

*Full Length Research Paper*

# Real-time decision support for airline schedule disruption management

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**This study applied a method of inequality-based multiobjective genetic algorithm (MMGA) for real-time airline schedule disruption management in response to the schedule disruption of short-haul, quick turnaround flights with an environmental consideration. Empirical study based on a real-world airline flight schedule demonstrated that the proposed model can recover a disrupted schedule within about 3 CPU min which is more sufficient for real-time operation control. Consequently, it can be employed as a real-time decision supporting tool for practical complex airline operations to save operation cost, increase passengers' convenience and reduce air pollution.**

**Key words:** Disruption management, multiobjective, genetic algorithms, schedule recovery.

## INTRODUCTION

Air travel is nowadays one of the most frequent modes of transportation for business, leisure, and tourism. The operation of an airline requires the allocation of resources and development of schedule plans over complex networks. A large airline can operate over a thousand flights everyday with several hundred aircraft and thousands of flight and cabin crews. Since those resources are costly, one of the key challenges for airlines is to handle their operations in an efficient way in order to lead the market and to maximize their profits and services in an increasingly competitive fare environment.

No matter how superior the schedule plan is, unfortunately, airlines frequently encounter various unanticipated events called disruptions on daily operations that prevent them from operating as planned. These disruptions are largely owing to mechanical problems, crew unavailability, poor weather, air traffic congestion and airport facility restrictions. Therefore, a minor perturbation of planned schedules might lead to chain reactions that can cause major disruptions throughout the whole schedules. Clarke and Smith (2004) points out that for a typical airline, approximately ten percent (10%) of its scheduled revenue is lost due to irregularities in

airline operations, with a large percentage being caused by severe weather conditions and associated loss of airport capacity. An airline's ability to recover the disrupted flight schedules in a quick and efficient approach will be very critical when trying to withstand the competition from other airlines.

Each minute a flight is delayed can result in extra fuel, crew time, and aircraft maintenance, delayed flight also drive the need for extra gates and ground personnel and inflict costs on airline customers in the form of lost productivity, wages and goodwill. In addition to the economic costs of delay, burning jet fuel during delays emits climate-disrupting carbon dioxide and local air pollutants. Since delayed aircrafts sat idle at the gate or circled in holding patterns, burning fuel during flight delays released an additional 7.1 million metric tons of climate-disrupting carbon dioxide into the atmosphere with airlines consuming an additional 740 million gallons of jet fuel in 2007 as a result of delays according to the Joint Economic Committee's report (JEC, 2008). Consequently, the ability to find efficient alternatives can significantly improve an airline's profitability and enhance the protection of environment.

The concept of disruption management refers to the real-time dynamic adjustment of an operation plan when disruptions occur. Due to the dynamic environment, disruption management problem in airline industry is extremely complex, and is well known as a NP-hard problem. Such problems are conventionally solved with mathematical modelling techniques, which always require precise mathematical models and are hard to define. According to Chan et al. (2006), application of a pure mathematical optimization approach to determine an optimal solution may not be efficient in practice, even in classical scheduling problems. On the other hand, heuristic approaches, which can obtain a near optimal solution in a relatively shorter period, are more appreciated and practical.

This study applies a method of Inequality-based multi-objective genetic algorithm (MMGA) to generate an aircraft routing in response to weather-related schedule disruption of short-haul, quick turnaround flights from an environmental perspective. The objectives are to discover the most appropriate alternative with the least schedule disruption to prevent additional cost, reduce emissions and minimize the inconvenience of passengers.

## PROBLEM STATEMENT AND FORMULATION

It is very difficult to specify the objectives of airline schedule disruption management. Usually, objectives fall into three broad categories: Deliver the customer promise, minimize the costs and get back to the original plan as soon as possible (Kohl et al., 2007). In multi-objective optimization problem, a solution does not necessarily exist that is best with respect to all objectives because of incommensurability and conflicting objectives in the case of multiple objectives. A solution may be best relative to one objective but worst with respect to another. Therefore, for a multiobjective optimization problem, we seek a set of non-dominated solutions from which the decision-maker can choose one at personal own discrimination.

The airline schedule disruption management problem can be briefly stated as: minimize the negative consequences of a perturbation that has made it impossible for one or more flights to depart on their scheduled time operated by their originally planned aircraft. The negative consequences are of course the (a) delays, (b) swaps, (c) cancellations and (d) positioning (ferrying) flights needed to solve the problem (Andersson and Värbrand, 2004). By the way, aircraft routing usually considered must be feasible with respect to the following constraints: (a) every flight in each aircraft route must depart from the airport where the immediately preceding flight arrived (flight connection constraint); (b) a minimum ground turnaround time must be enforced between each flight arrival and subsequent departure (ground turnaround time constraint).

## The airline schedule disruption management problem

Aircrafts are the most valuable resources of airlines and the efficient utilization of them is an important consideration in airlines operations. In order to minimize cost and maximize profits, most commercial airlines operate according to a published schedule that typically optimizes revenue and with resources allocated within the schedule, that is, they assume flight schedules can be carried out as planned without any uncertainties. However, those well-planned schedules are often subjected to numerous sources of disruption.

Airline schedule disruption usually arose from a local event such as an aircraft malfunction, a flight delay or an airport closure. In reality, even a small disruption might tend to extend far beyond the events that originated them because there is no slack available to accommodate any small unexpected events. Therefore, a small delay in the morning might trigger a cancellation in the evening if no appropriate recovery action taken. Meanwhile, these disruptions usually lead to lose of passenger revenues and induce additional costs.

This study uses a method of inequality-based multi-objective genetic algorithm (MMGA), which is proposed by Liu et al. (1994), to handle the schedule disruption management problem of short-haul and quick turnaround flights by optimizing five objective functions involving ground turn-around time, flight connection, flight swap, total flight delay cost and the flights over 15 min delay. Genetic algorithm has been used in help to solve the flight scheduling problem in recent years. The basic feature of genetic algorithms is the multiple directional and global searches, in which a population of potential solutions is maintained from generation to generation. By dealing simultaneously with a population of possible solutions; genetic algorithms allow us to find several members of the Pareto optimum set in a single run of the algorithm (Lee et al., 2007). Using an illustrative application example that obtained from a commercial airline, we show that the proposed method is able to solve the airline schedule disruption management problem efficiently.

## Formulations

Let  $\alpha$ ,  $\beta$ ,  $\omega$ , and  $\gamma$  denote the number of aircrafts, the maximum number of flights assigned to each aircraft, the number of airports, and the number of daily flights, respectively. Suppose that the set of  $\omega$  airports is  $\mathbf{P}$ . The timetable, denoted as a set  $\mathbf{F}$ , consists of  $\gamma$  daily flights. All the elements in the set  $\mathbf{F}$  are determined from the market demands, and can be validated using various factors, such as the number of aircraft, crew size, the laws and regulations. Hence, the value of  $\gamma$  is bounded in the range:  $1 \leq \gamma \leq \alpha \times \beta$ . The flight schedule can be

defined as the  $\mathbf{S}$  denoted as a two-dimensional  $\alpha \times \beta$  matrix in equation (1):

$$\mathbf{S} = \{s_{i,j} \mid s_{i,j} = (n_{i,j}, \hat{p}_{i,j}, \bar{p}_{i,j}, \hat{t}_{i,j}, \bar{t}_{i,j}, q_{i,j})\}$$

$$= \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,\beta-1} & s_{1,\beta} \\ s_{2,1} & \ddots & & & s_{2,\beta} \\ \vdots & & s_{i,j} & & \vdots \\ s_{\alpha-1,1} & & & \ddots & s_{\alpha-1,\beta} \\ s_{\alpha,1} & s_{\alpha,2} & \cdots & s_{\alpha,\beta-1} & s_{\alpha,\beta} \end{bmatrix} \quad (1)$$

$$\forall s_{i,j} \in \mathbf{F}, 1 \leq i \leq \alpha, 1 \leq j \leq \beta$$

where

subscript  $i$ : a specific aircraft

subscript  $j$ : a specific flight

$s_{i,j}$ : the  $j^{\text{th}}$  flight assigned to the  $i^{\text{th}}$  aircraft

$n_{i,j}$ : flight identification

$\hat{p}_{i,j}$ : origin of  $s_{i,j}$ , where  $\hat{p}_{i,j} \in \mathbf{P}$

$\bar{p}_{i,j}$ : destination of  $s_{i,j}$ , where  $\bar{p}_{i,j} \in \mathbf{P}$

$\hat{t}_{i,j}$ : departure time from  $\hat{p}_{i,j}$

$\bar{t}_{i,j}$ : arrival time in  $\bar{p}_{i,j}$

$q_{i,j}$ : original duty identification for each aircraft

$\hat{t}_{i,j_0}$ : original departure time from  $\hat{p}_{i,j}$

In this study, we formulate the airline schedule disruption management problem as a multiobjective optimization problem with many objectives functions, including hard objectives and soft objectives. The hard objectives must be satisfied by all feasible solutions, and the soft objectives are treated as goals to be reached, where the overall objective is to get as close as possible to these goals. The objectives in this research will be defined as (a) ground turnaround time; (b) flight connection; (c) flight swap; (d) total flights delay cost and (e) the flights over 15 min delay. In this research, the soft objectives are to minimize the total delay cost, the flights over 15 min delay and to make as few swaps as possible. However, there is a clear trade-off between these three objectives and the quality of a solution to airline schedule disruption management is ultimately a matter of preference.

The ground turnaround time for a short-haul flight is defined here as the time for an aircraft to complete full off-loading/loading passengers, performing the transit check, refuelling, catering and cabin cleaning procedures, etc. The ground turnaround time objective ensures that each aircraft has adequate ground turnaround time not less than the minimum ground turnaround time requested

by civil aviation authority, denoted as  $T_{GH}$ , to be allowed for the subsequent flight. The evaluation function of this objective is defined as equation (2):

$$\phi_1(\mathbf{S}) = \sum_{i=1}^{\alpha} \sum_{j=1}^{\beta-1} x_{i,j}^{(1)} \quad (2)$$

$$x_{i,j}^{(1)} = \begin{cases} 0 & \text{if } (\hat{t}_{i,j+1} - \bar{t}_{i,j}) \geq T_{GH} \\ T_{GH} - (\hat{t}_{i,j+1} - \bar{t}_{i,j}) & \text{otherwise} \end{cases}$$

where ,

The flight connection objective guarantees that the arrival airport of  $s_{i,j}$  is the same as the departure airport of  $s_{i,j+1}$  for each aircraft in  $\mathbf{S}$ , for  $1 \leq i \leq \alpha, 1 \leq j \leq \beta-1$ .

The attribute  $n_{i,j}$  of  $s_{i,j}$  and  $s_{i,j+1}$  stands for the order of the practical flights not necessary in sequence. So one can exchange  $n_{i,j}$  without effect  $s_{i,j}$ .

This objective reduces the extra cost of the ferry flight from  $\bar{p}_{i,j}$  to  $\hat{p}_{i,j+1}$ . The evaluation function of this objective is defined as equation (3):

$$\phi_2(\mathbf{S}) = \sum_{i=1}^{\alpha} \sum_{j=1}^{\beta-1} x_{i,j}^{(2)} \quad (3)$$

$$\text{Where, } x_{i,j}^{(2)} = \begin{cases} 0 & \text{if } \bar{p}_{i,j} = \hat{p}_{i,j+1} \\ 1 & \text{otherwise} \end{cases}$$

Swapping is to trade flights that have later assignments with flights that have earlier broken assignments. Swapped flights must be at the same airport where the violation occurs. This objective can reduce the unnecessary flight duty swaps and the inconvenience for crews during the aircraft change. The evaluation function of this objective is defined as equation (4):

$$\phi_3(\mathbf{S}) = \sum_{i=1}^{\alpha} \sum_{j=1}^{\beta-1} x_{i,j}^{(3)} \quad (4)$$

$$\text{where } x_{i,j}^{(3)} = \begin{cases} 0 & \text{if } q_{i,j} = i \\ 1 & \text{otherwise} \end{cases}$$

Since domestic flights in Taiwan are mostly short-haul flights, over long delay cost might cause extra cost to airlines by transferring passenger to other airlines or requiring the provision of meals and other services.

According to estimation of Air Transport Association (ATA) (2008), the direct operating cost of aircraft block (taxi plus airborne) time is US\$60.46 per minute in 2007. The total flight delay cost objective minimizes the sum of delay cost for each flight.

The evaluation function of this objective is defined as equation (5):

$$\phi_4(S) = \sum_{i=1}^{\alpha} \sum_{j=1}^{\beta} x_{i,j}^{(4)} \quad (5)$$

$$\text{where } x_{i,j}^{(4)} = \begin{cases} 0 & \text{if } (\hat{t}_{i,j} - t_{i,j_0}) = 0 \\ (\hat{t}_{i,j} - t_{i,j_0}) \times 60.46 & \text{otherwise} \end{cases}$$

According to the definition of U.S. Bureau of Transportation Statistics (BTS), a flight is counted as ‘on time’ if it operated less than 15 min later the scheduled gate arrival/departure time shown in the carriers’ Computerized Reservations Systems (CRS). In other words, the flight will be counted as a ‘real’ delay flight if the revise departure time  $\hat{t}_{i,j}$  is greater than the original departure time  $t_{i,j_0}$  plus 15 min. The evaluation function of this objective is defined as equation (6):

$$\phi_5(S) = \sum_{i=1}^{\alpha} \sum_{j=1}^{\beta} x_{i,j}^{(5)} \quad (6)$$

$$\text{where } x_{i,j}^{(5)} = \begin{cases} 0 & \text{if } (\hat{t}_{i,j} - t_{i,j_0}) \leq 15 \\ 1 & \text{otherwise} \end{cases}$$

**MMGA APPROACH FOR AIRLINE SCHEDULE DISRUPTION MANAGEMENT PROBLEM**

This study uses a method of inequality-based multiobjective genetic algorithm (MMGA), which is first proposed by Liu et al. (1994) in control system design, and further developed by Chou et al. (2008) in aircraft routing. These algorithm includes the following features: (1) a method of inequality to confine a genetic algorithm to search a Pareto optimal set in regions of interest with little computing effort; (2) an improved rank-based fitness assignment method to significantly increase the speed of fitness evaluation; and (3) a repairing strategy to relax the infeasible flight schedules to help reduce violations of solutions.

The details of the MMGA algorithm operation will be explained in the followings:

**Input**

- (1) A set of candidate solutions  $D^{(t)} = \{S_1^{(t)}, S_2^{(t)}, \dots, S_n^{(t)}\}$  with population  $n$  in generation  $t$ .
- (2) Two temporary sets of candidate solutions:  $D^{(t)}$ ,  $E^{(t)}$ .
- (3) The admissible bound vector  $\epsilon$ .

**Output**

A set of optimal candidate solutions within meeting the requirements of admissible bounds.

**Step 1:** Determine the MMGA parameters: population size  $n$ , maximum number of generations  $g$ , crossover rate  $r \in [0, 1]$ , and mutation rate  $\mu \in [0, 1]$ .

**Step 2:** Determine the admissible bound vector  $\epsilon = [\epsilon_1, \epsilon_2, \dots, \epsilon_5]$  of five objectives.

**Step 3:** Let  $t:=0$ . Initialize the population  $D^{(0)}$ .

**Step 4:** Evaluate the auxiliary vector perform index of each individual  $S^{(0)}$  in entire population  $n$ .

**Step 5:** Apply improved rank-based fitness assignment method to calculate the fitness of each individual  $S^{(0)}$ .

**Step 6:** If the number of current generation  $t$  reaches  $n$ , or all the objectives are satisfied, then stop the algorithm.

**Step 7:** Choose two individuals using the rank-based selection method.

**Step 8:** Perform crossover and mutation operations to generate the

populations of next generation  $t+1$  in the mating pool  $D^{(t)}$ . The mutation operation randomly selects two flights in the chromosome and exchanges their positions.

*Step 9:* Adopt the repairing strategy for the chromosomes in  $D^{(t)}$ .

**Step 10:** Evaluate the auxiliary performance index vector of each individual in  $D^{(t)}$ .

**Step 11:**  $D^{(t)} = D^{(t)} \cup D^{(t)}$

**Step 12:** Adopt improved rank-based fitness assignment method again to calculate the fitness of each individual in  $D^{(t)}$ , and let  $t = t + 1$ . Go to Step 7.

This study demonstrates that the flights assigned to each aircraft in random sequence by genetic algorithms may produce a temporary solution with high violation values, because some flights with earlier departure times are arranged after those with later departure time. Such a solution could be repaired to reduce the number of violations on the ground turnaround time objective. Hence, the repairing strategy is adopted to reorder all flights according to their departure times for each aircraft. For example, a flight with departure time 10:40 may be misplaced after a flight with arrival time 10:00. These conditions strongly violate the computed objective functions. Performing a repairing procedure, that is, ordering the flights according to their departure time, can help decrease the violations on the ground turnaround objective. The violations of the solution can be partially repaired after performing the repair procedure. Additionally, the Pareto optimal set of the flight schedules can be obtained easily.

**EMPIRICAL RESULTS**

Temporary closure of any airports and resulting flight schedule disruptions are the most extreme event in the daily operations of an airline. When the airport is temporary closed, major disruptions to an airline’s flight schedule are unavoidable when the airport served by a large number of flights is suspended for any length of time. And the airline must evaluate immediately if this situation would influence any flight by knock-on delay or connection delays. Intelligently rescheduling of aircraft routing in such situations can save airlines cost and minimize the adverse impact on passengers.

The purpose of this research is to determine a recovery schedule by optimizing five objectives functions mentioned above in response to the airport closure. In our proposed method allows for delaying flights and swapping flight duty in the same fleet. For example, the empirical study in this research limits that any alternative aircraft routing must be feasible with respect to the following constraints and assumptions:

- (a) Only flight swaps and flight delays are considerable in our research, that is, no flight cancellation or ferrying flights allowed.
- (b) The ground turn-around time must be greater than 20 min by the requisition of the authority.
- (c) No flights can depart from an airport when it is closed.
- (d) Any flights are planned to land at those airports during airport closure, their arriving times will be postponed to the reopening time. Any flights are planned to depart to those airports during airport closure, their departing times will be also postponed to the reopening time.
- (e) Airport time slots are assumed to be available.

Due to the complexity of schedule recovery problem, previous works on this similar question usually only use flight delaying, flight swapping, or cancellation separately. In this research, we will incorporate flight delays and flight swaps in a single model. We expect to minimize the perturbation as few as possible by reduce flight swaps and total flight delay cost to assure the passenger's satisfaction, and reduce environmental impact.

In this research, we uses a real flight schedule obtained from a Taiwanese domestic airline, comprising 12 aircrafts (C1, C2, ..., C12) with 140 flights of DH-8 fleet in one operation day. The Gantt chart of original schedule is illustrated as Figure 1. The flight routes involve 11 different airports and the flight network is showed as Figure 2. The two most common types of flight route networks in the world are point-to-point and hub-and-spoke. In the hub-and-spoke network airports are separated into two groups, called hubs and spokes. Most spoke airports are served from only one hub and hubs are connected by regular flights. If disruptions occur at one or more hub airports, tracking and recovering the downstream impact of these flights could be extremely challenging and time consuming. In the point-to-point networks, this type of operation is less dependent on overcrowded hubs and therefore is less sensitive to major operational disruptions that are usually associated with hubs (Kohl et al., 2007). From Figure 2, we can find the flight network is combining point-to-point and hub-and-spoke networks. In addition, all the flights are short-haul (less than one hour) and quick turn-around. These characteristics will increase the complexity while tackle the schedule disruption problem.

We will discuss a case of one-hour temporary closure from 14:00 to 15:00 of Taipei Sungshan Airport (TSA) due to a summer afternoon thunderstorm, and try to

recover this disrupted schedule and evaluate the difference between recovered schedule and original schedule. The hardware used in this study is a Pentium4 2.4G CPU computer with 512M RAM and the program is written by C language in Dev C++ development environment. The MMGA operators are population size 100, crossover rate 0.9, mutation rate 0.01 and generation number 50000. Simulation results demonstrate that the application is capable of presenting high-quality solutions in 3 CPU minute, and therefore can be used as a real-time decision supporting tool for practical complex airline operations. Table 1 shows the computed Pareto Optimal sets for DH-8 fleet.

There will be total 21 delay flights with 730 min total delay including 16 flights delay more than 15 min if no recovery action is taken after one-hour airport closure. Using the proposed method, a set of Pareto optimal set can be obtained in 3 min, compared to 15~20 min to create a manual solution. Comparisons of the MMGA approach result with a manual recovered schedule by a senior airline operation controller are given in Table 2.

In most recently airlines operation, the usage of APU or GPU are more common when delayed on the ground. We will use these two scenarios in our experiment and the environment benefits are shown in Table 3. The emission costs can be estimated for each pollutant and is represented as Table 4 (Carrier et al., 2006). The relative environmental cost reduction of MMGA approach is represented by pollutant type in the following Figure 3.

The fast solution times have made it possible to comprehensively evaluate the schedule creation process prior to the publication of a new recovered schedule by creating more proposed schedules. This demonstrates that the application is capable of presenting high-quality solutions, and can therefore be applied as a real-time decision support tool for practical complex airline operations.

## Conclusion

The process of airline schedule disruption management in present airline operations is under extreme time pressure and often without complete information. It is also depends strongly on personal experience judgments because it must involve humans in many key parts of the process. Since it is a time consuming and complex task to construct a recovered schedule, the operation controllers are often satisfied with producing a single feasible plan of action. In addition the controllers have little help in estimating the quality of the recovery action they are about to implement. Determining the quality of a single recovery option is also difficult because the objective function is composed of several conflicting and sometimes non-quantifiable goals: for example, minimizing the number of passenger delay min, returning to the original plan as quickly as possible, and at the



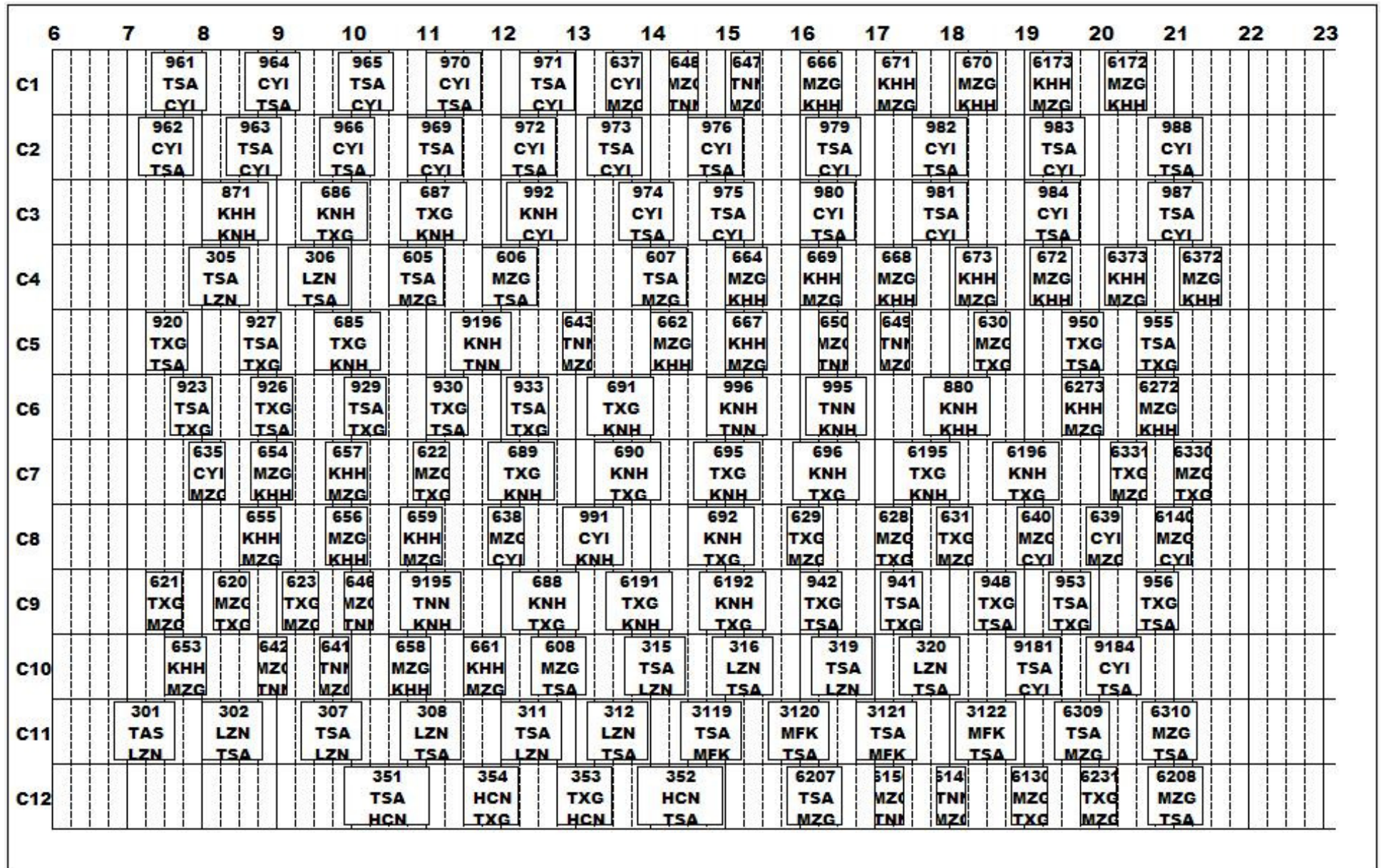


Figure 1. The Gantt chart of original schedule.

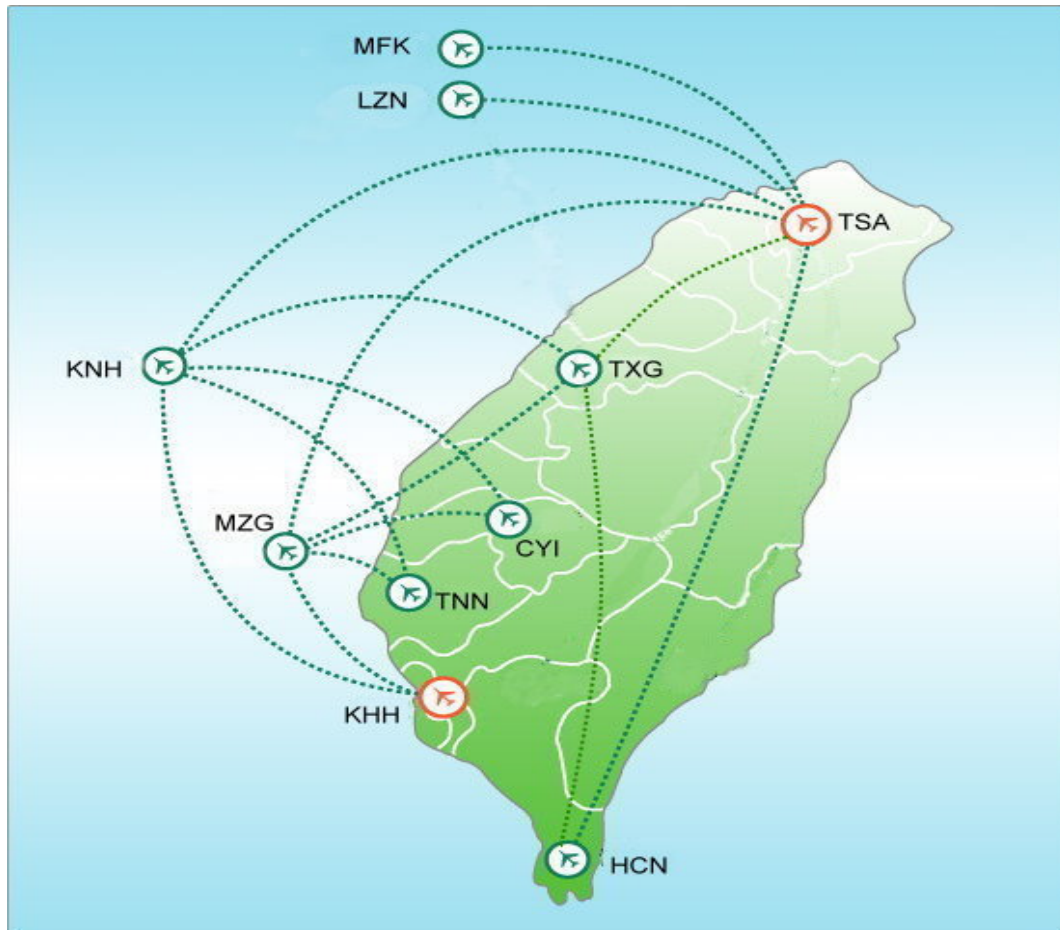


Figure 2. Flight network.

Table 1. Pareto solution set for DH-8 fleet.

Schedule	Total delay cost (US\$)	Delay over 15 min (Flights)	Delay flights	Flight swaps (Flights)
1	16,928.8	6	9	4
2	16,928.8	6	10	6
3	16,928.8	6	10	8
4	21,161	8	9	4
5	16,928.8	6	10	4

Table 2. Comparison of disrupted schedule, manual recovery and MMGA.

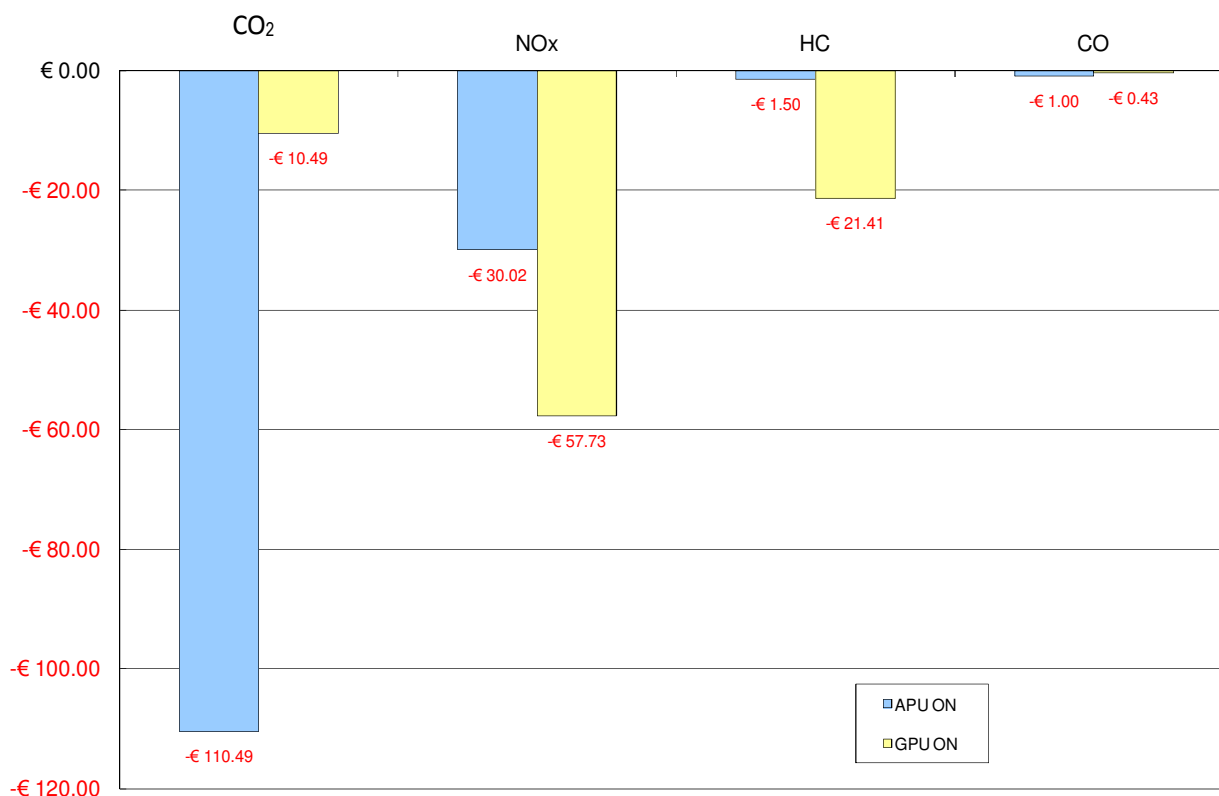
Comparison	Method		
	Disrupted Schedule (No action taken)	Manual Recovery by a senior controller	MMGA Recovery (schedule 1)
Solution time (Min)	-	20	3
Total delay cost (US\$)	44,135.8	24,184	16,928.8
Delay over 15 min. (Flights)	16	9	6
Delay flight (Flights)	21	12	9
Flight swaps (Flights)	0	2	4
Cost saving (US\$)	-	19,951.8	27,207

**Table 3.** Environment benefit of MMGA approach.

Parameter	Emission Method	CO <sub>2</sub>	NO <sub>x</sub>	HC	CO
		(6.636Kg/min)	(10.4g/min)	(0.6g/mim)	(15.6g/min)
APU on only	Disrupted Schedule	4,844.28Kg	7,592g	438 g	11,388 g
	MMGA Approach	1,858.08 Kg	2,912 g	168 g	4,368 g
	Benefit	-2,986.2 Kg	-4,680 g	-270 g	-7,020 g
GPU on only	Disrupted Schedule	459.9 Kg	14,600 g	4,562.5 g	4,891 g
	MMGA Approach	176.4 Kg	5,600 g	700 g	1,876 g
	Benefit	-283.5 Kg	-9,000 g	-3,862.5 g	-3,015 g

**Table 4.** Emission unit costs.

Pollutant type	Unit costs (€/ton)
CO <sub>2</sub>	37
NO <sub>x</sub>	6,414
HC	5,543
CO	142

**Figure 3.** Relative environmental cost reduction of MMGA approach.

same time minimizing the cost of the recovery operation.

An optimal solution is not always available in real-world airline disruption management problems, because of the

complex situations and limited resources. However, airline operations controllers have to discover a feasible solution in an acceptable short time to ensure the



promised service level and maintain the profitability of an airline. In this study, we develop an alternative optimization models based on the Method of Inequality-based Multiobjective Genetic Algorithm and using them generate recovery schedule that allow flight delaying, flight swapping, and ensure the compliance of the limitation including ground turnaround time as well as aircraft flight connection. The objective is to find the optimal trade-off between operating perspective (that is, total flight delay cost, flight swap) and service perspective (flights over 15 min delay). The focus of this proposed model is not to create the optimum solution under the strict academic assumption, but rather to provide a flexible tool that can help the airline schedule recovery process in real airline operations environment.

We evaluate our recovery solutions using real flight schedules representing the operation of a Taiwanese domestic airline. The flight cancellation does not take into consideration in our model, because the total effect of flight cancellation is very difficult to evaluate and the model will be hard to describe precisely. We assume that the time slots are still available; due to the airlines will not need to submit the new time slots during the real-time schedule disruption management. Computational experiments demonstrate that the proposed model can recover a disrupted schedule within a very short time, making it a very powerful supporting tool for decision-making during the airline disruption management process.

Since the particular operation environment of most low-cost carriers, that is, short-haul flight, quick turnaround, and very competitive market, airline operation controllers normally cannot wait very long to obtain a feasible solution for recovered schedule. Most airlines currently rely on humans to execute recovery process in the face of a disruption, rather than using optimization algorithms for this task. The operation controllers will certainly benefit from the use of a decision support system based on a recovery algorithm able to provide several recovery alternatives quickly in the complex and intensely competitive airline environment.

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