Airline Flight Frequency Determination and Adjustment in Response to Airline Emissions Charges

Yuh-Horng WEN

Department of Transportation Management, Tamkang University,
Tamsui, New-Taipei City 25137, Taiwan R.O.C.
E-mail: yhwen@mail.tku.edu.tw

Abstract: This study develops a multiobjective programming model for airline flight frequency determination and adjustment responsive to European Union airline emission charges, to determine the operational strategies in airline flight frequencies, routing, aircraft emission reduction, and aircraft re-assignment. The multiobjective programming model systematically minimizing the total emission charges, the total airline operating costs, and the total passenger generalized costs was formulated. The demand-supply interaction for airline flight frequency determination resulted from the changes in passenger demand was formulated. This study proposes an algorithm to solve the airline flight frequency multiobjective programming problem with demand-supply interactions. An example with selected airline flight network was provided to illustrate the results of the proposed models. The numerical results explored the effect of airline emissions charges on airline flight frequencies and aircraft type assignment. The results also provide higher flexibility on decision-making for airline flight frequency determination in response to airline emission charges.

Keywords: Airline Flight Frequency Determination, Airline Emissions Charges, European Union Emissions Trading Scheme, Multiobjective Programming

1. INTRODUCTION

As the implementation of the European Commission for including the aviation sector into the European Union Emission Trading Scheme (EU ETS), airlines faced the severe challenge on airline emission charges. From January 2012, all European and non-European airlines were included with their flights that operate in and out of the European Union (EU). According to EU ETS scheme, airlines receive 85% of their allowances (known as Aviation EUAs) free of charge, based on the 2004-2006 average of their emissions, with the remainder being auctioned. From 2013 to 2020 the number of free allowances will reduce to 82% and the remaining 15% will be auctioned. In addition, 3% will be set aside to create a reserve of allowances for new entrants and fast growing airlines. In 2012 emissions are capped at 97% of historical emissions; and from 2013, the emission will be capped at 95% of historical emissions. However, international aviation organizations and non-EU countries have expressed strong opposition to the scheme, with countries such as India and China instructing their airlines not to take part in the scheme. This could, in the long term, lead to non compliant airlines being banned from flying to EU countries. Thereby, European Commission deferred the ETS airline charges for one year until after the International Civil Aviation Organization (ICAO) General Assembly in autumn 2013. ICAO has long recognized the role that market-based measures can play in achieving environmental goals cost-effectively and in a flexible manner. The EU is committed to finding a comprehensive and non-discriminatory multilateral agreement within ICAO, and the EU legislation is designed to be amended in the light of such an agreement. In its statement the European Commission made clear that, should the 2013 ICAO General Assembly fail to make the necessary progress, the EU ETS legislation would be applied in full again to all flights to and from non-EU countries. Consequently, airline emission charges as well as reducing fuel consumption and greenhouse gas emissions will be still important issues for airline management.

Since EU airline emission charges are applied to all airlines that fly in and out of the EU, and airlines will be charged on carbon emissions created by flight between the-third country airports and EU airports. In response to airline emission charges, airlines could try to reduce aircraft weight and emissions, or rearrange flight routing and frequencies, or reassign new-type aircraft. Airlines may transfer the cost of carbon emission fees into the airfares, or apply passenger volunteer offset program; however, the increases in airfare will affect the decreases in passenger demand. Therefore, how to determine and adjust airline flight frequencies in response to EU emission charges and changes in demand are very important for airlines to enhance their performance and remain competitiveness. Studies about the impacts of EU ETS on airline industry focused on strategic reactions, aircraft types, and network reconfigurations in response of emission charges (e.g., Albers et al., 2009; Miyoshi and Mason, 2009; Brueckner and Zhang, 2010; Givoni and Rietveld, 2010). Albers et al. (2009) conducted a route-based analysis to simulate the cost and demand implications for case airlines, and their results indicated that airline costs increases but not high enough to instigate major route reconfigurations among European airlines. Miyoshi and Mason (2009) discussed a prototype methodology to assess the carbon emission levels in the UK domestic routes, the intra-EU routes, and the North Atlantic routes markets, and the results showed the differences in airlines' strategies such as aircraft type used, load factors and seat configurations. Brueckner and Zhang (2010) explored the effect of airline emissions charges on airfares, airline service quality, aircraft design features, and network structure using a duopoly competing model; their results showed that emission charges will raise fares, reduce flight frequency, increase load factors, and raise aircraft fuel efficiency. Givoni and Rietveld (2010) evaluated the environmental consequences for airline choice of service frequency and aircraft size; and their analysis showed that increasing aircraft size and adjusting the service frequency to offer similar seating capacity will decrease climate change impact and noise pollution.

The literature on airline networks has mostly addressed the shapes of airline networks, the determination of flight frequency, and the choice of aircraft (e.g., Teodorovic, 1983, 1986; Teodorovic and Krcmar-Nozic, 1989; Teodorovic et al., 1994; Hsu and Wen, 2000; 2002; 2003). Flight frequency programming problems that involve a single airline network and that are constructed using mathematical programming are considered. The passenger demand pattern is assumed to be exogenous, and demand is assumed to be inelastic, although passenger demand may be elastic to flight frequency in a competitive environment. However, few studies determine airlines' reactive strategies in response to EU ETS charges from the perspective of airline flight frequency determination. Airline flight frequency programming problem, including how to determine flight frequencies and routing, and assign aircraft types on individual routes, is a prerequisite for an airline's operational planning such as flight scheduling and crew assignment. Flight frequency determination is heavily emphasized since the chosen flight routing, flight frequency and aircraft type on individual routes directly influence the operating effectiveness of the airline and the quality of service provided to passengers. In response to emission charges, airlines strive to generate the lowest possible operating costs, achieve a higher load factor and reduce emissions by re-assigning emission-reduction aircraft, adjusting the service frequency on stopover flights. However, these strategies may also increase passenger schedule delays, and thus lose time-sensitive passengers. Emission charges prompting higher airfares will also affect passenger demand. Significant interaction between demand and supply necessitates the use of a systematic analysis approach to formulate airline flight frequency programming problem.

This study develops an airline flight frequency programming model responsive to EU airline emission charges, to determine the operational strategies in airline flight frequencies, routing, aircraft emission reduction, and aircraft re-assignment. The demand-supply interaction for airline network resulted from the changes in passenger demand is also formulated and discussed. The flight frequency programming is formulated as a multiobjective programming model that systematically minimizes the total emission charges, the total airline operating costs, and the total passenger generalized costs. An example with selected airline flight networks and other data will be provided to illustrate the results and the application of the proposed models. Moreover, a group of optimal airline network plans is determined by applying interactive multiobjective programming. These groups of solutions not only provide flexibility in decision making with three objectives, but also show the trade-offs between benefits of emission reduction and costs of airline and passengers.

The remainder of this paper is organized as follows. In Section 2, airline operating costs, passenger generalized travel costs, and airline emission charges are formulated. A multiobjective programming model for determining flight frequencies and aircraft assignment is formulated in Section 3, and an iterative algorithm to solve the airline flight frequency multiobjective programming problem with demand-supply interactions is also proposed. A numerical example involving the CI airline of Taiwan is presented in Section 4, illustrating the application of the models. Concluding remarks are offered in Section 5.

2. FORMULATION

Consider an airline network $G(\mathbf{N}, \mathbf{A})$, where $\mathbf{N}$ and $\mathbf{A}$ represent the set of nodes and set of links of graph G, respectively. Let $\mathbf{R}$ ($\mathbf{R} \subseteq \mathbf{N}$) denote the set of origin cities, and $\mathbf{S}$ represent the set of destination cities ($\mathbf{S} \subseteq \mathbf{N}$), where $\mathbf{R} \cap \mathbf{S} \neq \varnothing$. Since EU ETS are applied to airlines that fly in and out of the EU airports, and airlines are charged on carbon emissions created by flight between the-third country airports and EU airports. Let $\mathbf{N}^E$ denote the subset of EU cities (airports), and let $\mathbf{N}'$ denote the subset of non-EU cities (airports), where $\mathbf{N} \equiv \mathbf{N}^E \bigcup \mathbf{N}'$. All origin-destination (OD) pairs r-s can be divided into non-EU OD pairs and EU OD pairs. Let $J' \equiv \{r-s \mid \forall r, s \in N'\}$ denote the set of non-EU OD pairs, which both origin and destination nodes are non-EU nodes. Let $J^E \equiv \{r-s \mid \forall r, s \in J - J'\}$ denote the set of EU OD-pairs, which include both OD are EU nodes and either origin or destination node is EU node. Let $\mathbf{A}^E$ denote the subset of flight links connecting EU airports (including links connecting both EU nodes and links connecting one EU airport and one non-EU airport). Let $\mathbf{A}'$ denote subset of links connecting both non-EU airports, also $\mathbf{A} \equiv \mathbf{A}^E \bigcup \mathbf{A}'$. Next, any given OD city-pair r-s is connected by a set of routes P_{rs} $(r \in \mathbf{R}, s \in \mathbf{S})$ through the network.

2.1 Airline Operation Costs

In airline flight frequency programming, the major decision variables are arranged to determine flight frequencies, routing, and aircraft assignment. In determining flight frequencies, the transportation capacities offered in terms of the number of seats on each path must be equal to or greater than the number of passengers on the path, that is,

$$N_{rspq}\,\eta_{rspq} n_q \geq f_{rsp} \tag{1}$$

where,

N_{rspq} : the weekly flight frequency of aircraft *q* from *r* to *s* along route *p*,

η_{rspq} : the load factor of aircraft *q* flying from *r* to *s* along route *p*,

n_q : the number of available seats of the aircraft type *q*,

f_{rsp} : the weekly number of passengers on route *p* from *r* to *s*.

Furthermore, the link flow is the sum of the flows on all routes going through that link and can be expressed as a function of the route flows. That is,

$$f_a = \sum_{r,s}\sum_{p}\delta_{a,p}^{r,s} f_{rsp} \tag{2}$$

where,

f_a : the weekly number of passengers on link *a* ($a \in \mathbf{A}$),

$\delta_{a,p}^{r,s}$: the indicator variable, and if $\delta_{a,p}^{r,s}$ =1, then link *a* is a part connecting O-D pair *r*-*s*; otherwise, $\delta_{a,p}^{r,s}$ =0,

f_{rsp} : the weekly number of passengers flying from *r* to *s* along route *p*,

By using the same indicator variable, the relationship between the link frequency and the route frequency is

$$N_a = \sum_{r,s}\sum_{p}\sum_{q}\delta_{a,p}^{r,s} N_{rspq} \tag{3}$$

where,

N_a : the weekly flight frequency on link *a* ($a \in \mathbf{A}$).

In response to EU ETS, airlines' opportunities for reducing emissions arise from the optimization of airline route networks and flight frequencies and increasing load factors. In the long run, the accelerated introduction of more modern aircraft represents an opportunity to reduce emissions. However, aircraft are major investments that endure for many decades, and replacement of the international fleet is therefore a long-term proposition. In the short run, airlines could conduct the aircraft weight and emission reduction plans. The aircraft re-assignment decision is taken into consideration in the airline flight frequency programming. Consider the airline fleet has *q* types of aircraft, let q^0 denote the existed aircraft type and let q^+ denote the new introduced aircraft type. Each existed aircraft type q^0 could be decided to improve as an emission-reduction aircraft type q'. The emission-reduction aircraft q' with higher fuel efficiency will have lower fuel consumption and lower operating costs. Let $\beta_{rspq'}$ = {0,1} denote the binary option for deciding the aircraft emission-reduction plan or do nothing, where $\beta_{rspq'} = 1$ represents deciding the aircraft to improve as an emission-reduction aircraft along the path *p*.

Airline costs can be classified into operating costs and nonoperating costs. Nonoperating costs include those expenses not directly related to the operation of an air carrier. Therefore, while considering the air carrier costs, this study simply takes operating costs into account. Hsu and Wen (2000, 2002) systematized air carrier costs and passenger costs. Herein, this study follows the formulation of these costs. Airline operating costs are normally divided into direct operating cost and indirect operating costs. Direct operating costs are all those expenses associated with the type of operated aircraft, including all flying costs, all maintenance, and all aircraft depreciation expenses. Since different aircraft types {q^0, q', q^+} have different route direct operating costs, the direct operating cost for a flight over link *a* ($a \in \mathbf{A}$) with stage length d_a is denoted by dc_a, such as:

$$\mathrm{dc}_a = d_a \sum_{r,s} \sum_{p} \delta_{a,p}^{r,s} \left[\sum_{q^0,q'} ((1-\beta_{rspq'})c_{rspq^0} N_{rspq^0} + \beta_{rspq'} c_{rspq'} N_{rspq'}) + c_{rspq^+} \sum_{q^+} N_{rspq^+} \right] \tag{4}$$

where,

N_{rspq^0}, $N_{rspq'}$, N_{rspq^+} : the weekly flight frequency of aircraft type q^0, q', q^+, respectively, on route *p* from *r* to *s*,

c_{rspq^0}, $c_{rspq'}$, c_{rspq^+} : the unit direct operating cost of aircraft type q^0, q', q^+, respectively, flying route *p* from *r* to *s*.

Furthermore, the airline operating cost could be assumed to be a piece-wise linear function for each link (O'Kelly and Bryan, 1998; Wen and Hsu, 2006), the piece-wise linear cost function approximates a nonlinear cost function that allows costs to increase at a decreasing rate as traffic increases.

Indirect operating costs are those expenses related to passengers rather than related to aircraft. Kanafani and Ghobrial (1982) noted that the unit indirect operating cost per passenger can be considered as a constant. Then, the total indirect operating cost on link *a*, is

$$\mathrm{ic}_a = c_h \sum_{r,s} \sum_{p} \delta_{a,p}^{r,s} f_{rsp} \tag{5}$$

where,

ic_a : the indirect operating cost for a flight over link *a* ($a \in \mathbf{A}$),

c_h : the unit handling cost per passenger in dollars.

Furthermore, the cost for aircraft emission reduction plan is also considered, such as

$$\mathrm{de} = \sum_{r,s} \sum_{p} \sum_{q'} c_{q'} \beta_{rspq'} \tag{6}$$

where,

de : the total aircraft emission reduction cost,

$c_{q'}$: the costs for conduction the aircraft weight and emission reduction plans for each emission-reduction aircraft.

The total operating costs of the airline is

$$\mathrm{TC} = \mathrm{de} + \sum_a \mathrm{dc}_a + \sum_a \mathrm{ic}_a \tag{7}$$

2.2 Passenger Generalized Travel Costs

In airline flight frequency programming, the passenger generalized costs are taken into consideration in advance. The total passenger air-ticket cost on link *a*, pp_a, is

$$\mathrm{pp}_a = \sum_{r,s} \sum_p \delta_{a,p}^{r,s} \mathrm{p}_{rsp} f_{rsp} \tag{8}$$

where,

p_{rsp} : the air ticket per passenger on route *p*.

Moreover, the costs of passenger travel time can be divided into two components. The first component is the total passenger line-haul travel cost on link *a*, tt_a, which could be expressed by

$$\mathrm{tt}_a = \sum_r \sum_s \sum_p \sum_q \delta_{a,p}^{r,s} c_t (\gamma_q + \rho_q d_{rsp} + \Delta_{rsp}) f_{rspq} \tag{9}$$

where,

γ_q, ρ_q : travel time function parameters and depend on the speed of aircraft type *q*,

d_{rsp} : the stage length of route *p*,

Δ_{rsp} : the airport time including ground time in the nonstop route, stopover time, or transfer time in the multi-link route,

c_t : the average time value, a unit time-cost transformation reflecting the perceived money cost of line-haul travel time.

The second component is schedule delay cost, which is the time difference between the time that the passenger desires to travel and the time that it is actually possible due to the existing flight schedule. Total schedule delay cost on link *a*, st_a, is

$$\mathrm{st}_a = c_d \tau \frac{OT}{N_a} f_a \tag{10}$$

where,

OT: the average operating time of airport over a specific period, Teodorovic (1988) assumed that *OT* is 22.8 hours a day, and the weekly *OT* equals 7×22.8 hours;

OT/N_a : the average headway on link *a*,

c_d : the unit time-cost transformation reflecting the perceived money cost of schedule delay time,

τ : the multiplier affected by flight scheduling, τ is proved by Teodorovic (1983), Teodorovic and Krcmar-Nozic (1989) to equal 1/4.

Finally, the total passenger generalized travel costs is

$$\mathrm{TP} = \sum_a \mathrm{pp}_a + \sum_a \mathrm{tt}_a + \sum_a \mathrm{st}_a \tag{11}$$

Furthermore, consider the passenger demand elasticity, ε_{rsp}, such as

$$\varepsilon_{rsp} = \frac{\Delta f_{rsp}\%}{\Delta \mathrm{TP}\%} \tag{12}$$

The changes in route passenger traffic can be expressed as $\Delta f_{rsp}\% = \varepsilon_{rsp}\Delta\mathrm{TP}\%$. Since the determined flight frequencies, emission fees, and travel times will affect the passenger generalized travel costs, and the changes in passenger generalized travel costs will, in turn, affect passenger traffic. The changed passenger traffic can be expressed as

$$f'_{rsp} = (1 + \Delta f_{rsp}\%)\, f_{rsp} \tag{13}$$

2.3 EU Emission Charges

According ICAO Carbon Emission calculator (v.3, 2010), the calculated fuel burn can be converted into emissions of CO_2 by multiplication by an emissions factor of 3.157 kg-CO_2/kg-fuel. The emissions of link $a^E \in \mathbf{A}^E$ can be expressed as

$$CE_{a^E} = 3.157 \sum_{r,s \in J^E} \sum_p \sum_q \delta^{r,s}_{a^E,p}\, g_{rspq} N_{rspq} \tag{14}$$

where,

g_{rspq} : the fuel consumption of aircraft flying on route p from r to s.

Then the total weekly emissions of airline is

$$E = \sum_{a^E \in A^E} CE_{a^E} \tag{15}$$

According the directions of EU ETS, each airline is regulated a level of allowances, i.e., European Aviation Allowances (EUAA) and Emission Reduction Units (ERU); in 2012 airlines receive 85% of their allowances free of charge, based on the 2004-2006 average of their emissions, with the remainder being auctioned. However, if the total emissions are larger than the allowances, the airline will pay a penalty charge (€100 per ton emission). Let Q denote the allowance level, and let t be the unit emission auctioned price. Then the airline's total annual emission charges are

$$\begin{cases} T = 0, \text{ if } \quad 52E \le 0.85Q \\ T = (52E - 0.85Q) \times t, \text{ if } \quad 0.85Q < 52E \le Q \\ T = (52E - 0.85Q) \times t + 100(52E - Q), \text{ if } 52E > Q \end{cases} \tag{16}$$

3. PROGRAMMING MODEL

Herein, the airline flight frequency determination problem is formulated as a multiobjective programming model for airline network planning that systematically minimizes the total airline operating costs, the total passenger generalized costs, and the total emission charges (in dollars per week). The programming model determines the flight frequencies on individual routes, and also solves the routing problem of an airline network. The demand-supply interaction for airline flight frequency plan resulted from the changes in passenger demand is taken into consideration. This airline flight frequency multiobjective programming is formulated as follows:

$$\text{Min} \quad Z_1 = \text{TC} \tag{17a}$$

$$\text{Min} \quad Z_2 = \text{TP} \tag{17b}$$

$$\text{Min} \quad Z_3 = T / 52 \tag{17c}$$

s.t.

$$\sum_{r,s} \sum_{p} \sum_{q} \delta_{a,p}^{r,s} N_{rspq} \eta_{rspq} n_q \ge f_a \ , \quad \forall a \in A \tag{17d}$$

$$f_{rs} = \sum_{p} f_{rsp} \ , \quad p \in P_{rs} \ , \qquad \forall (r,s) \tag{17e}$$

$$\sum_{p} \sum_{q} N_{rspq} = \sum_{p} \sum_{q} N_{srpq} \ , \qquad p \in P_{rs} \ , \tag{17f}$$

$$\sum_{r} \sum_{s} \sum_{p} ft_{rspq} N_{rspq} \le u_q A_q \times 7 \ , \qquad \forall q \tag{17g}$$

$$\forall \ N_{rspq} \ , f_{rspq} \ge 0 \quad \text{and integer.} \tag{17h}$$

Eqns. (17a), (17b), and (17c) are three objective functions, and Eqns. (17d)–(17h) are constraints. Eqn. (17d) represents that the transportation capacities offered in terms of the number of seats on each link must be equal to or greater than the number of passengers on all routes that contain that link. Eqn. (17e) defines that the sum of the passengers carried by any aircraft q along any route p from r to s equals the total number of passengers traveling between these two cities. Eqn. (17f) determines that an equal number of take-off and landing operations occur at each airport in the network during a certain period of time. Eqn. (17g) suggests that the total aircraft utilization must be equal to or less than the maximum possible utilization. Finally, Eqn. (17h) confines all variables to be nonnegative and integer.

Determining flight frequency on routes, expressed by Eqns. (17a)–(17h) above, is a triple-objective nonlinear programming problem of the general form:

$$\text{Min} \ \{ Z_1(\mathbf{x}), Z_2(\mathbf{x}), Z_3(\mathbf{x}) \} \qquad \mathbf{x} \in \mathbf{X} \tag{18}$$

where,

$\mathbf{x}$: the set of decision variables, i.e. $\mathbf{x} = \left\{ N_{rspq}, f_{rspq}, \quad \forall r, s, p, q \right\}$,

$\mathbf{X}$: the set of feasible points defined by given constraints, Eqns. (17d)–(17h), $\mathbf{X} \in \boldsymbol{R}^{\boldsymbol{n}}$.

Using the weighted-sum method to solve the problem in (18) entails selecting scalar weights w_i and minimizing the following composite objective function:

$$\text{Min} \;\; U = w_1 Z_1 + w_2 Z_2 + w_3 Z_3 \quad \sum w_i = 1, \forall w_i \geq 0 \tag{19}$$

If all of the weights are positive, as assumed in this study, then minimizing (19) provides a sufficient condition for Pareto optimality, which means the minimum of Eqn. (19) is always Pareto optimal. The Pareto optimality is the solution where no objective can be reached without simultaneously worsening at least one of the remaining objectives (Cohon, 1978). In this manner, a variety of airline network flight frequency plans for routes can be generated from Pareto optimal solutions for decision makers. These Pareto optimal solutions can be plotted as a Pareto optimal boundary. Along this Pareto optimal boundary, this study attempts to obtain a solution nearest to the ideal point and farthest to the negative-ideal point. The ideal point is defined as the point $Z^{\text{ideal}} = \left(Z_1^{\min}, Z_2^{\min}, Z_3^{\min} \right)$, where $Z_1^{\min}$, $Z_2^{\min}$, and $Z_3^{\min}$ are the values of the objective function for single-objective programming that minimize Z_1, Z_2, and Z_3, respectively. The compromise solution is a Pareto optimal solution which has the shortest geometrical distance from the ideal point.

In the airline flight frequency programming (Eqns. (17a)–(17h)), the traffic flows on all routes are used as input parameters to the airline network programming model. Furthermore, the route flight frequencies and airfares (responsive to emission fees) determined by the airline network programming model influence passenger traffic. The changes in flight frequencies and airfares affect passenger generalized travel costs, and the changes in passenger generalized travel costs will, in turn, affect passenger traffic flows. This paper studies the above demand-supply interactions between passenger demand and flight frequencies on an airline network using an iterative algorithm. First, passenger traffic flows for all routes on the airline network are set as initial input data. Next, the airline's flight frequencies, routing, aircraft assignment and airfares on individual routes are determined by airline network modeling (Eqns. (17a)–(17h)). Then the changes in passenger traffic are calculated by Eqn (13), and then input the changed traffic into the second iteration for solving network modeling. This process is repeated for many more rounds. The process continues until the demand-supply equilibrium is reached.

This study proposes an algorithm that integrated weighted-sum method and an iterative scheme to solve the airline flight frequency multiobjective programming problem with demand-supply interactions. Figure 1 shows the iterative algorithm of the problem. The algorithm is described as following:

Step 1. Set the initial weight vector (w_1, w_2, w_3), and minimize the composite objective function (Eqn. (19)).

Step 2. Solving the weighted-sum programming problem with demand-supply interaction:

Step 2-1. Solving the initial solution of: N_{rspq}^0, f_{rsp}^0, p_{rsp}^0, $\forall r, s, p, q$. Calculate the changes in route passenger traffic (using Eqn. (13)): $f_{rsp}^{1} = (1 + \Delta f_{rsp}\%) f_{rsp}^{0}$, then input f_{rsp}^{1} to programming model for the second round.

Step 2-2. In the i-th round, input f_{rsp}^{i-1}, p_{rsp}^{i-1}, $\forall r, s, p$, to programming model, and determine N_{rspq}^{i}, f_{rsp}^{i}, p_{rsp}^{i}, $\forall r, s, p, q$.

Step 2-3. If $\left| f_{rsp}^{i} - f_{rsp}^{i-1} \right| / f_{rspq}^{i-1} < \varepsilon$, $\forall r, s, p$ (ε is small numbers=1%), then STOP. Otherwise, $i :=i+1$, and return to Step 2-2.

Step 3. Set various weight vector (w'_1, w'_2, w'_3), and back to Step 2.

Step 4. Determine $Z^{\text{ideal}} = \left(Z_1^{\min}, Z_2^{\min}, Z_3^{\min} \right)$, and determine the compromise solution.

4. EXAMPLE

An example is presented as follows to demonstrate the application of proposed model. In this example, the selected airline is China Airlines (CI) of Taiwan, and the proposed model was applied to a simplified version of CI's international network. The selected thirteen nodes consist of the home-base node Taipei (TPE) and twelve nodes, including Hong Kong (HKG), Tokyo (TYO), Bangkok (BKK), Kuala Lumpur (KUL), Singapore (SIN), Delhi (DEL), Los Angeles (LAX), San Francisco (SFO), Honolulu (HNL), Frankfurt (FRA), Vienna (VIE) and Amsterdam (AMS). Figure 2 shows the selected airline network in this example. The traffic among these selected countries is the major part of the traffic carried by CI. CI's international fleet comprises of 38 aircraft, including B747-400s, A340-300s, and A330-300s, serving among those routes. Herein, this study uses annual total city-pair passenger among these twelve cities for forecasting; these forecasted values are then translated to CI's city-pair traffic by multiplying its relative average market shares. These CI's relative market shares are roughly estimated on the basis of its historic data and time table. On the other hand, some of CI's operating cost data are unavailable. Thus, the passenger airline cost index data reported in ATA (Air Transport Association) are employed to estimate the airline operating costs. Aircraft characteristic data reported in Horonjeff and McKelvey (1994) are also used to estimate flight time and airport time. Moreover, the average unit time-cost reflecting line-haul travel time and delay time are assumed to be \$37.73/hr and \$49.37/hr, respectively, according to slight adjustments on the values of time obtained by Furuichi and Koppelman (1994). In this example, the maximum possible utilization of three types of aircraft is given to 16.8hr per day. Route fuel consumption and emission data are estimated using relevant data in ICAO Carbon Emission calculator (v.3, 2010).

In this study, the triple-objective airline flight frequency programming was solved by using LINGO (v.11.0), and the demand-supply interactions were then determined using the proposed algorithm. The Pareto optimal solutions are obtained by the weighted-sum method described in the previous section. Sets of weights $\{w_1, w_2, w_3\}$ = {1, 0, 0}, {0, 1, 0}, {0, 0, 1}, {1/3, 1/3, 1/3}, {1/2, 1/4, 1/4}, {1/4, 1/2, 1/4}, {1/4, 1/4, 1/2}, are tested, respectively, to obtain Pareto optimal solutions. Each Pareto optimal solution with different weight sets is determined by demand-supply convergence. For each set of weights, the demand-supply interactions converged soon after two or three rounds. Moreover, the compromise solutions on Pareto optimal boundaries are obtained by obtaining the solutions with the minimum geometrical distance from the ideal point. Figure 3 plots the Pareto optimal points in the decision space.

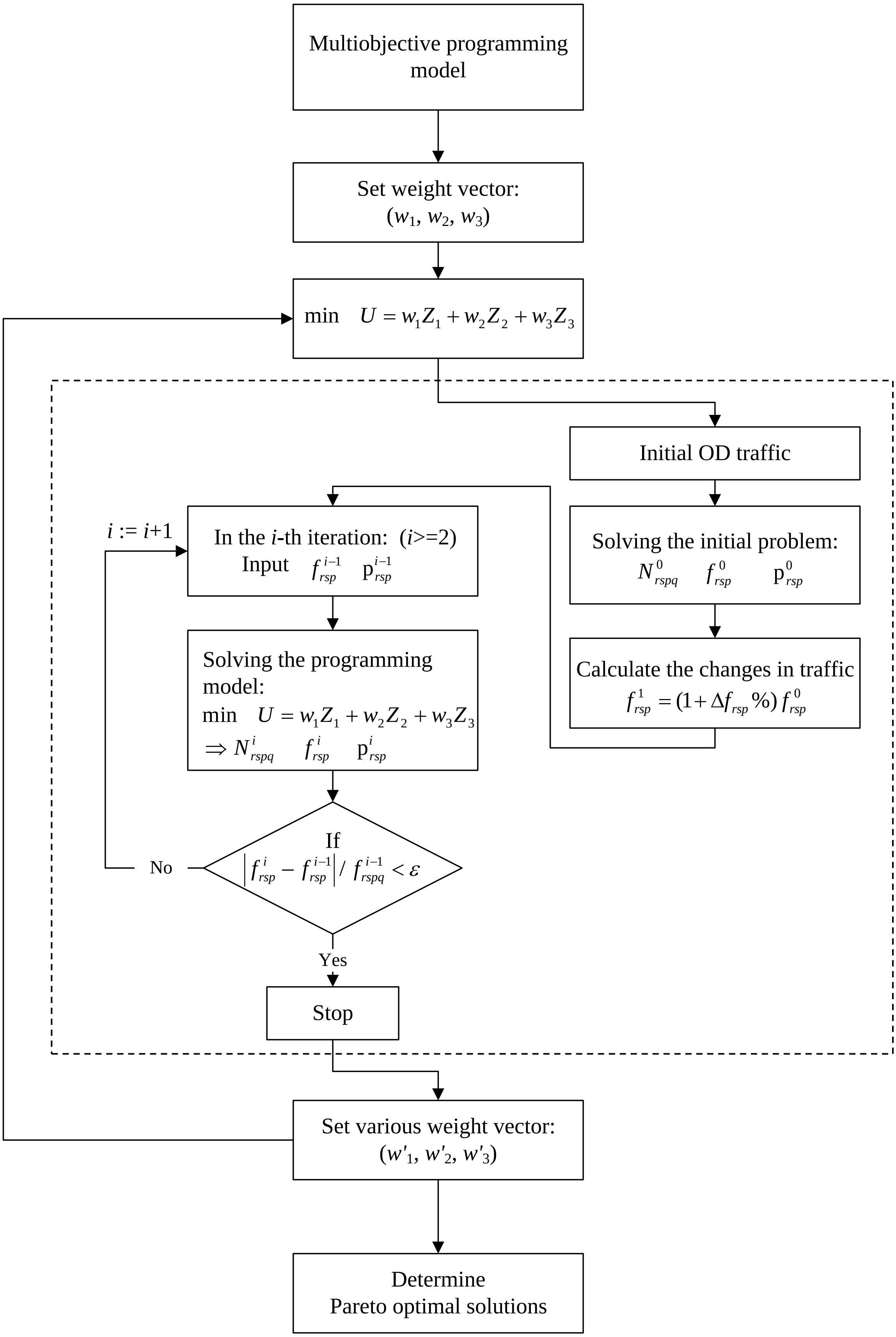

Figure 1. Iterative algorithm process of the problem

Table 1 lists the Pareto optimal solutions for the airline flight frequency programming with seven weight vectors. The results of weight vector (1/3, 1/3, 1/3) is the compromise solution, while those of weight vector (1, 0, 0) are the solutions that minimize total airline operating cost, and those of weight vectors (0, 1, 0) and (0, 0, 1) are, respectively, the solutions minimizing total passenger travel cost and minimizing total emission charges. These seven groups of solutions correspond to different objectives weighted-sum composition, and they are different groups of airline flight frequency plans and aircraft assignments.

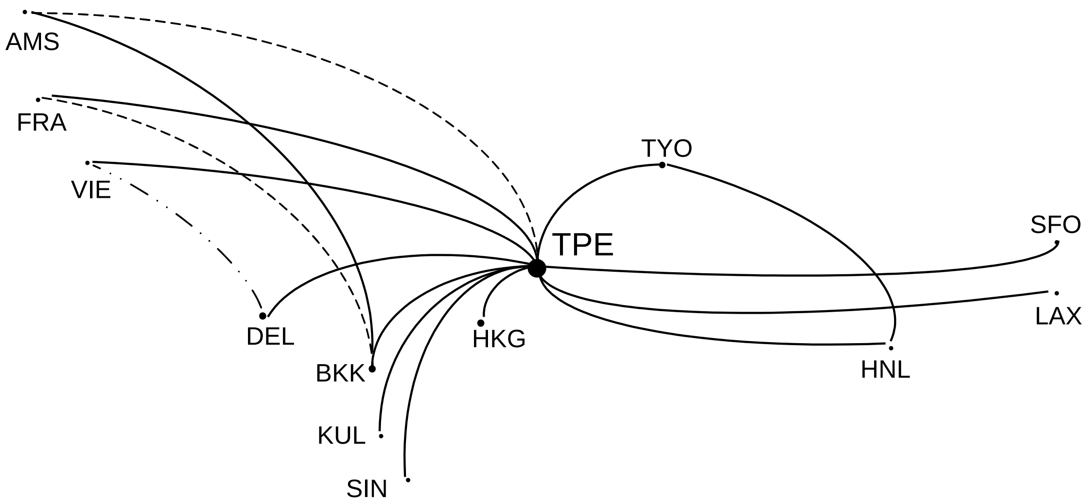

Figure 2. Selected airline network structure

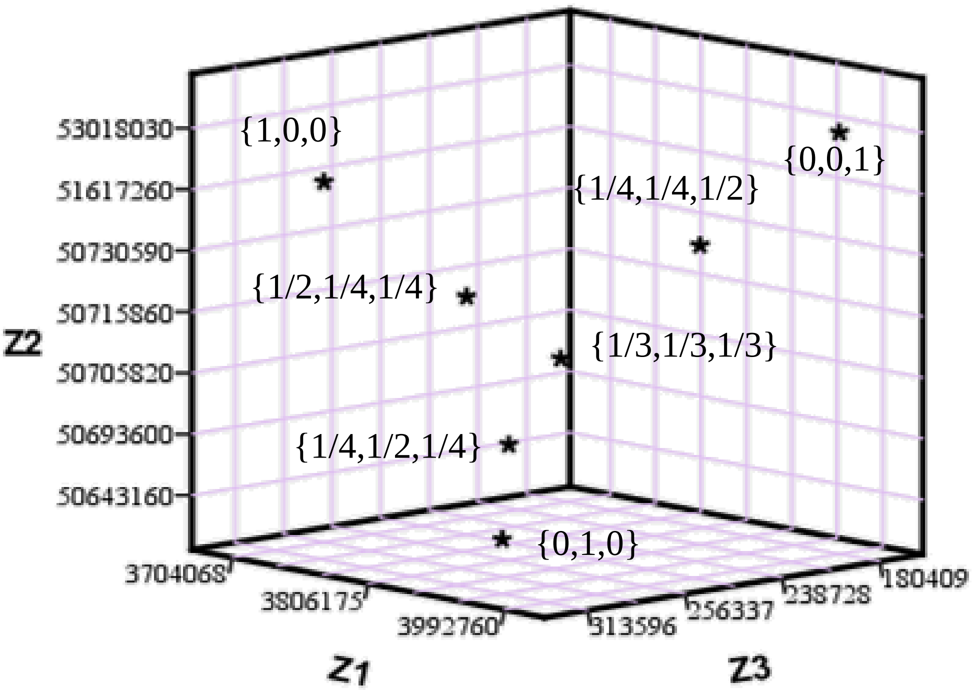

Figure 3. Pareto optimal points with various weight vectors

Table 1. The Pareto optimal solutions with various weight sets

Weight Vectors for Objective Functions			(1, 0, 0)	(0, 1, 0)	(0, 0, 1)	(1/3, 1/3, 1/3)
Objective Function Value ($)		Z_1:	3704068	3845533	3992760	3795850
		Z_2:	51617260	50643160	53018030	50705820
		Z_3:	308208	282828	180409	238728
Routes	Aircraft		Weekly Flight Frequencies (one direction)			
TPE-HKG	B747-400		76*	0	0	0
	A330-300		0	92	92*	92*
	A340-300		0	0	0	0
TPE-TYO	B747-400		21*	0	0	0
	A330-300		0	0	0	0
	A340-300		0	29	29	29
TPE-BKK	B747-400		0	0	0	3
	A330-300		16*	13	16*	14*
	A340-300		0	5	0	0
TPE-KUL	B747-400		13*	0	0	0
	A330-300		1	5	16*	16*
	A340-300		0	13*	0	0
TPE-SIN	B747-400		0	0	0	3
	A330-300		18*	18*	18*	16
	A340-300		0	0	0	0
TPE-LAX	B747-400		16*	16*	16*	16*
	A330-300		0	0	0	0
	A340-300		0	0	0	0
TPE-SFO	B747-400		0	16	16*	16*
	A330-300		20*	0	0	0
	A340-300		0	0	0	0
TPE-HNL	B747-400		0	0	0	0
	A330-300		3*	3*	3*	3
	A340-300		0	0	0	0
TPE-TYO-HNL	B747-400		0	3	5*	6*
	A330-300		0	4*	2*	0
	A340-300		9*	0	0	0
TPE-VIE	B747-400		3*	0	0	0
	A340-300		0	2	2*	2*
TPE-BKK-VIE	B747-400		0	0	0	0
	A340-300		0	0	0	0
TPE-DEL-VIE	B747-400		0	0	0	0
	A340-300		0	2	2*	2*
TPE-FRA	B747-400		4	1*	0	0
	A340-300		2	6*	6*	6*
TPE-BKK-FRA	B747-400		0	0	0	0
	A340-300		0	0	0	0
TPE-AMS	B747-400		6*	6*	0	6*
	A340-300		0	0	0	0
TPE-BKK-AMS	B747-400		0	4*	7*	1*
	A340-300		5*	0	4*	4*

Note: * represents assigning the emission-reduction type

(cont.)

Weight Vectors for Objective Functions		(1/2, 1/4, 1/4)	(1/4, 1/2, 1/4)	(1/4, 1/4, 1/2)
Objective Function Value ($)	Z_1:	3811572	3816175	3811615
	Z_2:	50716490	50693600	50730590
	Z_3:	237218	256337	233777
Routes	Aircraft	Weekly Flight Frequencies (one direction)		
TPE-HKG	B747-400	0	0	0
	A330-300	92*	92*	92*
	A340-300	0	0	0
TPE-TYO	B747-400	0	0	0
	A330-300	0	0	0
	A340-300	29	29	29
TPE-BKK	B747-400	5*	0	3
	A330-300	11	16*	14*
	A340-300	0	0	0
TPE-KUL	B747-400	0	0	0
	A330-300	16*	9*	16*
	A340-300	0	8*	0
TPE-SIN	B747-400	0	0	0
	A330-300	18	18*	18
	A340-300	0	0	0
TPE-LAX	B747-400	16*	16*	16*
	A330-300	0	0	0
	A340-300	0	0	0
TPE-SFO	B747-400	16*	16*	16*
	A330-300	0	0	0
	A340-300	0	0	0
TPE-HNL	B747-400	0	0	0
	A330-300	3*	3*	3*
	A340-300	0	0	0
TPE-TYO-HNL	B747-400	6*	6*	6*
	A330-300	0	1	0
	A340-300	0	0	0
TPE-VIE	B747-400	0	0	0
	A340-300	2*	2*	2*
TPE-BKK-VIE	B747-400	0	0	0
	A340-300	0	0	0
TPE-DEL-VIE	B747-400	0	0	0
	A340-300	2*	2*	2*
TPE-FRA	B747-400	1*	0	0
	A340-300	6*	6*	6*
TPE-BKK-FRA	B747-400	0	0	0
	A340-300	0	0	0
TPE-AMS	B747-400	6*	6*	6*
	A340-300	0	0	0
TPE-BKK-AMS	B747-400	0	2*	1*
	A340-300	5*	2*	4*

Note: * represents assigning the emission-reduction type

If decision-makers decide to aim at the operating economies, then they may obtain those optimal solutions with higher weight of Z_1; and if decision-makers decide to aim at minimizing the emission charges, then they may obtain those optimal solutions with higher weight of Z_3. On the other hand, if decision-makers pay more attention to the service levels, they may use those optimal solutions with higher weight of Z_2. In the compromise solution, all EU routes were assigned by emission-reduction aircraft, the passenger emission fees were US$45.29 (for FRA route), US$51.06 (for AMS route), and US$38.47 (for VIE route).

From Table 1, when decision-makers decide to aim at reducing emission charges, i.e., with weight vectors = (0, 0, 1), the aircraft types on EU routes were also all assigned by emission-reduction aircraft; and for TPE-VIE and TPE-AMS routes, some flight frequencies were shifted from nonstop direct flights to one-stopover transit flights, i.e. TPE-DEL-VIE and TPE-BKK-AMS, respectively. Since airlines are charged on carbon emissions created by flight between the-third country airports and EU airports, the emissions created by DEL-VIE and BKK-AMS links are less than nonstop direct flights from TPE to VIE and AMS. With other decision considerations, also EU routes were tended to assign emission-reduction aircraft, but the route structures were not changed. Moreover, these Pareto optimal solutions could provide airlines with higher flexibility of aiming and weighting on different objectives on decision making. Consequently, a group of flight frequency plans responsive to EU ETS emission charges can be generated to satisfy different objectives on prerequisite planning for an airline’s route network design.

5. CONCLUSIONS

This study developed a multiobjective programming model for airline flight frequency determination that systematically minimizes the total airline operating costs, the total passenger generalized costs, and the total emission charges. In response to emission charges, airlines strive to generate the lowest possible operating costs, achieve a higher load factor and reduce emissions by re-assigning emission-reduction aircraft, and adjusting the service frequency on stopover flights. However, these strategies may also increase passenger schedule delays, and thus lose time-sensitive passengers. Emission charges prompting higher airfares will also affect passenger demand. Herein, the demand-supply interaction for airline flight frequency determination resulted from the changes in passenger demand was also formulated and discussed. This study also proposes an algorithm that integrated weighted-sum method and an iterative scheme to solve the airline flight frequency multiobjective programming problem with demand-supply interactions.

The model is applied to a simplified version of CI’s network that includes thirteen selected cities. The determined flight frequency plans for groups of solutions correspond to different objectives were obtained by demand-supply convergence. The numerical results showed that all EU routes were tended to assign emission-reduction aircraft. As decision-makers pay more attention on reducing emission charges, some flight frequencies on TPE-VIE and TPE-AMS routes were shifted from nonstop direct flights to one-stopover transit flights (i.e. TPE-DEL-VIE and TPE-BKK-AMS, respectively); since airlines are charged on carbon emissions created by flight between the-third country airports and EU airports. For other decision considerations, also EU routes were tended to assign emission-reduction aircraft, but the route structures were not changed. The groups of solutions provided flexibility in decision-making with three different objectives in response to EU ETS emission charges. Consequently, this study demonstrates how airline flight frequency determination and adjustment with demand-supply interactions might be considered well in advance in solving an airline flight frequency programming in response to EU emission charges, and provides a decision-support tool for airline to determine solutions for EU emission charges.

This study mainly focuses on an airline's decisions in flight frequency and aircraft assignment responsive to EU ETS emission charges. The effects of emission charges on the competitors' responses and the airline industry's behavior are beyond the scope of this study. Future studies could further incorporate competition models into airline network programming models. Further studies also are required to consider the economies of density on cost functions, the number of competitors, and the existence of low cost carriers. The proposed interactive programming procedure could further be developed with some modifications to analyze the low-cost airlines' flight frequency determination and aircraft assignment responsive to EU airline emission charges

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