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ARTICLE

Disruption Management of an Inequality-Based Multi-Fleet Airline Schedule by a Multi-Objective Genetic Algorithm

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ABSTRACT This paper presents a novel application of a Method of Inequality-based Multi-objective Genetic Algorithm (MMGA) to generate an efficient time-effective multi-fleet aircraft routing algorithm in response to the schedule disruption of short-haul flights. It attempts to optimize objective functions involving ground turn-around times, flight connections, flight swaps, total flight delay time and a 30-minute maximum delay time of original schedules. The MMGA approach, which combines a traditional Genetic Algorithm (GA) with a multi-objective optimization method, can address multiple objectives at the same time, then explore the optimal solution. The airline schedule disruption management problem is traditionally solved by Operations Research (OR) techniques that always require a precise mathematical model. However, airline operations involve too many factors that must be considered dynamically, making a precise mathematical model difficult to define. Experimental results based on a real airline flight schedule demonstrate that the proposed method,

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Multi-objective Optimization Airline Disruption Management by GA, can recover the perturbation efficiently within a very short time. Our results further demonstrate that the application can yield high quality solutions quickly and, consequently, has potential to be employed as a real-time decision support tool for practical complex airline operations.

KEY WORDS: Disruption management; multi-objective optimization; genetic algorithm; airline; schedule recovery; method of inequalities

Introduction

Investment in the airline industry is highly capital-intensive. Given the high costs of aircraft acquisition and maintaining aircraft fleets, the airline industry is a major success story with respect to the application of optimization-based algorithms and tools in schedule planning. To maximize the utilization of their fleets, airlines spend much effort in developing their flight schedules by creating aircraft routings with limited buffer times to accommodate any variation from an optimal solution, and assume that every single flight departs and arrives according to their well-planned schedules. In their daily operations, however, airlines frequently encounter many uncertainties and unforeseen events 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 schedule.

Although the real cost induced by airline schedule disruptions is extraordinarily difficult to estimate, Shavell (2000) estimated that the total direct costs to the airlines of irregular operations incurred by 10 US airlines was US$ 1826 billion based on the 1998 Airline Service Quality Performance (ASQP) data of the US Department of Transportation. Cancellations and delays dominated with total costs of US$ 858 million and US$ 909 million, respectively, while diversions imposed an additional US$ 59 million in costs. According to the US Bureau of Transportation Statistics (BTS), the average airline fuel cost increased from US$ 0.86/gallon in 2000 to US$ 1.96/gallon in 2006, this surge in aviation fuel price must inevitably make those costs larger.

When any disruption occurs during implementing a daily schedule, the Operations Dispatchers (ODs) in an Airline Operation Control Center (AOCC) take the responsibility for handling the disrupted schedule, and are typically the ones who first decide what action to take. They invest a significant amount of time and effort in developing a revised flight schedule that is affected by any disruption. The recovery solution should have as little change as possible from the original schedule, and return to the normal schedule after a particular time.

To recover from the disturbed flight schedule, ODs can apply a mixture of flight delays and swaps, including a flight leg flown by an aircraft not originally assigned to it, cancellations, diversions, spare aircraft and ferried aircraft. However, the usage of a spare or ferried aircraft is exceptional, due to the very high costs of either option. In the majority of situations, flight delays and cancellations are feasible solutions to recover the original schedule (Thengvall *et al*., 2000). Of priority concern for the ODs is then to restore the original flight schedule as soon as possible to minimize the negative consequences of the disturbance. Nevertheless, any modification to the original schedule must be feasible for the crew as well as for the aircraft, and should preferably minimize passengers' inconvenience. Clausen *et al.* (2001) represented this process of monitoring and scheduling the resources close to the day of operations as 'Disruption Management'. Yu and Qi (2004) defined disruption management returning to regular operations as quickly as possible, and minimizing the loss and adverse effect in the recovery process.

According to US Federal Aviation Regulations (FARs) Part 121.533, one of the major responsibilities of ODs is to monitor the progress of every flight and the deviation of the original schedule. A small disruption might require no reaction, due to the inherent flexibilities and slack in the original schedule. If the deviation between the disrupted and original schedule exceeds a particular threshold, then schedule recovery needs to be taken. First, the ODs must determine which constraint might be considered, e.g. a company's policies, aircraft availability and airport condition, so as to make some feasible alternatives. Consequently, they must dynamically revise the original schedule, and select a new revised schedule that can minimize the adverse effect of the disruption. Figure 1 shows and illustrates this airline disruption management process.

In the real world, airline disruption management is a continuing sensitive process for ODs where the presence of real-time information frequently compels reconsideration and revision of the original schedule. Presently, they do it manually with the assistance of various decision support tools that enable easy access to information on the current situation. Since Taiwan domestic flights are mostly short-haul, typically less than one hour, and the markets are very competitive with buses, high-speed railway and other airlines, disruptions in the schedule become increasingly serious with time if no reactions are taken. Therefore, the ODs must make very quick decisions, in most situations, and cannot wait a long time for the optimal solution. Although Løve *et al.* (2002) recommended that the process should be less than three

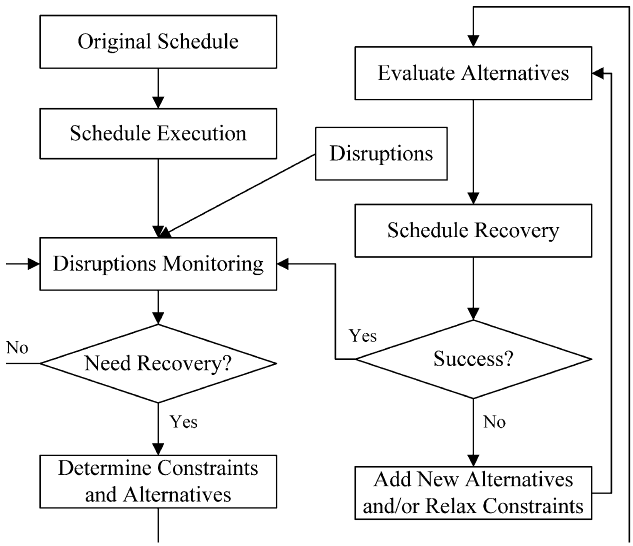

Figure 1. The process of airline disruption management

minutes, this naturally varies depending on the airline, the severity and urgency of the problem, and on the quality of the solution generated by the decision support tool.

The disruptions to schedules influence airline costs via three distinct paths. The first path is the direct costs such as additional fuel, crew time and maintenance; the second path is passenger-related costs, such as meals and lodging for passenger or payments to other airlines when passengers transfer to competitors, and the third path is secondary costs such as the ill-will created among passengers (Shavell, 2000). Rakshit *et al.* (1996) obtained 251 cases of aircraft delays during one day, and saved 8495 minutes using simple swaps between aircraft. For a conservative value of US$ 20 per minute of delay, this translates into US$ 169,900 savings in delay costs in the given period. Consequently, the ability to find good alternatives can significantly improve an airline's profitability and enhance its competitive position.

Due to the dynamic environment, the disruption management problem in airline operations is extremely complex, and is well known as a NP-hard problem. Such problems are conventionally solved with Operations Research (OR) 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. Conversely, heuristic approaches, which can obtain a near-optimal solution in a relatively shorter period, are more appreciated and practical.

Among the various heuristic approaches available, Genetic Algorithms (GAs) have already demonstrated significant success in providing suitable and efficient solutions to many NP-hard optimization problems. The traditional method involves a search process to find a candidate solution one-by-one and step-by-step. However, a GA can find numerous candidate solutions simultaneously. This paper presents a method of inequality-based Multi-Objective Optimization Airline Disruption Management (MOADM) by GAs to quickly generate a time-effective multi-fleet aircraft routing in response to schedule disruption by short-haul, quick turn-around flights, and to optimize objective functions involving ground turn-around time, flight connection, flight swap, total flight delay time and 30-minute maximal delay time of the original schedules. The objectives are to discover the most appropriate alternative with the least schedule disruption to prevent additional cost and minimize the inconvenience to passengers.

Airline Schedule Disruption Problem and Methodology

Airline Schedule Disruption Problem

Although flight scheduling research has been popular in recent years, the body of research in airline disruption management is still small. Teodorović and Guberinić (1984) were the first to explore the problem from an OR perspective. They considered a situation where an aircraft is taken out of service, and attempted to minimize the total passenger delay by swapping and delaying flights. The concept was further developed in Teodorović and Stojković (1990) to include cancellations and station curfews. Their main objective was to minimize cancellations, but if several solutions have the same number of cancelled flights, then the second objective function minimizes the total passenger delay.

Jarrah *et al.* (1993) introduced two minimum cost network flow models. They outlined two separate network flow models that provide solutions in the form of a set of flight delays (the delay model), or a set of flight cancellations (the cancellation model), while allowing for aircraft swapping among flights and the usage of spare aircraft. Unfortunately, these models cannot consider delays and cancellations simultaneously. Yan and Yang (1996) were the first to combine flight cancellations, delays and ferry flights into a single model. They developed a basic time-space network representation of the problem, which can be extended to include options to ferry aircraft and delay flights. The framework introduced was extended by

Yan and Lin (1997) to handle station closures, and by Yan and Tu (1997) to handle multiple fleets.

A real-time decision support tool for the integration of airline flight cancellations and delays has been discussed by Cao and Kanafani (1997a,b). This study developed a 0–1 Quadratic Programming (QP) model to address cancellations and delays. The study was based on the delay model of Jarrah *et al.* (1993), which they extended to include both delays and cancellations simultaneously, as well as an entire network of stations. The Airline Schedule Recovery Problem (ASRP) developed by Clarke (1997) provided a comprehensive framework that addresses how airlines can efficiently reassign operational aircraft to scheduled revenue flights after irregularities. The mathematical formulation of the problem allows flight delays and cancellations to be considered simultaneously, i.e. in the same decision model. The decision model allows for multiple fleet type aircraft swapping in flight rescheduling, provided that the candidate aircraft is capable of flying a given flight segment.

Thengvall *et al.* (2000) adopted the models presented in Yan and Yang (1996) and Yan and Tu (1997), and extended them to incorporate the ability to penalize deviations from the original schedule. The model is capable of handling cancellations, delays and flight swaps, but does not address crew or maintenance issues. Thengvall *et al.* (2001) continued their work involving serious disruption caused by airport closures. As in Yan and Lin (1997), no destination changes are allowed, meaning that the models address the typical set of actions, i.e. cancellations, delays, swapping and ferrying.

Løve *et al.* (2001) proposed a local search heuristic method to solve the flight disruption problem. Cancellations, delays, and swaps between aircraft of the same type are permitted. Rosenberger *et al.* (2003) developed a model that considered each aircraft type as a single problem. The model principally follows an approach traditionally employed in planning problems, namely a Set Partitioning master problem and a route generating procedure. Andersson and Värbrand (2004) proposed a mixed-integer multi-commodity flow model with side constraints. Cancellations, delays, and aircraft swaps are applied to resolve the perturbation, and the model ensures that the schedule returns to normal within a particular time.

Many factors affect schedule recovery performance following disruptions. These factors include static recovery scheduling, stochastic flight delays and real-time schedule recovery. Most research on recovery scheduling has focused on enhancing static recovery scheduling models, while none has analyzed these factors from a systems perspective. Yan *et al.* (2005) proposed a framework embodying a simulation process. Their framework not only analyzes the effect of stochastic flight delays on static recovery scheduling, but also designs more effective flexible buffer times and real-time schedule recovery rules.

Genetic Algorithms (GAs) and Multi-Objective Optimization

GAs are search algorithms based on the mechanisms of natural selection and natural genetics. They combine the concept of survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search. GAs are also nature-based stochastic computational methods. The major merits of these nature-based algorithms are their broad applicability, flexibility, ease of implementation and potential for finding near-optimal solutions (Goldberg, 1989).

GAs have received a rapidly growing interest in the combinatorial optimization community in the past few years, and have demonstrated significant power with very promising results from experimentation and practice in many engineering areas. A major difference between GAs and other local search heuristics, e.g. tabu search and simulated annealing, is that GA searches are based on a population of solutions instead of a single solution. They adopt a structured but stochastic way to employ genetic information in finding new directions of search. As the name suggests, they apply the concepts of natural selection and genetics. The major genetic operators reflecting nature's evolutionary process are reproduction, crossover and mutation. These techniques can be applied to global optimization in a complicated search space.

Although GAs are some types of stochastic search method, and have been applied to NP-hard problems in many areas, only a few approaches have tried to apply them to real-world scheduling problems until now. Furthermore, most of these have been restricted to job shop, flow shop or production scheduling problems (Mori & Tseng, 1997). The method of GAs for combinatorial optimization problems can be effective if an appropriate representation of the state space and feasibility preserving genetic operators has been defined. Adachi *et al.* (2004) took a practical-scale aircraft scheduling problem, and constructed a solution model that utilizes a GA. They set up a problem that simultaneously sets departure times, determines aircraft types, assigns aircraft and also minimizes the total number of aircraft.

The airline schedule disruption management problem can be formulated as a multi-objective optimization problem because, each objective has a different definition of optimality. Most multi-objective genetic algorithms (MOGAs) formulate multiple objectives as a vector, and the set of Pareto optimal solutions, which are non-dominated solutions, are generally calculated. However, practical applications require admissible solutions rather than a large number of Pareto optimal solutions. Unlike conventional multi-objective algorithms, the method of inequalities (MOI) seeks an admissible solution, which is not necessarily a Pareto optimal solution.

The Method of Inequality-based MOGA (MMGA) is a multi-objective optimization approach comprising MOI, Pareto optimization and GA. An auxiliary vector performance index (AVPI) related to the set of design specifications is introduced for the effective application of multi-objective optimization GAs (Liu & Ishihara, 2005). They developed a simple MMGA with the Pareto ranking to be applied with the auxiliary vector index. Simulation examples are then presented to present the effectiveness of the proposed MMGA. The AVPI can restrict the MMGA to search the Pareto optimal set in the regions of interest with a smaller computing effort for decision-making under multiple conflicting objectives. For the application to the MOI, the search capability of a MMGA is more significant than the characterization of the Pareto optimal set when the problem has no solution.

This study models the problem using MOI to search the utopian or Pareto optimization. An admissible set is provided as the specifications of our solution. The tunable parameter set is then tuned to discover the solution. Since the multiple objectives of the problem contain various non-compromised conflict constraints or objectives, the weights for each objective are very hard to determine. Therefore, this study adopts the Pareto optimization set to identify the non-dominance solution in GA search. A decision-making must be given when MMGA can only find a Pareto optimization set. The most suitable solution can be selected from the searching results in the Pareto optimization set. GA is applied here as a searching method to improve the decision result.

Problem Statement and Formulation

Airline schedule disruptions resulting from temporary closures of an airport are an extreme occurrence in the daily operations of an airline. When an airport is temporarily closed, the airline must evaluate immediately whether this situation would affect any flight by knock-on delay or connection delays. To absorb minor stochastic flight delays during real-time operations, the airline may add some buffer time when planning the flight schedules. It can enhance the punctuality for the airline, and decrease passenger inconvenience. However, an excessively long buffer time would eventually decrease the fleet's productivity.

Previous research on recovery scheduling has focused on improving recovery models. However, the real world has many unpredictable factors that influence the performance of airline disruption management during its operations, e.g. passenger demand, aircraft availability, company policies and uncertainty of weather condition. The entire recovery process is very subjective and time consuming. Mistakes are easy to make in human decisions. Providing an objective, efficient and Artificial Intelligence-based decision-making tool for airlines seems be very important in the current competitive environment.

This study develops a method of adopting MMGA to handle the disruption management problem of short-haul flights by optimizing five objective functions involving ground turn-around time, flight connections, total flight delay time, flight swaps and 30-minute maximum delay time. The effectiveness of the proposed method is certified using a real flight schedule obtained from a Taiwan domestic airline.

Definition of Airline Schedule Disruption Problem

The airline schedule disruption management problem has many objective functions, including hard and soft constraints. The hard constraints must be satisfied by all feasible solutions, and the soft constraints 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 are formulated as a multi-objective optimization problem. In the practical application, the objectives can be defined as total flight delay time, flight swaps, flight connections, ground turn-around time and the 30-minute maximum delay time, i.e. service promised delay time.

Let α, β, ω, and γ denote the number of aircraft, the maximal number of flights assigned to each aircraft, the number of airports, and the number of daily flights, respectively. Suppose that the set of ω airports is **P**. The timetable, denoted as a set **F**, consists of γ daily flights. All the elements in the set **F** are determined from market demands, and can be validated using various factors, such as the number of aircraft, crew size, laws and regulations. Hence, the value of γ is bounded in the range: $1 \leq \gamma \leq \alpha \times \beta$. The flight schedule can be defined as **S**, represented as a two-dimensional $\alpha \times \beta$ matrix in Eq. (1).

$$\mathbf{S} = \{s_{i,j} | s_{i,j} = (n_{i,j}, \hat{p}_{i,j}, \bar{p}_{i,j}, \hat{t}_{i,j}, \bar{t}_{i,j}, q_{i,j})\} \qquad (1)$$
$$\forall s_{i,j} \in \mathbf{F}, \quad 1 \leq i \leq \alpha, 1 \leq j \leq \beta$$

where

$S_{i,j}$	the *j*th flight assigned to the *i*th aircraft
subscript *i*	a specific aircraft
subscript *j*	a specific flight
$n_{i,j}$	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 $\bar{p}_{i,j} \in \mathbf{P}$
$\underset{\frown}{t}_{i,j}$	departure time from $\hat{p}_{i,j}$
$\hat{t}_{i,j}$	arrival time in $\bar{p}_{i,j}$
$q_{i,j}$	original duty identification for each aircraft
t_{i,j_0}	original departure time from $\hat{p}_{i,j}$

The first attribute $n_{i,j}$ of $s_{i,j}$ represents the order of an aircraft assignment of a flight. It belongs to Schedule code {1, 1, ..., 2, 2, ..., 3, 3, 3, ..., 19, 19, ..., 19} which is defined by Table 2. The other properties of $s_{i,j}$ are followed by $n_{i,j}$ and given in Table 1.

This study tries to generate a recovered flight schedule **S** by MMGA to fulfill the basic requirements of ground turn-around time, flight connections, flight swaps, total flight delay time and 30-minute maximum delay time. However, these requirements are often conflicting and violated for a given flight schedule **S**, i.e. the problem typically has no unique, perfect solution, but a set of non-dominated, alternative solutions, known as the Pareto-optimal set. Hence, the violations and conflicting requirements have to be resolved to generate a feasible solution to the current airline schedule disruption management problem.

Considering the objectives of the airline disruption management problem, because each objective has a different definition of optimality, the objectives are normally combined into a single scalar function in conventional approaches. However, a set of appropriate weights to combine the objectives is difficult to find. Furthermore, a set of weights may exist to make different solutions identical through a weighted-sum process. This study formulates the problem as a multi-objective optimization problem, defined as $\Phi(\phi_1(\mathbf{S}), \phi_2(\mathbf{S}), \phi_3(\mathbf{S}), \phi_4(\mathbf{S}), \phi_5(\mathbf{S}))$.

Table 1. Airport code

Airport code	Airport
0	TSA
1	TXG
2	CYI
3	TNN
4	KHH
5	HCN
6	MZG
7	KNH
8	TTT
9	MFK
10	LZN

The objectives of the hard constraints addressed here are ground turn-around time and flight connections. The objectives of the soft constraints considered here are total flight delay time, flight swaps and 30-minute maximal delay time. If one flight schedule violates any of the hard constraints, then it is not considered as feasible. According to Gen and Cheng (1997), the infeasible solutions are handled by rejecting, repairing, penalizing and modifying genetic operators. Traditionally, if the objective of ground turn-around time is modeled in the form of a hard constraint, then one candidate solution that violates the hard constraint is rejected. The rejection strategy works well when the feasible region is convex. However, this strategy has restrictions when the feasible region is non-convex. Additionally, the chance to discover a better solution would be reduced when rejecting a temporary infeasible solution if it is repairable. Moreover, the optimum can be potentially reached when a repairing strategy is applied because, it can help across an infeasible region. Hence the objective is modeled in the form of a soft constraint. Each element in the vector of multiple objectives denotes a violation of each objective $\phi_1(\mathbf{S})$, $\phi_2(\mathbf{S})$, $\phi_3(\mathbf{S})$, $\phi_4(\mathbf{S})$ and $\phi_5(\mathbf{S})$.

The ground turn-around time objective ensures that, each aircraft has adequate ground turn-around time not less than the legal minimum ground turn-around time requested by a civil aviation authority, denoted as T_{GH}, to be allowed for the subsequent flight. The evaluation function of this objective is defined as Eq. (2).

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

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

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 additional 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 Eq. (3).

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

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

The flight duty swap objective ensures that the original flight duty is assigned to the same aircraft in **S**, for $1 \leq i \leq \alpha$, $1 \leq j \leq \beta$. This objective reduces the additional cost of the non-profit duty swap for flights and the inconvenience of crew change. The evaluation function of this objective is defined as Eq. (4).

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

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

The total flight delay time objective minimizes the sum of delay time for each flight. The evaluation function of this objective is defined as Eq. (5).

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

$$\text{where } x_{i,j}^{(4)} = \begin{cases} 0 & \text{if } (\hat{t}_{i,j} - \hat{t}_{i,j0}) = 0 \\ \hat{t}_{i,j} - \hat{t}_{i,j0} & \text{otherwise} \end{cases}$$

Providing a reliable service to passengers is important in order to attract high-value passengers who are sensitive to on-time reliability, raise customer loyalty and customer retention rates, since satisfied customers are less likely to defect (Suzuki, 2000), and lower direct and indirect costs resulting from passenger disruptions (Bratu & Barnhart, 2006). Since domestic flights in Taiwan are mostly short-haul flights, long delay times might cause extra cost to airlines by transferring passengers to other airlines or requiring the provision of meals and other services. To fulfill the promised service level, the maximum flight delay time objective ensures that every flight has a delay time of not more than 30 minutes. The evaluation function of this objective is defined as Eq. (6).

$$\phi_5(\mathrm{S}) = \{Max\ x_{i,j}^{(5)} \mid \forall_{i,j}, 1 \leq i \leq \alpha,\ 1 \leq j \leq \beta\} \tag{6}$$

$$\text{where } x_{i,j}^{(5)} = \begin{cases} 0 & \text{if } (\hat{t}_{i,j} - \hat{t}_{i,j0}) \leq 30 \\ \hat{t}_{i,j} - \hat{t}_{i,j0} & \text{otherwise} \end{cases}$$

Auxiliary Vector Performance Index in MOI

This study employs the concept of the AVPI introduced by Liu and Ishihara (Liu & Ishihara, 2005) for the effective application of MMGA.

The AVPI can restrict the MMGAs to search the Pareto optimal set in the regions of interest with a smaller computing effort for decision-making under multiple conflicting objectives.

The auxiliary performance indices related to the inequality performance specifications are defined as Eq. (7).

$$\lambda_i(\mathbf{S},\ \varepsilon_i) = \begin{cases} 0 & (\text{if } \ \phi_i(\mathbf{S}) \le \varepsilon_i) \\ \phi_i(\mathbf{S}) - \varepsilon_i & (\text{if } \ \phi_i(\mathbf{S}) > \varepsilon_i) \end{cases}, \qquad i = 1, 2, ..., M \tag{7}$$

An AVPI is defined as Eq. (8).

$$\Lambda(\mathbf{S}, \varepsilon) = [\lambda_1(\mathbf{S}, \varepsilon_1), \lambda_2(\mathbf{S}, \varepsilon_2), \ldots, \lambda_M(\mathbf{S}, \varepsilon_M)]' \tag{8}$$

where $\varepsilon_i \in \varepsilon$ represents an admissible bound for each objective ϕ_i, and **S** denotes a given flight schedule defined in Eq. (1). The admissible bound vector has two effects in a GA: first, concentrating on searching a solution in the areas of interest, and second, decreasing the inefficient searches by relaxing some constraints, irrespective of whether an optimal solution exists.

The AVPI related to the inequalities is transformed from the MOI problem to a multi-objective optimization problem. The multi-objective formulation using the AVPI is helpful for MOI, because the admissible bounds can be combined for all objectives. Hence, each objective can be transformed into inequalities.

Consider two auxiliary vector performance indices $\Lambda_1(\mathbf{S}^{(a)}, \varepsilon)$, $\Lambda_2(\mathbf{S}^{(b)}, \varepsilon)$ with M objectives. Based on the definition of Pareto dominance by Fonseca and Fleming (1998), '$\Lambda_1(\mathbf{S}^{(a)}, \varepsilon)$ dominates $\Lambda_2(\mathbf{S}^{(b)}, \varepsilon)$' can be denoted as $\Lambda_1(\mathbf{S}^{(a)}, \varepsilon) \prec \Lambda_2(\mathbf{S}^{(b)}, \varepsilon)$ if and only if the following relation is satisfied:

$$(\forall i)(\lambda_i(\mathbf{S}^{(a)}, \varepsilon) \le \lambda_i(\mathbf{S}^{(b)}, \varepsilon)) \wedge (\exists i)(\lambda_i(\mathbf{S}^{(a)}, \varepsilon) < \lambda_i(\mathbf{S}^{(b)}, \varepsilon)) \tag{9}$$

For a two-objective optimization example$\Lambda(\mathbf{S}, \varepsilon) = [\lambda_4(\mathbf{S}, \varepsilon_4), \lambda_5(\mathbf{S}, \varepsilon_5)]$, we consider two scenarios:

Scenario 1: One flight is delayed by 30 minutes, but all other flights are delayed only slightly, or even return to normal schedule.

Scenario 2: 10 or 20 flights are delayed by 29 minutes.

The solutions of these two scenarios are represented as $\Lambda_1(\mathbf{S}^1, \varepsilon) = [1, \lambda_5^1(\mathbf{S}^1, \varepsilon_5)]$ and $\Lambda_2(\mathbf{S}^2, \varepsilon) = [0, \lambda_5^2(\mathbf{S}^2, \varepsilon_5)]$. The relations between Λ_1 and Λ_2 have the following three conditions:

Condition 1: If $\lambda_5^2 < \lambda_5^1$, then Λ_2 dominates Λ_1. This is an utopian solution of Λ. A decision-maker should undoubtedly select Λ_2 as the decision. In this condition, Objective 5 improves the confidence of decision-making.

Condition 2: If $\lambda_5^2 < \lambda_5^1$, then Λ_2 dominates Λ_1. Objective 5 plays a critical role in decision-making.

Condition 3: If $\lambda_5^2 < \lambda_5^1$, Λ_1 and Λ_2 cannot dominate each other, then both survive and await further decision-making. In this case, Objective 5 plays a counteracting role to avoid making the wrong decision.

According to Chou *et al.* (2008) solution can be called a non-dominated solution, or a Pareto optimal solution, if no other solutions exist to dominate it. Additionally, the set of Pareto optimal solutions is called a Pareto optimal set. Herein, the Pareto optimal solutions of the AVPI are not the same as those of the original objectives. The set of Pareto optimal solutions of the AVPI is the subset of the entire solution space that is restricted within the region of interest. If MOI does not have a solution, then the Pareto optimal set for the AVPI gives the decision maker helpful information to modify the admissible bounds so that a solution is obtainable.

Assume that the MMGA population comprises a set $\Pi = \{\Lambda_1, \Lambda_2, \ldots, \Lambda_N\}$, where N denotes the population size, and the AVPI set is $\Lambda_i = \{\lambda_{i1}, \lambda_{i2}, \lambda_{i3}, \ldots, \lambda_{iM}\}$, where M denotes the auxiliary vector size. This study has five objectives to be optimized, so $\Lambda_i = \{\lambda_{i1}, \lambda_{i2}, \lambda_{i3}, \lambda_{i4}, \lambda_{i5}\}$ is applied to deal with the auxiliary vector with five objectives, representing Eqs. (2) to (6), in each individual. The admissible bound ε_i can then be adjusted to search the optimal population.

Method of Inequality-Based Multi-Objective Genetic Algorithm (MMGA) Approach to the Airline Disruption Problem

Figure 2 shows the flowchart of the MMGA algorithm for the airline disruption problem. The details of the algorithm are explained as follows:

Chromosome representation. This study applies the symbolic chromosome representation method to encode an airline schedule. The chromosome length is determined simultaneously by the number of aircraft and the number of airports. Each gene represents a flight of an aircraft, and a chromosome can be indirectly decoded into a schedule. Table 1 shows the mapping relation of the airport code, and Table 2 shows the flight schedule code.

For [1, 1,..., 1, 2, 2,..., 2, 3, 3,..., 3, 4, 4,..., 4, 5, 5,...,5,...,19, ..., 19] example, is the chromosome that represents the scheduling

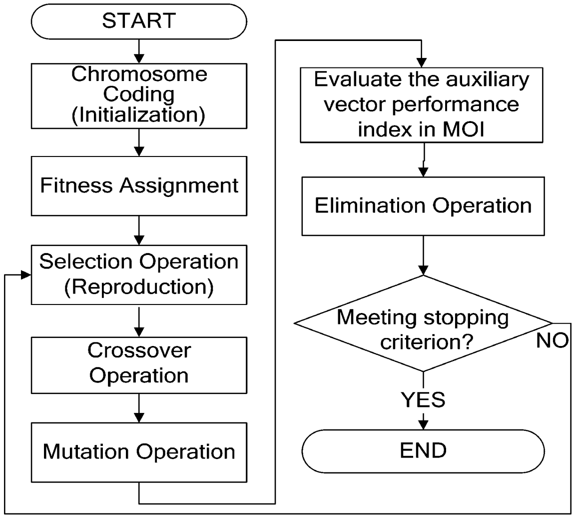

Figure 2. The flowchart of the MMGA algorithm for airline disruption problem

for the airline of flights shown in Table 2. Every number in a chromosome represents flights by a particular aircraft, e.g. '1' represents the flights of the first aircraft, and '2' represents that of the second aircraft and so on. The chromosome takes the order of classes that may receive the perturbation. This mechanism can be applied to avoid the duplicate assignment of a flight to different aircraft. Mapping Tables 1 and 2 are used to guarantee the attributes of

Table 2. Schedule code

Airport	4–0	0–4	4–0	...	0–4
Number	802	803	810	...	811
ETD	0630	0750	0910	...	1050
ETA	0720	0840	1000	...	1140
Code	1	1	1	...	1
Airport	4–0	0–4	4–0	...	0–4
Number	804	805	812	...	813
ETD	0720	0840	1010	...	1210
ETA	0810	0930	1100	...	1300
Code	2	2	2	...	2
...	...	...	...	...	...
Airport	0–5	5–1	1–5	...	6–0
Number	351	354	353	...	6208
ETD	0955	1130	1245	...	2040
ETA	1105	1215	1330	...	2125
Code	19	19	19	...	19

each flight. The flight coded by a gene in a chromosome is always with reference to its original assignment. Consequently, with this mechanism, the code of order of flight is adopted, rather than the flight itself. This can ensure the satisfaction of ground turnaround time hard constraints for the same aircraft, then applies the repair strategy (departure time sorting for each aircraft) to repair the fatal chromosome. This treatment can be used to obtain the feasible chromosome in the gene pool.

Selection. The purpose of selection is to choose an individual from the current population to the mating pool according to its fitness. The opportunity of an individual to enter the mating pool is calculated by a selection probability. GAs have several selection methods, such as random selection, tournament selection and roulette-wheel selection. The selection process in this study applies the roulette-wheel selection method. Each individual is chosen with a selection probability. The selection probability of each individual is determined from its fitness in the population. A higher fitness leads to a higher probability of entering the mating pool.

Crossover. Asexual crossover, defined by Chatterjee *et al.* (1996) as simply a swap of two randomly selected genes in a chromosome, is applied here as a one-cut-point crossover operator. The chromosome in this study has two parts, for a real-flight and for a dummy-flight. The real-flight genes are taken to resolve the new schedule. The dummy-flight genes perform gene patching. Therefore, one-swap-point between real-flight genes and dummy-flight genes is selected. The procedure is shown as follows, and an example is shown in Figure 3:

Step 1: Generate randomly two positions, P1 and P2, from real-flight genes and dummy-flight genes in the chromosome.

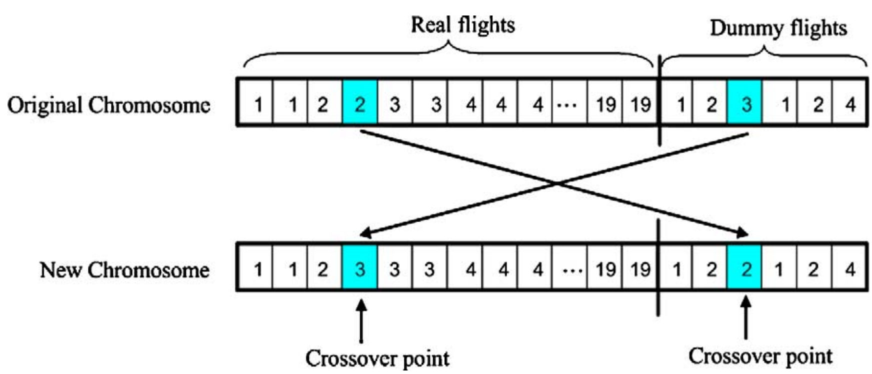

Figure 3. Example of the asexual crossover operation

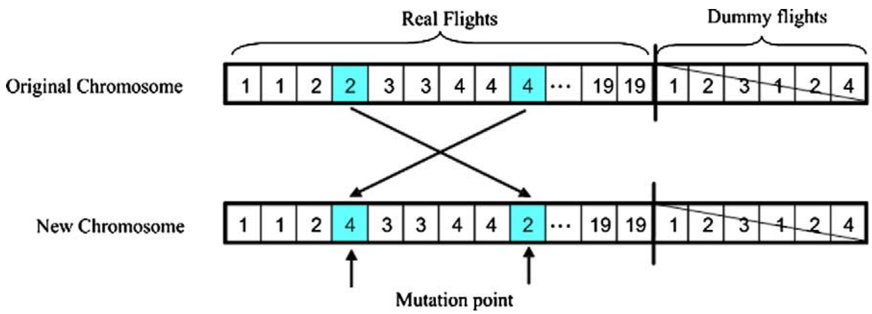

Figure 4. Example of the mutation operation

Step 2: If the two genes are the same, return to Step 1 and continue through Step 2.

Step 3: Exchange genes.

Mutation. The mutation operation applied here is the order-based mutation, which is the same as the crossover operation but using only real-flight genes. The procedure is described as follows, and an example is shown in Figure 4:

Step 1: Generate randomly two positions, P1 and P2, in the real-flight gene part.

Step 2: If the two genes are the same, return to Step 1 and continue through Step 2.

Step 3: Exchange genes.

Fitness function. The fitness function is a mathematical equation for evaluating each chromosome, and also indicates the objective function of the problem. It is an important performance index of GA, and determines which chromosomes to eliminate in the course of evolution. In this paper, we denote five objectives $\lambda_1(\mathbf{S},\varepsilon_1)$, $\lambda_2(\mathbf{S},\varepsilon_2)$, $\lambda_4(\mathbf{S},\varepsilon_4)$ and $\lambda_5(\mathbf{S},\varepsilon_5)$ as Eq. (7), where $\phi_1(\mathbf{S})$, $\phi_2(\mathbf{S})$,$\phi_3(\mathbf{S})$,$\phi_4(\mathbf{S})$ and $\phi_5(\mathbf{S})$ are the objective functions in Eqs. (2) to (6). This rule is followed to calculate the fitness value.

The fitness function comprises the MOI and Pareto optimization methods. The Pareto set has numerous solutions. A GA can find and improve the Pareto optimal set in each generation. If an utopian solution that satisfies all the admissible values ε_i is available, then the designer can simply use it as the solution. If the utopian solution does not exist, then the designer can select the candidate solution in the

Pareto set in which the first two values, i.e. the hard constraints, are satisfied.

This study demonstrates that the flights assigned to each aircraft in random sequence by GAs may produce a temporary solution with high violation values, because some flights with earlier departure times are arranged after those with later departure times. Such a solution could be repaired to reduce the number of violations on the ground turn-around time objective. Hence, the repairing strategy is adopted to reorder all flights according to their departure times for each aircraft. For instance, a flight with departure time 14:00 may be misplaced after a flight with arrival time 15:00. These conditions strongly violate the computed objective functions. Performing a repairing procedure, i.e. ordering the flights according to their departure times, can help decrease the violations on the ground turn-around 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.

Experimental Analysis

This paper determines the best solution when two airports are reopened following a one-hour temporary closure. This situation represents the extreme of foreseeable disruptions. Major disruptions to an airline's flight schedule are unavoidable when an airport served by a large number of flights is suspended for any length of time. Intelligent rescheduling of aircraft routing in such situations can save airlines costs and minimize the adverse impact on passengers.

The aim of this study is to determine a recovered schedule by optimizing the five objective functions above in response to the airport closure. The proposed method allows delay flights and flight duty swaps between the same fleet. For instance, the experimentation in this study requires any alternative aircraft routing to be feasible with respect to the following constraints and assumptions:

1. This problem uses the flight schedule including MD90 and DH8 aircraft type fleets.
2. All flights will be resumed after Taipei Sungshan Airport (TSA) and Taichung (TXG) are reopened from a one-hour temporary closure from 14:00 to 15:00.
3. Only flight swaps and flight delays are permissible, i.e. no canceling or ferrying flights.
4. The minimum ground turnaround time is 30 minutes for the MD90 and 20 minutes for the DH8.

5. Every flight in each aircraft routing must depart from the airport where the immediately preceding flight arrived.
6. No flights can depart from an airport when it is closed.
7. Any flights are planned to land at those airports during airport closure, and their arriving times are postponed to the reopening time.
8. Airport time slots are assumed to be available.

Due to the complexity of the schedule recovery problem, previous work on this similar question generally only adopts flight delaying, flight swapping or cancellation separately. This study incorporates flight delays and flight swaps in a single model. The perturbation is minimized by reducing flight swaps and flight delays to assure the passenger's satisfaction and decrease the airline's cost.

Generally, GAs are adopted to search the optimal solution. However, in the case of airline disruption management, the schedule needs to be recovered in a limited time, rather than finding the optimal result. This study uses the flight schedule of one Taiwan domestic airline, comprising 7 MD90 aircraft (C1, C2, ..., C7) operating 70 flights and 12 DH8 aircraft (C8, C9, ..., C19) operating 140 flights, in one operational day, as shown in Figures 5 and 6. The flight routes involve 11 different airports, including Taipei Sungshan (TSA), Taichung (TXG), Chiayi (CYI), Tainan (TNN), Kaohsiung (KHH), Hengchun

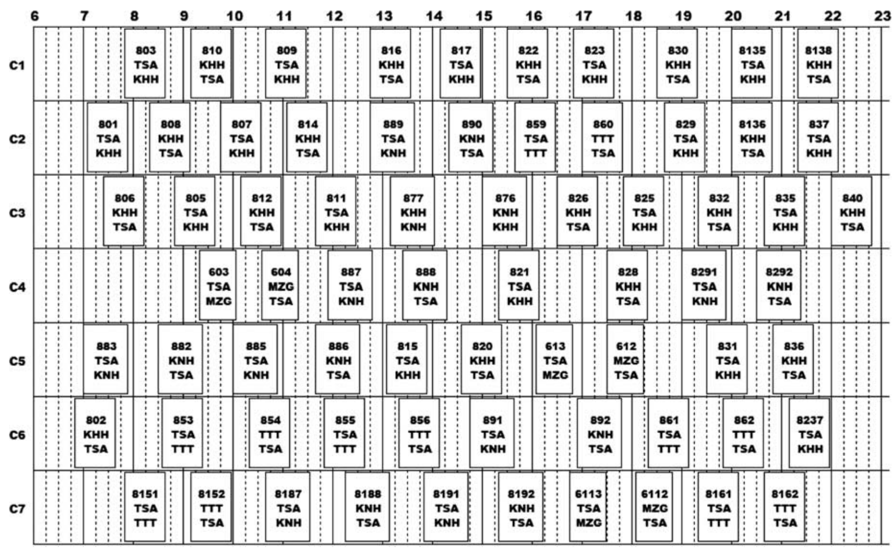

Figure 5. The Gantt chart of original MD90 schedule

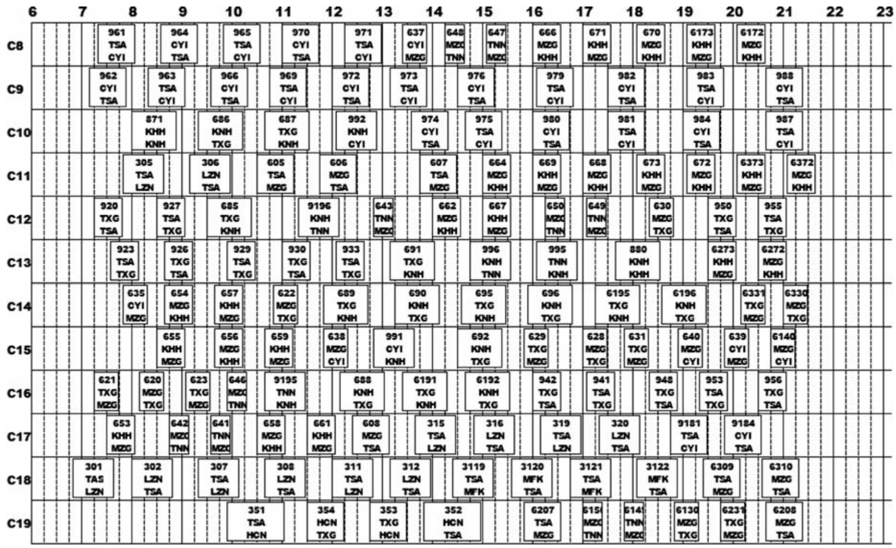

Figure 6. The Gantt chart of original DH8 schedule

(HCN), Makung (MZG), Kinmen (KNH), Taitung (TTT), Matzu North (MFK) and Matzu South (LZN). This study discusses the case of a one-hour temporary closure of TSA and TXG due to a summer afternoon thunderstorm, and attempts to recover the disrupted schedules and evaluate the difference between the recovered schedule and the original schedule.

The computing power applied in this study is a Pentium4 2.4G CPU computer with 512M RAM, and the program is coded using 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 50,000. Simulation results demonstrate that the application is capable of presenting high-quality solutions in minutes, and therefore has the potential to be applied as a real-time decision support tool for practical complex airline operations.

This study involves a multi-objective optimization problem. The objectives consist of three soft constraints, i.e. flight swaps, total delay time and maximum flight delay time, and two hard constraints, i.e. ground turn-around time and flight connection. Table 3 shows the computed Pareto Optimal sets for the MD90 fleet, and Table 4 shows those for the DH8 fleet. Those solution sets provide the user with the opportunity for decision-making. From this point of view, the objective of flight swap of schedule 1 is a superior schedule 2 for the MD90 fleet. The objectives of total delay time and delay flights of schedule 1 are

Table 3. Pareto solution set for MD90 fleet

	Total delay times (Min.)	Delay over 30 minutes (Flights)	Delay flight	Flight swaps (Flights)
Schedule 1	525	6	17	0
Schedule 2	435	6	14	2

inferior to those of schedule 2. Furthermore, schedules 1 and 2 cannot dominate each other, according to Eq. (9), as the solutions to the problem. These two schedules are said to constitute a Pareto set. This Pareto set of schedules 1 and 2 indicates that schedule 1 has the minimum flight swaps, and schedule 2 has the minimum total delay time.

For the DH8 fleet, the objective of flight swap of schedule 2 is inferior to schedules 1 and 3. The objective of total delay time of schedule 1 is inferior to schedules 2 and 3, and the objective of delay flights of schedules 1 and 2 are superior to schedule 3. Furthermore, among them, schedules 1, 2 and 3 that cannot dominate each other, according to Eq. (9), as the solutions to the problem. These three schedules are considered as a Pareto set, where schedules 1 and 3 are found to have the minimum flight swaps, and schedules 2 and 3 have the minimum total delay time. For a clear view, Figure 7 shows a Gantt chart of the recovered schedules.

Although schedule 2 of the MD90 fleet has more flight swaps than schedule 1, it has a shorter total delay time and fewer delayed flights than schedule 1. Additionally, schedule 2 of the DH8 fleet has a shorter total delay time and fewer delayed flights than schedules 1 and 3. From the customer perspective, schedule 2 of the MD90 fleet and Schedule 2 of the DH8 fleet might be good solutions. Conversely, schedule 1 of the MD90 fleet, and schedules 1 or 3 of the DH8 fleet might be good solutions from the airline perspective, because fewer swap flights mean fewer disruptions for crews and aircraft.

Table 5 shows the results of the proposed MOADM for schedule 2 of the MD90 fleet and schedule 3 of the DH8 fleet. The MD90 fleet has

Table 4. Pareto solution set for DH8 fleet

	Total delay times (Min.)	Delay over 30 minutes (Flights)	Delay flight	Flight swaps (Flights)
Schedule 1	645	9	22	4
Schedule 2	640	9	22	5
Schedule 3	640	9	23	4

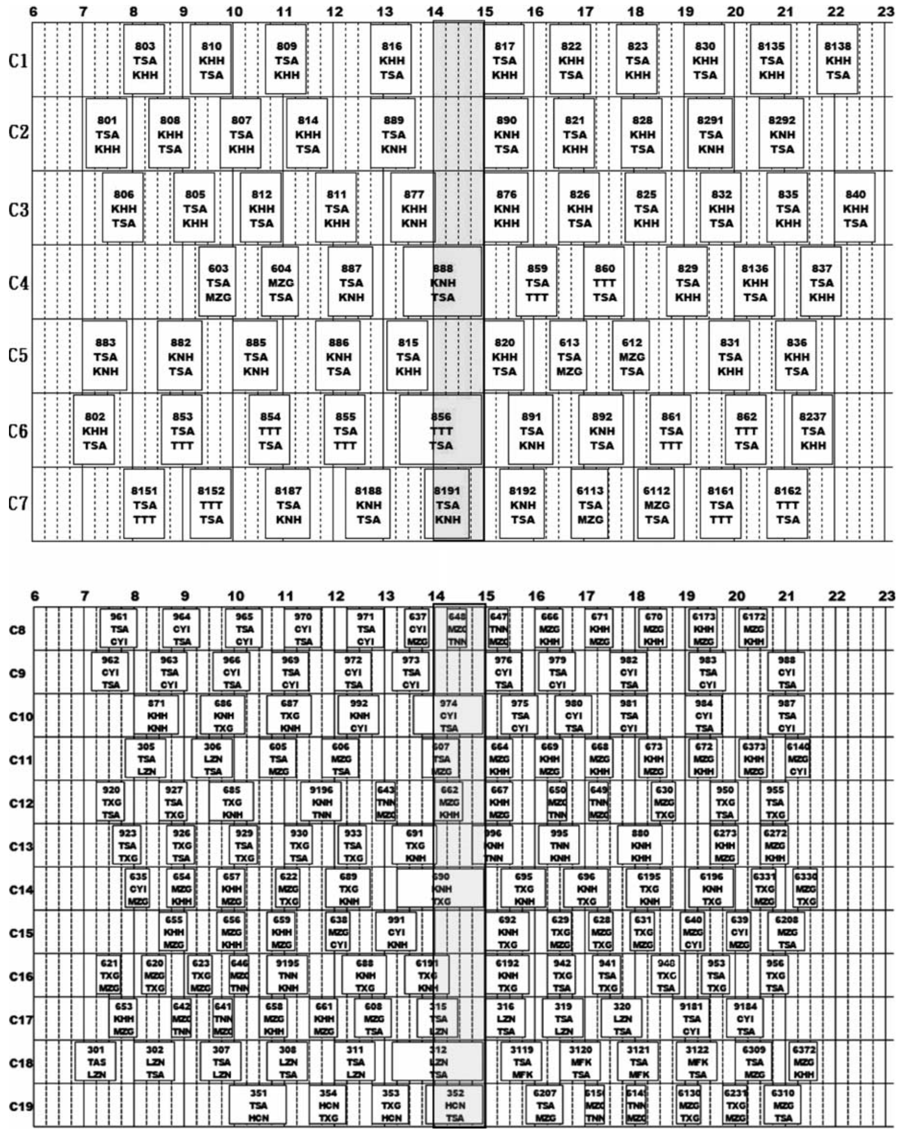

Figure 7. The Gantt chart of recovered schedule

only two flight swaps, 14 delayed flights, a total delay time of 435 minutes, and six flights delayed by more than 30 minutes, while the DH8 fleet has a total of four flight swaps, 23 flights delayed, total delay time 640 minutes, and nine flights delayed by more than 30 minutes.

Table 5. Original and recovered schedule

Original schedule						Recovered schedule				
A/C No.	Flt. No.	From	To	ETD	ETA	A/C No.	ETD	ETA	Delay (Min.)	Swap
C1	817	TSA	KHH	1410	1500	C1	1500	1550	50	No
C2	890	KNH	TSA	1420	1515	C2	1500	1555	40	No
C18	3119	TSA	MFK	1425	1515	C18	1520	1610	55	No
C9	976	TSA	CYI	1430	1515	C9	1500	1545	30	No
C15	692	KNH	TXG	1430	1525	C15	1500	1555	30	No
C5	820	KHH	TSA	1435	1525	C5	1500	1550	25	No
C14	695	TXG	KNH	1435	1530	C14	1520	1615	45	No
C10	975	TSA	CYI	1440	1525	C10	1520	1605	40	No
C16	6192	KNH	TXG	1440	1535	C16	1500	1555	20	No
C6	891	TSA	KNH	1445	1540	C6	1530	1625	45	No
C17	316	LZN	TSA	1450	1540	C17	1500	1550	10	No
C4	821	TSA	KHH	1520	1610	C2	1625	1715	65	Yes
C1	822	KHH	TSA	1530	1620	C1	1620	1710	50	No
C18	3120	MFK	TSA	1535	1625	C18	1630	1720	55	No
C2	859	TSA	TTT	1540	1630	C4	1540	1630	0	Yes
C15	629	TXG	MZG	1550	1620	C15	1615	1645	25	No
C14	696	KNH	TXG	1555	1650	C14	1635	1730	40	No
C16	942	TXG	TSA	1600	1635	C16	1615	1650	15	No
C10	980	CYI	TSA	1600	1645	C10	1625	1710	25	No
C5	613	TSA	MZG	1605	1650	C5	1620	1705	15	No
C18	3121	TSA	MFK	1645	1735	C18	1740	1830	55	No
C1	823	TSA	KHH	1650	1740	C1	1740	1830	50	No
C2	860	TTT	TSA	1700	1750	C4	1700	1750	0	Yes
C15	628	MZG	TXG	1700	1730	C15	1705	1735	5	No
C16	941	TSA	TXG	1705	1740	C16	1710	1745	5	No

Table 5 (*Continued*)

Original schedule						Recovered schedule				
A/C No.	Flt. No.	From	To	ETD	ETA	A/C No.	ETD	ETA	Delay (Min.)	Swap
C14	6195	TXG	KNH	1715	1810	C14	1750	1845	35	No
C4	828	KHH	TSA	1730	1820	C2	1745	1835	15	Yes
C5	612	MZG	TSA	1730	1815	C5	1735	1820	5	No
C15	631	TXG	MZG	1750	1820	C15	1755	1825	5	No
C18	3122	MFK	TSA	1805	1855	C18	1850	1940	45	No
C1	830	KHH	TSA	1830	1920	C1	1900	1950	30	No
C14	6196	KNH	TXG	1835	1930	C14	1905	2000	30	No
C2	829	TSA	KHH	1840	1930	C4	1840	1930	0	Yes
C4	8291	TSA	KNH	1900	1955	C2	1905	2000	5	Yes
C18	6309	TSA	MZG	1925	2010	C18	2000	2045	35	No
C1	8135	TSA	KHH	2000	2050	C1	2020	2110	20	No
C2	8136	KHH	TSA	2000	2050	C4	2000	2050	0	Yes
C14	6331	TXG	MZG	2010	2040	C14	2020	2050	10	No
C4	8292	KNH	TSA	2030	2125	C2	2030	2125	0	Yes
C18	6310	MZG	TSA	2035	2120	C19	2030	2120	0	Yes
C15	6140	MZG	CYI	2045	2115	C11	2100	2130	15	Yes
C14	6330	MZG	TXG	2100	2130	C14	2110	2140	10	No
C11	6372	MZG	KHH	2105	2140	C18	2105	2140	0	Yes
C2	837	TSA	KHH	2120	2210	C4	2120	2210	0	Yes
C1	8138	KHH	TSA	2120	2210	C1	2140	2230	20	No

Conclusions

Airline operations occur in an environment that is notoriously difficult to predict. Moreover, airlines face an unprecedented, difficult business environment due to the recent surge in aviation fuel prices. To maintain profitability, airlines have to deploy their most expensive capital assets and their associated variable factors very efficiently. Recovering a perturbed flight schedule efficiently to provide a consistent service level for passengers and maintain airline profitability is becoming increasingly important and worthy of study.

The process of schedule disruption management in current airline operations depends strongly on personal experience judgments among ODs. Providing a powerful interactive tool for airline ODs to recover the disrupted schedule becomes increasingly important in the complex and intensely competitive airline environment. This study demonstrates the success of MOADM by GA. Due to the particular civil aviation operation environment in Taiwan, e.g. short-haul flights, quick turn-arounds, and very competitive market, airline ODs normally cannot wait long to obtain a feasible solution for recovered schedule. Computational experiments based on a real airline flight schedule demonstrate that the proposed model can recover a disrupted schedule within a very short time, making it a powerful supporting tool for decision-making during the airline disruption management process.

An optimal solution is not always available in real-world airline disruption management problems, because of complex situations and limited resources. However, airline ODs have to discover a feasible solution in an acceptable short time to ensure the promised service level and maintain the profitability of an airline. Pareto optimization and MOI seem to be good solutions for this problem, since Pareto optimization provides a multiple objective optimization consideration, and MOI provides a decision-making tool to manage the conflict conditions. The proposed model adopting employing MOI and Pareto optimization can deal with these problems very well.

The Method of Inequality-based MMGA combining GA with Pareto optimization and MOI has the abilities of global searching, multi-objective optimization and decision-making. MMGA has a good chance of finding optimal solutions when they exist, and otherwise finds a feasible solution to compromise the conflicting objectives. MMGA can also effectively manage the dynamic variation of the airline disruption management problem efficiently. From the experimental results, the proposed method has demonstrated the ability to solve the dynamic and complex problem of airline disruption management.

References

Adachi, N., Sato, M. & Kobayashi, S. (2004) Application of genetic algorithm to flight schedule planning, *Systems and Computers in Japan*, 35(12), pp. 888–895.

Andersson, T. & Värbrand, P. (2004) The flight perturbation problem, *Transportation Planning and Technology*, 27(2), pp. 91–117.

Bratu, S. & Barnhart, C. (2006) Flight operations recovery: New approaches considering passenger recovery, *Journal of Scheduling*, 9(3), pp. 279–298.

Cao, J. M. & Kanafani, A. (1997a) Real-time decision support for integration of airline flight cancellations and delays: Part I: Mathematical formulations, *Transportation Planning and Technology*, 20(3), pp. 183–199.

Cao, J. M. & Kanafani, A. (1997b) Real-time decision support for integration of airline flight cancellations and delays: Part II: Algorithms and computational experiments, *Transportation Planning and Technology*, 20(3), pp. 201–217.

Chan, F. T. S., Chung, S. H. & Chan, P. L. Y. (2006) Application of genetic algorithms with dominant genes in a distributed scheduling problem in flexible manufacturing systems, *International Journal of Production Research*, 44(3), pp. 523–543.

Chatterjee, S., Carrera, C. & Lynch, L. A. (1996) Genetic algorithms and traveling salesman problems, *European Journal of Operational Research*, 93(3), pp. 490–510.

Chou, D. Y., Liu, T. K., Lee, C. N. & Jeng, C. R. (2008) Method of inequality-based multiobjective genetic algorithm for domestic daily aircraft routing, *IEEE Transactions on Systems Man and Cybernetics Part A-Systems and Humans*, 38(2), pp. 209–308.

Clarke, M. D. (1997) *The Airline Schedule Recovery Problem*, Working Paper, MIT International Center for Air Transportation. (Boston, MA: Massachusetts Institute of Technology).

Clausen, J., Hansen, J., Larsen, J. & Larsen, A. (2001) Disruption management, *ORMS Today*, 28, pp. 40–43.

Fonseca, C. M. & Fleming, P. J. (1998) Multiobjective optimization and multiple constraint handling with evolutionary algorithms – part I: A unified formulation, *IEEE Transactions on Systems Man and Cybernetics Part A-Systems and Humans*, 28(1), pp. 26–37.

Gen, M. & Cheng, R. (1997) *Genetic Algorithms and Engineering Design* (New York: John Wiley).

Goldberg, D. E. (1989) *Genetic Algorithms in Search, Optimization, and Machine Learning* (Boston, MA: Addison-Wesley).

Jarrah, A. I., Yu, G., Krishnamurthy, N. & Rakshit, A. (1993) A decision support framework for airline flight cancellations and delays, *Transportation Science*, 27(3), pp. 266–280.

Liu, T. K. & Ishihara, T. (2005) Multiobjective genetic algorithms for the method of inequalities, in: V. Zakian (Ed) *Control Systems Design – A New Framework*, Chapter 8, 231–248 (London: Springer-Verlag).

Løve, M., Sørensen, K. R., Larsen J. & Clausen, J. (2001) Using heuristics to solve the dedicated aircraft recovery problem, *Technical Report IMM-TR-2001-18, Department of Informatics and Mathematical Modelling, Technical University of Denmark, Lyngbvy, Denmark.*

Løve, M., Sørensen, K. R., Larsen, J. & Clausen, J. (2002) Disruption management for an airline – rescheduling of aircraft, *Lecture Notes in Computer Science*, 2279, pp. 315–324.

Mori, M. & Tseng, C. C. (1997) A genetic algorithm for multi-mode resource constrained project scheduling problem, *European Journal of Operational Research*, 100(1), pp. 134–141.

Rakshit, A., Krishnamurthy, N. & Yu, G. (1996) System operations advisor: A real-time decision support system for managing airline operations at united airlines, *Interfaces*, 26(2), pp. 50–58.

Rosenberger, J. M., Johnson, E. L. & Nemhauser, G. L. (2003) Rerouting aircraft for airline recovery, *Transportation Science*, 37(4), pp. 408–421.

Shavell, Z. A. (2000) The effects of schedule disruptions on the economics of airline operations, in: *3rd USA/Europe Air Traffic Management R&D Seminar,* Naples, June.

Suzuki, Y. (2000) The relationship between on-time performance and airline market share: A new approach, *Transportation Research Part E*, 36(2), pp. 139–154.

Teodorović, D. & Guberinić, S. (1984) Optimal dispatching strategy on an airline network after a schedule perturbation, *European Journal of Operational Research*, 15(2), pp. 178–182.

Teodorović, D. & Stojković, G. (1990) Model for operational daily airline scheduling, *Transportation Planning and Technology*, 14(4), pp. 273–285.

Thengvall, B. G., Bard, J. F. & Yu, G. (2000) Balancing user preferences for aircraft schedule recovery during irregular operations, *IIE Transactions*, 32(3), pp. 181–193.

Thengvall, B. G., Yu, G. & Bard, J. F. (2001) Multiple fleet aircraft schedule recovery following hub closures, *Transportation Research Part A*, 35(4), pp. 289–308.

Yan, S. & Lin, C. G. (1997) Airline scheduling for the temporary closure of airports, *Transportation Science*, 31(1), pp. 72–82.

Yan, S., Tang, C. H. & Shieh, C. L. (2005) A simulation framework for evaluating airline temporary schedule adjustments following incidents, *Transportation Planning and Technology*, 28(3), pp. 189–211.

Yan, S. & Tu, Y. (1997) Multifleet routing and multistop flight scheduling for schedule perturbation, *European Journal of Operational Research*, 103(1), pp. 155–169.

Yan, S. & Yang, D. (1996) A decision support framework for handling schedule perturbations, *Transportation Research Part B*, 30(6), pp. 405–419.

Yu, G. & Qi, X. (2004) *Disruption Management: Framework, Models, Solutions and Applications* (Singapore: World Scientific Publishing).