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RESEARCH PAPER

An Integrated Model for Crew, Aircraft and Passenger Recovery Problem: A Real Case Study

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Abstract

Airlines try to reduce costs by improving the quality of their operational schedules. However, numerous uncontrollable factors make disruptions inevitable. A flight delay or cancellation caused by disruption may spread throughout the network and increase the operational costs by affecting the schedule of other flights, including aircraft, crew, and passengers' itineraries. While previous researchers have focused on one of these aspects or sequential approaches, the resulted solutions cannot lead to a reliable operational solution due to the complex relationships between these factors in practice. Therefore, integrated recovery approaches are highly essential. The main objective of this research is to provide a fully integrated recovery model that contains various recovery scenarios to tackle the disruption and delay propagation with more flexibility and acceptable solution time. So, an integrated model for crew, aircraft, and passenger recovery problem is proposed in this paper. The proposed model is formulated as MILP, based on individual flight legs to achieve a more accurate schedule with better recovery solution. Options such as aircraft reassignment, crew swapping, reassignment of passengers, and ticket refunds are considered as alternatives to face disruption. Moreover, the considerations related to crew rest-time and maintenance requirements are also included in the model. Due to the NP-Hard nature of the problem, the Genetic algorithm is used as the solution approach successfully for the real-world data to limit delay propagation on various random flights.

Keywords:
Integrated Airline Recovery Problem;
Mathematical Modeling;
Delay Propagation;
Genetic Algorithm

Introduction

The aviation industry has a direct impact on the quality of global transportation systems and economic growth [1]. However, high costs and low profits are the two main challenges for the airline industry. The industry faced net losses of $52 billion in 2021 and cutting these losses to $12 billion in 2022. Airlines are expected to cut costs by 31% in 2021 vs 2019 [2]. According to the IATA annual report, Airline industry is recovering gradually from COVID-19, but demands for air travel are still estimated to be only 40% of pre-crisis levels in 2021. According to the Bureau of transportation statistics [3], the number of disrupted flights has increased gradually as well. As an instance, 19.36% of flights were delayed in 2022 in the United States, which is 8.36% greater than 2021. Also, cancelled flights increased from 2.45% to 3.99%. Flight network expansion for an airline is vital as a competitive advantage to cover more cities.

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However, this growth may cause a grave problem for these companies. Based on studies, each 1% increase in number of flights may increase 5% delays in entire flight network [4]. Disruption is an inseparable part of the airline's operations. Atmospheric condition, airport issues, air traffic, aircraft technical failure, crew unavailability, and management decisions may lead to the disruption. To overcome this challenge, recovering the schedule to prevent propagation is essentially needed [5]. Scheduling is an intricate operation for airlines that includes various aspects of aircraft, crew and passenger itinerary [6]. A slight disruption in an individual flight can cause a serious issue for the flight network [7]. The issue may propagate to other flights of the network owing to deployment of common resources (see the references [8-9]). Aircrafts, crews and passengers are key elements of the recovery process. While some studies have addressed each element solely, some others have considered them sequentially. In this case, the output of each stage is applied the next one as an input. This approach may considerably reduce the complexity of the problem. However, the risk of reaching to infeasible solutions is highly expected. To overcome this issue, the fully integrated recovery models are strongly recommended.

Here, the evolution of an integrated airline schedule recovery approach is discussed to illustrate how it might cover all elements of aircraft, crew, and passengers concurrently. The current model is exceedingly different from the previous pieces of research. According to Hassan et al. [10], few pieces of research have considered aircraft, crew and passenger recovery in their models. In some of these researches, the aircraft, crew or passenger recovery has been defined as a multi-stage problem. Thus, the aircraft recovery formulated on time-space network concept as the initial stage of the recovery. Then, the results of the initial stage have been utilized for the crew rescheduling and recovery. Similarly, the results of the second stage have been deployed as input for passenger recovery. Compared to the space-time network, connection-based network provides more flexible schedule recovery options (see the references [11-13]). Maher [12] used a *flight string* concept to simplify the integrated recovery problem, but, this may lead to non-optimal solutions. On the other hand, the integrated model represented by Arikan et al. [13] has been formulated as a conic quadratic model. The current integrated model is configured to lead to optimum solutions by rescheduling individual flight legs in addition to using an exact solution approach. Furthermore, the current linear model may reduce CPU time to operate compared to Arikan et al. [13] approach and the solution will be global optimum as well.

The main contribution of this paper is as follow: First, the fully integrated aircraft-crew-passenger recovery model is formulated for total network instead of using flight strings concept. So, all flight legs are considered in the process to evaluate all possible options for the optimum recovery solution. Moreover, different fleet types are considered in the model as they have different seat capacities. Also, conditions related to ground operation time, crew rest, and maintenance requirements are also considered. Also, the variation of recovery scenarios such as under controlled flight delay or cancellations, rerouting of aircraft/crew, resource swapping and using deadhead options, passenger reallocation/refunding are available for more flexibility. Finally, due to the Np-hard nature of the problem, the genetic algorithm - one of the well-known metaheuristic solution approaches- is used to solve the case study generated with real world data. The objective function of the model defined as minimum cost. The rest of this paper is organized as follows: The literature of the airline recovery solutions is presented in Section 2. Section 3 is dedicated to the problem statement and proposed model. Genetic algorithm structure for the recovery model is described in Section 4. Various numerical examples and the case study of real world data are solved in Section 5 to evaluate the model performance. Section 6 is devoted to the review of the proposed model and other studies. At last, the conclusion is presented in Section 7.

Literature Review

Over the last few decades, there has been an increase in publications of airline disruption recovery. In particular, in of works integrating two or more resources (i.e., aircraft, crew, passengers) [10]. Some surveys and review papers were presented by Kohl et al. [14], Clausen et al. [6], Hassan et al. [10] and Su et al. [15] to evaluate the various aspects of the airline recovery problem. Kohl et al. [14] focused on how disruption management and large scale disruptions impact on airline performance. Clausen et al. [6] presented a comprehensive review of variation of flight networks and both the traditional and modern recovery policies for aircraft, crew and passengers. Su et al. [15] listed the disruption sources and how basic models are trying to tackle the disruption side effects. Hassan et al. [10] presented a review of optimization approaches that applied for airline recovery problem. Below, the brief review of related studies are represented based on aircraft, crew and passenger recovery. Moreover, multi-stage and integrated approaches are described. Finally, common types of flight network structure used in the integrated approaches is provided.

Single aspect recovery

Aircraft recovery problem has been discussed in many studies. The classic approach to this problem usually involves revising the fleet and available routes for aircraft (see the references [16-17]). Liang et al. [18] considered the maintenance requirements and airport capacity aspects to reduce aircraft recovery cost. Vink et al. [19] proposed a MILP aircraft recovery model to handle Two different types of maintenance operations for multi-fleet airlines.

The main objective of crew recovery is to reassign available crew to existing flights for duty. In this process, only the flights that defined in recovery time window get considered to avoid extra complexity of the problem [15]. By deploying the set partitioning concept, Guo [20] applied set partitioning, linear programming relaxation and genetic algorithm to solve the crew recovery problem. Due to the NP-HARD nature of the problem, Chang [21] used the Genetic Algorithm to solve his proposed crew recovery model. Bayliss et al. [22] studied the effects of crew unavailability and reserved crew in the airline recovery process. Also, simulation based optimization also get applied by Scherp et al. [23] to estimate the optimum number of reserved crew.

Passenger recovery problem has a great impact on the airline performance. Bratu and Barnhart [24] formulated couple of different models with reserved crew and aircrafts, so they can study the impact of passenger delays and operational costs on total costs for airlines. The results of their study showed that passenger reallocation may significantly reduce the total cost. The approach proposed by Jafari and Zegordi [25] includes a sequential mixed integer programming for aircraft rotations - passenger itineraries recovery based on Abdelghany's [26] work with independent flight resources. By better understanding of passenger itinerary, McCarty [27] focused on improving more possible routes for passenger recovery. Therefore, the passenger itinerary changes get minimized. McCarty et al. [28] proposed a novel stochastic programming model to preventative rerouting and re-accommodating passengers under uncertain delays.

Multi-stage and integrated approaches

As mentioned before, separating the crew, aircraft, and passenger recovery as an individual problem may strikingly dwindle the complexity of the recovery problem. Though, the final solution to real-world problems cannot be expected to be completely optimized. This situation can become worse by reaching an infeasible solution. To overcome this problem, an integrated recovery approach is essential. Integrated airline solutions are effective for both creating the original schedule and recovering process as well. However, creating and solving an integrated model is exceptionally difficult and challenging. Therefore, there are a few number of research published in this field of study. Rashidi et al. [29] proposed an integrated model of fleet assignment and crew scheduling. Their approach provided better results for allocating the appropriate fleet and crew to the flight schedule. From the recovery aspect, Petersen et al. [30] proposed mixed integer based sub problems for a single day operation period. Flight schedule, aircrafts, crew, and passengers get considered in each sub problem. The proposed integrated model was based on “flight strings” concept, but the solution approach utilized column generation and Benders decomposition sequentially. Sinclair et al. [31] adopted the Bisaillon [32] recovery model to reach better final solutions. As an extension of their previous research, an integrated aircraft-passenger model proposed by Sinclair et al. [33] through a smaller model for better run-time in a hub and spoke networks. Maher [11] proposed an integrated model that included all three aspects of aircraft-crew-passengers. His string-based model was able to reallocate the passengers from the cancelled flight to other available flights. However, the model was not designed for multi-fleet airlines and did not include the maintenance aspects. Maher [12] presented another flight string-based model including which could handle reserved crew. To reduce the problem size, the column and row generation approach was used for daily operation as a solution method. Hu et al. [17] adopted a similar approach to evaluate the decisions about passenger reallocation thru his integrated aircraft-passenger recovery by using a connection network. Arikan et al. [34] studied the role of cruise speed control on the quality of their solutions for aircraft-passenger recovery model. The results show that this option may mitigate the side effects of the disruption. The integrated model of Arikan et al. [13] includes aircraft, crew, passengers, and a diverse number of recovery scenarios which get defined through a simple innovative flight network. However, the model is non-linear. Finally, Khiabani et al. [35] presented a fully integrated aircraft and crew recovery model formulated as MILP. They solved the model successfully by deploying Benders decomposition with an acceptable solution time. But their model does not support the maintenance requirements and passenger aspects.

Schedule network

The airline's operational schedule is provided via flight network. Each flight network may necessarily include the flight route, maintenance requirements, or other needed flight resources. Liang et al. [36]. As explained in their report, the time-space network (e.g. Petersen et al. [30] and Zhang et al. [37]) and connection network (e.g. Aguiar et al. [38] and Arikan et al. [13]) are frequently used for multi-stage / integrated airline recovery problem [10]. The time-space network is an improved form of time-line networks, contains all possible landing and takeoff events connect with time lines. This may help for easier scheduling [39]. The connection network is the modified version of the string-based network with more flexible options proposed by Barnhart et al. [40]. This network includes more additional variables and constraints for each flight leg. When a disruption happens middle of the schedule, the flight *string* concept helps to simplify the reassignment and rescheduling of the remaining flights for the specific pairing. So, other pairings and flights are not affected (see the references [11-12]). for integrated models. Studies shows that the connection networks have better performance for large airlines compare to the string-based networks by allowing them to monitor aircraft, crew, and passengers through a unique network [13]. So, all scheduled flights may be adjusted during the recovery operation. Also, when the number of the strings and related variables increase in the string-based network compared to the leg-based approach, the risk of leading to non-optimal answers in practice increase as well [41]. Therefore, by taking all flights in the rescheduling process, it is ensured to reach to the optimum solution in a more flexible way [13,36,42].

In conclusion, simultaneous recovery of aircraft-crew-passengers is very rare in existing studies. The majority of these studies have used a multi-stage approach. Solving the model sequentially, may ends to non-optimal or even infeasible solutions. Bratu and Barnhart [24] proposed the first fully integrated recovery problem. However, they focused on reserved crews and cost trade-offs between recovery cost and passenger costs. Maher's [11] model formulated as the flight *string*, which has the risk of non-optimal solutions. At the other hand, the CPU time of Arikan et al. [13] non-linear approach is substantially increased. while shorter solution time is crucial for recovery models in practice. Moreover, the risk of reaching to local optimum solution is high in a non-linear approach. The main objective of this study is to present a fully integrated aircraft-crew- passenger recovery model by using a mix integer linear programming approach. Individual flight legs concept gets applied to the model to ensure the optimal solution is achievable. Our recovery model includes various scenarios such as under controlled flight delays / cancellation, rerouting, deadheading, and swapping of aircraft / crew, passenger reallocation and refunding. Also, the model is multi-fleet and includes maintenance requirements. Comparison between the current research with the previous studies is presented in Table 1.

Problem Statement: Integrated Airline Recovery Problem (IARP)

This research is dedicated to introduce a novel linear mathematical model for the *Integrated Airline Recovery Problem* (IARP) by considering aircraft-crew-passengers. For this purpose, it is assumed that the original daily flight schedule is already available. Disruption may happen for any unexpected reason and involve one or more different flights at the operation day. Unlike the rest of other studies, the IARP takes advantage of single flight legs in the rescheduling process instead of the *flight-string* concept. So, the model has better opportunity to reach better solutions. Moreover, each flight in this model can be done on time, with delay, or may be cancelled. The resource swapping, deadheading, and rerouting are considered as recovery options by considering the availability of aircraft and crew. In the case of cancellation, passengers may be refunded or reassigned to other flights of the same or other airline. In the case of passenger reassignment, free seats of other flights are considered. Moreover, IARP reassigns flights to the proper aircraft according to the maintenance and multi-fleet requirements. For more realistic aspect of the IARP, sit / ground time constraints are applied for flight resources.

IARP is formulated as a multi-fleet problem with different types of aircraft. Naturally, each cockpit crew can handle specific types of aircraft. Also the real world data of American airline published by Kaggle.com is used to create all examples for this study.

Mathematical model

Current section dedicated to describe the formulation of the mathematical model and its flight network in detail. The objective function of IARP includes flight deadhead, swapping, delay, cancellation, reassignment, and refunding options with minimum cost. The set of *resources* is used for crew and aircraft, to prevent similar constraints for, both of these elements. So, the set of R represents all flight resources in the model. Likewise, A and C are representing the set of every aircraft and crew as the flight resources and the set of F indicates the flights.

The other concept used in the model is *flight round*, which is shown by index n. It refers to each movement (flight) done by a resource, either crew or aircraft. Let's suppose that an aircraft is going to be assigned to three different flights in a single duty day. For the first flight, n equals to one as it is the first travel of the aircraft in that day. Similarly, for the second and third flights, n equals to two and three, respectively.

Table 1. Recovery studies from the literature

study	flighy network	solution approach	schedule		aircraft recovery scenario			crew recovery scenario			passenger recovery	multi-fleet	maintenance	model characteristic				data
			flight	flight	Swap	ferry	cruise	deadhead	Swap	reserve				linear	non-linear	sequential	Integrated	real world
Bisaillon et al. [32]	time space	Metaheuristic	✓	✓	✓						✓	✓	✓	✓		✓		✓
Jafari et al. [25]	connection	rolling horizon	✓	✓	✓	✓					✓	✓	✓		✓	✓		✓
Petersen et al. [30]	time space	Benders	✓	✓	✓			✓	✓		✓	✓	✓	✓			✓	✓
Aguiar et al. [38]	connection	Metaheuristic	✓	✓	✓			✓					✓	✓		✓		
Le and Mei Long [43]	time space	Metaheuristic	✓	✓	✓		✓	✓		✓		✓	✓			✓		
Castro et al.[44]	time space	multi-agent sys.		✓	✓			✓	✓	✓	✓	✓	✓	✓		✓		✓
Sinclair et al. [31]	time space	Metaheuristic	✓	✓	✓						✓	✓	✓	✓		✓		✓
Maher [11]	string	column & row generation	✓	✓	✓		✓		✓	✓	✓		✓	✓			✓	
Sinclair et al. [33]	time space	Metaheuristic	✓	✓	✓						✓	✓	✓		✓	✓		✓
Zhang et al. [37]	time space	2stage heuristic	✓	✓	✓			✓	✓			✓	✓	✓		✓		✓
Hu et al. [45]	time space	Metaheuristic	✓	✓	✓	✓	✓				✓			✓		✓		✓
Maher [12]	string	column & row generation	✓	✓	✓			✓	✓	✓			✓	✓			✓	
Zhu et al. [46]	time space	Metaheuristic	✓	✓	✓	✓		✓	✓	✓	✓	✓			✓		✓	✓
Arikan et al. [13]	connection	conic quadratic	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓		✓	✓
Wu et al. [47]	connection	integer programming	✓	✓	✓									✓				✓
liang et al. [18]	connection	column generation	✓	✓	✓								✓	✓				✓
McCarty et al. [28]	none	stochastic-benders									✓				✓			✓
Shaochang [48]	time space	Metaheuristic	✓	✓	✓									✓				
Bayliss et al. [22]	time space	Heuristic						✓	✓	✓								
Scherp et al. [23]	none	simulation based optimization							✓	✓								
Khiabani et al. [35]	Connection	Benders	✓	✓	✓			✓	✓	✓				✓			✓	✓
IARP	**individual flights Total network**	**Genetic algorithm**	✓	✓	✓			✓	✓	✓	✓	✓	✓	✓			✓	✓

Now, decision variables can be described: the binary variable of X_{rfn} is indicating whether flight f is done by resource r in its n^{th} travel. Y_f is a positive variable that represents the real departure time of flight f. Also, Z_f is a binary variable that shows if flight f is cancelled or not. S_f is a binary variable indicating if flight f is swapped or not. If a flight is handled by another crew rather than the originally assigned one, it is labeled as a swapping flight. Del_f is a positive variable counts the amount of delay per minute for flight *f*. If a flight is cancelled, the passengers may be reassigned to other flights or refunded. The number of passengers of flight f that are reassigned to flight f' is shown by an integer variable, $NRA_{ff'}$. Also, NR_f shows the number of unassigned passengers that should be refunded.

The sets, parameters, and variables of the model is as what follows:

Sets and indices

R	Set of flight resources, (aircrafts, crew)
r	Index for resource of the flight
C	Set of the crew
A	Set of the aircrafts
FL	Set of the flights (offered by either the assumed airline or other airlines)
F	Set of the flights offered by the assumed airline
$Fcom_f$	Set of the flights that their origin and destination are similar to flight *f*
$f.f'$	Index for individual flight
N	Set of the flight rounds
n	Index of flight round
FO_r	Set of the flights that depart from the home base of resource *r*
c_f	The crew of flight *f* according to original schedule (before disruption)
C'_f	Set of crew who have not been originally assigned to flight *f* $(C - c_f)$
C_a	Set of all crew who can handle aircraft *a*
$netreq_a$	Set of all flights with maintenance requirement
net_f	Set of all flights that their destinations are equipped with a maintenance facility

Parameters and scalars

$ground_r$	Minimum ground / sit time of specific resource *r* to operate two flights in sequence
NP_f	Number of passengers in flight *f*
ar_f	Flight *f* Arrival time
de_f	Flight *f* departure time
dur_f	Duration time of flight *f*
US_f	Number of unequipped (free) seats of flight *f*
cc_f	Cost of cancellation for flight *f*
dc_f	Cost of delay for flight *f* (per minute)
sc_f	Swapping costs for flight *f*
$ac_{ff'}$	Reassignment cost for passengers of flight *f* to *f* '
rc_f	Refund cost of passengers of flight *f*
dhc_f	Deadheading cost of flight *f*
$od_{ff'}$	A binary parameter to show if the destination of flight *f* is the similar origin of the flight *f* '
M	A large number

Variables

X_{rfn}	Binary variable to track the movement of each resource r. this variable equals 1 if the flight f uses resource r in the nth flight round
Y_f	represent the real time of flight f
Z_f	Binary variable that show if flight f is cancelled when it is equal to 1
S_f	Binary variable equal 1 to show that if the flight f gets swapped.
Del_f	variable that counts the delay minutes for flight f
$NRA_{ff'}$	Counts the number of passengers from flight f that reallocate to flight f'
NR_f	The number of other passengers that booked flight f that are not reallocated to any other flights

IARP model is formulated as follows:

$$Min \sum_{f\in F} dhc_f(\sum_{r\in C}\sum_{n\in N} X_{rfn} - 1 + Z_f) + \sum_{f\in F} sc_f S_f + \sum_{f\in F} dc_f Del_f + \sum_{f\in F} cc_f Z_f + \sum_{f\in F}\sum_{f'\in FL} ac_{ff'} NA_{ff'} + \sum_{f\in F} rc_f NR_f \quad (1)$$

S.t.

$$\sum_{r\in C}\sum_{n\in N} X_{rfn} + Z_f \geq 1 \quad \forall f \in F \quad (2)$$

$$\sum_{r\in C}\sum_{n\in N} X_{rfn} \leq M \sum_{r\in A}\sum_{n\in N} X_{rfn} \quad \forall f \in F \quad (3)$$

$$Y_f + dur_f + ground_r \leq Y_{f'} + M\left(2 - X_{rfn} - X_{rf'n+1}\right)$$
$$\forall r \in R. n \in N. f. f' \in F: f \neq f' \quad (4)$$

$$\sum_{f\in F} X_{rfn+1} \leq \sum_{f\in F} X_{rfn} \quad \forall r \in R. n \in N \quad (5)$$

$$\sum_{f\in F} X_{rfn} \leq 1 \quad \forall r \in R. n \in N \quad (6)$$

$$X_{rfn} + X_{rf'n+1} \leq od_{ff'} + 1 \quad \forall r \in R. n \in N. f. f' \in F: f \neq f' \quad (7)$$

$$Y_f \geq de_f\left(1 - Z_f\right) \quad \forall f \in F \quad (8)$$

$$Y_f \leq M\left(1 - Z_f\right) \quad \forall f \in F \quad (9)$$

$$Del_f \geq Y_f - de_f \quad \forall f \in F \quad (10)$$

$$\sum_{f\in FO_r} X_{rfn} = 1 \quad \forall r \in R. n = 1 \quad (11)$$

$$1 - (\sum_{n\in N} X_{rfn} + Z_f) \leq S_f \quad \forall f \in F. r = c_f \quad (12)$$

$$\sum_{n\in N} X_{rfn} \leq \sum_{r'\in C_a}\sum_{n\in N} X_{r'fn} \quad \forall r \in A. f \in F \quad (13)$$

$$\sum_{f\in net_f}\sum_{n\in N} X_{rfn} \geq 1 \quad \forall r \in netreq_a \quad (14)$$

$$\sum_{f'\in Fcom_f} NRA_{ff'} + NR_f = NP_f Z_f \quad \forall f \in F \quad (15)$$

$$\sum_{f\in F} NRA_{ff'} \leq US_{f'} \quad \forall f' \in FL \quad (16)$$

$$\sum_{r\in C}\sum_{n\in N} X_{rfn} \leq M(1 - Z_f) \quad (17)$$

$$Y_f, Del_f \geq 0 \quad (18)$$

$$X_{rfn}, S_f, Z_f: Binary \quad (19)$$

$$NRA_{ff'}, NR_f: Integer \quad (20)$$

The objective function of the IARP model includes flight deadhead, swapping, delay, cancellation, reassignment, and refunding cost with minimum cost. Eq. 2 guarantees that each flight must be assigned to a crew or get canceled. Constraint (3) ensures to assign an aircraft to the flight which the crew is assigned to it as well. Constraint (4) states that the minimum sit / ground time for a resource used in two consecutive flights must be considered. Constraint (5) ensures that a resource cannot handle its $n+1^{st}$ trip without handling its n^{th} trip. Eq. 6 shows that each resource cannot be assigned to more than one flight in each travelling round. Eq. 7 ensures integrality of two consecutive flights. Constraint (8) insures that a flight prohibited to be done before the scheduled departure time. Constraint (9) shows the relationship between decision variables. It shows that if Y_f takes value, Z_f should take zero. The delay in a flight is calculated by Constraint (10). Constraint (11) ensures that the first flight of each resource must be done from its defined home base. Constraint (12) guarantees that if a flight is neither cancelled nor handled by its originally assigned crew, it is swapped. Eq. 13 ensures that a crew member is assigned to the fleet type that he/she can technically handle. Constraint (14) ensures that aircraft with maintenance requirements handles a flight to one of the equipped airports. Constraint (15) shows that all passengers of a cancelled flight are either reassigned to other flights or refunded. Constraint (16) indicates that only free seats of a flight can be used for reassignment of passengers. Similar to Constraint (9), Constraint (17) shows the relationship between decision variables. Finally, Eqs. 18 to 20 show the type of variables.

Genetic Algorithm

Many decisions in operations management belong to the class of Non-Deterministic Polynomial hard problems and thus metaheuristic search methods have been applied to improve these decisions [49]. Metaheuristic approaches commonly get used for the airline recovery problem. Hu et al. [17] used neighborhood search algorithm to solve their aircraft recovery problem. Chen et al. [50] applied the genetic algorithm II for crew rescheduling. Bisaillon [32], Sinclair et al. [31,51] used the neighborhood search algorithm to recover aircraft and passengers in his model. Aguilar et al. [38] applied the hill climbing algorithm for aircraft and crew recovery problem successfully. Genetic algorithm (GA) is a well-known metaheuristic algorithm that is inspired by the biological evolution process [52]. The GA is a promising tool for searching rapid and accurate solutions with basic elements of chromosome representation, fitness selection, and biological inspired operators [53]. Lee [49] presented a comprehensive survey of GA applications in operation management. Also, Katoch et al. [53] discussed the evolution of GA variations among the time in their state of art. Both of these studies includes the applications of GA in airline scheduling problems as well. (For more GA applications on recovery problems see [20-21, 54-56].

Solution display

To solve the IARP, the solution display has been designed in a chromosome with four parts. In the first part of the chromosome, it is determined which flights may have made or get canceled. For this matter, a chromosome is formed with columns equal to the number of flights *F*. Then a random number is assigned to each flight. At the end, each number is converted to the binary number by using the rounding technique. In the second part of the chromosome, the number of flights *F* that can be assigned to the crew *C* is estimated. First, *F- 1* number of columns are considered. A random number get assigned for each column. Then, the columns are reordered descending by using the sorting technique. *C-1* elements of the chromosome are selected as separators and get applied to estimate number of flights covered by each crew. In the third part, each flight is assigned to the specific crew and the flight sequence of each crew is determined.

This part of the chromosome has F rows and F columns. According to the FO_{rf}, $od_{ff'}$ and outcome of the part 2, each flight get assigned to the specific crew. In the fourth part, according to the required maintenance capabilities of the destination as well as the compatibility of the crew and the aircraft, the aircraft is assigned to the designated flight and crew. This part of the chromosome has columns equal to number of aircraft A, which get separated based on rel_{ca} parameter for each crew. Then similar to the previous parts, each aircraft is assigned to the chosen flight and crew by using the sorting technique. Finally, the passengers of the canceled flight reassign/rebook through the network. Fig. 1 illustrates the general scheme of the chromosome. To avoid infeasible solutions by crossover and mutation operators, penalty amount of M has been defined for each part cumulated in objective function.

Part 1: flight done/canceled	0.44	…	0.81
Part 2: estimating the number of flights to crew	0.64	…	0.09
Part 3: crew assignment and sequencing	0.25	…	0.01
	⋮	…	⋮
	0.3	…	0.2
	0.63	…	0.74
Part 4: aircraft assignment	0.64	…	0.09

Fig. 1. Chromosome illustration of IARP

Generating the initial solution and new solution

To generate the initial solution of our paper, the flights, aircrafts and available crew are randomly placed together. To generate the new solutions, crossover and mutation operators are applied to the chromosomes.

Crossover operator

Several methods have been defined for the crossover operator, but the method used in this research is the uniform crossover. In this type of crossover, a gene from both parents has an equal chance to be present in the chromosome of an offspring independently. The structure of this operator as follow:

$$X1 = \{X11, X12, \ldots\ldots, X1n\} \tag{21}$$
$$X2 = \{X21, X22, \ldots\ldots, X2n\} \tag{22}$$
$$Y1 = \{Y11, Y12, \ldots\ldots, Y1n\} \tag{23}$$
$$Y2 = \{Y21, Y22, \ldots\ldots, Y2n\} \tag{24}$$
$$Y1 = \boldsymbol{\alpha} \,.\, X1 + (1-\boldsymbol{\alpha}).X2 \qquad \mathbf{0 \le \boldsymbol{\alpha} \le 1} \tag{25}$$

$$Y2 = \boldsymbol{\alpha} \,.\, X2 + (1-\boldsymbol{\alpha}).X1 \tag{26}$$

Mutation operator

The mutation of the chromosome is obtained based on the parameters of the probability of mutation and the number of genes. For better understanding, consider a chromosome with 6 genes as follow.

$$y = \begin{array}{l} [\\ \\ \end{array} \begin{array}{cccccc} 0.2 & 0.55 & 0.32 & 0.75 & 0.9 & 0.56] \\ \text{Gene 1} & \text{Gene 2} & \text{Gene 3} & \text{Gene 4} & \text{Gene 5} & \text{Gene 6} \end{array}$$

$$number\ of\ mutations = nomber\ of\ Genes * mutation\ probability \tag{27}$$

Now, the number 0.1 is multiplied by the difference between the highest value and the lowest value of the genes.

$$sigma = 0.1 * (VarMax - Varmin) = 0.1(1 - 0) = 0.1 \quad (28)$$

Random numbers between 0 and 1 are generated for the selected genes. The resulting number is multiplied by the number obtained from the previous step.

$$y(j) = y(j) + sigma * (randn) \quad (29)$$

For gene 6 we have:

$$y(6) = y(6) + 0.1 * (0.56) \quad (30)$$

Parameter tuning

The higher efficiency of the meta-heuristic algorithm depends on the proper setting of the parameters. In this research the Taguchi method get used to estimate the optimum value of the iterations, population, crossover and mutation rates. Table 2 illustrates the three different levels of GA parameter tuning. Also Table 3 and Fig. 2 represent the final results of the tuning process.

Table 2. Parameters and Levels of GA applied to the model

Parameter	**Level**		
	1	**2**	**3**
Iterations	100	200	300
Pop size	90	100	110
Cross over rate	0.5	0.6	0.7
Mutation rate	0.2	0.3	0.4

Table 3. Adjusted value of GA parameters applied to IARP

	Iterations	Pop size	Cross over rate	Mutation rate
parameters value	300	90	0.6	0.4

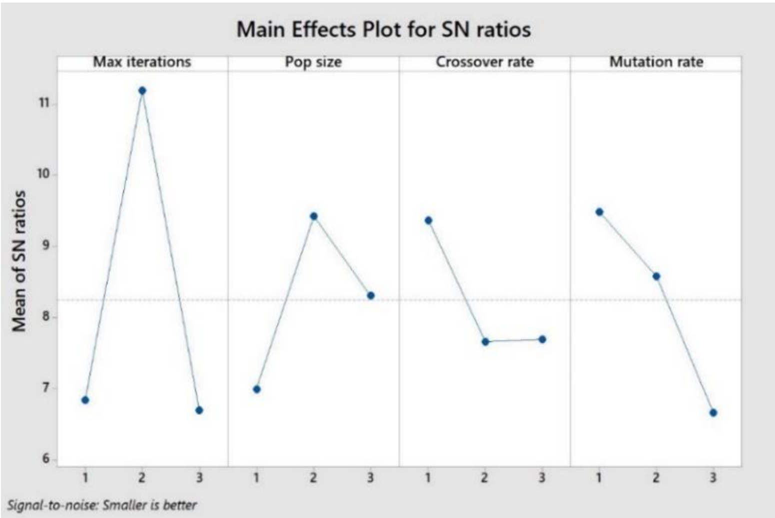

Fig. 1. GA signal to noise ratio

Computational Results

Demand for travel, aviation infrastructures and airline resources availability have a major impact on the number of daily flights get done by commercial airlines. As mentioned before, Schaefer et al. (2005) reported that every 1% increase in flight numbers in each network may end to delays increasing up to 5%. Despite the significant decrease in number of flights made in 2021 due to Covid-19, 10.84% of flights have been reported to be delayed for more than 15 minutes (Transtats 2022[†]). The proposed IARP model performance has been tested with real-world data extracted from Kaggle.com[‡]. The data includes daily flight schedule information for the first 4 months of 2015 related to 10 greatest north American airlines published by the Department of Transportation's (DOT). The New Year vacations period has been selected to create various test cases and final case study. This may help to evaluate the model performance in conditions of high air transportation demand and tight scheduling situations. The database includes various information about variables of flights, airports, fleet type, planned/actual departure-arrival time and flight duration, disruption, cause of disruption and delay cancelation etc. First, the raw data extracted from the main database by choosing the specific airline and the operational day. Then, all flights had been sorted based on the aircraft tail numbers to discover their sequences throw the schedule. some overlapped /missing data got cleaned. The remaining flights data had been restructured to apply to the model. The case study includes 375 flights, 119 crew, 107 aircraft and 67 different airports. The route of each tail number of aircraft got tracked for a single day operation time window. Crew members' rest periods, their compatibility to the aircraft and daily flight allowances were also taken into account. It was also determined which airports can carry out maintenance operations for each class of aircraft. Moreover, the capacity of each aircraft and number of empty seats got estimated. Finally, some of the flights got disrupted randomly in order to analyze the performance of the model in preventing delay propagation in the flight network. A basic test problem with five flights is illustrated in details for better understanding. Table 4 and Fig. 3 presents the main schedule. In this small scale problem, the minimum ground time and sit time for aircraft and crew are assumed 30 and 45 minutes, respectively.

Table 4. original flight schedule for 5 flights

Flight ID	Resources	Origin	Destination	Departure	Arrival	Duration (min)
F1	*A1,C1*	*MIA*	*DFW*	06:04	08:15	130
F2	*A1,C1*	*DFW*	*SJU*	10:41	16:30	349
F3	*A2,C2*	*PHL*	*DFW*	06:30	09:05	155
F4	*A2,C2*	*DFW*	*IAH*	09:51	11:01	70
F5	*A2,C2*	*IAH*	*LAS*	11:50	12:55	65

As represented in Table 4, the first two flights are assigned to *A1* and *C1* (the first aircraft and crew) and the other three ones are assigned to *A2* and *C2*. A schematic view of the primary assignment is also illustrated in Fig. 1. If the departure time of *F3* is delayed for 45 minutes due to the national aviation system delay. In this case, its arrival time to *DFW* will be 9:50. Therefore, *F4* is disabled to depart on time due to sit / ground time considerations. As sit time is 45 minutes, the earliest departure time of *F4* from *DFW* is 10:35 and it experiences a 44-minutes delay. Also, *F5* will face an extra 40-minutes delay and total propagated delay for network will be 129 minutes. By applying the proposed IARP model, the delay propagation is considerably reduced. The model provides various options to decrease the delay impact and its propagation to the flight network. These options are delay, cancellation, swapping aircraft/crew, reserved aircraft/crew and deadhead flights. The recovered schedule generated from the IARP model is shown in Fig. 4. Based on the model results, flights *F4* and *F5* are reassigned to crew *C1* and aircraft *A1*. to put it another way, *C2* and *A2* handle *F3* and *F2* sequentially. Similarly, *C1* and *A1* handle *F4* and *F5* after covering *F1*. As a result, there is no delay spread in entire network and the delay is successfully limited to *F3*.

[†] https://www.transtats.bts.gov/OT_Delay/OT_DelayCause1.asp?20=E
[‡] https://www.kaggle.com/usdot/flight-delays

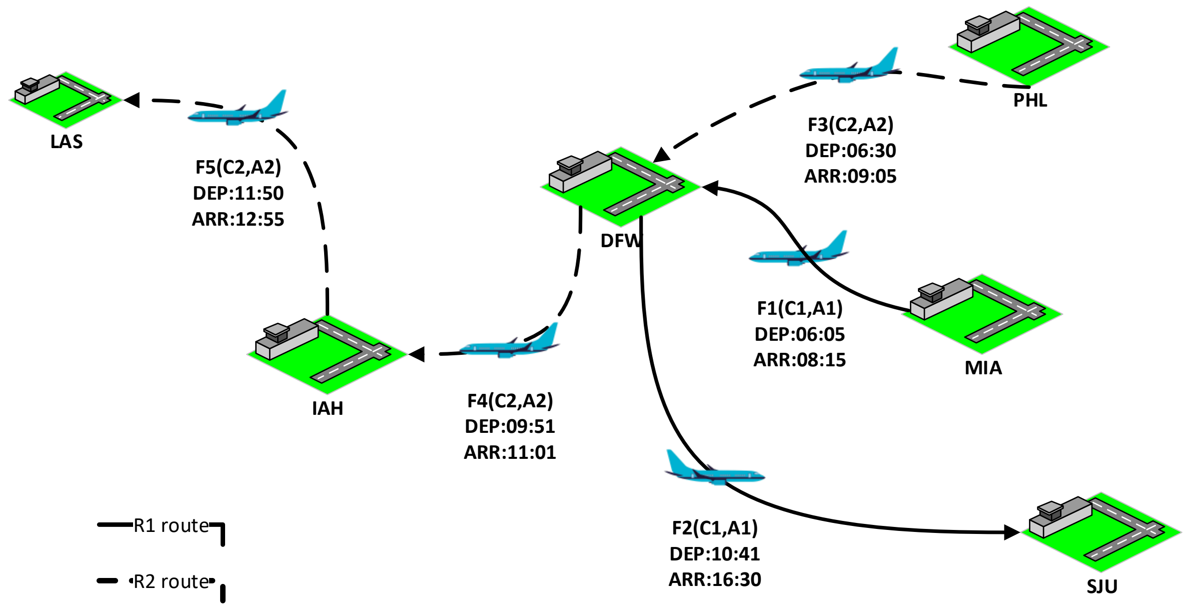

Fig. 2. Overview of original flight schedule before disruption

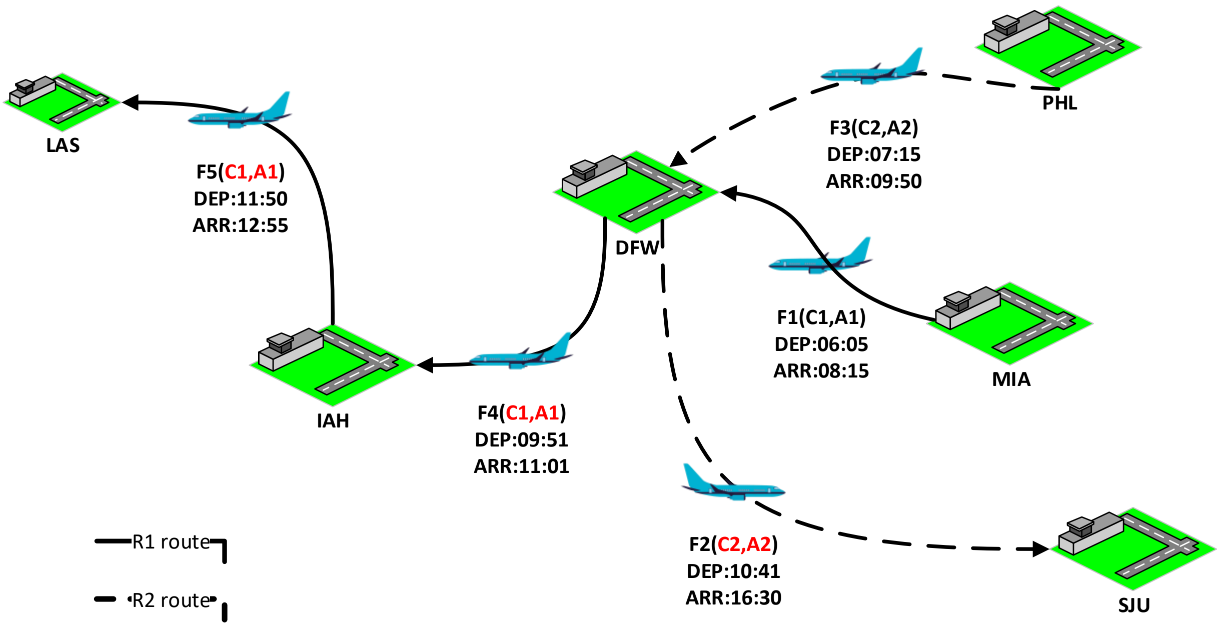

Fig. 3. Overview of recovered schedule after applying IARP

To analyze the performance of the IARP model, 34 test problems of varying scales were evaluated. Furthermore, a case study extracted from real-world data was considered. Several number of flights of each original schedule were intentionally disrupted in order to examine the performance of the model in recovering the schedule and preventing delay propagation. A system with Core i7 8th Gen, 16 GB RAM is used for CPLEX solver in GAMS software to solve the model for test problems. Increasing the number of flights defined in the flight network leads to a drastic increase in the number of variables. Also, diversity of recovery strategies and binary variables intensify the complexity of the problem. Through the NP-Hard nature of the IARP problem, GA has been used to solve the model as well. The algorithm coded in MATLAB 2014a. The brief summary of the solver and GA results is shown in Table 5. Since the GAMS may not solve medium or large size test problems, CPU time was set 10800s and 14400 for medium and large data sets respectively to find out the feasible solution from the solver. The dimensions of the problems presented in second column of Table 5. The next four columns present optimum solution as well as CPU time for both solver and GA. The last column presented the gap between solver and GA results. Table 6 also represents the details of each test case and scenarios used for the recovery. Columns 2 to 4 show number of flights, crew and aircraft, respectively. The column 5 shows how many disruptions have been occurred to the original schedule before applying the proposed model. Columns 6 - 7 represents the number of flight swapping and deadheads occurred to recover the schedule. Columns 8 - 9 shows the number of flights effected by propagation delay and cancelled flights after recovery process (final results of the recovery model). The last column refers to the number of refunded passengers due to the flight cancelation and lack of open seats to get reallocation. while we imposed 60 to 110 minutes' delay in the flights of original schedule, CPU time did not exceed 21 minutes. The average gap between the solver and GA for test cases is 0.26. Also, the maximum gap for all test cases is equal to 1.06%. This is a great advantage to recover a schedule in a fully integrated platform. Fig. 5 illustrates the solution time for all test problems. The red and blue columns refer to GA and solver CPU time. According to this graph, the performance of GA to find the solution for medium and large problems is clearly better than the Solver. Also, Fig. 6 shows the objective function get achieved by solver (red line) and GA (green line).

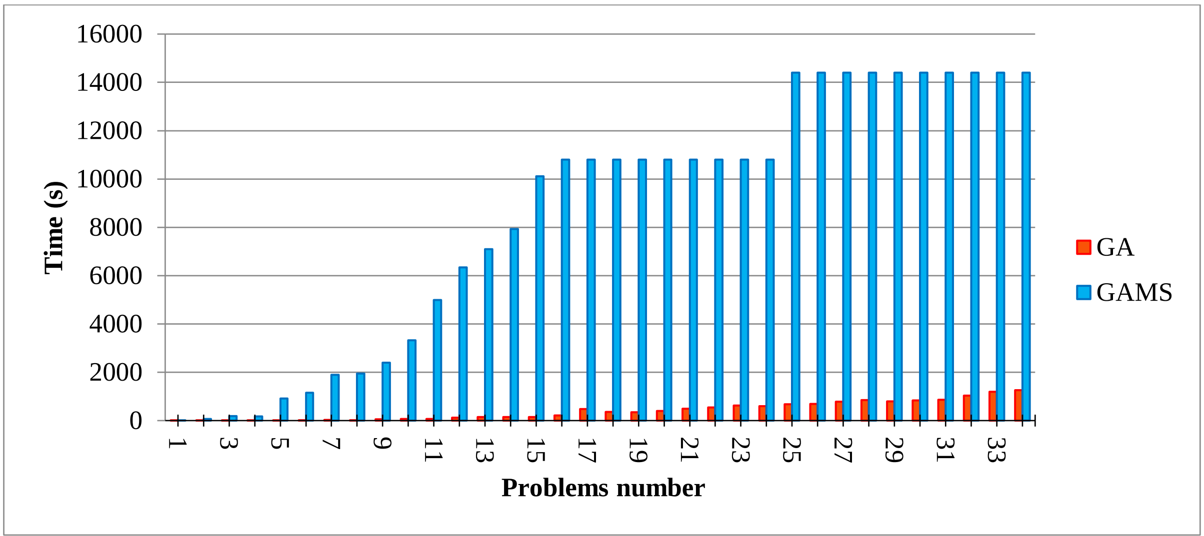

Fig. 5. comparison of solution time between the solver and GA

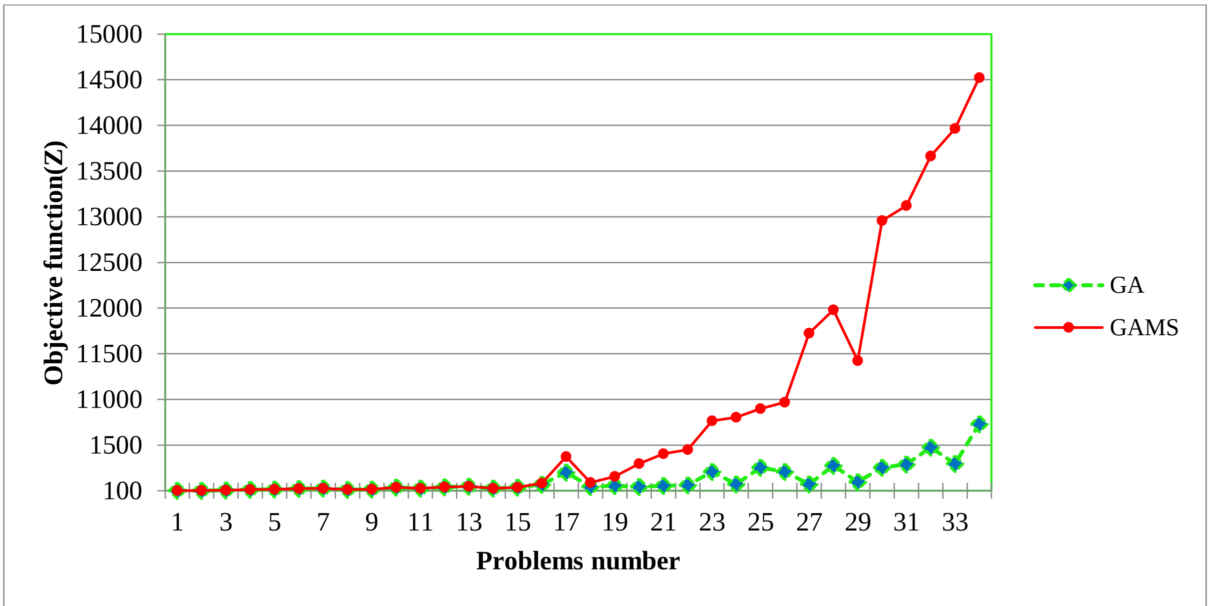

Fig. 6. Comparison between objective function value achieved from solver and GA

Table 5. Results comparison between solver and GA

Case	No. of flights	Solver		GA		Gap
		Objective value ($)	CPU time (s)	Objective value ($)	CPU time (s)	
1	7	27	3.1	27	0.7	0
2	10	30	67.3	30	0.8	0
3	16	556	184.1	556	1.3	0
4	19	1079	176.8	1079	1.2	0
5	23	1563	917.6	1564	6	0.06398
6	27	2087	1154.7	2089	19.1	0.095831
7	30	2610	1897.9	2611	33.4	0.038314
8	36	1116	1942.7	1119	21.1	0.268817
9	40	1600	2395.6	1601	48.8	0.0625
10	45	3605	3326.4	3633	73.5	0.776699
11	49	2609	4991.4	2617	69.7	0.306631
12	52	4132	6342.5	4166	117.2	0.822846
13	56	4636	7094.1	4661	146.3	0.539258
14	59	2639	7933.4	2649	151.8	0.378931
15	62	3662	10113.5	3701	149.6	1.064992
16	67	8365	10800	6667	215.1	
17	71	37346	10800	20271	472.8	
18	74	8952	10800	4379	361.5	
19	78	15632	10800	5398	344.9	
20	81	29541	10800	4271	403.1	
21	85	40346	10800	5405	486.7	
22	89	44860	10800	6189	541.5	
23	92	76573	10800	20852	628.1	
24	96	80317	10800	7216	601.3	
25	101	89674	14400	25221	677.7	
26	111	96749	14400	20971	686.9	
27	121	172353	14400	7281	783.4	
28	132	197880	14400	27492	854.2	
29	145	142365	14400	9765	798.6	
30	153	295681	14400	25293	842.1	
31	187	312224	14400	28927	861.7	
32	221	366548	14400	47561	1035.6	
33	226	396512	14400	29486	1187.4	
34	332	452307	14400	73032	1260.3	

Case study

After the genetic algorithm is successfully evaluated on test problems, the IARP model is applied to recover American Airlines carrier. The original schedule including 375 flights between 67 bases using 119 crew and 107 aircraft in a single day horizon has been given. Fig. 7 illustrates the crew and aircraft home base location details. 17 flights got chose randomly and postponed intentionally with 60 to 110 minutes' delays. As a consequence of these disruptions, 46 other flights in the original schedule are affected by delay propagation as well (Table 7).

The performance of the IARP is illustrated in Table 8. Without applying the model for the recovery, all 63 flights shown in Table 7 are faces with considerable amount of delays. Total delay will be 4055 minutes and delay cost will be 81100$. Also, five flights (*F203, F232, F308, F272* and *F297*) will be cancelled with total cancellation cost of 60600$. In this case, the total cost will be 141700$. By applying the IARP, only 34 flights are delayed (see Table 8). This shows a 53.9% decrease in number of flights effected by propagation delay. Moreover, total delay is reduced to 2109 minutes (This value is equal to 844 minutes for flights with delay propagation).

Table 6. Final state of test cases after schedule recovery

# Case	No. of flights	No. of crew	No. of aircraft	No. of disrupted flights	No. swapped flight	No. of deadhead	No. of delayed flights	No. cancelled flights	No. of refunded passenger
1	7	2	2	1	1	0	0	0	0
2	10	4	3	1	0	1	0	0	0
3	16	5	4	2	2	0	1	0	0
4	19	6	5	2	3	0	2	0	0
5	23	6	6	2	2	0	3	0	0
6	27	8	7	3	3	0	4	0	0
7	30	9	8	3	3	1	5	0	0
8	36	11	9	4	3	1	2	0	0
9	40	11	10	4	2	1	3	0	0
10	45	13	11	5	3	0	7	0	0
11	49	14	13	5	3	0	5	0	0
12	52	15	13	5	3	1	8	0	0
13	56	16	14	5	4	0	9	0	0
14	59	17	14	6	4	0	5	0	0
15	62	18	15	6	4	1	7	0	0
16	67	19	18	6	5	0	13	0	0
17	71	21	18	6	4	1	11	1	23
18	74	21	19	6	5	0	9	0	0
19	78	22	20	6	4	2	9	0	0
20	81	24	21	6	7	1	8	0	0
21	85	25	22	7	5	1	10	0	0
22	89	26	23	7	3	2	12	0	0
23	92	26	24	8	7	1	13	1	18
24	96	28	24	7	6	0	14	0	0
25	101	29	25	7	9	2	18	1	36
26	111	31	28	8	6	2	13	1	19
27	121	35	30	8	7	1	14	0	0
28	132	38	35	9	8	0	21	1	44
29	145	41	36	9	5	1	19	0	0
30	153	45	41	9	10	2	15	1	51
31	187	55	49	8	9	3	17	1	77
32	221	66	58	11	13	4	16	2	144
33	226	65	60	15	16	2	22	1	56
34	332	96	84	18	22	3	31	3	198

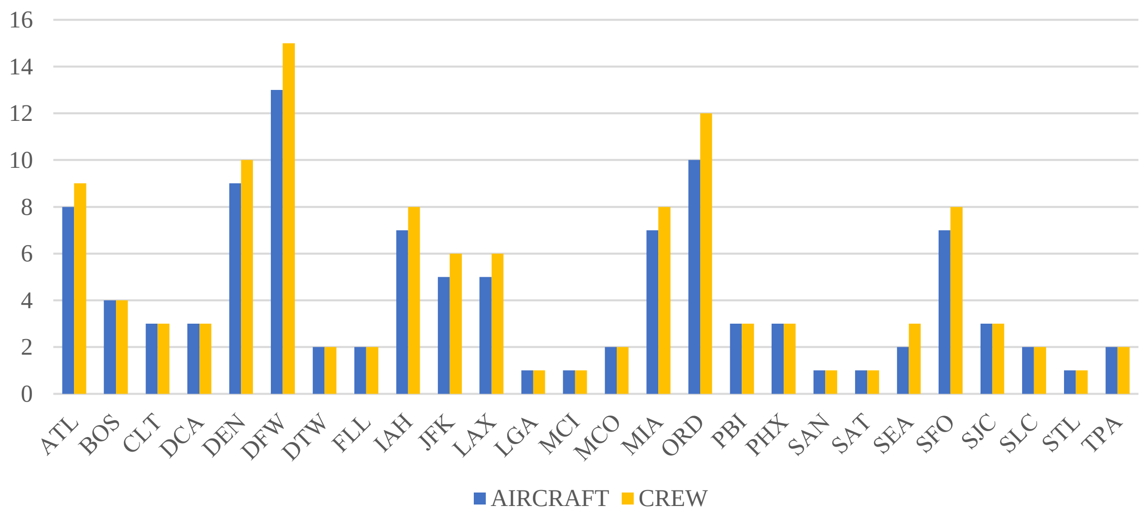

Fig. 4. Home base of aircraft and crew in original schedule

Table 7. Disrupted flights and other affected flights

postponed flight	Delay per min	Delay propagation
F7	60	F13, F63, F96
F19	60	F27,F54,F79,F203
F24	100	F46, F97, F158,F232
F33	60	F67,F95,F172,F308
F46	70	F81,F110,F142
F55	85	F84,F169,F253,F272
F62	60	F74,F85,F159
F64	60	F141
F71	60	F108,F152
F88	110	F247,F316
F101	60	F149,F165,F242,F297
F165	60	F199,F275
F177	90	F198,F251,F295
F209	60	F226,F303
F234	90	F312
F271	90	F290,F315,F344
F317	90	F321

Table 8. List of flights affected by delay propagation after the recovery process

disrupted FLIGHT	DELAY per min	disrupted FLIGHT	DELAY per min	disrupted FLIGHT	DELAY per min
F36	34	F151	11	F239	21
F44	27	F158	48	F242	49
F58	36	F159	15	F250	13
F72	22	F165	50	F252	24
F76	32	F168	13	F253	6
F85	10	F188	27	F274	22
F91	17	F193	15	F279	28
F97	39	F197	10	F301	30
F123	23	F211	17	F303	23
F141	41	F227	10	F317	31
F147	16	F236	22		
F149	43	F237	19		

According to the results of the model, 4 deadheads and 24 swaps occurred during the recovery process. Number of cancelled flights also reduces from five to two, which flights *F232 and F297* are got cancelled. Also 97 out of 283 passengers of these flights were refunded. Table 9 shows the advantage of applying the proposed model. Total recovery cost is reduced to 49724$ (64.9% improvement). The GA CPU time for case study was 1472.6 seconds.

Table 9. Summery of recovery solution vs disrupted original schedule.

	without recovery	After recovery	Improvement (%)
Number of flights get delayed	63	34	53.9
Total delay propagation per min	4055	844	79.18
Delay cost ($)	81100	12760	75.3
Number of deadheads	0	4	
Cost of deadhead ($)	0	80	
No. of swaps	0	24	
swap cost ($)	0	480	
Number of cancellations	5	2	60
Cost of cancellation ($)	60600	22700	62.5
Number of refunds		97	
Cost of refunding ($)		9700	
Total cost ($)	141700	49724	64.9

Discussion

One of the fundamental factors of creating a proper flight schedule is choosing a suitable network type. The chosen network and its capability to handle the flight resources may affect the recovery process as well. The flight networks evolved over time to improve the quality of the schedule. Discussing about the creation of these networks or any possible novel networks is beyond of the current research scope. Therefore, only the use of existing networks has been considered. Previously, multiple applications of time-space and connections networks (string based networks are also considered as connection networks) in flight schedule recovery were discussed in Section 2. Time-space network applied by Petersen et al. (2012) is easy to use, but more variables are needed to be handle to achieve better results in recovery process. The string based networks applied by Maher (2015,2016) simplify the rescheduling process by limiting the changes to specific pairings but may led to non-optimal solutions. Taking all flights and related variables in to account throw a connection network is a critical challenge as well. However, this ensure to reach to the optimum solution (see Sherali et al. 2013, Arikan et al., 2017). To produce more accurate results IARP uses all flight legs for recovery. The variation of recovery options is another challenge for the recovery model. The diversity of the recovery options has been observed more in recovery models which are limited to one aspect such as aircraft or crew. However, the complexity of the model devastatingly increases by extending the scope of the model to a multi aspect recovery problem. This issue reaches its peak in fully integrated approaches. To tackle this problem, Arikan et al., (2017) formulated a non-linear integrated model. But, the non-linearity, increased the CPU time significantly. While the solution time is very critical and should be as short as possible. Moreover, local optimum solution may be reached in a non-linear approach. The IARP formulated as a MILP to avoid the mentioned issues. Due to the NP-Hard nature of the recovery problem the heuristic approaches are widely applied to solve this problem. The GA used to solve the IARP provided an accurate answer for the test cases in acceptable CPU time as well. Therefore, the IARP may be considered more suitable version of previous works for operational field.

Conclusions

An accurate and swift schedule recovery solution for airlines has become more necessary in today's competitive environment. High operating costs, long-term effects of Covid-19 and extensive competition of airlines to attract more customers and reduce losses are all among the factors that encourage airlines to create better operational schedule with less vulnerability. In the meantime, the occurrence of a disruption in the flight schedule can be very challenging. Due to the uncertainty nature of the disruption and delay propagation on entire flight network, the importance of managing this phenomenon increases even more. The integrated recovery of the flight schedule is an effective method in controlling the disruption and preventing its side effects. The fully integrated airline recovery model presented in current essay provides reliable results for various test cases in an acceptable time. The IARP presents various recovery options for all aircraft, crew, and passengers in a solid integrated recovery problem, formulated as a mixed-integer linear programming model. Also, to deal with the NP-Hard nature of the problem, genetic algorithm has been used to solve medium and large-scale problems successfully. The solution time is one of the most important factors in the applicability of the recovery models in real world operations. While the GAMS solver couldn't able to reach to the optimal solution at the proper CPU time for medium and large scale test cases, the GA provided more accurate solutions for these test cases in much less time frame. The computational results show that the average gap between the solver and GA for test cases is 0.26%. Also, the maximum gap for all test cases is equal to 1.06%. This is a great advantage to recover a schedule in a fully integrated platform. In addition, IARP had admirable performance on the case study. Postponing random 17 from 375 flights with 119 crew and 107 aircraft caused 63 flights get disrupted and 5 flights cancellation. The IARP successfully reduced the cost of delays to less than 75%. The flight cancellation dropped to 2 from 5 and total cost of the network significantly reduced to 64.9% in an acceptable CPU time of 1472.6 seconds. Since the IARP have been designed to cover various recovery scenarios, it has vast options to recover the disrupted schedule at operational level. Also decision makers can modify the recovery cost related parameters the way it is more suitable for their needs. In this case, IARP provides a great capability to get used as a main model for analytical data base in airline disruption decision support system. Therefore, the decision makers may analyses their what-if scenarios about how to tune their recovery options in strategic level. The scope of this paper includes all three major aspects of aircraft, crew, and passenger recovery with some ground operations such as maintenance requirements which is rare in literature review. However, it doesn't consider options like cruise speed control to reduce the size of the model. Also, using the robust optimization approach may help to deal with uncertainty in more flexible way. Data oriented methods also may help to reduce the complexity of the recovery problem for future works. Therefore, lighter models can deploy to solve the integrated recovery problem in shorter period of time. Moreover, by applying other metaheuristic methods to the IARP and compare the results may help to converge to the optimum with lower CPU time in future studies.

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