertainty of the environment for the FCS problem. In the following, the impact of the probability event on the total cost of FCS and the amount of fuel consumed in a sample problem has been investigated. Since in the analysed example the probability of occurrence was considered equal to 50%, in Table 6 the changes of the OBFs for different occurrences are shown for the first efficient solution.

Table 6 Changes in the OBFs in the probability of occurrence of different scenarios

Scenario	*Probability in first scenario*	*OBF1*	*OBF2*
1	10%	6,120	4,240
2	20%	6,180	4,290
3	30%	6,230	4,310
4	40%	6,370	4,330
5	50%	6,490	4,350
6	60%	6,540	4,370
7	70%	6,680	4,410
8	80%	6,790	4,450
9	90%	6,840	4,480

Figure 5 Changes in the OBFs in the different uncertainty rate (see online version for colours)



According to the results of Table 6, it can be seen that with the increase in the probability of occurrence in the second scenario due to the increase in the costs of this scenario as well as the change in the flight schedule of the planes and the interference in the schedule, the costs related to the FCS have increased. Also, this has led to an increase in the amount of fuel consumed.

Figure 5 also shows the amount of OBFs in different uncertainty rates. The results of Figure 5 show that with the increase of the uncertainty rate, there is interference in the schedule and the flights do not take place on time. This includes the increase in total costs associated with rescheduling flights under robustness state. While the amount of fuel consumption has not changed.

5.3 *Tuning of algorithm parameters*

Due to the NP-hardness of the FCS problem, the sample problem is analysed with MOPSO, MOSCA, and MOPSSCA again, and the set of efficient solutions are compared with each other. Before solving numerical examples in large size, tuning of algorithm parameters is done by Taguchi method.

Table 7 Comparison indices of effective solutions

Index	*Equation*	*Effective*
Number of Pareto front (NPF)	-	A higher value is better
Maximum spread index (MSI)	$\sqrt{\sum_{m=1}^{M}\left(\max_{i=1:\lvert Q\rvert} f_m^i - \max_{i=1:\lvert Q\rvert} f_m^j\right)^2}$	A higher value is better
Space metric (SM)	$\sqrt{\frac{1}{\lvert Q\rvert}\sum_{i=1}^{\lvert Q\rvert}\left(\min_{k\in Q\cap k\neq i}\sum_{m=1}^{M}\lvert f_m^i - f_m^k\rvert - \sum_{i=1}^{\lvert Q\rvert}\frac{\min_{k\in Q\cap k\neq i}\sum_{m=1}^{M}\lvert f_m^i - f_m^k\rvert}{\lvert Q\rvert}\right)^2}$	A lower value is better
CPU time		A lower value is better

Table 8 Tuned parameter of algorithms

Algorithm	*Parameter*	*Best level*	*Best value*
MOPSSCA	*N population*	3	200
	Max it	3	300
	c_1	1	1.5
	c_2	2	2
	a	3	3
MOPSO	*N particle*	3	200
	Max it	3	300
	c_1	1	1.5
	c_2	2	2
MOSCA	*N population*	2	150
	Max it	3	300
	a	2	2

Tuning the initial parameters of meta-heuristic algorithms is done in order to better search for solutions in achieving near-optimal solutions. In this method, a set of different levels is defined for each parameter and an initial parameter value is proposed for each row. Then, based on Taguchi's tests consisting of the number of parameters and defined levels, the mathematical model of the solution and the value of RPD is obtained based on equations (35) and (36) (Taguchi and Konishi, 1987). The best value of each parameter level is obtained based on the results obtained from the means of SN ratios.

$$Fitness_i = \frac{|NPF + MSI + SM + CPUTime|}{4} \tag{35}$$

$$RPD_i = \frac{Fitness_i - Best\ Fitness}{Best\ Fitness} \tag{36}$$

In the above equations, $Fitness_i$ is the test solution obtained from the integration of four indicators *NPF*, *MSI*, *SM* and *CPUTime*. Also, *Best Fitness* is defined as the best value of all tests obtained. The indicators used in each test are described in Table 7.

Based on the results of Taguchi's test, the tuning of the algorithms is as shown in Table 8.

5.4 Analysis of numerical example in large size

Table 9 shows the set of efficient solutions for the sample problem with different solution methods.

Table 9 The set of effective solutions with different solution methods

Efficient solution	*EPC*		*MOPSSCA*		*MOPSO*		*MOSCA*	
	OBF1	*OBF2*	*OBF1*	*OBF2*	*OBF1*	*OBF2*	*OBF1*	*OBF2*
1	6,490	4,350	6,470	4,490	6,380	4,480	6,410	4,430
2	6,550	4,270	6,510	4,350	6,490	4,350	6,530	4,270
3	6,600	4,190	6,550	4,270	6,570	4,230	6,600	4,190
4	6,660	3,980	6,570	4,240	6,600	4,190	6,690	3,990
5	6,730	3,820	6,590	4,200	6,690	3,970	6,710	3,940
6	6,820	3,740	6,600	4,190	6,710	3,910	6,730	3,820
7	6,940	3,650	6,630	4,120	6,730	3,820	6,820	3,740
8	7,300	3,510	6,740	3,860	6,820	3,740	6,830	3,700
9			6,820	3,740	6,950	3,630	6,890	3,680
10			6,940	3,660	7,300	3,510	6,940	3,650
11			7,300	3,510				

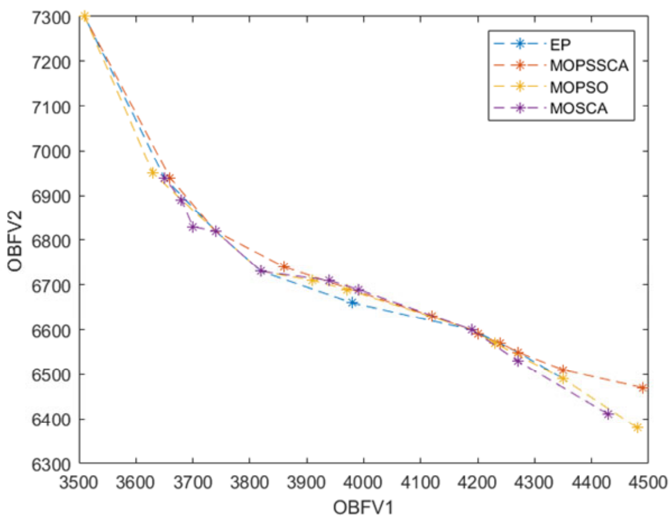
Table 10 Indices obtained from different solution methods (Small scale)

Algorithm	*EPC*	*MOPSSCA*	*MOPSO*	*MOSCA*
$\overline{OBF1}$	*3,938.75*	4,057.27	3,983.00	3,941.00
$\overline{OBF2}$	6,761.25	*6,701.81*	6,724.00	6,715.00
NPF	8	*11*	10	10
MSI	1,166.92	1,284.25	*1,336.90*	943.027
SM	*0.224*	0.480	0.397	0.507
CPUtime	620.18	46.90	44.37	*38.17*

According to the results of Table 9, it can be seen that with the reduction of the amount of fuel consumed per consecutive flights, the costs related to the allocation of the crew to the flights have increased. Also, based on the observed results of the hybrid MOPSSCA, it has been able to obtain 11 different efficient solutions. Table 10 also compares the indicators obtained from the analysis of different efficient solutions.

The results of Table 10 show the very closeness of the averages obtained by each solution method. Based on the indicators used, it can be seen that the best OBF1 and SM is by the EPC, the best OBF2 and NPF by the MOPSCA, the best MSI by the MOPSO and the best problem solving time by the MOSCA. The closeness of the values of the OBFs to each other shows the high efficiency of the proposed meta-heuristic algorithms in solving the FCS problem. Figure 6 also compares the Pareto front obtained from solving a sample problem with different solution methods.

Figure 6 Pareto front obtained with different solution methods (see online version for colours)



Due to the ineffectiveness of the EPC method in solving large-scale sample problems, ten large-scale sample problems have been solved with meta-heuristic algorithms. Therefore, Table 11 shows the scale of sample problems and Table 12 shows the average OBFs and indices obtained from with meta-heuristic algorithm. Also, the parameters of the problem are based on the values presented in Table 2.

Table 11 The scale of sample problems

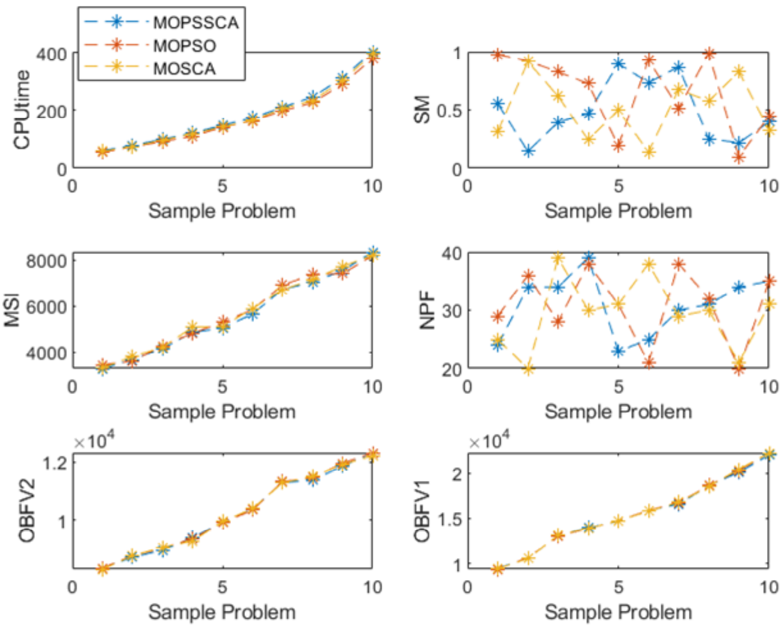
Sample problem	$\|J\|$	$\|I\|$	$\|S\|$	$\|D\|$	*Sample problem*	$\|J\|$	$\|I\|$	$\|S\|$	$\|D\|$
1	4	4	2	7	6	6	6	4	20
2	4	4	2	10	7	8	7	5	22
3	5	5	3	12	8	8	8	5	25
4	5	5	3	15	9	10	9	6	28
5	6	6	4	18	10	10	10	6	30

Table 12 Indices obtained from different solution methods (large scale)

Sample problem	*Algorithm*	$\overline{OBF1}$	$\overline{OBF2}$	*NPF*	*MSI*	*SM*	*CPUtime*
1	MOPSSCA	9,460	8,320	24	3,283.67	0.554	60.61
2		10,540	8,710	34	3,671.94	0.143	78.15
3		13,090	8,950	34	4,154.24	0.393	99.67
4		13,970	9,380	39	4,854.21	0.470	120.37
5		14,690	9,920	23	5,039.78	0.896	148.34
6		15,890	10,390	25	5,643.7	0.734	173.67
7		16,610	11,290	30	6,721.2	0.868	210.64
8		18,620	11,360	31	7,034.98	0.252	246.39
9		20,140	11,870	34	7,531.76	0.217	312.34
10		22,110	12,330	35	8,333.87	0.396	403.14
1	MOPSO	9,370	8,340	29	3,443.18	0.975	54.55
2		10,640	8,760	36	3,602.93	0.920	73.46
3		12,980	9,020	28	4,272.24	0.825	91.70
4		13,900	9,340	38	4,818.19	0.726	109.54
5		14,750	9,905	31	5,285.73	0.190	140.92
6		15,900	10,340	21	5,839.13	0.930	163.25
7		16,780	11,320	38	6,894.98	0.513	198.00
8		18,640	11,450	32	7,380.68	0.983	226.68
9		20,340	11,970	20	7,397.86	0.097	290.48
10		22,340	12,320	35	8,179.90	0.444	378.95
1	MOSCA	9,430	8,300	25	3,293.38	0.311	58.19
2		10,540	8,760	20	3,811.71	0.913	74.24
3		13,100	9,050	39	4,205.85	0.618	96.68
4		13,910	9,260	30	5,074.46	0.242	117.96
5		14,730	9,950	31	5,113.31	0.496	142.41
6		15,830	10,390	38	5,878.76	0.139	164.99
7		16,790	11,280	29	6,714.87	0.674	206.43
8		18,530	11,490	30	7,127.39	0.576	234.07
9		20,480	11,930	21	7,723.08	0.826	302.97
10		22,320	12,220	31	8,179.72	0.328	395.08

Based on the analysis, MOPSSCA has obtained the best average of the first and second objective function in solving 10 large scale sample problems with an average solution time of 185.33 seconds. Also, this algorithm has the ability to achieve more effective solutions with the lowest SM value. The MOPSO also has the lowest average solution time and the MOSCA has the highest MSI value. Figure 7 shows the average indices of comparison between three meta-heuristic algorithms in solving large scale sample problems of the FCS problem.

Figure 7 The average indices of comparison of efficient solutions (see online version for colours)



Based on the obtained results, it can be said that the hybrid MOPSSCA with the ability to use the operators of the MOPSO and MOSCA has achieved more efficient solutions than other algorithms. This is despite the fact that the average of the OBFs was lower than the other two algorithms. Also, the problem solving time has no significant difference with the calculation time of MOPSO and MOSCA. Therefore, this algorithm can be used as an effective algorithm in solving the FCS problem.

6 Conclusions

Flight scheduling is a challenging issue in airports. In flight scheduling, there is a set of issues of FC, FA, FR, and CS. Therefore, this problem is considered as one of the NP-hard problems that has attracted the attention of many researchers today. In this paper, the modelling of a FCS problem under uncertainty in the landing/departure time of flights and also the costs of consecutive flights, in which all flight rules are observed, was discussed. In the designed model, there are two OBF of minimising the total costs of consecutive flights and minimising the amount of fuel consumed by airplanes. To achieve these OBFs at the same time, decisions such as FC, FA, FR, and CS were made. Also, uncertainty parameters were presented in different scenarios, and the results of the analysis of the model using the EPC method showed that the costs associated with consecutive flights have increased with the reduction in the amount of fuel consumed. Also, in different scenarios, it was observed that with the change in the flight schedule due to the interference of the flights with each other, the costs related to the flight and the amount of fuel consumed have increased. The positive values of EVPI showed that the uncertainty in the departure has a greater impact on the problem than the landing time.

Therefore, managers should bear more costs in order to achieve high accuracy of the network. Also, to measure the benefits of using the TSSRP method compared to the deterministic method, VSS was calculated and the positive results of this index showed that this method has a higher ability to deal with uncertainty in the network.

In this paper, in order to solve the problem and achieve the Pareto front, a new hybrid algorithm based on MOPSO and MOSCA was presented, in which the operators of the two algorithms are present. The results of problem solving with the MOPSSCA show the high efficiency of the algorithms in solving numerical examples with the lowest error coefficient. So that the maximum percentage of relative difference with the obtained optimal solution was less than 2%. Therefore, the comparison of indices such as *NPF*, *MSI*, *SM* and *CPU-time* in large scale sample problems showed that the proposed new MOPSSCA has a higher efficiency in solving the FCS problem compared to the MOPSO and MOSCA.

For future research, it is suggested that the issue of aircraft maintenance and repair after each flight, as well as the presence of bad weather conditions that lead to excessive delays in the flight and schedule, should be addressed. Also, the development of new meta-heuristic algorithms is suggested in solving the problem.

References

Androutsopoulos, K.N., Manousakis, E.G. and Madas, M.A. (2020) 'Modeling and solving a bi-objective airport slot scheduling problem', *European Journal of Operational Research*, Vol. 284, No. 1, pp.135–151.

Antunes, D., Vaze, V. and Antunes, A.P. (2019) 'A robust pairing model for airline crew scheduling', *Transportation Science*, Vol. 53, No. 6, pp.1751–1771.

Baradaran, V. and Hosseinian, A.H. (2021) 'A multi-objective mathematical formulation for the airline crew scheduling problem: MODE and NSGA-II solution approaches', *Journal of Industrial Management Perspective*, Spring, Vol. 11, No. 1, pp.247–269.

Bean, J.C. (1994) 'Genetic algorithms and random keys for sequencing and optimization', *ORSA Journal on Computing*, Vol. 6, No. 2, pp.154–160.

Ben-Tal, A., El Ghaoui, L. and Nemirovski, A. (2009) *Robust Optimization*, Vol. 28, Princeton University Press, USA.

Cecen, R.K. (2022) 'A stochastic programming model for the aircraft sequencing and scheduling problem considering flight duration uncertainties', *The Aeronautical Journal*, Vol. 126, No. 1304, pp.1736–1751.

Chin, C.H.Y. (2021) *Disruptions and Robustness in Air Force Crew Scheduling*, Doctoral dissertation, Massachusetts Institute of Technology.

Cordeau, J.F., Stojković, G., Soumis, F. and Desrosiers, J. (2001) 'Benders decomposition for simultaneous aircraft routing and crew scheduling', *Transportation Science*, Vol. 35, No. 4, pp.375–388.

Crego, A., Hanne, T. and Dornberger, R. (2023) 'Multiobjective optimization of airline crew management with a genetic algorithm', *Innovations in Bio-Inspired Computing and Applications: Proceedings of the 13th International Conference on Innovations in Bio-Inspired Computing and Applications (IBICA 2022)*, 15–17 December 2022, Springer Nature Switzerland, Cham, pp.109–119.

Dai, J., Zhang, Y., Zhang, M. and Wang, M. (2021) 'Simulation and optimization of flight scheduling in dual-runway cargo airport for vaccine transport based on artificial bee colony algorithm', *International Conference of Artificial Intelligence, Medical Engineering, Education*, October, Springer, Cham, pp.206–218.

Deveci, M. and Demirel, N.Ç. (2018) 'A survey of the literature on airline crew scheduling. *Engineering Applications of Artificial Intelligence*, Vol. 74, pp.54–69 [online] https://www.sciencedirect.com/science/article/abs/pii/S0952197618301234.

Dixit, V. (2022) 'Applications of operational research in airline management and scheduling', *International Journal of Mechanical Engineering*, Vol. 7, No. 2, pp.853–864.

Du, Z., Zhang, J. and Kang, B. (2023) 'A data-driven method for arrival sequencing and scheduling problem', *Aerospace*, Vol. 10, No. 1, p.62.

Garg, A., Agarwal, Y., Srivastava, R.K. and Jakhar, S.K. (2024) 'Integrated commercial and operations planning model for schedule design, aircraft rotation and crew scheduling in airlines', *Networks*, Vol. 83, No. 4, pp.653–672.

Gopalakrishnan, B. and Johnson, E. (2005) 'Airline crew scheduling: state-of-the-art', *Annals of Operations Research*, Vol. 140, No. 1, pp.305–337.

Gui, D., Le, M., Huang, Z., Zhang, J. and D'Ariano, A. (2023) 'Optimal aircraft arrival scheduling with continuous descent operations in busy terminal maneuvering areas', *Journal of Air Transport Management*, Vol. 107, p.102344 [online] https://www.sciencedirect.com/science/article/abs/pii/S0969699722001636.

Gürkan, H., Gürel, S. and Aktürk, M.S. (2016) 'An integrated approach for airline scheduling, aircraft fleeting and routing with cruise speed control', *Transportation Research Part C: Emerging Technologies*, Vol. 68, pp.38–57 [online] https://www.sciencedirect.com/science/article/abs/pii/S0968090X16000723.

Hu, Y., Liao, H., Zhang, S. and Song, Y. (2017) 'Multiple objective solution approaches for aircraft rerouting under the disruption of multi-aircraft', *Expert Systems with Applications*, Vol. 83, pp.283–299 [online] https://www.sciencedirect.com/science/article/abs/pii/S095741741730249X.

Jangizehi, M., Rasouli Kenari, A. and Hosseinkhani, J. (2023) 'Proper process selection during flight schedule disruption using a fuzzy multi-criteria decision-making expert system', *Iranian Journal of Fuzzy Systems*, Vol. 20, No. 2, pp.121–133.

Kasirzadeh, A., Saddoune, M. and Soumis, F. (2017) 'Airline crew scheduling: models, algorithms, and data sets', *EURO Journal on Transportation and Logistics*, Vol. 6, No. 2, pp.111–137.

Katsigiannis, F.A. and Zografos, K.G. (2021) 'Optimising airport slot allocation considering flight-scheduling flexibility and total airport capacity constraints', *Transportation Research Part B: Methodological*, Vol. 146, pp.50–87 [online] https://www.sciencedirect.com/science/article/pii/S0191261521000254.

Kenan, N., Jebali, A. and Diabat, A. (2018) 'An integrated flight scheduling and fleet assignment problem under uncertainty', *Computers & Operations Research*, Vol. 100, pp.333–342 [online] https://www.sciencedirect.com/science/article/abs/pii/S0305054817302216.

Klabjan, D., Johnson, E.L., Nemhauser, G.L., Gelman, E. and Ramaswamy, S. (2002) 'Airline crew scheduling with time windows and plane-count constraints', *Transportation Science*, Vol. 36, No. 3, pp.337–348.

Lee, L.H., Lee, C.U. and Tan, Y.P. (2007) 'A multi-objective genetic algorithm for robust flight scheduling using simulation', *European Journal of Operational Research*, Vol. 177, No. 3, pp.1948–1968.

Li, J., Zhong, Q., Yi, L., Wang, Q., Zuo, J. and Liu, Y. (2022) 'Hybrid optimization of arrival and departure flight schedules', *Proceedings of the 5th China Aeronautical Science and Technology Conference*, Springer, Singapore, pp.103–119.

Liang, W. and Li, Y. (2014) 'Research on optimization of flight scheduling problem based on the combination of ant colony optimization and genetic algorithm', *2014 IEEE 5th International Conference on Software Engineering and Service Science*, June, IEEE, pp.296–299.

Liu, M., Ding, Y., Sun, L., Zhang, R., Dong, Y., Zhao, Z., … and Liu, C. (2023) 'Green airline-fleet assignment with uncertain passenger demand and fuel price', *Sustainability*, Vol. 15, No. 2, p.899.

Liu, T.K., Chen, C.H. and Chou, J.H. (2010) 'Optimization of short-haul aircraft schedule recovery problems using a hybrid multiobjective genetic algorithm', *Expert Systems with Applications*, Vol. 37, No. 3, pp.2307–2315.

Mirjalili, S.M., Mirjalili, S.Z., Saremi, S. and Mirjalili, S. (2020) 'Sine cosine algorithm: theory, literature review, and application in designing bend photonic crystal waveguides', in Mirjalili, S., Song Dong, J. and Lewis, A. (Eds.): *Nature-Inspired Optimizers. Studies in Computational Intelligence*, Vol. 811, Springer, Cham., https://doi.org/10.1007/978-3-030-12127-3_12.

Nafstad, G.M., Haugseth, A., Høyland, V. and Stålhane, M. (2021) 'An exact solution method for a rich helicopter flight scheduling problem arising in offshore oil and gas logistics', *Computers & Operations Research*, Vol. 128, p.105158 [online] https://www.sciencedirect.com/science/article/pii/S0305054820302756.

Nozari, H., Ghahremani-Nahr, J. and Szmelter-Jarosz, A. (2023) 'A multi-stage stochastic inventory management model for transport companies including several different transport modes', *International Journal of Management Science and Engineering Management*, Vol. 18, No. 2, pp.134–144.

Orhan, I. (2022) 'Bi-objective goal programming for airline crew pairing', *Eskişehir Technical University Journal of Science and Technology A – Applied Sciences and Engineering*, Vol. 23, No. 1, pp.126–136.

Ouyang, W. and Zhu, X. (2023) 'Meta-heuristic solver with parallel genetic algorithm framework in airline crew scheduling', *Sustainability*, Vol. 15, No. 2, p.1506.

Rodič, B. and Baggia, A. (2017) 'Airport ground crew scheduling using heuristics and simulation', *Applied Simulation and Optimization 2*, Springer, Cham, pp.131–160.

Saemi, S., Rashidi Komijan, A., Tavakkoli-Moghaddam, R. and Fallah, M. (2022) 'An integrated crew scheduling problem considering reserve crew in air transportation: ant colony optimization algorithm', *Journal of Optimization in Industrial Engineering*, Vol. 15, No. 2, pp.167–177.

Salem, I.E., Mijwil, M.M., Abdulqader, A.W. and Ismaeel, M.M. (2022) 'Flight-schedule using Dijkstra's algorithm with comparison of routes findings', *International Journal of Electrical and Computer Engineering*, Vol. 12, No. 2, p.1675.

Shambour, M.K. and Abu-Hashem, M.A. (2023) 'Optimizing airport slot scheduling problem using optimization algorithms', *Soft Computing*, Vol. 27, No. 12, pp.7939–7955.

Shao, S., Sherali, H.D. and Haouari, M. (2017) 'A novel model and decomposition approach for the integrated airline fleet assignment, aircraft routing, and crew pairing problem', *Transportation Science*, Vol. 51, No. 1, pp.233–249.

Stojković, G., Soumis, F., Desrosiers, J. and Solomon, M.M. (2002) 'An optimization model for a real-time flight scheduling problem', *Transportation Research Part A: Policy and Practice*, Vol. 36, No. 9, pp.779–788.

Taguchi, G. and Konishi, S. (1987) *Taguchi Methods, Orthogonal Arrays and Linear Graphs, Tools for Quality*, pp.8–35, American Supplier Institute, USA.

Wei, K. and Vaze, V. (2018) 'Modeling crew itineraries and delays in the national air transportation system', *Transportation Science*, Vol. 52, No. 5, pp.1276–1296.

Wen, X., Chung, S.H., Ji, P. and Sheu, J.B. (2022) 'Individual scheduling approach for multi-class airline cabin crew with manpower requirement heterogeneity', *Transportation Research Part E: Logistics and Transportation Review*, Vol. 163, p.102763.

Wen, X., Ma, H.L., Chung, S.H. and Khan, W.A. (2020) 'Robust airline crew scheduling with flight flying time variability', *Transportation Research Part E: Logistics and Transportation Review*, Vol. 144, p.102132.

Wen, X., Sun, X., Sun, Y. and Yue, X. (2021) 'Airline crew scheduling: models and algorithms', *Transportation Research Part E: Logistics and Transportation Review*, Vol. 149, p.102304.

Yaakoubi, Y., Soumis, F. and Lacoste-Julien, S. (2021) 'Structured convolutional kernel networks for airline crew scheduling', *International Conference on Machine Learning*, July, PMLR, pp.11626–11636.

Yan, S. and Tseng, C.H. (2002) 'A passenger demand model for airline flight scheduling and fleet routing', *Computers & Operations Research*, Vol. 29, No. 11, pp.1559–1581.

Zeighami, V., Saddoune, M. and Soumis, F. (2020) 'Alternating Lagrangian decomposition for integrated airline crew scheduling problem', *European Journal of Operational Research*, Vol. 287, No. 1, pp.211–224.

Zhao, S., Shao, W. and Zhu, H. (2019) 'The intelligent decision of flights adjusting rule-based flight scheduling optimisation', *ACM WSDM*.

Zhou, T., Chen, X., Wu, X. and Yang, C. (2023) 'A hybrid multi-objective genetic-particle swarm optimization algorithm for airline crew rostering problem with fairness and satisfaction', *Machine Learning for Cyber Security: 4th International Conference, ML4CS 2022, Proceedings, Part III*, 2–4 December 2022, Guangzhou, China, pp.563–575, Springer Nature Switzerland, Cham.