OPTIMAL AIRLINE FLEET PLANNING AND MANAGEMENT STRATEGIES UNDER STOCHASTIC DEMAND

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By

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ABSTRACT

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Teoh Lay Eng

The stochastic nature of the world has posed significant challenges to such a competitive airline industry. There are many unexpected events, e.g. fuel price volatility and natural disaster that could affect airline’s travel demand and profit margin. As such, how airlines make a strategic fleet planning decision to meet stochastic demand profitably is important. To properly capture supply-demand interaction, traveler's response and subjective perception of airline's management are significant to assure an adequate fleet supply. Besides, it is important to note that aircraft operations are strictly controlled under regulated limits at some airports and hence airlines certainly require a proper fleet planning (by incorporating optimal slot purchase) to meet increasing demand with additional service frequency. In addition, the environment should not be compromised in fleet planning. By having a green fleet in operations, a win-win situation between airlines and the environment could be achieved.

With the aim to solve the fleet planning problem strategically, a novel methodology is developed to formulate long-term fleet planning model, in the form of probabilistic dynamic programming model, to determine the optimal quantity of the respective aircraft type (with corresponding service frequency)

to be acquired/leased under uncertainty. By developing a modeling framework of stochastic demand, the level of demand could be determined realistically. Besides, mode choice modeling and Analytic Hierarchy Process are adopted to comprehend supply-demand interactions in greater detail so that airline's fleet supply is sufficiently adequate to meet stochastic demand. To consider multiple criteria in making fleet planning decision, bi-objective and two-stage fleet planning models are formulated mathematically to optimize the fleet planning problem. By examining numerous case studies, it was found that the results are comparable with airline’s actual performance and the findings showed that the developed methodologies are practically viable to assure airline's sustainability in terms of economy, social and environment.

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I understand that University will upload softcopy of my thesis in pdf format into UTAR Institutional Repository, which may be made accessible to UTAR community and public.

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(Teoh Lay Eng)

DECLARATION

I TEOH LAY ENG hereby declare that the dissertation is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UTAR or other institutions.

(TEOH LAY ENG)

Date:

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LIST OF ABBREVIATIONS

c_{biz,F_i}	Airfare of business class
c_{dec,F_i}	Discounted fare of economy class
c_{fec,F_i}	Full fare of economy class
$close$	End of working hours at airport
$f\left(D_t^s, A_t^i\right)$	Function of the number of flights in terms of D_t^S and A_t^i
$f_{n,F_i}^m\left(D_t^S, A_t^n\right)$	Service frequency of operating route
$f_A\left(M\right)$	Aircraft noise level at approach stage
$f_L\left(M\right)$	Aircraft noise level at lateral stage
$f_F\left(M, E\right)$	Aircraft noise level at flyover stage
$gf\left(D_t^S, A_t^n\right)$	Function of the traveled mileage in terms of the number of flights, $f\left(D_t^S, A_t^n\right)$
$hg\left(D_t^S, A_t^n\right)$	Function of the maintenance cost in terms of the traveled mileage, g
m	Aircraft status (1:new aircraft, 2:aging aircraft)
n	Aircraft type
$open$	Start of working hours at airport
p_S	Probability to have I_t^P and I_t^L (corresponds to phenomenon S)
r_t	Discount rate for which the discount factor is $\left(1+r_t\right)^{-t}$
t	Operating period
v_{biz,F_i}	Operating cost of business class
v_{dec,F_i}	Discounted cost of economy class

v_{fec,F_i}	Full cost of economy class
w	Environmental factor
y	Aircraft age
y_1	Local leisure trip
y_2	Local business trip
y_3	Trans-border leisure trip
y_4	Trans-border business trip
$\Delta p^*_{biz,F_i}$	Number of passenger in business class
$\Delta p^*_{dec,F_i}$	Number of passenger that pay discounted fare for economy class
$\Delta p^*_{fec,F_i}$	Number of passenger that pay full fare for economy class
$\Phi = \left(biz, fec, dec\right)$	Set of classification of passengers
ϕ	Classification of passengers (*biz*: business class, *fec*: economy class (full fare), *dec:* economy class (discounted fare))
θ	Parameter of environmental sustainability
α	Significance level of demand constraint
β	Significance level of lead time constraint
γ	Significance level of selling time constraint
$\lambda_{\max}$	The largest eigenvalue
A_t^n	Total operated aircraft
Af^t_{n,F_i}	Additional service frequency resulted from slot purchase decision
AVT^t_{n,F_i}	Aircraft availability (number of days)

$Biz_{\%}$	Portion of passenger in business class
BLK_{n,F_i}^{t}	Block time
$C\left(fuel_{tn}\right)$	Function of fuel expenses
C_i	Decisional criteria
C_{F_i}	Slot price
CE	Consultancy of experts
CI	Consistency index
CR	Consistency ratio
D_f^t	Forecasted demand with mean, μ_f and standard deviation, σ_f
$D_{f(inc)}^t$	Possible increment of forecasted demand
D_t	The demand level of the operating period *t*
D_{t,F_i}^S	Stochastic demand of operating route (corresponds to phenomenon *S*)
$Dec_{\%}$	Portion of passenger in economy class (discounted fare)
$DEP_t^L=\left(dep_{t1y}^L,dep_{t2y}^L,\ldots,dep_{tny}^L\right)$	Depreciation value of leased aircraft
$DEP_t^P=\left(dep_{t1y}^P,dep_{t2y}^P,\ldots,dep_{tny}^P\right)$	Depreciation value of purchased aircraft
DIS_{F_i}	Distance of a particular operating route
$DL_t=\left(dl_{t1},dl_{t2},\ldots,dl_{tn}\right)$	Payable deposit for aircraft leasing
$DLT_t=\left(DLT_{t1},DLT_{t2},...,DLT_{tn}\right)$	Desired lead time of aircraft acquisition
DP	Decision policy of airline
$DP_t=\left(dp_{t1},dp_{t2},\ldots,dp_{tn}\right)$	Payable deposit for aircraft acquisition
$DST_t=\left(DST_{t1},DST_{t2},...,DST_{tn}\right)$	Desired selling time of aging aircraft

E	Number of engines
$E(\cos t_{tn}^{S})$	Expected value of flight cost per passenger
$E(fare_{tn}^{S})$	Expected value of flight fare per passenger
$E(seat_{tn}^{S})$	Expected number of seats (capacity) of aircraft
EC_{GFI}^{t}	Environmental cost
EFF_t	Network efficiency factor
ER_t^n	Emission rate of aircraft
EX_t	Total aircraft emission
EXN_t	Cumulative noise level
F_{ex}	Existing operating network
F_i	Operating route (flight)
F_{nw}	New operating network
$F_{s_k}^{w}$	The relevant component of key aspect, s_k
FC_{n,F_i}^{m}	Fuel consumption
$Fec_{\%}$	Portion of passenger in economy class (full fare)
FEL_t	Fuel efficiency index
FV_{ti}	Existing variety of fleet composition
GFI	Green fleet index
GI_E	Green emission index
GI_{FE}	Green fuel efficiency index
GI_N	Green noise index

$I_t = \left(I_{t1y}, I_{t2y}, ..., I_{tny}\right)$	Initial quantity of purchased/leased aircraft
$I_t^L = \left(I_{t1y}^L, I_{t2y}^L, ..., I_{tny}^L\right)$	Initial quantity of leased aircraft
$I_t^P = \left(I_{t1y}^P, I_{t2y}^P, ..., I_{tny}^P\right)$	Initial quantity of purchased aircraft
$Index_t$	Stochastic demand index (SDI)
$LEASE_t = \left(lease_{t1}, lease_{t2}, \ldots, lease_{tn}\right)$	Lease cost of aircraft
LF_{n,F_i}^t	Load factor
M	Aircraft weight
$MAX_{budget(t)}$	Allocated budget for aircraft leasing and acquisition
MXU_{n,F_i}^t	Maximum utilization of aircraft (in terms of service frequency)
NA	Function of the number of aircraft
Net_d	Operating network
Net_1	Short-haul network
Net_2	Medium/long-haul network
NEW	Proportion of new aircraft
NP_{n,F_i}^m	Number of passengers
$O_t = \left(O_{t1}, O_{t2}, ..., O_{tn}\right)$	Quantity of aircraft to be ordered
OLD	Proportion of aging aircraft
$ORDER_t$	Quantity of aircraft that could be purchased in the market
P_{ij}	Choice probability
$P_t\left(hc\right)$	Probability of unexpected event *c* happens with a probable occurrence of *h*
$P\left(I_t^P + I_t^L\right)$	Discounted profit function

$PARK_t$	Area of parking space
PP	Past performance of airline
PP_t	Product of the probability of unexpected event for operating period t
$PURC_t = (purc_{t1}, purc_{t2}, \ldots, purc_{tn})$	Purchase cost of aircraft
R_{t,F_i}	The revenue of operating route (flight)
R_r	Random number
$R_t = (R_{t1}, R_{t2}, ..., R_{tn})$	Quantity of aircraft to be released for sale
$RESALE_t = (resale_{t1y}, \ldots, resale_{tny})$	Resale price of aircraft
RG_n	Aircraft range (maximum distance flown)
RI	Random consistency index
$RLT_t = (RLT_{t1}, RLT_{t2}, ..., RLT_{tn})$	Real lead time of aircraft acquisition
$RST_t = (RST_{t1}, RST_{t2}, ..., RST_{tn})$	Real selling time of aging aircraft
$S = (s_1, s_2, \ldots, s_k)$	Probable phenomena
$SEAT_{n,F_i}^t$	Seat (capacity) of aircraft
$SIZE = (size_1, size_2, \ldots, size_n)$	Aircraft size
$SOLD_t = (sold_{t1y}, sold_{t2y}, \ldots, sold_{tny})$	Quantity of aircraft sold
T	Planning horizon
$TC(I_t^P + I_t^L)$	Total cost of airline
TEC_t	Total emission cost
TNC_t	Total noise charges
$TR(I_t^P + I_t^L)$	Total revenue of airline

$TUN^{t}_{n,F_i,k}$	Turn round time at airport
U_{ij}	Utility function of an alternative *j* for an individual *i*
$U_t = \left(u_{t1}, u_{t2}, \ldots, u_{tn}\right)$	Setup cost for aircraft acquisition
UEC^{t}_{n,F_i}	Unit cost of emission
UFS_t	Unit fuel cost
UNC^{t}_{n,F_i}	Unit noise charges
W_{F_i}	Willingness to pay for slot purchase
$X_t^L = \left(x_{t1}^L, x_{t2}^L, \ldots, x_{tn}^L\right)$	Quantity of aircraft to be leased
$X_t^P = \left(x_{t1}^P, x_{t2}^P, \ldots, x_{tn}^P\right)$	Quantity of aircraft to be purchased

CHAPTER 1

INTRODUCTION

1.1 Background

Fleet planning determines the optimal quantity of the respective aircraft type that is needed by an airline to maintain a targeted level of service while maximizing its profit margin. In fleet planning, there are two major decisions to be made, i.e. to determine the optimal quantity and the type of aircraft to be purchased and leased throughout the long-term planning horizon in order to meet stochastic demand profitably. A proper fleet planning is important as it would affect the economic efficiency of airline and it has an influential impact on customer satisfaction (Zak et al., 2008). An oversized fleet implicates an increased cost while an undersized fleet implicates an unsatisfied demand and consequently resulting to a decrease in revenue and profit (Czyzak and Zak, 1995; Crainic and Laporte, 1997; Crainic, 2000).

In order to maintain a good level of service for an airline, there is a need to balance the supply and demand when optimizing fleet planning. By incorporating the supply and demand in making optimal fleet planning decision, airlines would obtain utmost profit while providing a desired service level. Consequently, an airline’s sustainability in terms of economy, social and environment could be assured effectively under stochastic demand. The demand is defined as the number of passengers asking for service while the supply refers to services (aircraft, service frequency, service slots, etc.) that could be provided by airlines to fulfill the demand. As such, these aspects become the most critical components that need to be considered in fleet planning models.

Travel demand forecasting is an important component as it could influent the results' robustness. There are two types of travel demand, i.e. deterministic and stochastic demand, that are involved in the modeling. The deterministic demand associates itself with the level of travel demand that could be determined with certainty. It is inelastic and known as a priori. Conversely, stochastic demand, as a random variable, refers to demand fluctuation which is uncertain at varying degrees primarily due to the occurrence of unexpected events which could take place unexpectedly. Instead of deterministic demand, stochastic demand should be considered because airline's operating environment is stochastic in nature due to the presence of uncertainty (Barnhart et al., 2003). Past studies revealed that by considering stochastic demand, the solution obtained is more robust and closer to realistic implementation (Listes and Dekker, 2005; Yan et al., 2008; Hsu et al., 2011a, 2011b).

According to the airlines (Malaysia Airlines, 2010a; AirAsia Berhad, 2010a), some possible unexpected events include fuel price volatility, political instability (e.g. terrorist attacks), global economic downturns, natural disasters, and others. When these events occur, the demand level would decrease tremendously. Nevertheless, stochastic demand is always being neglected by past studies in solving the fleet planning problem. In other words, the incorporation of stochastic demand in long-term fleet planning is under research. As such, existing approaches and models for airline fleet planning which are formulated by past studies might not be functional for real practice. This has motivated the development of a well-defined long term fleet planning decision model in order to assure that airlines can achieve their targeted profit at a sustainable manner.

In view of the fact that air travelers (passengers) are the main users of airline's services which constitutes the main income to airlines, the needs and expectation of passengers are important to airlines in order to gain a larger market share under such a competitive airline industry. As such, how airlines make an optimal fleet planning decision, i.e. a multiple criteria decision-making, for each operating period throughout the planning horizon is important not only to ensure profitable returns but also to meet the travel demand at a desired service level. Therefore, fleet planning decision-making which is governed by multiple criteria (with numerous key aspects) should be handled with care.

Among the key aspects that received great concern from airlines are the operational and economy aspects (AirAsia Berhad, 2010a; Malaysia Airlines, 2010a). These aspects are crucial for airlines not only to sustain profitably but also to assure the feasibility of aircraft operations in supporting the operating networks. If the relevant key aspects are not taken into consideration properly in fleet planning, the resultant decision-making may not be viable to support the operating system. Undeniably, this would consequently result in a substantial loss to airlines not only in terms of monetary aspect but also the interest or loyalty of air travelers. In the past, there are some studies that adopted various approaches to solve fleet planning problems. However, they did not show how optimal fleet planning decision is made with regard to the influential key aspects of fleet planning decision-making that may vary differently among airlines.

While providing an adequate fleet supply, it is important to capture the mode choice analysis (traveler's response) in view of their needs and expectation which would affect airline's service and profit margin to a great extent. Furthermore, traveler's behavior changes with the extensive growth of multimode transportation networks. Therefore it is necessary to frame this scenario in a better manner. In the past, some studies, including Mason (2000, 2001), Evangelho et al. (2005), O'Connell and Williams (2005, 2006), Pels et al. (2009) and Abda et al. (2011), had been conducted and contributed on the mode choice analysis of travelers. However, there is no study that incorporates mode choice modeling in making optimal fleet planning decision.

To meet passengers demand desirably, airlines need to provide an adequate number of service frequency to support their operating system profitably. As such, how airlines determine a desired service frequency for each operating route is important as service frequency determination is greatly affected by travel demand (Wei and Hansen, 2005; Pitfield et al., 2009) and aircraft choice (Zou and Hansen, 2014). Furthermore, the demand fluctuation could affect airline's service frequency to a great extent. Wen (2013) highlighted that service frequency determination that is closely associated with aircraft type is crucial for airlines to assure operating effectiveness. Without this element, the resultant fleet planning decision may not be appropriate to support current operating networks under stochastic demand.

However, it is important to note that the service frequency of airlines is strictly constrained by regulatory limits, especially the arrival/departure restriction slots at particular airports. Therefore, the strategy of airlines to provide a higher service frequency (to meet increasing demand) may not be workable, unless prior approval (e.g. via slot purchase) is obtained. In the case that an increasing service frequency is not feasible for airlines to meet the demand increment, airlines may need to select specific aircraft type, especially larger aircraft, to accommodate the demand increment. Yet, the selection of aircraft by airlines is highly dependent on aircraft specification (type) which is closely associated with its corresponding service frequency. As such, service frequency needs to be included in fleet planning (Wei and Hansen, 2005; Pitfield et al., 2009). Practically, additional service frequency could be obtained by incorporating slot purchase in making optimal fleet planning decision. The lack of desired slots for additional service frequency may lead to a loss in revenue due to the inability of airlines to meet passenger's demand.

While meeting stochastic demand at a profitable level, environmental issues could not be neglected in view of an increasing concern of green issue nowadays. According to recent statistics, transport sector has emerged as one of the major sources of carbon dioxide emission in the world (Janic, 1999; Chapman, 2007; Dekker et al., 2012) which contributes about 14% of total global emission recorded (Stern, 2006; European Environment Agency, 2011). This has caused notorious environmental problem such as acid rain, global warming and ozone layer depletion (Button, 1993; European Commission, 1996). Air transport sector is claimed to be the most unsustainable transport mode (Chapman, 2007) and there are three critical environmental factors, i.e. aircraft emission, noise and fuel efficiency (Janic, 1999; IPCC, 1999; ICAO, 2010; Sgouridis et al., 2011) for airlines. Lee et al. (2009) reported that the net effect of nitrogen oxides emission from aircraft is estimated to be 24%. In addition, the effect of contrails is approximated to be 21% and the combined effect of water vapour, sulfur oxides and soot is about 2.1% of the total effects. The carbon dioxide emission is about 2.5%-3% (Scheelhaase and Grimme, 2007; Anger, 2010). Approximately, the burning of 1kg of fuel by the aircraft engine would produce about 0.011 kg of nitrogen oxides, 3.16 kg of carbon dioxide and 1.25 kg of water vapour (Ralph and Newton, 1996). As such, with the forecasted annual air traffic growth at 5% (Airbus, 2007; International Air

Transport Association, 2009; Boeing, 2009), the pollution level will escalate to an alarming level if it is left untreated.

The aircraft noise is another source of aviation pollution to the environment and society, particularly to those who are living in the airport vicinity. Janic (1999) revealed that there are two sources of noise from the aircraft engine, i.e. machinery and primary jet noise. Machinery noise is produced by the engine's components such as fan, compressor and turbine while the generation of primary jet noise is formed when the high-speed gases exhaust from the engine mix with the surrounding air. Specifically, the main source of noise during take-off stage is primary jet noise while the machinery noise emerges as the major source during landing phase (Ashford and Wright, 1979; Horonjeff and McKelvey, 1983). Noise annoyance generated from aircraft operations could affect sociology (human) health from numerous aspects, including hypertension (Meister and Donatelle, 2000), high blood pressure (Black et al., 2007) and cardiovascular diseases (Franssen et al., 2004). Besides, aircraft noise especially from night flights has also affected the quality of life of the residents living in the airport vicinity (Hume et al., 2003; Kroesen et al., 2010).

Fuel consumption is also one of the environmental issues faced by airlines. It is known that aircraft emissions are directly related to fuel burnt. A more efficient aircraft engine not only save cost, but also reduce carbon dioxide emissions. Each kilogram of fuel saved reduces carbon dioxide emission by 3.16 kg. As such, one of the key areas for airlines to minimize environmental (green) impact is to operate fuel-efficient aircraft (International Air Transport Association, 2013).

Desirably, airlines could make optimal fleet planning decision by acquiring/leasing aircraft type which could reduce environmental impacts. In other words, green aircraft is preferable. Comparatively, a newer aircraft with advanced technology is preferred in reducing aircraft emission. For instance, jumbo aircraft A380 is preferred as it is fuel-efficient and emits lesser emission and noise per seat (Airbus, 2013). However, fleet planning decision-making does not depend on the environment issue as the sole factor. Airlines need to consider the operational issues and more importantly profit earning. As such, acquiring/leasing new and large aircraft may not always be the preferred choice.

In recent years, numerous local governments and airport authorities, e.g. in Australia, Sweden, Switzerland and Germany (Lu, 2009), have implemented stricter environmental policy and regulation in order to direct airlines to be greener. Environmental fines, including emission and noise penalty, are imposed on airlines that produce excessive pollutants. For instance, British Airways has paid almost €20,500 per annum as emission charge to Frankfurt Airport (Scheelhaase, 2010) while in the United States, the penalties of aircraft noise violations at John Wayne Airport may involve stiffer fines as high as $500,000 and the disqualification of airline (Girvin, 2009). Undeniably, such policies would affect airline's profit margin. As a result, it is necessary for airlines to consider the environmental issue in fleet planning. It is foreseen that, by having 'green fleet' in place, a win-win situation between airlines and the environment could be achieved.

In brief, there is a need to develop more effective fleet planning mechanisms and management strategies in order to meet stochastic demand desirably. How to manage fleet planning profitably under uncertainty is not a simple task. There may be more issues and concerns besides those that have been highlighted above. Essentially, this research is concentrated on how to optimize fleet planning and management strategies of airlines to secure a higher efficiency and profit under various situations and practical constraints as well as subject to unpredictable uncertainty. Overall, it is anticipated that the findings of this research could provide useful guidelines to airlines to operate in a better and sustainable manner which will benefit air travelers in return.

1.2 Research Objectives

This research study has five objectives as listed below:

1. To optimize airline's fleet planning decision by determining the optimal quantity and aircraft type that generates maximum profit (subject to practical constraints).

2. To propose a modeling framework for stochastic demand.

3. To model and analyze the impacts of mode choice modeling in fleet planning.

4. To compare and assess the impacts of the subjective judgment of airline's management in making fleet planning decision.

5. To promote green fleet planning.

1.3 Research Scope

This research comprises four major scopes, namely fleet planning decision model under stochastic demand (to capture the occurrence of unexpected events), strategic fleet planning modeling framework (to deal with supply-demand interaction), two-stage fleet planning (to assure adequate service frequency by incorporating slot purchase) and green fleet planning (to incorporate environmental concerns).

Basically, there are two major elements, i.e. demand and supply aspects, that affect airlines in making optimal fleet planning decision to acquire/lease aircraft to meet travel demand profitably. Specifically, the occurrence of unexpected events (e.g. natural disaster, outbreaks of flu disease, fuel price volatility, etc.) would constitute stochastic demand which behaves uncertain in nature. This would affect the operations and profit of airlines to a great extent. As such, how airlines provide a desired service level, with adequate fleet supply to meet stochastic demand is extremely important. Mathematically, an optimal fleet planning model (aircraft acquisition and leasing decision model) is developed with the aim to find optimal profits while meeting uncertain demand at a desired service level (subject to various practical constraints). The decision variables of fleet planning decision model are optimal quantity and aircraft type that need to be purchased and/or leased to meet stochastic demand profitably.

In order to meet stochastic demand realistically with sufficient aircraft supply, there are various key aspects (probable phenomena) that need to be quantified and incorporated in optimizing fleet planning model. Remarkably, operational, economy and environmental aspects were found to be the three probable phenomena (key aspects) in making optimal fleet planning decision for which the probability of probable phenomena (with regards to respective various key aspect) indicates the likelihood of aircraft possession to meet stochastic demand. In other words, probable phenomena would assure an adequate fleet supply to meet demand fluctuation at a desired level of service. To capture supply-demand interaction in a better manner, traveler's response (in terms of mode choice analysis) and the subjective judgment of decision makers (airline's management) towards numerous decisional criteria of fleet planning (including airline's decision policy, expert's consultancy as well as airline's past performance) are necessarily incorporated in solving fleet planning problem. These elements are important to achieve a targeted level of service profitably from various key aspects (i.e. operational, economy and environmental aspects).

To meet stochastic demand desirably, it is also vital for airlines to assure that there is a desired service frequency which associates closely with the respective aircraft type in supporting current operating networks. It is of utmost importance for airlines to assure a higher operating efficiency and profit margin. However, the service frequency of airlines is strictly controlled by airports operators in compliance to standard regulations of airport in terms of aircraft operations, especially during peak period or night time. In such a case, how airlines monitor and manage their service frequency to meet demand fluctuation (especially demand increment) necessitates a proper fleet planning. Specifically, slot purchase plays an important role to provide additional service frequency to airlines to meet demand increment. Without this element, stochastic demand may not be met desirably and this would affect traveler's expectation and subsequently results in a loss of airlines not only in terms of operating revenue/profit but also the loyalty of travelers.

Environmental sustainability is another crucial component in fleet planning. In view of the increasing concerns to preserve the environment, green performance of airlines (in terms of aircraft emission, noise and fuel efficiency) needs to be monitored closely. Only by having a green fleet in place, a win-win situation between the airline and the environment could be achieved. As such, this requires a well-defined fleet planning model to determine optimal quantity of respective aircraft type in order to yield a greener performance while meeting stochastic demand satisfactorily at a profitable service level. Ideally, the fleet supply (for both aircraft composition and the corresponding service frequency) of airlines should be in place, right on time, to support the current operating networks profitably. Besides, the developed environmental (green) assessment performance model is able to provide insightful direction and suggestion to airlines to achieve greener performance, by assessing the effectiveness of respective mitigation strategy. The developed approach could capture three major environment factors, namely aircraft emission, noise and fuel efficiency. It is also capable to capture the occurrence of unexpected events that could affect airlines' operations to a great extent. As such, the developed methodology is useful not only in fleet planning, but also practically beneficial for aircraft operations in real practice.

This research distinguishes from the past studies as it shows how the environmental factor (including aircraft emission, noise and fuel efficiency) could be incorporated into fleet planning model (with numerous practical constraint) under uncertainty. In addition, it shows that airlines could sustain a significant amount of cost savings if green fleet planning is carried out with some beneficial improvement strategy (to yield a greener performance).

For all the above-mentioned research scope, the computational results were verified by making empirical comparisons with the actual operating performance of airlines. Overall, the findings of illustrative case studies show that this research is practically viable for which the overall framework to produce optimal fleet planning decision-making, as an effective management strategy for airlines, is displayed in Figure 1.1.

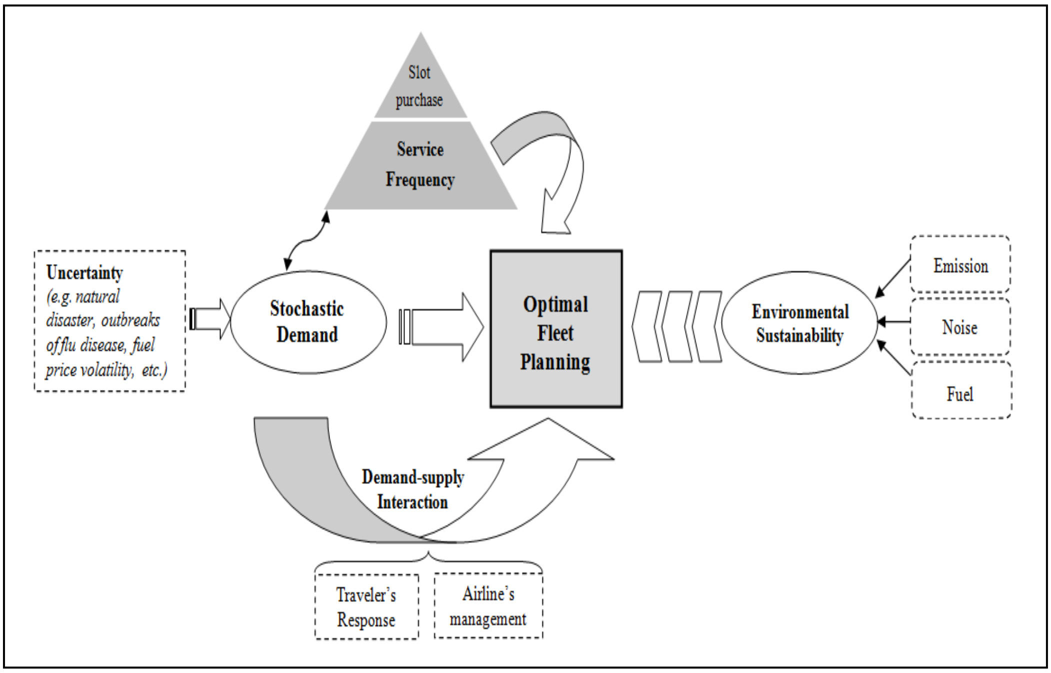

Figure 1.1: The Overall Framework of Fleet Planning

1.4 Thesis Overview

This research is organized as follows:

Chapter 1: Introduction presents the relevant problem statement, significance and motivation of carrying out this research, together with the research objectives and scopes. Besides, this thesis overview lists out systematically all the topics that are included in this research.

Chapter 2: Literature review discusses past studies which are closely related to this research. Basically, there are five major discussion areas, namely travel demand forecasting: deterministic vs stochastic, airline fleet planning approach, strategic fleet planning modeling framework, slot purchase and service frequency in fleet planning, as well as green fleet planning. A thorough and updated review, including the strengths and shortcomings of past studies, had been addressed accordingly.

In ***Chapter 3: Fleet planning decision model under stochastic demand***, the first part of the discussion focuses on a novel modeling framework of stochastic demand in order to determine the level of stochastic demand realistically under uncertainty. To solve fleet planning model, aircraft acquisition decision model (without aircraft leasing) is then developed and solved optimally with a realistic case study (as linear programming model) under stochastic demand. Subsequently, aircraft acquisition and leasing decision model is presented to obtain optimal fleet planning decision throughout the long-term planning horizon. An illustrative case study in the form of nonlinear programming model is presented to examine the feasibility of the developed approach to acquire and/or lease aircraft at optimal profit.

Chapter 4: Strategic fleet planning modeling framework mainly covers two parts, namely mode choice analysis and Analytic Hierarchy Process (AHP) modeling framework. Mode choice analysis focuses on the modeling of traveler's response towards airline's services and market share under multimode transportation networks. The analysis of mode choice modeling is then incorporated in AHP modeling framework to work out a strategic fleet planning by assuring an adequate fleet supply to meet stochastic demand satisfactorily. To do this, the subjective judgment of decision makers (airline's management) is incorporated necessarily.

In ***Chapter 5: Optimal fleet planning with slot purchase***, slot purchase decision model is first discussed (in stage 1), followed by fleet planning decision model (in stage 2). In this chapter, influential impacts of slot purchase in providing additional service frequency to meet increasing demand are investigated explicitly so that airlines could make a proper decision-making (via slot purchase) to obtain optimal solutions for fleet planning. The relations of slot purchase, service frequency, fleet supply and airline's profit level are discussed explicitly.

Chapter 6: Environmental performance assessment for fleet planning quantifies the green performance of airlines mathematically from three major perspectives, namely Green Emission Index, Green Noise Index and Green Fuel Efficiency Index. The overall green performance of airlines is then compiled in terms of Green Fleet Index (GFI). Besides, some improvement strategies (i.e. increasing load factor, operating new aircraft, reducing service frequency and reducing fuel consumption) are suggested to achieve greener performance.

Chapter 7: Green fleet planning decision model primarily focuses on the problem formulation and solution methods to assist airlines to obtain optimal profit while achieving greener performance. Mathematically, it is formulated in the form of bi-objective optimization model. By examining a realistic case study, effective improvement strategy to yield a greener performance are discussed explicitly. Besides, potential environmental cost savings by having a green fleet is revealed.

Chapter 8: Conclusions presents a comprehensive summary of this research. Some possible directions for future research and research accomplishment are also included.

CHAPTER 2

LITERATURE REVIEW

This chapter discusses past studies which are closely related to the fleet planning problem of airlines. Basically, past studies can be categorized into five major discussion contexts, namely (i) travel demand forecasting: deterministic vs stochastic, (ii) airline fleet planning approach, (iii) strategic fleet planning modeling framework, (iv) service frequency and slot purchase in fleet planning, and (v) green fleet planning. In each context, a thorough and updated review, which includes the strengths and shortcomings of past studies, has been discussed explicitly in order to provide some insightful overviews on the relevant evolution of fleet planning in the airline industry.

2.1 Travel Demand Forecasting: Deterministic vs Stochastic

In most of the research studies pertaining to air transport, deterministic demand is forecasted and used in the modeling and planning. New (1975) forecasted the travel demand based on the types of flights (short, medium and long-haul) and number of flights operated by airline. Teodorovic and Krcmar-Nozic (1989) estimated the total expected number of passengers based on the market share of airline which is assumed to follow normal distribution. Hsu and Wen (2003) forecasted the demand level of individual operating route by adopting grey theory, which is a time series forecasting approach that solely requires a small amount of data for forecasting. However, its capability is limited to the time series that exhibits exponential growth. Furthermore, it necessitates regular and new data to enhance forecasting accuracy. To solve the fleet assignment problem, Barnhart et al. (2002) forecasted the level of demand based on the average demand data and also on the respective scheduled itinerary as requested by the passengers.

A fundamental assumption in deterministic demand forecasting is that the demand of passengers is inelastic. With the lack of ability to handle stochastic features, it could not capture demand fluctuations, i.e. the resultant forecasting of deterministic demand is not responsive to the changes in demand. Thus, deterministic demand forecasting is not sufficiently robust to reflect the stochastic nature of fleet planning problem and hence it may not be a good approximation for the actual practice (Listes and Dekker, 2005; Tan et al., 2007; Yang, 2010). This may result in the loss of optimality for a deterministic modeling in view of the fact that the impacts of demand variability in actual operations is neglected (Yan et al., 2008). In comparison, stochastic demand forecasting provides more practical results, with realiable consistency (Yang, 2010). It is more effective and useful than deterministic modeling for which the detailed and realistic data on demand patterns are not available (Diana et al., 2006; Yan et al., 2008). Notably, Listes and Dekker (2005) highlighted that airlines would secure a higher profit margin, approximately to be 11-15%

more, by capturing stochastic demand. Correspondingly, the load factor would increase about 2.6% while potential spill and turned-away passengers would decrease about 3.3% and 2.3%, respectively. This shows that stochastic demand modeling is much more beneficial to airlines (compared to deterministic demand modeling).

The travel demand of air transport is stochastic in nature, primarily due to the occurrence of unexpected event (e.g. economic recession, natural disaster, biological disaster, political stability, etc.) which is unpredictable in the real practice (Malaysia Airlines, 2010a; AirAsia Berhad, 2010a). When these events take place, the level of demand would be affected to a great extent and hence results in demand fluctuation which behaves in a state of uncertainty (stochastic). In view of this and recognizing the limitations of deterministic demand modeling, researchers had started to adopt stochastic demand in modeling. List et al. (2003) used a partial moment measure of risk to inspect the uncertainty of travel demand. Listes and Dekker (2005) adopted scenario aggregation-based approach to determine the best choice of aircraft by assuming that travel demand follows normal distribution. Yan et al. (2008) captured the demand fluctuations by developing passenger-flow networks and passenger choice model for which passenger utility and market demand functions are formed in order to determine the choice probability function of travelers. Pitfield et al. (2009) employed a simultaneous-equations approach to analyze demand elasticity and aircraft choice. Hsu et al. (2011a) adopted grey topological models with Markov-chain to capture demand fluctuations while

Hsu et al. (2011b) combined grey topological forecasts with Markov-chain model to inspect demand fluctuations and also to determine the probability of demand. They imposed a penalty cost function if the actual demand is more than the forecasted demand.

In other areas (not air transportation), stochastic demand is assumed to follow certain distribution. For example, Berman et al. (1985) and Batta et al. (1989) adopted Poisson distribution to model stochastic demand for queuing systems. Du and Hall (1997) proposed a dynamic model to capture the stochastic demand for port operation. Bojovic (2002) modeled the demand of railroad network as a Gaussian probability density function while Tan et al. (2007) assumed that stochastic demand has a normal distribution in solving vehicle routing problem.

The proposed methods used in the past studies to capture stochastic demand are remarkable, but they have some limitations. One major shortcoming is that they did not quantify the occurrence of unexpected events in their attempts to model stochastic demand. For example, List et al. (2003) modeled the demand entirely based on a one-sided risk measure (instead on demand variation) for which the likelihood of objective function in meeting travel demand is controlled not to exceed a threshold value. Hsu et al. (2011b) adopted Markov-chain model by taking into account only one set of transition probability to model travel demand. Both studies ignored the possibility of events that could take place unexpectedly. Instead of demand fluctuations modeling, the probability of occurrence of unexpected event should be quantified systematically as it could affect stochastic demand to vary differently. Without this element, the level of stochastic demand may not be modeled as close to reality as it is. Moreover, the assumption of fixed type of distribution to quantify demand fluctuation might be too restrictive. The proposed methodology might not be applicable if real demand pattern does not follow the type of distribution as assumed. Furthermore, demand forecasting methods as proposed in the existing studies are only applicable for short-term period. For example, Tan et al. (2007) and Yan et al. (2008) modeled the demand fluctuation within a day. Listes and Dekker (2005) and Pitfield et al. (2009) modeled weekly and monthly demand, respectively. Such short-term forecasting methods are not applicable to model long-term demand fluctuation which is required in solving fleet planning problem.

2.2 Airline Fleet Planning Approach

To formulate and optimize the fleet planning problem, past studies had adopted various approaches. Wei and Hansen (2005) built a nested logit model to inspect the influence of aircraft size, flight frequency, seat availability and airfare on airline's demand. They highlighted that airlines can obtain higher returns from increasing the service frequency than from increasing the aircraft size, i.e. airline's market share is super-proportional to airline frequency share.

Therefore, there is a tendency for airlines to use smaller aircraft since an increase of frequency can attract more passengers. Despite a closed relation between aircraft size and service frequency in making optimal fleet planning decision, there is no proper mechanism or clear indication on how airlines could acquire and/or lease specific aircraft type (with corresponding service frequency) to service the estimated market share. Furthermore, the occurrence of unexpected event is not taken into consideration.

Wei and Hansen (2007) developed game-theoretic models to investigate airlines' decisions on aircraft size and service frequency under competitive environment. They also examined the operating cost and the demand level of competing airlines. They revealed that aircraft size, depending on market types, is a significant factor for fleet planning decision-making. The results show that airlines tend to use the smallest, yet cost-efficient, aircraft to accommodate different demand levels, and only increase the service frequency to meet the increasing demand. It was highlighted that airlines with more small aircraft can manage flexibly aircraft operations (including scheduling and route planning) which are closely related with optimal aircraft acquisition/leasing decision. However, it is assumed that competing airlines know each other's payoffs, available strategies and other releavant information in selecting optimal aircraft size and service frequency. As such, the reliability and applicability of their model might be questionable at certain extent.

Wei (2006) employed game-theoretical model to investigate how airport landing fees affect two competing airlines to make decision on aircraft size and service frequency (at optimal profit) in duopoly markets. The results show that a higher landing fee will force airlines to operate larger aircraft and fewer frequency (to retain the same number of passengers). This shows that airline's optimal aircraft size and service frequency are affected significantly by landing fees. However, his model assumes that both airlines know all the available choices and resultant profit for each other. This might not be realistic. Besides, the optimal decision is made solely based on the landing fees. This might be too restrictive in view of some other important elements, e.g. demand uncertainty and budget constraint are neglected in making optimal decision.

Kozanidis (2009) developed a multi-objective optimization model to maximize aircraft availability. He showed that flight and maintenance requirements are two important factors in fleet planning. Besides maximizing the fleet availability level, it was found that it is also vital to minimize its variability in order to assure that the availability level remains relatively constant over time. However, his model is limited to military operations instead of commercial flight application.

Givoni and Rietveld (2010) analyzed the environmental impacts of airlines' choice on aircraft size and service frequency. The results show that environmental impacts could be reduced by operating a lower service frequency (with larger aircraft). Besides, it was found that increasing the supply through larger aircraft rather than additional services (with more frequency) exhibits a better use of existing capacity. As such, the results highlight that a large aircraft (wide body) designed for short-haul flight would be needed not only to make use the available runway capacity in a better manner but also to reduce the environmental impact from aircraft operations. This shows that the respective aircraft type (with different size and corresponding service frequency) is an important element for airlines to make fleet planning decision profitably and environmentally. However, they did not consider possible route distance and aircraft weight in their analysis despite the fact that aircraft specification (including aircraft range and engine weight) would affect aircraft performance.

Hsu et al. (2011a) formulated stochastic dynamic programming model to optimize airline decisions in purchasing, leasing and disposing of the aircraft. The results show that airlines tend to lease rather than purchase aircraft to meet demand fluctuation. Besides, airline tends to form its aircraft composition by operating a single type of aircraft for each operating period. By considering strategic alliance between airlines, Hsu et al. (2011b) developed a dynamic programming model that deals with aircraft purchase, dry/wet leasing and disposal. The findings reveal that airline can achieve more cost savings through interactive bargaining (for aircraft acquisition/leasing) rather than leasing from non-allied airlines. These studies are interesting but posed some limitations. The methods proposed by Hsu et al. (2011a, 2011b) are used to tackle the fleet planning problem with stochastic demand but they did not capture the occurrence of unexpected events in modeling stochastic demand. In addition, their formulation might be too simplistic by considering demand as the sole constraint. In fact, there are other crucial constraints, such as budget constraint, lead time and selling time constraint, which are important in fleet planning.

2.3 Strategic Fleet Planning Modeling Framework

An efficient fleet planning under stochastic demand over a long-term planning horizon still remains a major concern for many airlines. This happens mainly due to the supply-demand interaction that needs to be handled with great care, not only because of stochastic demand that fluctuates greatly from time to time but also owing to various key aspects (multi-criteria) of fleet planning decision-making that correlate closely to demand fluctuation. For airlines, the operations and economy emerge to be the key aspects when making optimal fleet planning decision (AirAsia Berhad, 2010a; Malaysia Airlines, 2010a). Undeniably, these aspects are greatly affected by stochastic demand, i.e. the main factor of airline's services and income. As such, the supply-demand interaction should be captured explicitly in solving the fleet planning problem strategically. This certainly necessitates a well-developed and strategic fleet planning model.

There are some past studies that adopted various approaches to solve the fleet planning problems (as discussed in section 2.2). However, they did not show how optimal fleet planning decision is made with regard to the influential key aspects of fleet planning decision-making that may vary differently among airlines. As discussed in section 2.2, the existing studies primarily focus on the technical aspect in solving fleet planning problem, i.e. they mainly analyze how airlines make fleet planning decision to obtain optimal aircraft composition to meet travel demand, but they did not quantify the key aspects of fleet planning decision-making for which the extent of the respective key aspect affecting fleet planning decision-making is not measurable. Furthermore, the supply-demand interaction is not studied explicitly by existing studies. Without this element, the resultant fleet planning decision may not be strategic to support airline's operating networks.

As such, two major components, i.e. demand management (in terms of mode choice analysis) and significant key aspects of fleet planning decision-making are exceptionally crucial for airlines in solving fleet planning problems strategically. In terms of demand management, traveler's response is important to be understood and captured explicitly by airlines in order to gain a larger market share (for more profit). Thus, mode choice analysis is required to examine the needs and perception of travelers towards airline's services, especially under such a competitive multimodal transportation system (Yan et al., 2008). By doing this, airlines would be able to understand their users in a better manner and hence they could meet passenger's expectations desirably with a much better service quality (including an adequate aircraft supply). In order to meet travel demand at a desired service level, various key aspects (e.g. operational and economy) need to be quantified precisely to make optimal fleet planning decision-making under uncertainty. To do this, Analytic Hierarchy Process (AHP) which is capable to deal with uncertainty (Saaty and Tran, 2007) plays the role to quantity the probability of respective key aspect in solving fleet planning problem. It is anticipated that by incorporating mode choice modeling and the AHP in the fleet planning model, the supply-demand interaction could be captured explicitly to yield a strategic fleet planning decision-making. The reviews on mode choice analysis and AHP are discussed in the following subsections.

2.3.1 Mode Choice Analysis: Air and Ground Transport

The mode choice of travelers would constitute the market share of airlines and hence mode choice modeling needs to be analyzed properly. Furthermore, the mode choice of travelers could be different nowadays with the development of multimodal transportation networks (Yan et al., 2008). Thus, mode choice analysis should be done regularly and up to date in order to understand the current travel trend and traveler's needs in a better manner so that an adequate aircraft supply could be provided, right on time, to meet traveler's expectation. For such a competitive multimodal transportation system nowadays, the competition is intensifying not only among airlines but also between airlines and ground transport.

Globally, the competition between low-cost carriers (LCCs) and full service carriers (FSCs) is escalating mainly due to the evolution and substantial growth of LCCs. Past studies, including Mason (2000, 2001), Gillen and Morrison (2003), Barrett (2004), Evangelho et al. (2005), O'Connell and Williams (2005, 2006), Fageda and Fernandez-Villadangos (2009), Pels et al. (2009) and Abda et al. (2011) reported that FSCs had lost a significant proportion of travelers to LCCs, and this subsequently led to substantial financial losses. Besides, the presence of LCCs had significant impacts in lowering the average fares of airline industry. Therefore, the competition between LCCs and FSCs has become one of the challenges for airlines in assuring a profitable market share which is crucial for airlines. In such a case, how to sustain and stand out in such a competitive airline industry certainly requires operational and managerial efficiency. Recognizing the need to improve the services especially to gain a larger market share, mode choice decision of travelers, which is a key policy element in demand management, should not be neglected.

Apart from intensifying competition between the LCCs and FSCs, in fact, there's a direct competition between the air transport and ground transport. To analyze the demand of travelers, the competition between high-speed train (HST) and air transport were examined by Gonzalez-Savignat

(2004) and Roman et al. (2007) for Madrid-Barcelona route, Givoni (2007) for London-Paris route, Ortuzar and Simonetti (2008) for Santiago-Concepcion route in Chile and Adler et al. (2010) for the European Union network. Although these studies examined the competition of air transport with ground transport at certain extent, other types of ground transport (e.g. bus, car) and specific type of airlines (e.g. low-cost airlines) were not considered explicitly in these studies. Furthermore, the study area was limited to European countries. Therefore, it could be seen that existing studies on the competition of air transport and ground transport are very limited.

As reported in People's Daily Online (2011), upon the completion of Kunming-Singapore High-Speed Railway in 2020, it will take travelers about 10 hours to travel between Kunming, China and Singapore (i.e. passing by Bangkok, Thailand and Kuala Lumpur, Malaysia). The completion of this transport network would then affect the choice of travelers in using ground transport and air transport. The above-mentioned instances confirmed the intensifying competition between air transport and ground transport not only for the present and but also for the future. As such, it is exceptionally essential for airlines to understand and to analyze the mode choice of travelers in order to flourish in a competitive transportation system. This aspect is certainly necessary for airlines in implementing appropriate marketing strategy to attract more travelers as well as to increase their mode share. In addition, mode choice analysis is significant for airlines in managing their travel demand and also in predicting future travel trend. From the social aspect, air travelers would then benefit by getting a better service enhanced by the airlines.

For airline industry, the advent of low cost carriers (LCCs) has reshaped the competitive environment and has made a significant impact on travelers' mode choice. The LCCs pursue simplicity, efficiency, productivity and high utilization of assets in order to offer low fares (O'Connell and Williams, 2005). Besides, LCCs offer only a single class of service, high density seating, no free food and drinks, no connecting services, and they commonly use under-utilized secondary airports (Pels et al., 2009). This reduces the operational cost overall which could attract travelers to use LCC's service at a lower price. Such revamp of the airline service has brought vicious competition to FSCs. It was found that LCCs had taken up a large market share of travelers who are concerned with travel cost. Evangelho et al. (2005) found that LCCs are preferred by smaller companies with minimum expenditure policies. Mason (2000, 2001) added that LCCs are preferred by short-haul business travelers, while O'Connell and Williams (2005, 2006) found that it has dominated leisure trip market. Apart from travel cost, the flexibility of flight schedule, convenience in ticket booking (through internet), attractive holiday package, and promotional parking at airports (Barrett, 2004; Evanlogelho et al., 2005) are among the factors advocating the choice of LCC services. The socio-demographic characteristics of travelers such as ethnics and level of education are found to be significant as well (Ong and Tan, 2010).

The competition of LCC is not limited to FSC, as it also has ground transport. Numerous studies have shown that there is a direct competition between HST and air transport. Rus and Inglada (1997) showed that the introduction of HST had induced a fall in demand of 20%-50% of the air transport while Gonzalez-Savignat (2004) revealed that over 50% of air travelers (with leisure purpose) would divert to HST. The journey travel time is one of the significant factors that affect the mode choice between HST and LCC. Gonzalez-Savignat (2004) commented that HST might be able to compete with the LCC for the journey which is less than three hours. Roman et al. (2007) found that HST is more competitive for short journey as the travelers choose HST with the aim to reduce delay time. In addition, Adler et al. (2010) showed that HST would attract almost 25% of medium-distance journey (up to 750km) but only 9% for longer haul markets. Travelers' socioeconomic background is found to be one of the significant factors. Ortuzar and Simonetti (2008) found that older travelers prefer to travel with HST. In the Malaysian context, O'Connell and Williams (2005) showed that there is a mode shift from buses and trains when AirAsia was first launched in 2001. They showed that students, who accounted for the second largest non-business market, have switched to AirAsia instead of traveling with buses and trains. Furthermore, a large proportion of AirAsia's travelers are first time flyers and majorities are youngsters. Nevertheless, the study was carried out many years ago and it did not investigate the contributing factors that cause the mode shift.

To model the mode choice decision of travelers explicitly, stated preference (SP) survey has been used extensively in the past to investigate the choice of travelers. Principally, the SP survey aims to investigate traveler's response towards hypothetical scenarios in selecting the travel mode (alternative) that is most beneficial for traveling situation and purpose (Train, 2003). To conduct the SP survey, the design of questionnaire could be outlined with various traveling attributes (with different levels) which could be selected accordingly based on the findings of the past literatures, pilot survey or transport operator’s operational data and records (Yang, 2005; Hess et al., 2007; Loo, 2008; Wen and Lai, 2010). However, under the circumstances for which the number of traveling attributes and level increase, it is not realistic to present all possible combinations of choice to respondents in the real practice. In such a case, fractional factorial design and confounding factorial design (blocking approach) could be adopted to present the questionnaire reasonably to targeted respondents (Train, 2003; Montgomery, 2005). There are several models that could be tested to model the mode choice decision of travelers. Some possible models include logit, probit and generalized extreme value (GEV) models (Ortuzar and Willumsen, 2001; Train, 2003; Montgomery, 2005).

There are some studies which were conducted and analyzed using SP survey. By undertaking SP survey, Hess et al. (2007) modeled airport and airline choice behavior in the form of multinomial logit (MNL) structures while Loo (2008) made use of SP survey to model passengers’ airport choice, specifically for Hong Kong for which the MNL model was found to be significant to model passengers' choice. Besides, Wen and Lai (2010) discovered that airlines choice of passengers, collected from SP survey, fitted well in the MNL model. To model the intercity mode choice decision of passengers, Yang (2005) developed several models, including MNL, heterogenous logit kernel (HLK), mixed logit (ML), latent class (LCM), competing destination (CD) and heterogenous competing destinations (HCD) models. In comparison to MNL model (as base model), he showed that HCD model is significant to improve the model's explanatory power by considering multiple-heterogeneity while the ML model, that adopts the specification of continuous probabilistic distribution, emerges to be the best explanatory model in terms of the heterogeneity of taste variation.

Apparently, many mode choice models in the existing studies were outlined based on the MNL model to analyze the behavior of travelers. This happens mainly due to its inherent property of Independence from Irrelevant Alternatives (IIA). However, MNL model is governed by Independent and Identically Distributed (IID) error term that assumes homogeneity in unobservable components of utility. In other words, the MNL model could not capture heterogeneity properly (Train, 2003; Yang, 2005).

2.3.2 Analytic Hierarchy Process: A Tool to Quantify the Key Aspects of Fleet Planning Decision-Making

Analytic hierarchy process (AHP) was first introduced by Saaty (1977) with the attempt to select and prioritize a number of actions by evaluating a group of predetermined criteria in making multi-criteria decision. Conceptually, the AHP is originated from the fuzzy set theory which is developed by Zadeh (1965). As a multiple criteria decision-making approach, the AHP allows the respective judgments to vary over the values of a fundamental scale 1-9. In such a way, the AHP possesses the capability to capture fuzziness (uncertainty) in making multi-criteria decision (Saaty and Tran, 2007). As such, fleet planning decision-making of airlines which is, in fact, uncertain (primarily due to stochastic demand) and greatly governed by various key aspects (multi-criteria) could be solved strategically with the aid of the AHP.

To estimate drivers' preferences towards available transportation alternatives, Arslan and Khisty (2006) adopted AHP to explain the route choice behavior from a behavioral point of view. Hsu et al. (2009) utilized AHP to examine the preferences of tourists by identifying the influential factors in selecting their destinations. Besides, AHP is widely applied in other sectors, including resource management, corporate policy and strategy (Velasquez and Hester, 2013). Apparently, none of the literatures apply AHP to solve fleet planning problem under uncertainty. Specifically, there is no study that applies AHP to quantify the key aspects of fleet planning decision-making. Moreover, it could be seen that existing studies did not consider mode choice analysis when making fleet planning decision (as discussed in section 2.3.1). Most of the studies in mode choice analysis (e.g. Mason, 2000, 2001) only focused on the traveling attributes of airlines and traveler’s preference for which the impacts of traveling attributes in affecting the supply (fleet) planning are not inspected. This (supply-demand) aspect should be considered owing to the fact that the utilization of aircraft and airline's operations correlate closely with the trend of travel market especially under uncertainty. This necessitates the incorporation of mode choice modeling and the AHP in the fleet planning model not only to yield a strategic fleet planning decision-making, but also to capture supply-demand interaction in a better manner.

2.4 Service Frequency and Slot Purchase in Fleet Planning

This section reviews the relevant papers which discussed and analyzed the service frequency of airlines. Specifically, past studies could be grouped into two categories: (i) service frequency determination in fleet planning, and (ii) slot purchase. It is anticipated that airlines would gain more profit and meet more demand (with a higher service frequency) by incorporating slot purchase necessarily in solving fleet planning problem.

2.4.1 Service Frequency Determination in Fleet Planning

There are some studies that inspect airline's service frequency. Pitfield et al. (2009) and Mikio (2011) discussed the trade-off between aircraft size and service frequency. Their results showed that airlines would tend to increase flight frequency (and hence decrease aircraft size) when demand increases (Pitfield et al., 2009) and also when runway capacity expands (Mikio, 2011). However, they did not show how airlines could provide service frequency adequately (with corresponding aircraft type) to meet increasing demand. Particularly, from an environmental aspect, Givoni and Rietveld (2010) discussed airline's choice on aircraft size and service frequency. A lower service frequency (by operating larger aircraft) was found to produce lesser amount of emission and noise. This signifies that aircraft size and service frequency are closely related to each other and this would affect the fleet planning decision of airlines.

By building a nested logit model, Wei and Hansen (2005) investigated airlines' decisions on aircraft size and service frequency. They revealed that the service frequency and corresponding aircraft size of different market types could vary differently according to passengers' choice model estimation. Similarly, by estimating passenger's flight choice that contributes to varying market shares (travel demand), Hsu and Wen (2003) determined airline's flight frequency at optimal profit. However, their solutions of service frequency were found to be lower than the actual flight frequency of airline because the market shares were underestimated. This shows that the changes of demand (demand fluctuation) as well as service frequency could not be captured precisely. Thus, a well-defined model is indeed required to deal with airline's service frequency in order to meet stochastic demand desirably.

Focusing on profit maximization of a game-theoretic model (under competitive environment), Hansen (1990) determined the service frequency for the respective airline, given the flight frequency of the competing airlines. However, he assumed the fixed airfare which in fact has an inelastic demand with respect to price and service. Later, Wei and Hansen (2007) developed game-theoretic models to analyze airlines' decision-making on aircraft size and service frequency. The service frequency of respective airline is determined optimally based on maximum profit of airlines in a competitive market. Similarly, Wei (2006) employed game-theoretical model to inspect how airport landing fees could affect the decisions of airlines on aircraft size and flight frequency in order to produce airline's optimal profit. However, the sole focus on landing fees in affecting airline's decision-making might be too restrictive. Furthermore, the demand fluctuation that could affect aircraft selection and its corresponding service frequency is not tackled.

More recently, airline's decision to determine weekly flight frequency (for different aircraft type) in response to aircraft emission charges could be seen in Wen (2013) for which service frequency on individual route is determined by minimizing the operating cost of a multi-objective programming model. He showed that some direct flights of a particular aircraft type were shifted to one-stopover transit flights to reduce emission. This reveals that aircraft type would affect service frequency determination.

With the aim to maximize airline's profit, Listes and Dekker (2005) adopted scenario aggregation-based approach to determine the fleet composition (aircraft choice) to meet short-term stochastic demand. Apparently, long-term fleet planning model may not be solved strategically in view of the fact that the developed model only capture the short-term demand. Despite selecting a particular aircraft type to meet travel demand, service frequency of respective operating route which deals closely with aircraft choice is not determined optimally to meet demand fluctuation. Besides, the accuracy of their model to determine the optimal profit may not be accurate in view of the specific airfare of passenger's class (business and economy) is neglected. From the airline's business principles, the airfare of different passenger's class, as a major income for airlines, is a crucial element and hence this component needs to be tackled appropriately in fleet planning.

Hsu et al. (2011a, 2011b) formulated stochastic dynamic programming model to solve fleet planning problem by minimizing airline’s cost. In spite of the respective service frequency of existing operating networks, how airlines make optimal decision to operate additional service frequency to meet increasing demand is not explored explicitly. Besides, their formulations might be too simplistic by considering travel demand as sole constraint in fleet planning. This may affect airline's services in providing a desired service frequency to meet demand fluctuation. Furthermore, the airfare of specific passenger's class is ignored and hence the accuracy of airline's profit and revenue are questionable at some extent.

From the aforementioned studies, it could be seen that the service frequency of airlines is closely related not only to aircraft size and type but also to the demand fluctuation. In other words, there is a strong interaction between supply (service frequency and fleet composition) and demand. This points out that the service frequency of airlines which associates closely with fleet combination (aircraft size/type) needs to be monitored wisely to meet the demand fluctuation at a desired service level. This necessitates the inclusion of service frequency in the fleet planning model. Nevertheless, until today, none of the existing studies capture the service frequency explicitly in solving the fleet planning problem which deals closely with aircraft composition. Moreover, stochastic demand which has a great impact on aircraft type and service frequency is not taken into consideration by most of the existing studies.

2.4.2 Slot Purchase

In view of the constant growth of air traffic (travel demand), i.e. approximately 5% annually (International Air Transport Association, 2009), and the constraint of service frequency at particular airports, there will still be a challenging issue to airlines to meet demand fluctuation profitably in such a competitive airline industry. In order to capture the service frequency explicitly and to support the current operating networks, slot purchase offers a greater opportunity to increase airline's service frequency in order to meet the travel demand at a desired service level (Fukui, 2010; Babic and Kalic, 2011, 2012). For instance, US Airways had increased a total of 142 flights via slot purchase decision at LaGuardia Airport, New York from year 1992 to 2000 (Fukui, 2010). Basically, when the airport capacity is not able to accommodate the requests of all airlines, the number of aircraft movements is regulated by airport slots on a specific date (Jones et al., 1993; Pellegrini et al., 2012). Slot controls, the most effective demand-management tool, have been widely used at some major airports especially in Europe and the United States (Mehndiratta et al., 2003). Based on the IATA system, slot allocation is made twice a year, at the IATA Scheduling Conference (Babic and Kalic, 2012). Subsequently, secondary slot trading was introduced based on airline's willingness to pay for slots (Mott, 2006) for which slot price is commonly airport-specific and greatly influenced by time of the day, airline regulation, travel demand, etc. (Gillen, 2006). Due to the fact that the service frequency of airlines is limited to a fixed number for a particular time period, airlines must possess a slot for the provided time period for arrival/departure (Mehndiratta et al., 2003). For airlines, slot purchase is extremely useful and vital to increase flight frequency and operations efficiency (Brueckner, 2009), to reduce delay (Mehndiratta et al., 2003; Gao et al., 2011), to meet fluctuating demand (Fukui, 2010) as well as generate more profit (Babic and Kalic, 2011, 2012). For air travelers, Swaroop et al. (2012) highlighted that slot purchase of airlines could improve travelers' welfare, by providing a better connectivity between flights (with lesser delay time and more service frequency from airlines).

There are some studies that discuss slot purchase, especially on the underlying benefits of slot purchase decision-making. Focusing on new flight scheduling in order to expand airline route network, Babic and Kalic (2011, 2012) optimized the slot purchase decision-making (with maximum revenue). They found that slot purchase could increase airline's profit and service quality by adding new destination, increasing flight frequency and improving schedule connectivity. By using welfare based approach, Swaroop et al. (2012) analyzed the welfare effects of slot controls including the benefits from queuing delay reduction and costs. They showed that slot control is effective and it would improve travelers' welfare by reducing system delays (with additional service frequency). Mehndiratta et al. (2003) estimated the impact of slot controls by adopting a market-based allocation mechanism. They showed that slot control is constructive for demand management as well as to alleviate unnecessary delay. By adopting price and quantity-based approaches, Brueckner (2009) discussed the benefits of slot purchase to manage airport congestion. Slot purchase was found to be beneficial to airlines in providing efficient operations as long as slot purchase decision is optimally made. Similarly, by comparing congestion pricing and slot trading, Basso and Zhang (2010) revealed that the total air traffic is higher under slot auctions and this in fact signifies that slot purchase is able to meet more travel demand. Focusing on competitive markets, Fukui (2010) used regression analysis to examine whether if slot-holding airlines have restricted service expansion and market entry by other airlines. It was found that although slot markets might possess the potential to enhance competition, there are still plenty of improvement areas in the slot markets. Thus, the results highlighted that it is necessary to design additional enhancement mechanisms for slot trading system to yield more benefits to airlines.

As revealed by the afore-mentioned past studies, it could be seen that slot purchase is certainly beneficial to airlines in assuring higher profit, via a higher service frequency in meeting more demand. However, there is no exact approach or proper model in the existing studies that could assist airlines to make use of slot purchase wisely in providing appropriate flight frequency to meet stochastic demand profitably. As such, a suitable and well-defined model is required to determine optimal slot purchase as well as fleet planning decision so that airlines could meet stochastic demand desirably (with optimal service frequency and fleet composition).

In overall, it could be inferred that the service frequency of airlines (to meet corresponding demand level) is associated closely with the aircraft type and size, thus it can't be denied that slot purchase, a vital element to provide more services (with additional service frequency), would also influence the fleet planning decision of airlines to a great extent (in terms of optimal quantity of respective aircraft type). In view of the implication of slot purchase in providing more services, i.e. a higher service frequency to meet increasing demand, which necessitates the inclusion of slot purchase (with associated service frequency) in solving the fleet planning problem. By having slot purchase, airlines would not only be able to improve their services quality by providing a desired service frequency, via an adequate fleet supply, to meet demand increment (Brueckner, 2009; Fukui, 2010), but would also be able to achieve passenger's satisfaction desirably. More importantly, the incorporation of slot purchase in fleet planning would increase airline's revenue and profit (Babic and Kalic, 2011, 2012). This is definitely crucial for airlines to sustain its profitability in such a challenging airline industry.

In view of the fact that fleet composition and airline's profit may vary to a great extent by incorporating slot purchase and service frequency of each operating route, there is a need to improve the existing approaches in solving the fleet planning problem. It could be seen from the existing studies, the availability of slot purchase was neglected. This may result in the unfeasibility of airline's fleet supply to meet stochastic demand satisfactorily. Besides, the specific airfare of each passenger class, which is neglected by many past studies, should be incorporated necessarily to solve the fleet planning problem in order to capture airline's business principles in a better manner.

2.5 Green Fleet Planning

Three major environmental issues pertaining to air transport system are aircraft emission, noise, and fuel consumption (Janic, 1999; IPCC, 1999; ICAO, 2010; Sgouridis et al., 2011). In the following subsections, the contributing factors that cause environmental issue are discussed accordingly. Subsequently, several mitigation strategies that correspond to the respective environmental issues are discussed. Besides, some relevant studies that examine environmental impacts are reviewed.

2.5.1 Environmental Issues of Air Transport System

In view of the increasing concern on green issues, it is crucial for airlines to identify the contributing factors that could affect their environmental (green) performance. This is necessary not only to quantify the overall green impacts accurately, but also to carry out improvement strategies effectively (for greener performance). It was found that aircraft cruising altitude (Williams et al., 2002), load factor, aircraft age, cabin density configuration (Miyoshi and

Mason, 2009), aircraft size and service frequency (Givoni and Rietveld, 2010) are the factors that could affect aircraft **emission** level.

The aircraft **emission** level varies significantly on cruising altitudes and flight paths (Williams et al., 2002). Generally, a lower altitude and longer cruising stage will tend to generate more pollutants. However, a high altitude of flight may result to the formation of contrails that causes negative impact to the environment. The aircraft load factor, i.e. a measure of utilization amount of total available capacity of aircraft, has been recognized as one of the significant contributing factors to aircraft emission. For a higher load factor, the fuel consumption of aircraft is lower (in terms of unit load factor) and hence the corresponding emission level tends to be lesser. Therefore, an increasing load factor was found to be more environmental beneficial, particularly due to a lower amount of pollutants per unit load factor (Miyoshi and Mason, 2009; Givoni and Rietveld, 2010). Another contributing factor worth mentioning is the cabin density configuration, i.e. the structure of seats supplied for which the aircraft with a higher seating density would increase aircraft weight and hence more emission would be produced (Miyoshi and Mason, 2009). Besides, aircraft age have an influential impact in aircraft emission. Miyoshi and Mason (2009) mentioned that aircraft technology could be a determining factor in this aspect. Usually, newer aircraft with advanced technologies (by incorporating a better fuel efficiency system) would emit lesser emission compared to aging aircraft (Janic, 1999). In addition, aircraft size also influences the emission level. Usually, a smaller aircraft (single-aisle) which is operated for short-haul networks emit lesser pollutants compared to large aircraft (twin-aisle) for long-haul networks (Givoni and Rietveld, 2010). Larger aircraft produces more emission, mainly due to a large proportion of carbon emission, especially from cruising stage of long-haul flights (Morrell, 2009; Miyoshi and Mason, 2009). As such, it could be deduced that aircraft size would produce different emission level. Furthermore, service frequency is also one of the contributing factors. By having a higher service frequency, airlines would consume more fuel to support their operating networks and hence the level of aircraft emission would increase proportionally. In other words, a higher service frequency (more flights) would consequently emit more aircraft emission (due to more fuel burning).

The level of aircraft **noise** emitted from aircraft operations depends on several factors, such as aircraft type (Janic, 1999) and aircraft trajectories (Clarke, 2003; Visser, 2005; Prats et al., 2010, 2011). Heavier aircraft usually generates louder noise due to more powerful engine setting (ICAO, 2011). It was found that the engine parts such as fan, compressor and turbine are the main sources of aircraft noise. Aircraft trajectories contribute to noise during the take-off and landing stage by having different flight speed, thrust setting as well as flap and slat configuration (Prats et al., 2011). Besides, the aircraft noise level produced by a particular flight trajectory (during take-off and landing stages) is also relatively influenced by the navigation system and terminal airspace.

In terms of **fuel consumption**, Janic (1999) and Morrell (2009) highlighted that technological innovation is one of the significant factors affecting aircraft fuel consumption level. They revealed that improved technology on engine propulsive and thermal efficiency could result in more fuel savings. Aircraft engine with a higher bypass ratio would also have lower fuel consumption (Janic, 1999). Besides, advances in structures or materials to develop a new generation of aircraft would be able to reduce aircraft weight and fuel consumption. Airbus (2013) claimed that the fuel consumption of A380 is about 17% lesser (per passenger) than its competitor. This is achieved by having a highly aerodynamic and efficient fuselage design and also the usage of innovative composite materials to reduce weight. For aircraft operations, it is important to note that fuel consumption directly contributes to aircraft emission level.

In terms of aircraft size, Morrell (2009) showed that fuel efficiency appears to be higher for smaller aircraft (especially for short/medium-haul) comparing to a larger size of aircraft (for long-haul). Smaller aircraft was found to be more fuel-efficient mainly due to its seat density and load factor which is usually higher than larger aircraft. This shows that the aircraft type in terms of aircraft size with varying seat density and load factor would affect the fuel efficiency of airlines. Specifically, Tsai et al. (2014) showed that a lower fuel consumption (and hence emission level) could be achieved by reducing the weight of seats in passenger cabins. Abdelghany et al. (2005) showed that fuel management strategy in response to aircraft's operational conditions would affect the fuel efficiency of airlines. In general, excessive fuel loading (particularly to serve subsequent flight) would add on to the aircraft weight and heavier aircraft would consume more fuel. In addition, Nikoleris et al. (2011) showed that idling and taxiing states at constant speed or braking emerged to be two largest sources of fuel burnt during landing and take-off (LTO) cycle, which accounts about 18% of fuel consumption. The fuel efficiency is relatively sensitive to thrust level assumptions (i.e. 5% and 7% respectively for taxiing and turning states) and depends very much on the number of stops during taxi, duration of each stop, number of turns on taxiway as well as accelerating time.

2.5.2 Mitigation Strategies

Various mitigation strategies are proposed and in-place to alleviate deteriorating environmental problems resulting from aircraft activities. These strategies could be categorized into three categories, namely technological innovation, operational and fleet, policy and rules & regulations.

In terms of **technological innovation**, an improvement in engine and aerodynamics design as well as using lightweight material to reduce aircraft weight are found to be beneficial to the environment (Hellstrom, 2007; Sgouridis et al., 2011). Miyoshi and Mason (2009) showed that a newly developed aircraft through the incorporation of technological advances into the fleet (such as B737-700 and B777) produced lower emission than older generation aircraft. Besides, Morrell (2009) reported that most of the efficiency gains of B737-800 come from new technology. Janic (1999) highlighted that the improvement in the engine’s propulsion and thermal efficiency has increased the engine pressure ratio and turbine temperature for which the engine with a higher bypass ratio (e.g. B777) has lower fuel consumption. Generally, fuel consumption decreases by about 4% for each increment in the engine's bypass ratio. Besides, the introduction of the high bypass technology to the aircraft engine has reduced the engine noise significantly (Air Transport Action Group, 1996). At the same time, the engine has become bigger and stronger to propel bigger and faster aircraft. The larger and faster (more productive) aircraft which is powered by stronger turbofan and high bypass engines have generated a lower level of noise. Furthermore, turbofans with ultra-high-bypass ratio and open rotor prop-fans are identified as possible solutions to reduce aircraft noise (Smith, 1992). Besides, Airbus (2013) reported that the largest aircraft A380 is producing ultra low noise with a significant reduced aircraft weight through the use of lightweight materials.

In terms of **operational efficiency**, the improvement efforts include flight optimization (e.g. by generating optimal aircraft trajectories) and ground operation optimization such as aircraft taxiing operation (Sgouridis et al., 2011). Recent advances in navigation technology have guided the cockpit crew to operate effectively and safely under Instrument Flight Rules (IFR) environment. For instance, the Area Navigation (RNAV) system allows the pilot to create aircraft trajectory based on a series of arbitrary reference points while the Global Positioning System (GPS) generates precise estimates for a particular position at any location around the world (Logsdon, 1992). By combining RNAV and GPS, the system enables the approach and departure trajectories to be adjusted for noise reduction. Similarly, Visser (2005) introduced a noise optimization tool that could generate aircraft trajectories or flight paths for both arrivals and departures which reduce aircraft noise impact under operational and safety constraints. Furthermore, Clarke (2003) developed a simulation system that aims to assist air traffic controllers in determining appropriate sequencing and spacing for optimal (maximum) takeoff and landing rates in heavy traffic condition. Besides, by increasing the density cabin configurations and load factor, the emission rate per passenger could be reduced (Miyoshi and Mason, 2009). In addition, the lower service frequency (by operating larger aircraft) could produce lesser emission and thus a larger aircraft for short-haul operation is encouraged in order to retain similar capacity in meeting travel demand (Givoni and Rietveld, 2010).

In terms of **policies and rules & regulations**, noise charge is imposed on airlines that have generated noise level over allowable limit. Generally, noise charges are imposed based on individual aircraft or cumulative noise recorded. Individual aircraft noise charge is computed based on aircraft's maximum takeoff weight (MTOW) in accordance with the Federal Aviation Administration (FAA) noise certification standards. Heavier aircraft customarily incur higher landing and noise charges and busier airports charge higher noise fee per landing. Noise charges, however, vary across airports, i.e. depending greatly on operation time of departure and/or arrival (Girvin, 2009). On the other hand, cumulative noise limit (in the form of noise quotas/limits) refers to noise exposure over a specific period. It is imposed by airports to control the total noise generated by airlines. Based on yearly maximum total noise level for each planning year at airports, the airport authority would curtail the operations of airlines if their operations exceed the regulated limit of noise volume. In the United States, the airport authority may increase or reduce the flight slots available to airlines based on their cumulative noise exposure from previous year (Girvin, 2009). Nighttime curfew is another most common noise-abatement measure for which airports ban aircraft operations over a predetermined night time period and enforce penalties on airlines that violate the curfew. Operations during curfew hours are limted to a maximum number and curfew regulations are highly airport-specific. Some of the examples of airports that regulate noise limits for daytime and night time operations are the UK's Leeds, Czech Republic's Prague and Austria's Salzburg.

Emission charge is introduced to reduce aircraft emission level. The charge is generally computed based on nitrogen oxide and hydrocarbon emission level at airports. This concept was introduced in Switzerland and Sweden in 1997 and 1998, respectively. There were five classes of emission charges in Switzerland and seven classes in Sweden that are ranked according to a specific emission level of turbofan engines (Scheelhaase, 2010). In 2003, the European Civil Aviation Conference (ECAC) created ERLIG formula that provides a standard approach to compute emission level from aircraft engines (ECAC, 2003). This was then adopted by the European airports, including London Heathrow airport in 2004 and Munich airport in 2008. However, emission charges vary across airports. For instance, €3 per emission value unit (in ton) is charged in Germany, €5.5 in Sweden, €1-€3 in Switzerland and €1.60 in the UK. Generally, emission charge differs depending on the type and number of engines of aircraft. In Germany, emission charges of B747-200 (with JT9D-7FW engines) at €385.02 are much higher than the emission charges of A340-300 (with CFM56-5C4 engines) at €104.43. Generally, low emission charges are levied for small turboprops and high emission charges are set on bigger and heavier aircraft, mainly due to more powerful engines than smaller aircraft (Scheelhaase, 2010). Although aircraft engine was shown to be a major factor on emission charge, Scheelhaase (2010) highlighted that the decision on the engine type used on aircraft depends on a bundle of managerial factor, not just on the implementation of emission charges.

More recently, the European Union (EU) implemented Emission Trading Scheme (ETS) to alleviate global warming by reducing carbon dioxide emission. Starting with intra-European flights in 2011, it's required for the airlines to hold allowances for their carbon dioxide emission and non-European airlines was included from 2012 for their aircraft operations that operate in and out of the EU (Albers et al., 2009). Under this scheme, airlines will obtain an initial set of free-of-charge allowances, i.e. 85% based on the 2004-2006 average emission while the remainder (15%) being auctioned (Wen, 2013). However, airlines have to acquire additional allowances if they require more. The allowance (emission) price of ETS ranges between €10 and €30 for each ton of carbon dioxide emission (European Commission, 2005; Ernst and Young, 2007; Scheelhaase and Grimme, 2007). Approximately, this would result in an additional cost of €20/ton of carbon dioxide per passenger. However, the implementation of ETS system in aviation sector received responsive debates since its proposal.

2.5.3 Environmental Assessment Approaches

Till to date, there are very limited studies that quantify the environmental impacts of transportation sector. To assess the environmental impacts for a highway route and paving project, Boclin and Mello (2006) presented a decision support method by using fuzzy logic approach. They showed that 'park-highway' is the most promising alternative in giving the best ecological, economic and social performance. Rossi et al. (2012a, 2012b) examined three-dimensional concept of sustainability to identify the preferences of decision makers and also to obtain the most important characteristics of alternative transportation policies. The limitation of these studies is that they primarily focused on transportation alternatives analysis and forecasting for which there is no exact quantification approach that could be used to evaluate the green performance of transport operators. In other fields (not transportation system), Silvert (2000) evaluated the impacts of finfish mariculture on coastal zone water quality by adopting the fuzzy logic approach. Four fuzzy sets (nil, moderate, severe and extreme impacts) were defined and the corresponding partial memberships have been combined to yield a single comprehensive score as an overall measure of environmental quality. Valente et al. (2011) categorized old mining sites and described their environmental impact as low, medium and high. They showed that the use of fuzzy logic to obtain the environmental impact index allowed the integration of quantitative and qualitative components. Some other relevant studies to evaluate the environmental impacts by employing fuzzy logic could be seen in Andriantiatsaholiniaina et al. (2004), Shepard (2005) and Peche and Rodriguez (2009). However, these studies greatly depend on fuzzy membership of the concerned variables which, in fact, does not possess a clear and specific mechanism for exact formulation or combination. The way to integrate the memberships of variables depends on real application and this would be getting difficult for complex situations (Silvert, 2000). As pointed out by Valente et al. (2011), the membership functions are generally formed with the aid of some probability distribution. In other words, the results are distribution-oriented. Yet, it is important to note that in real practice, some concerned variables may not possess specific distribution. Even if they do, the way to identify the best distribution may not be easy and straightforward.

Besides, Singh et al. (2012) presented an overview of sustainability assessment methodologies, including environmental sustainability index (ESI), environment quality index (EQI) and environmental performance index (EPI). However, most of the assessment approaches generate composite index merely based on aggregate value or the weighted sum value of relevant indicators. These approaches are relatively simplistic to a certain extent for which there is no clear indication on the application for more complicated problem. Furthermore, these indices did not capture the occurrence of unexpected event. The occurrence of unexpected event should be incorporated as it would affect the operations of transport operators and hence the environmental performance will vary differently. None of the indices address this aspect in quantifying the environmental performance.

Apparently, many research studies had shown that the choice of aircraft type, size, age, and aircraft technology are among the key factors in addressing environmental issue. As such, the first and the best step to deal with aviation-related environmental problem is to consider having a green fleet that produces the least pollution impact to the environment. By having green fleet, airlines could then further optimize their operations to minimize the environmental impact. In the light of this, there is a need to consider the environmental factor during fleet planning (Rosskopf et al., 2014). Past studies such as Listes and Dekker (2005), Wei (2006), Wei and Hansen (2007), Pitfield et al. (2009), Hsu et al. (2011a, 2011b) and Wen (2013) have a limitation in addressing the environmental issue in fleet planning. Most of them considered revenue and profit only as the main objective when making optimal decision in fleet planning. Recently, Rosskopf et al. (2014) formulated fleet optimization model as a multi-objective, mixed-integer programming model with the aim to balance the economic and environmental goals in fleet planning. By maximizing airline's asset value and minimizing total nitrogen oxide emissions from flight operations, they showed that airline would have to deviate about 3% from its economic optimum to improve a 6% of the environmental goal. However, the occurrence of unexpected event that would affect aircraft operations is not tackled. Furthermore, only nitrogen oxide is considered to reduce environmental impacts. In fact, aircraft noise and fuel efficiency are also crucial environmental factors that ought to be taken into consideration to improve the green performance of airline. Some crucial practical constraints for fleet planning, e.g. aircraft range constraint, lead time constraint and selling time constraint, are also left out. In addition, there is no clear indication on how to quantify the weights for the economic and environmental goals in solving the fleet planning problem. As such, there is a need for further research effort pertaining to this issue.

2.6 Summary

In overall, the limitations of the existing studies and the needs for improvement could be summarized below:

For *travel demand forecasting*:

- Most of the studies forecasted deterministic demand (inelastic) which could not capture demand fluctuations. Hence, the resultant forecast is not robust and this may result in the loss of optimality.

- Past studies that captured stochastic demand did not consider the occurrence of unexpected events in modeling stochastic demand.
- Some studies assumed the fixed type of distribution to quantify demand fluctuation. This might not be realistic.
- Some studies focused on short-term demand forecasting. This may not be applicable to solve long-term fleet planning problem.

In view of the fact that the travel demand of airlines behaves in a state of uncertainty (stochastic) primarily due to the occurrence of unexpected events which is unpredictable in the real practice, airlines would require a well-defined modeling framework to model stochastic demand. The developed modeling framework of stochastic demand (as described in Chapter 3) is not limited to any statistical distribution in solving the long-term fleet planning problem under uncertainty.

For *airline fleet planning approach*:

- Although many studies focused on the analysis between aircraft size and service frequency, there is no proper mechanism on how airlines could acquire/lease specific aircraft type (with corresponding service frequency).
- The occurrence of unexpected event is neglected in solving fleet planning problem**.**
- Some studies assumed that competing airlines know all the available information in selecting the optimal aircraft size and service frequency. This might not be sensible.

- It might be too restrictive with sole dependence on particular constraint (e.g. landing fees, demand constraint) to obtain optimal fleet planning decision.
- Past study did not consider possible route distance and aircraft weight despite the fact that aircraft specification (including aircraft range and engine weight) would affect the aircraft composition and performance.

Apparently, there is no study that formulates a proper fleet planning model to optimize aircraft acquisition/leasing decision to meet stochastic demand under uncertainty. To obtain optimal fleet planning decision for each operating period throughout the planning horizon, numerous practical constraints that realistically capture various technical and operational considerations of airlines (including aircraft performance) have to be included necessarily. This is vital to assure that the aircraft operations of airlines are practically viable to support the current operating networks at a desired and profitable service level.

For *strategic fleet planning modeling framework*:

- Past studies primarily focus on the technical aspect in solving fleet planning problem but did not quantify the key aspects (probable phenomena) of fleet planning decision-making.
- Existing studies did not consider mode choice analysis in making fleet planning decision as they only focused on the traveling attributes of airlines and traveler's preference.
- For mode choice analysis, the study area of most of the past studies was limited to European countries.

- Other types of ground transport (e.g. bus, car) and specific type of airlines (e.g. low-cost airlines) were not considered explicitly by past studies.
- Some studies were carried out many years ago and the findings may not reflect the current demand trend and traveler's response.

From the aforementioned limitations, it could be seen that supply-demand interaction is not studied explicitly by the existing studies. For airlines, the supply-demand interaction is crucial in view of the needs and expectations of travelers (demand) which would affect airline's service (supply) to a great extent. Therefore, a strategic fleet planning modeling framework is developed to optimize the fleet planning decision of airlines by incorporating mode choice analysis and subjective perceptions of airline's management (decision makers) for which the key aspects (probable phenomena) of fleet planning decision-making plays the role to assure the feasibility of aircraft operations in supporting the operating networks. By providing a desired service level (i.e. optimal supply via fleet planning decision), airlines could retain not only a higher profit level but also the interest or loyalty of their passengers.

For *service frequency determination in fleet planning*:

- Existing studies did not show how airlines could provide service frequency adequately (with corresponding aircraft type) to meet increasing demand.
- Some studies highly depended on particular constraint (e.g. landing fees, demand constraint) to determine service frequency. This might be too restrictive.

- Demand fluctuation that could affect aircraft selection and its corresponding service frequency is not tackled.
- Past studies only assigned a particular aircraft type to meet travel demand for which the service frequency of respective operating route which deals closely with aircraft choice is not determined optimally to meet demand.
- Some studies assumed the fixed airfares which imply an inelastic demand with respect to price and service. The specific airfare of passenger's class (business and economy) is neglected and hence the accuracy of airline's profit and revenue are questionable.
- There is no proper fleet planning model in the existing studies that could assist airlines to make use of slot purchase wisely in providing appropriate flight frequency to meet stochastic demand profitably.
- For fleet planning studies, existing studies ignored the availability of slot purchase. This may result in the unfeasibility of airline's fleet supply.

To meet stochastic demand at a desired service level, airlines would need to possess a proper aircraft composition that could provide an appropriate service frequency, right on time, to support the operating networks under uncertainty. This is particularly important for airlines to meet increasing demand not only to assure a higher profit level but also to sustain competitively. However, it could be seen that there is no existing study that could provide proper mechanism to assist airlines to provide additional service frequency under numerous practical constraints (including the regulated limits of aircraft operations at particular airports). As such, slot purchase plays a vital role to provide additional service frequency (particularly to meet increasing demand) and a well-defined fleet planning model is indeed required to determine optimal aircraft composition and corresponding service frequency. Besides, the developed fleet planning model should include the specific airfare of passenger's class (business and economy). From the airline's business principles, the airfare of different passenger's class, as a main income for airlines, is an essential element and hence this component needs to be tackled necessarily in fleet planning.

For *green fleet planning*:

- Many studies considered the single environmental factor (aircraft emission, noise and fuel efficiency) or mitigation strategy at one time. Hence, the impact of the respective strategy on other green issues could not be captured.
- Past studies focused on transportation alternatives analysis and forecasting, i.e. there is no exact quantification approach that could be used to evaluate the green performance.
- Existing studies are greatly dependent on fuzzy membership which is generally formed by some probability distribution, i.e. the results are distribution-oriented.
- Most of the existing assessment approaches generate a composite index based on aggregate value or weighted sum value of relevant indicators. These approaches are relatively simplistic to a certain extent.
- Most of the past studies of fleet planning considered revenue and profit only as the main objective when making optimal decision in fleet planning.

- The occurrence of unexpected event that would affect aircraft operations is not tackled.
- Only a particular pollutant (e.g. nitrogen oxide) is considered to reduce environmental impacts. Some other environmental factors, e.g. aircraft noise and fuel efficiency are neglected.
- Some crucial practical constraints for fleet planning, e.g. aircraft range constraint, lead time constraint and selling time constraint, are left out.
- There is no clear indication on how to quantify the weights for the economic and environmental goals in solving fleet planning problem.

While meeting stochastic demand at a profitable level, environmental issues could not be neglected in view of the increasing concerns of green issue nowadays. However, there is no study that incorporates green concern in solving the fleet planning problem. By formulating green fleet planning, airlines would determine the optimal aircraft type and quantity that could minimize environmental impacts while attaining maximal profit. Instead of a single environmental factor, the developed model could quantify the overall green performance of airlines. It would also evaluate the effectiveness on respective environmental factor (aircraft emission, noise and fuel efficiency). Furthermore, airlines could sustain a significant amount of cost savings if green fleet planning is carried out with some beneficial improvement strategy (to yield a greener performance).

CHAPTER 3

FLEET PLANNING DECISION MODEL UNDER STOCHASTIC DEMAND

3.1 Making Optimal Aircraft Acquisition and Leasing Decision under Stochastic Demand

This chapter (with three major sections) outlines the development of long-term fleet planning decision model to meet demand fluctuation which is stochastic in nature. To capture the demand fluctuation (for first section), a novel modeling framework of stochastic demand is necessarily developed to determine the level of travel demand under uncertainty. In the framework, the probability of possible occurrence of demand uncertainty is quantified in terms of Stochastic Demand Index (SDI). To solve the fleet planning problem of airlines, an aircraft acquisition decision model (in second section) is formulated to determine the optimal quantity and aircraft type that is to be acquired (without aircraft leasing) to meet stochastic demand under numerous practical constraints. This model is able to assure that stochastic demand (represented by a particular probability distribution) is met profitably at a desired service level. In view of the fact that aircraft leasing also plays a vital role in providing an adequate fleet supply to airlines in supporting their operating networks, an optimal aircraft acquisition and leasing decision (in third section) is then developed accordingly with the aim to determine the quantity and aircraft type that is required by airlines (via acquisition and/or leasing) to meet the stochastic demand desirably. The level of stochastic demand is quantified by using the SDI (based on the modeling framework of stochastic demand). The developed models are able to make optimal fleet planning decision for each operating period throughout the long-term planning horizon. In order to examine the feasibility of the developed methodologies, illustrative case studies were presented and solved in the form of linear and nonlinear programming models (depending on airlines' operational data). Concisely, the findings empirically deduced that the developed methodologies are effective and beneficial for airlines to meet stochastic demand profitably under uncertainty.

3.2 Modeling Stochastic Demand under Uncertainty

Globally, airlines forecast the future growth of travelers annually in order to obtain the latest trend of travel demand. Typically, forecasting (or prediction) of demand growth is found to be positive (i.e. implying positive growth) in accordance with the increase in population size and income level (Malaysia Airlines, 2010a; International Air Transport Association, 2010). However, when there is an occurrence of an unpredicted event which could affect traveler’s decision, there would be a reduction in demand during a certain period of time. This is referred to as a negative effect. A 5-step modeling framework (as displayed in Figure 3.1) is developed to determine the level of demand fluctuation. In the framework, a Stochastic Demand Index (SDI) is defined to quantify the probability of possible occurrence of demand uncertainty. It is assumed that the value of SDI for the base year (year 0) is 1. The Monte Carlo simulation (Taha, 2003; Winston, 2004) is used to determine the occurrence probability of positive and negative effects with no prior assumption of a fixed distribution. The general procedure of the developed framework is elaborated as follows:

Step 1: Determine possible occurrence of unexpected event

Consider a set of uncertain events that could affect travel demand. For example, the occurrence of biological disease, economic downturn and natural disaster which could take place unexpectedly in real life. The probability distribution of these events is determined. To form the respective probability distribution, airlines could obtain and analyze the historical data of unexpected events over a period of time.

Step 2: Determine the probability of unexpected event (negative effect)

Based on the pre-determined probability distribution in Step 1, the probability of unexpected events is simulated by using the Monte Carlo simulation. The probability of occurrence can be expressed as follows:

$$PP_t = \prod_{c=1}^{C} \sum_{h=1}^{H} P_t(hc)\Phi \text{ for } t = 1,\dots,T, \Phi = \begin{cases} 1, \text{if } h \text{ happens} \\ 0, \text{if } h \text{ does not happen} \end{cases} \tag{3.1}$$

for which $P_t(hc)$ is the probability that the unexpected event, *c* happens with a possible occurrence of *h*.

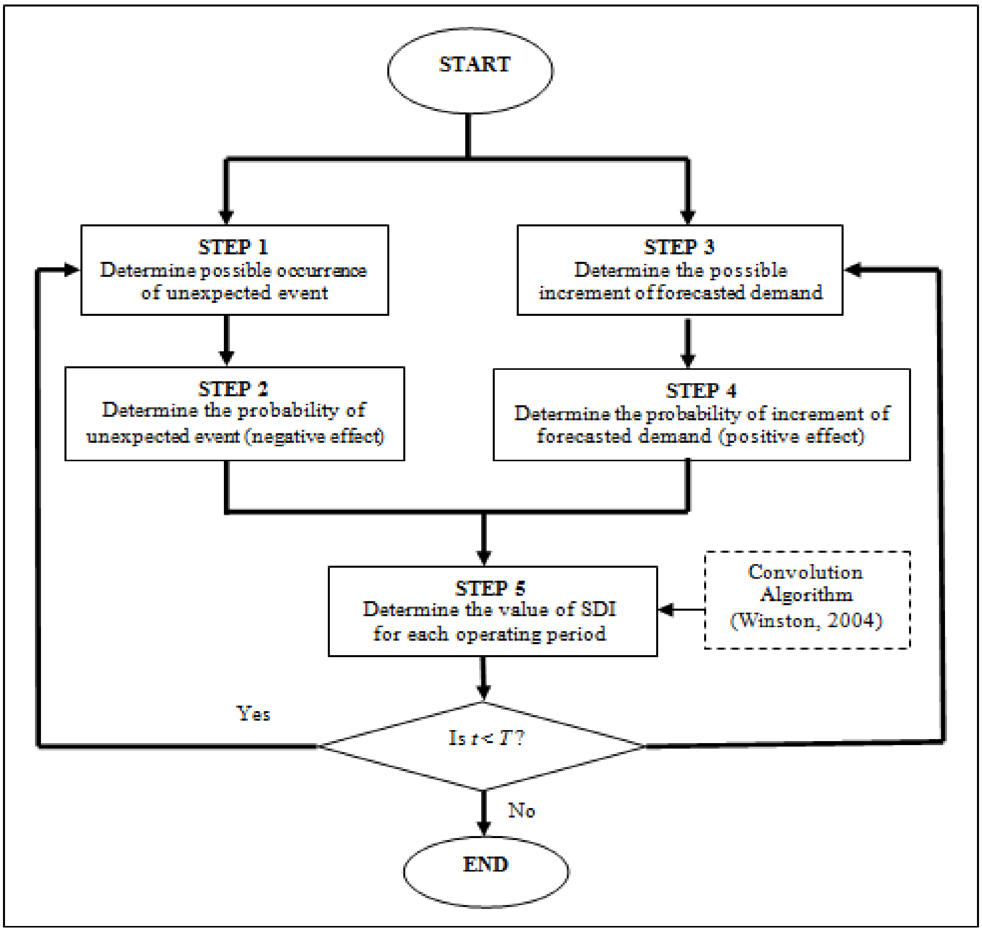

Figure 3.1: Modeling Framework of Stochastic Demand

Step 3: Determine the possible increment of forecasted demand

The possible increment of forecasted demand (positive effect) needs to be estimated. Demand growth is estimated based on past travel trend (from the historical data published by airlines or Non-Government Organization) and future travel trend forecasting. The probability distribution that describes the projected growth of demand needs to be modeled as well.

Step 4: Determine the probability of the possible increment of forecasted demand

Based on the demand growth as projected in Step 3, the possible increment of forecasted demand for each operating period as well as its probability is determined accordingly with the aid of Monte Carlo simulation.

Step 5: Determine the value of SDI for each operating period

For each operating period, the SDI, $Index_t$, is determined subject to both positive and negative effects. The probability of both effects are compiled together to work out the SDI owing to the fact that the level of stochastic demand is affected not only by the occurrence of unexpected event (negative effect) but also influenced positively by demand growth (positive effect). By considering both effects (i.e. to sum up both effects), the SDI could be expressed as follows:

$$Index_t = \left(PP_t + D^t_{f(inc)}\right) + 1 \text{ for } t = 1, \ldots, T \qquad (3.2)$$

for which the constant of 1 is the index value for the base period (year 0). Specifically, $Index_t > 1$ means that in overall (due to both positive and negative effects), the level of stochastic demand of year t is higher than the level of demand in previous year (i.e. year $t-1$). Similarly, $Index_t < 1$ indicates that the level of stochastic demand of year t is lower than the level of demand of previous year, $t-1$. $Index_t = 1$ implies that the demand of year t and its previous year (i.e. year $t-1$) is the same. This is possible due to the nature of uncertainty and the growth of demand which is stochastic.

By using the SDI, the demand level of each operating year, D_t, is determined based on the following equation:

$$D_t = \begin{cases} Index_t \times D_0, & \text{for } t = 1 \\ Index_t \times D_{t-1}, & \text{for } t = 2, \dots, T \end{cases} \tag{3.3}$$

For operating year 1, the demand level is determined by using the convolution algorithm as described by Winston (2004) (as outlined in Appendix A). According to Winston (2004), convolution algorithm can be adopted to generate normal random variates. Besides, this algorithm incorporates random number, which is a significant component for simulation to capture the vagueness and randomness. The demand level of airline's projected demand could be defined as follows:

$$D_0 = \mu_f + \sigma_f \left(\sum_{r=1}^{12} R_r - 6 \right) \tag{3.4}$$

for which the forecasted demand, D_f^t has mean μ_f and standard deviation σ_f. For Equation (3.4), the component of R_r signifies the respective random number that is needed to work out the modeling of stochastic demand. The component of R_r, as parts of the Convolution Algorithm (Winston, 2004), is needed mainly to capture demand fluctuation which is stochastic in the nature. Note that for subsequent operating period, the level of stochastic demand is determined by considering the current SDI and the level of stochastic demand of previous operating period.

3.2.1 An Illustrative Example (To Determine the Probability of the Occurrence of Unexpected Events)

In order to determine the probability of the occurrence of unexpected events by using Equation (3.1), consider two types of unexpected events, i.e. $c = 1, 2$ which respectively represents biological disaster (flu) and economic recession for the operating period 5 (i.e. $t = 5$). The relevant information for each unexpected event is summarized in Table 3.1. For the case that biological disaster (flu) and economic recession to happen simultaneously, the probability of occurrence of these unexpected events can be compiled accordingly (based on Equation (3.1)) as below for the operating period 5:

$$
\begin{aligned}
PP_5 &= \prod_{c=1}^{2} \sum_{h=1}^{2} P_5\left(hc\right)\Phi \\
&= \sum_{h=1}^{2} P_5\left(h1\right)\Phi \text{ x } \sum_{h=1}^{2} P_5\left(h2\right)\Phi \\
&= \left[P_5\left(11\right)(1) + P_5\left(21\right)(0) \right] \text{x} \left[P_5\left(12\right)(0) + P_5\left(22\right)(1) \right] \\
&= \left[\left(0.60\right)(1) + \left(0.40\right)(0) \right] \text{x} \left[\left(0.89\right)(0) + \left(0.11\right)(1) \right] \\
&= 0.066 \\
&\approx 7\%
\end{aligned}
$$

The component of 7% indicates the probability for which the biological disaster and economic recession to happen simultaneously in the operating period 5.

Table 3.1: The Information of the Respective Unexpected Event

Unexpected event, c	Biological disaster (flu), $c = 1$	Economic recession, $c = 2$
Statistical distribution (Poisson distribution with mean μ)	$Pois(\mu = 7)$	$Pois\left(\mu = \frac{1}{9}\right)$
Possible occurrence, h and its probability (where X is the occurrence quantity of unexpected event)	For $h = 1,\ P(X \leq 7) = 0.60$	For $h = 1, P(X = 0) = 0.89$
	For $h = 2,\ P(X > 7) = 0.40$	For $h = 2, P(X \geq 1) = 0.11$
Actual occurrence of h in the operating period 5 (can be determined with the aid of simulation)	$h = 1$	$h = 2$

Remarks:

1. For biological disaster (flu), the actual occurrence of h = 1 indicates that the probability for which the biological disaster (flu) to happen at most 7 times (in the operating period 5) is 0.60.
2. For economic recession, the actual occurrence of h = 2 indicates that the probability for which the economic recession to happen in the operating period 5 is 0.11.

3.3 Aircraft Acquisition Decision Model

Assume that there is a choice of n types of aircraft that could be purchased and operated for a set of origin-destination (OD) pairs. The objective of aircraft acquisition decision model is to find optimal quantity and type of aircraft that should be purchased in order to maximize the operational profit of airlines. The level of demand is stochastic and it could be expressed by some random distributions. To deal with this stochastic element, aircraft acquisition problem is formulated as a probabilistic dynamic programming problem. This approach is adopted primarily due to its ability to decompose the long-term fleet planning problem into a chain of simpler sub-problems for more tractable optimal solutions. The objective function is to maximize the expected profit of airlines by considering various practical constraints in fleet planning. For the developed model, the operating period, t , in terms of years is the stage variable of the model while the state variable at each stage consisted of various inter-correlated variables, namely the quantity of aircraft to be purchased (i.e. main decision variable), initial quantity of aircraft owned, quantity of aircraft to be sold, quantity of aircraft to be ordered and quantity of aircraft to be released for sales. With the aim to maximize airline's expected profit, the optimal decision (i.e. alternatives at each stage) is the acquisition decision of new aircraft to meet stochastic demand while making decision to sell aging aircraft.

The suitability of the developed long-term fleet planning model could be explained by the lead time and order placing time (in advance) of aircraft acquisition. According to some airlines (Malaysia Airlines, 2010a; AirAsia Berhad, 2010a), the acquisition of new aircraft requires a period of five years (in average) to be completely delivered by the aircraft manufacturer. Under certain circumstances (e.g. manufacturing issues), the actual lead time might be longer than the agreeable lead time (between the airline and aircraft manufacturer). This will result in the late or delay of aircraft delivery and hence the airline would receive the new aircraft much more later. Besides, the airlines also have to place their acquisition/leasing order in advance (earlier) in order to receive the respective aircraft on time for operations. As such, it could be deduced that the developed long-term fleet planning model (with the corresponding demand forecasting) is reasonably and practically needed to optimize aircraft acquisition/leasing decision.

3.3.1 Constraints

There are some practical constraints that need to be considered in optimizing aircraft acquisition decision model. They are explained as follows:

Budget constraint This is the most practical constraint in order to ascertain that the solution obtained is financially feasible for airlines. Accordingly, total purchase cost of aircraft should be less than or equal to airline's allocated budget for aircraft acquisition. This constraint could be expressed as follows:

$$\sum_{i=1}^{n} purc_{ti} x_{ti}^{P} \leq MAX_{budget(t)} \text{ for } t = 1, \ldots, T \tag{3.5}$$

Demand constraint Let α indicates the significance level to meet stochastic demand, the following expression can be formulated to achieve airline's targeted level of service.

$$P\left(\sum_{i=1}^{n} \left(SEAT_{i}^{t} \right) \left(f\left(D_{t}^{S}, A_{t}^{i} \right) \right) \geq D_{t}^{S} \right) \geq 1-\alpha \text{ for } t = 1, \ldots, T; S = s_{1}, \ldots, s_{k} \tag{3.6}$$

where $1-\alpha$ is the confidence level (i.e. targeted service level) of airlines to meet stochastic demand while P is the probability of occurrence of a desired service level. Note that stochastic demand can be represented by some probability distributions. If travel demand is assumed to follow normal distribution with mean μ and standard deviation σ, demand constraint could be expressed as follows:

$$\sum_{i=1}^{n}\left(SEAT_i^t\right)\left(f\left(D_t^S, A_t^i\right)\right) \geq F^{-1}(1-\alpha)\sigma+\mu \text{ for } t=1,\ldots,T; S=s_1,\ldots,s_k \quad (3.7)$$

where $F^{-1}(1-\alpha)$ is the inverse cumulative probability of 1- α .

Parking constraint When aircraft is "off-duty", it has to be parked at the hangar or apron of airport. In such a case, aircraft selection would sometimes be constrained by the geometry layout of airports. As such, parking constraint is ought to be considered feasibly. This constraint could be outlined as follows:

$$\sum_{i=1}^{n}\sum_{y=0}^{m}\left(I_{tiy}^P+x_{ti}^P\right)\left(size_i\right) \leq PARK_t \text{ for } t=1,\ldots,T \quad (3.8)$$

Sales of aircraft constraint For some airlines, aging aircraft which is less cost-effective might be sold at the beginning of a certain operating period *t* when airlines make decision to purchase new aircraft. However, to maintain a certain level of operational efficiency, the quantity of aircraft sold should not be more than what was possessed by airlines. This constraint can be expressed as follows:

$$sold_{tiy} \leq I_{(t-1)i(y-1)}^P \text{ for } t=1,\ldots,T; i=1,\ldots,n; y=1,\ldots,m \quad (3.9)$$

Order delivery constraint The delivery of new aircraft is greatly dependent on the efficiency of aircraft manufacturer. Sometimes, there might be a delay in delivering new aircraft. As such, the aircraft that one could purchase should not be more than the number of aircraft available in the market. This constraint can be expressed as follows:

$$x_{ti}^{P} \leq ORDER_t \text{ for } t=1,...,T; i=1,...,n \tag{3.10}$$

Lead time constraint It is important to note that in real practice, airlines would get an agreeable lead time (the period between placing and receiving an order) from aircraft manufacturer when they order new aircraft (to be purchased). However, the real lead time might be longer than the agreeable lead time and this will result in the delay of aircraft delivery. This signifies that lead time constraint is necessary as it is able to indicate when airlines are supposed to place an order for new aircraft. This constraint can be expressed as follows:

$$P\left(RLT_{ti} \geq DLT_{ti}\right) \leq \beta \text{ for } t=1,...,T; i=1,...,n \tag{3.11}$$

By assuming that lead time is normally distributed with mean μ_{LT} and standard deviation σ_{LT}, this constraint could then be stated as follows:

$$DLT_{ti} \geq F^{-1}(1-\beta)\sigma_{LT} + \mu_{LT} \text{ for } t=1,...,T; i=1,...,n \tag{3.12}$$

where $F^{-1}(1-\beta)$ is the inverse cumulative probability of 1-β .

Selling time constraint Airline's aging aircraft which is less effective might be sold during a particular operating period. In such a case, airlines need to know the most suitable time to release their aging aircraft for sales particularly to look for prospect buyers in advance. In real practice, the real selling time might be longer than the desired selling time. Therefore, this constraint is formed with the aim to reduce the possibility of this incident as least as possible. This constraint could be defined as follows:

$$P\left(RST_{ti} \geq DST_{ti}\right) \leq \gamma \text{ for } t = 1,...,T; i = 1,...,n \tag{3.13}$$

Subsequently, this constraint could be stated as follows by assuming selling time is normally distributed with mean μ_{ST} and standard deviation σ_{ST}:

$$DST_{ti} \geq F^{-1}(1-\gamma)\sigma_{ST} + \mu_{ST} \text{ for } t = 1,...,T; i = 1,...,n \tag{3.14}$$

where $F^{-1}(1-\gamma)$ is the inverse cumulative probability of 1-γ.

3.3.2 Objective Function

The objective of the aircraft acquisition decision model is to maximize the expected operational profit of airlines for which the profit could be derived by getting the subtraction of the total operating cost from the total revenue obtained by airlines. For airlines, the total revenue comes from the operational income (i.e. sales of air tickets) and the sales of aging aircraft. Conversely, the total operating cost comprises of operational cost, aircraft purchase (acquisition) cost, maintenance cost, depreciation expenses and payable deposit for new aircraft to be purchased. In general, the total revenue of operating period *t*, $TR(I_t^P)$, can be expressed as follows:

$$TR\left(I_t^P\right) = E\left(fare_t^S\right)D_t^S + \sum_{i=1}^{n}\sum_{y=1}^{m} sold_{tiy} resale_{tiy} \text{ for } t = 1,...,T; S = s_1,...,s_k \tag{3.15}$$

The first term of the right hand side of Equation (3.15) indicates the expected income obtained from the sales of flight tickets by considering the level of stochastic demand D_t^S for which $D_t^S \geq F^{-1}(1-\alpha)\sigma + \mu$. The second term indicates the revenue obtained by selling aging aircraft. On the other hand, the total operating cost of operating period t, $TC(I_t^P)$ can be expressed as follows:

$$TC\left(I_t^P\right) = E\left(\cos t_t^S\right)D_t^S + \sum_{i=1}^{n} u_{ti} + purc_{ti}\left(x_{ti}^P\right) + \sum_{i=1}^{n} hgf\left(D_t^S, A_t^i\right) + \sum_{i=1}^{n}\sum_{y=1}^{m}\left(I_{tiy}^P\right)\left(dep_{tiy}^P\right)$$
$$+ \sum_{i=1}^{n} dp_{ti}\left(x_{ti}^P\right) \text{ for } t = 1,...,T; S = s_1,...,s_k \tag{3.16}$$

The terms of the right hand side of Equation (3.16) respectively indicate the expected operating cost, setup cost of aircraft acquisition, aircraft purchase cost, maintenance cost, total depreciation expenses, and total payable deposit for n types of aircraft.

3.3.3 Probable Phenomena in Fleet Planning

Airlines encounter many challenging unexpected events, for instance the occurrence of natural disaster, economic downturn and outbreak of diseases which are unpredictable in nature. In accordance to the occurrence of unexpected events (risks), an efficient risk management is necessary. According to Malaysia Airlines (Malaysia Airlines, 2010a), risk management process produces a risk map and likelihood scale for airline's management to prioritize the action plans in mitigating possible risks. This highlights that different action may be required to solve different issues and a particular issue may be handled differently at different times. This signifies that the fleet supply to meet stochastic demand which is relatively influenced by the risks (unexpected events) could be outlined similarly, i.e. in terms of the likelihood scale. As such, the probable phenomena, $s_1,...,s_k$ for a total of k phenomena, are defined to describe the possible scenario of aircraft possession in meeting stochastic demand under uncertainty. The probability of probable phenomena, $p_{s_1},..., p_{s_k}$ quantifies the likelihood (probability) of aircraft possession to meet stochastic demand. In other words, they define how well the respective aspect of fleet supply of airline in meeting demand. Preferably, the quantity of operating aircraft should be available adequately to meet a desired level of service.

If probable phenomena and its probability are not defined, it means that airlines only deals with one possible scenario to meet stochastic demand, i.e. they have perfect confidence that a certain level of stochastic demand will be met perfectly for a particular operating period during the planning horizon. However, this should not be the case as there is no perfect assurance of the future. As such, this indicator is necessary to take into consideration the respective key aspect in making fleet planning decision under uncertainty. The number of probable phenomenon varies depending on the perception and consideration of airlines in decision-making. Generally, two probable phenomena (key aspects) are considered for two major aspects, i.e. operational and economic aspects. The operational aspect refers to the relevant perspectives such as operating routes that could be flown with a particular aircraft and traffic rights. The economic aspect may cover the cash balance and debt/lease financing of airlines. These are the key considerations of airlines in fleet planning (AirAsia Berhad, 2004; Malaysia Airlines, 2010a).

In fact, fleet planning model is a multi-criteria decision-making problem in which several key aspects (such as operational and economic aspects) have to be considered. The term “phenomenon” is used to represent various situations that occur owing to the impacts of these different aspects on the fleet planning model. Different risk consideration of the management would lead to different possible scenarios of aircraft possession because the associated fleet planning outcome would be different. For example, if the airline perceives that local flight is less risky (as it is operated at home country), this would cause the airline to purchase more aircraft with smaller capacity and offer higher service frequency. However, if it is an established airline with good record of long-haul flight, it would consider buying larger aircraft with higher capacity and adjust its frequency. As such, different risk consideration would certainly contribute to different scenarios. In the first case (local flight), the airline will own more aircraft with smaller capacity while the second case (long-haul flight), the airline will have bigger size aircraft.

Probabilistic approach can be adopted to quantify the risk as the outcome is not deterministic at the point of planning. The airline would amend their strategy by considering various risk aspects. As such, it is reasonably for the airline management to possess varying possible scenarios of aircraft possession (with different fleet composition) by considering all key aspects (phenomena) in place. Notably, the consideration of all relevant phenomenon (key aspect) in fleet planning constitutes the formation of 'probable phenomena', i.e. 'probable phenomena' is termed to reflect all key aspects (including operational and economic aspects) which could impact optimal fleet planning decision (note: the term of 'probable phenomena' is not used to imply the risk consideration of the airline management that lead to the possible scenarios of aircraft possession).

In view of the probable phenomena is greatly driven by the risk considerations which associate closely with the operating aircraft of the airline (as explained in the abovementioned example), the resultant probable phenomena may vary (with different impacts) across a variety of aircraft type. In other words, it is likely for the probable phenomena to vary in accordance to the existing aircraft composition of the airline, i.e. the existing fleet supply (aircraft composition) of the airline is an influential input which constitutes the formation of the probable phenomena. Airline would consider existing fleet composition during the fleet planning. This is to maintain the fleet homogeneity to ease the training of pilot and flight attendant, as well as the training of aircraft maintenance engineer and technician. In addition, the facility (such as mock aircraft and maintenance garage) has to be maintained as well. As such, an airline which is owning a fleet of Airbus is less likely to purchase or lease Boeing’s aircraft, unless the airline has the plan to expand its personnel (pilot and engineer team) and infrastructure. This is subjected to the airline strategy upon risk consideration. Accordingly, the probable phenomenon is defined to capture the occurrence of various possible scenarios under the risk consideration.

Practically, the probable phenomena and its corresponding probability could be estimated based on the decision policy of airlines, qualitative judgment of experts or consultants, past performance of airlines and travelers' response. Generally, the decision policy of airlines refers to the compliant business strategies and corporate framework which have been practiced closely by the decision makers (i.e. airline's management). Decision policy is playing the role to assure that the managerial and operational decision-making is practiced under the documented rules, in line with the mission and vision of airlines. As a rule, airlines have to obtain governmental approvals to operate their business networks. As such, they have to ensure that their fleet operations (which are driven by the business structure (framework) and strategies) are always in compliance with the obtained approvals while accomplishing business goals (mission and vision) in achieving a desired service level.

On the other hand, the consultancy of the experts refers to the advisory of a group of experts/panels towards the performance of airlines which may range from the financial management to the operational practices as the key considerations for decision-making. The consultancy of the experts could be obtained via contract-basis or permanent employment. Besides, a questionnaire survey study could be undertaken appropriately to obtain the professional opinions/judgments of the experts in the relevant field. For instance, when airlines plan to expand their operating networks, a comprehensive analysis is certainly needed particularly to analyze the potential of expansion as well as the possible difficulties or risks for expanding. Thus, the employment of a group of experts or consultants is necessary for a professional, complete and detailed analysis on the business planning to achieve the level of service satisfactorily.

The past performance of airlines includes both the demand and supply aspects of airlines for which the aspect of demand primarily focuses on the statistical data or operating records of the number of travelers as well as the travel trend which is associated closely to the fleet planning of airlines. From the perspective of supply, the performance and capability of the fleet in servicing the operating networks has to be taken into consideration in analyzing the past achievement of airlines. The adequacy of fleet in meeting the travel demand of airlines is particularly important to achieve a desired service level. Both of these aspects (demand and supply) have to be considered due to their great effect on each other.

Travelers' response refers to the reaction of the travelers which may change from time to time towards the services of airlines. This component has to be considered for the reason that it reveals the behaviors and expectations of the travelers towards the provided services. By having this component in place, airlines can certainly capture the needs of their travelers in a better manner for the enhancement of their services. Traveler's response can be obtained by conducting mode choice modeling analysis via travel survey. For instance, some airlines had undertaken regular travel surveys in order to monitor their services as well as to identify the area of improvement (AirAsia Berhad, 2010a).

3.3.4 Problem Formulation

The existence of indeterminacy (stochasticity) and the variability of unexpected events to occur introduce a probabilistic element. The absence of determinism implies that future events are unpredictable. Aircraft acquisition decision model is probabilistic as travel demand is stochastic (not deterministic) due to the occurrence of unexpected event which is unpredictable in the real practice. The characteristic of fleet planning problem is that some elements are random, including the level of travel demand which is uncertain that giving rise to the element of stochastic demand and this results in a probabilistic issue. As such, a probabilistic dynamic programming model is adopted to solve the fleet planning problem. With the aim to maximize airline's expected profit by acquiring new aircraft to meet stochastic demand under uncertainty, the formulation of aircraft acquisition decision model can be phrased as follows:

For $t = 1, 2, \ldots, T$

$$P\left(I_t^P\right)$$

$$= \max_{X_t} \frac{1}{\left(1+r_t\right)^t} \left\{ \begin{array}{l} p_{s_1} \left(\begin{array}{l} E(fare_t^{s_1}) D_t^{s_1} + \sum_{i=1}^{n} \sum_{y=1}^{m} sold_{tiy} resale_{tiy} - E\left(\cos t_t^{s_1}\right) D_t^{s_1} - \sum_{i=1}^{n} u_{ti} + purc_{ti}(x_{ti}^P) \\ -\sum_{i=1}^{n} hgf(D_t^S, A_t^i) - \sum_{i=1}^{n} \sum_{y=1}^{m} \left(I_{tiy}^P\right)\left(dep_{tiy}^P\right) - \sum_{i=1}^{n} dp_{ti}(x_{ti}^P) \end{array} \right) + \ldots + \\ p_{s_k} \left(\begin{array}{l} E(fare_t^{s_k}) D_t^{s_k} + \sum_{i=1}^{n} \sum_{y=1}^{m} sold_{tiy} resale_{tiy} - E\left(\cos t_t^{s_k}\right) D_t^{s_k} - \sum_{i=1}^{n} u_{ti} + purc_{ti}(x_{ti}^P) \\ -\sum_{i=1}^{n} hgf(D_t^S, A_t^i) - \sum_{i=1}^{n} \sum_{y=1}^{m} \left(I_{tiy}^P\right)\left(dep_{tiy}^P\right) - \sum_{i=1}^{n} dp_{ti}(x_{ti}^P) \end{array} \right) + P_{t+1}\left(I_t^P\right) \end{array} \right\} \tag{3.17}$$

subject to constraints (3.5)-(3.10), (3.12) and (3.14) for which D_t^S, X_t, I_t, $SOLD_t, O_t, R_t \in Z^+ \cup \{0\}$. The term, $\frac{1}{\left(1+r_t\right)^t}$ is needed to obtain discounted value across the period of time while k indicates the k-th probable phenomenon for owning I_t^P as initial fleet size. It is important to note that fleet planning model is solved by assuming that the developed model would subsequently lead to strategic operational decision of airlines (e.g. flight routing and scheduling).

3.3.5 Solution Method

The developed aircraft acquisition decision model, in the form of probabilistic dynamic programming model, can be solved by decomposing it into a chain of simpler sub-problems. By using working backward mechanism, the solution method commences by solving the sub-problem at the last period of planning horizon, *T*. The optimal solutions found for the states at current stage leads to the problem solving at the period of $T-1,\ T-2,...,1$. This procedure continues until all sub-problems have been solved optimally so that the decision policy to acquire new aircraft can be determined profitably. For the developed optimization model (3.17), the type of solution method (i.e. linear programming problem or non-linear programming problem) can be identified clearly with a careful inspection particularly from the key components as follows:

- function of number of flights, $f\left(D_t^S, A_t^n\right)$
- function of maintenance cost, $hgf\left(D_t^S, A_t^n\right)$
- practical constraints (3.5)-(3.10), (3.12) and (3.14)

In general, the developed model could be converted equivalently either to the linear programming model or nonlinear programming model based on the nature of linearity. For model (3.17), modeling parameters would appear to be discrete or continuous variables while the objective function and practical constraints could be a linear or nonlinear function. If they are in the form of linear function in terms of decision variables, then model (3.17) can be solved as a linear programming model, or else it is solved as a nonlinear programming model. In reality, the linearity of these components could be confirmed based on the operational data of airlines. It shall then be validated by using a regression test with the aid of some mathematical software. For the illustrative case study as shown in the following section, linear relationship was adopted for the above mentioned components and hence it is solved as a linear programming model.

3.3.6 An Illustrative Case Study: Linear Programming Model

An illustrative case study is shown to examine the developed model. To make an optimal aircraft acquisition decision, assume that there are two types of aircraft where $n=1$ for A320-216 and $n=2$ for A340-300. Airlines need to decide when and which type of aircraft should be purchased over the planning horizon, i.e. eight years. To avoid choosing some unrealistic value for modeling parameters and functions, realistic data and relevant information are compiled accordingly from published reports and accessible websites of airlines. Tables 3.2 and 3.3 show the data input of the model. From Airbus published statement (Airbus, 2010a, 2010b), it is obtained that the capacity of aircraft A320-216 and A340-300 is 180 (with a total size of 1300 m^2) and 295 (with a total size of 3900 m^2) respectively. The expected flight fare and cost as shown in Table 3.2 is generated based on the available financial reports of Malaysia Airlines

(MAS) (Malaysia Airlines, 2010a). In addition, the purchase prices of aircraft as shown in Table 3.3 were obtained from the published data of Airbus (Airbus, 2010c). With the purchase price of aircraft and estimated useful life of aircraft, i.e. five years, the depreciation value of aircraft are calculated accordingly by using the sum of the years' digits approach. The resale prices and depreciation values of aircraft as shown in Table 3.3 are obtained based on assumed residual value, i.e. salvage cost of aircraft, which is 10% of aircraft purchase cost.

Table 3.2: The Expected Value of Flight Fare and Cost per Passenger

Operating period, t	1	2	3	4	5	6	7	8
$E\left(fare_t^{s_1}\right)$, \$	235	243	254	263	273	284	294	304
$E\left(fare_t^{s_2}\right)$, \$	205	216	228	237	246	256	265	274
$E\left(\cos t_t^{s_1}\right)$, \$	152	158	162	167	171	176	181	186
$E\left(\cos t_t^{s_2}\right)$, \$	135	140	146	150	154	158	163	167

Table 3.3: Aircraft Resale Price, Depreciation Value and Purchase Price ($ millions)

y	$resale_{51y}$	$resale_{52y}$	dep_{51y}	dep_{52y}	$purc_{51}$	$purc_{52}$
1	56	159.6	24	68.4	80	228
2	36.8	104.88	19.2	54.72		
3	22.4	63.84	14.4	41.04		
4	12.8	36.84	9.6	27.36		
5	8	22.78	4.8	13.7		
		Average	14.4	41.0		

There are many variables and parameters in aircraft acquisition decision model. Since not all real data can be obtained, it is interesting to investigate how the results vary if the values of variables and parameters are changed. The data input for benchmark scenario is listed as follows:

- Two probable phenomenon are considered, where $k = 2$

- At t = 1, initial fleet size is $I_{11}^{P} = 50$ and $I_{12}^{P} = 50$
- At t=1, initial fleet size to be two years old is $I_{112}^{P} = I_{122}^{P} = 2$
- The probability of aircraft possession is $p_{s_1} = 0.5$ and $p_{s_2} = 0.5$
- The budget, $MAX_{budget(t)} = \$6,500,000,000$
- Area of parking space, $PARK_t = 500,000m^2$
- Order delivery, $ORDER_t = 25$
- Discount rate, $r = 5\%$ per annum
- Confidence level of demand constraint, $1-\alpha = 95\%$
- Significance level of lead time constraint, $\beta = 5\%$
- Significance level of selling time constraint, $\gamma = 5\%$
- Salvage cost of aircraft = 10% of aircraft purchase cost
- $D_t^{s_2} = 0.95 D_t^{s_1}$ (3.18)
- The function of number of flights is

$$f\left(A_t^n\right) = 54379 + 483 A_t^n \;\; [\mathrm{R}^2 = 0.81\%] \tag{3.19}$$

- The function of maintenance cost is

$$hgf\left(A_t^n\right) = 81031 + 705 A_t^n \;\; [\mathrm{R}^2 = 0.85\%] \tag{3.20}$$

- The function of number of aircraft is

$$NA = 17.9 + 2\mathrm{x}10^{-6} NP \;\; [\mathrm{R}^2 = 0.82\%] \tag{3.21}$$

where NP is the number of passengers.

Equation (3.19) indicates that 483 flights are operated practically for each additional aircraft. The constant in this equation has no practical interpretation. Equation (3.20) denotes that \$705 is the estimated increase of maintenance cost for each additional aircraft and \$81031 is the overall maintenance cost without considering additional aircraft. These functions signify that respective function is strongly affected by the quantity of aircraft owned, A_t^n. Equation (3.21) implies that each additional 500,000 passengers require one additional aircraft (or one passenger requires 0.000002 aircraft). By using backward working mechanism, model (3.17) is simplified to model (3.22)-(3.30) when $t = T = 8$.

$$P(I_8^P)$$
$$= \max_{X_8} \frac{1}{(1.05)^8} \left[\begin{array}{l} p_{s_1} \left(\begin{array}{l} 118D_8^{s_1} + \left(8\text{x}10^6 sold_{815} + 2.278\text{x}10^7 sold_{825}\right) - \left(8\text{x}10^7 x_{81}^P + 2.28\text{x}10^8 x_{82}^P\right) \\ -\left(81031 + 705A_8\right) - \left(1.44\text{x}10^7 I_{81}^P + 4.1\text{x}10^7 I_{82}^P\right) - \left(8x10^6 x_{81}^P + 2.28x10^7 x_{82}^P\right) \end{array} \right) + \\ p_{s_2} \left(\begin{array}{l} 96.3D_8^{s_2} + \left(8\text{x}10^6 sold_{815} + 2.278\text{x}10^7 sold_{825}\right) - \left(8\text{x}10^7 x_{81}^P + 2.28\text{x}10^8 x_{82}^P\right) \\ -\left(81031 + 705A_8\right) - \left(1.44\text{x}10^7 I_{81}^P + 4.1\text{x}10^7 I_{82}^P\right) - \left(8x10^6 x_{81}^P + 2.28x10^7 x_{82}^P\right) \end{array} \right) \end{array} \right] \tag{3.22}$$

subject to

$$80x_{81}^P + 228x_{82}^P \leq 6500 \tag{3.23}$$

$$I_{81}^P + I_{82}^P + x_{81}^P + x_{82}^P \geq 93 \tag{3.24}$$

$$D_8^{s_1} \geq 10645000,\ D_8^{s_2} \geq 10645000 \tag{3.25}$$

$$13I_{81}^P + 13x_{81}^P + 39I_{82}^P + 39x_{82}^P \leq 5000 \tag{3.26}$$

$$sold_{815} \leq I_{81}^P,\ sold_{825} \leq I_{82}^P \tag{3.27}$$

$$x_{81}^P + x_{82}^P \leq 25 \tag{3.28}$$

$$DLT_{81} \geq 30,\ DLT_{82} \geq 30 \tag{3.29}$$

$$DST_{81} \geq 30,\ DST_{82} \geq 30 \tag{3.30}$$

where D_t^S, X_t, I_t, $SOLD_t, O_t, R_t \in Z^+ \cup \{0\}$. Equation (3.23) takes the budget constraint of \$6500 million. The total demand simulated for $t = 8$ follows normal distribution, i.e. $D_8 \sim N\left(9\text{x}10^6, 1\text{x}10^6\right)$. With a 95% confidence level, it is found that total aircraft owned at this period must be greater than 93, i.e. $A_8 \geq 93$, which is indicated in Equation (3.24). Equation (3.25) indicates that with verified normal distribution, actual level of demand for t = 8 is predicted to be at least 10645000 at a confidence level of 95%, which is derived by Equations (3.6)-(3.7). Equation (3.26) is parking constraint; Equation (3.27) is the sales of aircraft constraint, which is derived with the assumption that aircraft at the age which is equal to or greater than five years old are considered to be sold, thus: $sold_{815} \leq I_{714}^{P}$, and $sold_{825} \leq I_{724}^{P}$. Equation (3.28) indicates order delivery constraint. With assumed normal distribution of $RLT_{8n} \sim N(1.918, 0.3613)$ and $RST_{8n} \sim N(1.918, 0.3613)$, Equations (3.29) and (3.30) represent lead time and selling time constraints respectively for which the desired period to order new aircraft as well as the period to release aging aircraft for sales is at least 30 months (i.e. 2.5 years $\approx$ 3 years) in advanced. The objective function and practical constraints are both linear functions in terms of decision variables and hence the developed model (3.22) is solved as a linear programming model. Iteratively, the procedure is repeated to formulate the optimization model for operating period, $t = 7, 6, 5, 4, 3, 2, 1$.

Another six scenarios (with variations to some of the modeling parameters used in the benchmark scenario) are developed to investigate the impact of the changes on the results. The following lists the developed scenarios and the values of parameters used for sensitivity analysis.

- Scenario A and B has confidence level of 90% and 99% respectively
- Scenario C and D has the probability of aircraft possession at 0.6:0.4 and 0.4:0.6 respectively
- Scenario E and F has order delivery constraint, $ORDER_t \leq 20$ and $ORDER_t \leq 30$ respectively

3.3.7 Results and Discussions

The results of the benchmark scenario are shown in Table 3.4. Table 3.4 shows a consistent increasing trend of discounted annual profit except the period for which there's a decrease in stochastic demand or when a payment is charged for the acquisition deposit and purchase cost of new aircraft. This shows that the developed model is able to capture the demand uncertainty in a fairly better manner. In addition, the findings provide an insightful view for airlines in making an optimal aircraft acquisition decision to account for the demand fluctuation.

For Scenario A and B, the results show that the confidence level has an impact on airline's total demand and profit level. The confidence level indicates the level of service targeted by an airline and hence airline's profit is affected if the targeted level of service changes. The results of Scenario A and

B established the fact that a higher profit is gained when the value of confidence level is on the rise. Apart from this, the results show that there is a tendency for airline to acquire more aircraft to meet the increase in demand, yet subject to practical constraints as elaborated earlier. In overall, the results show that airlines have to set their target properly in order to maximize their operational profit.

Table 3.4: The Results of Benchmark Scenario (Aircraft Acquisition Decision Model)

Operating period, *t*		1	2	3	4	5	6	7	8
Annual profit (millions)		$1,752	$1,317	$1,433	$1,068	$264	$1,773	$659	$2,861
Quantity of aircraft to be ordered	A320-216	0	7	0	12	5	0	0	0
	A340-300	0	7	0	12	5	0	0	0
Quantity of aircraft to be received	A320-216	0	0	0	0	7	0	12	5
	A340-300	0	0	0	0	7	0	12	5
Initial quantity of aircraft	A320-216	50	50	50	50	55	55	67	72
	A340-300	50	50	50	50	55	55	67	72
Quantity of aircraft to be released for sales	A320-216	0	2	0	0	0	0	0	0
	A340-300	0	2	0	0	0	0	0	0
Quantity of aircraft to be sold	A320-216	0	0	0	0	2	0	0	0
	A340-300	0	0	0	0	2	0	0	0
Total demand (million)		16	15	14.96	15	20	18	30	35

From the results of Scenario C and D, it could be observed that the profit level of airline has a smaller effect when the probability of aircraft possession changes. Contrary to Scenario D, the expected profit generated by Scenario C is higher as it is outlined at a higher probability of s_1, i.e. $p_{s_1} = 0.6$ which is 20% higher than p_{s_1} of Scenario D. Similarly, the profit gained by Scenario C is higher than benchmark scenario throughout the planning horizon. This shows that a higher value of p_{s_1} which corresponds to a higher level of demand subsequently results in a higher return. Therefore, the developed model is sensitive to the setting of aircraft possession of airline (probable phenomena) to meet stochastic demand.

The results of Scenario E and F show that the order delivery constraint could affect the optimal decision of aircraft acquisition. This happens mainly due to the consideration (or decision) of airlines in purchasing the least quantity of aircraft as long as the total quantity of aircraft owned is sufficient to provide the targeted service level. Hence, it is important to note that it's not certainly profitable to acquire more aircraft as a higher aircraft purchase cost and maintenance cost will occur. In other words, to purchase less aircraft probably contributes to higher expected profit (due to the less charged costs).

In a nutshell, it could be seen that the setting up of modeling parameters in the developed model could affect optimal results, to some extent. Comparatively, the results are more sensitive to the confidence level compared to other parameters. Besides, the findings revealed that there is no ideal means to obtain a supreme profit as optimal acquisition decision is decidedly dependent on several factors, i.e. management policy of airlines, the desired scenarios to be optimized and also the occurrence of unpredictable unexpected events. Therefore, in order to improve the decision making in fleet planning, those aspects as mentioned and illustrated earlier should be taken into consideration favourably.

3.3.8 Summary

An optimal aircraft acquisition decision model is formulated with the aim to maximize airline's profit. To do this, a mathematical optimization model is developed by using probabilistic dynamic programming approach in order to capture stochastic demand which is assumed to be normally distributed. The proposed model and solution method is tested with an illustrative case study, in which most of the input data and functions are either obtained or simulated by using airline's real data. The developed model is solved optimally to determine airline's decision for the quantity and type of new aircraft that should be purchased during the planning horizon. It is observed that the computational outputs are sensitive to the values of the modeling parameters, at varying degrees, and the results indicated that the proposed methodology is viable.

With reasonable assumptions that pertain closely to realistic practice, the results revealed that aircraft acquisition decision is strongly influenced by stochastic demand as well as the policy of airlines (for instance, the pre-determined age of aircraft to be sold). Generally, the profit of airlines is increasing when the level of demand is on the rise except for an unexpected drop in demand, which could take place unpredictably in real practice or when acquisition deposit and purchase cost are charged for new aircraft. In addition, six scenarios are created to test the sensitivity of the parameters' setting to the outcome. Remarkably, the order delivery constraint has a little impact for the aircraft acquisition decision. Nonetheless, the aircraft acquisition decision is comparatively influenced by the confidence level and the probability of aircraft possession. It is shown that the resultant findings are able to steer the relevant authorities at management level as well as the decision makers in making a wise and profitable fleet planning decision.

3.4 Aircraft Acquisition and Leasing Decision Model

To optimize the fleet planning decision of airlines (via aircraft acquisition and leasing), the aircraft acquisition and leasing decision model is formulated as a probabilistic dynamic programming model. Specifically for a set of origin-destination (OD) pairs, assume that there is a selection of *n* types of aircraft that could be purchased or leased. The decision variables of the model are the quantity and type of aircraft to be purchased or leased in order to maximize the operational profit of airlines. The stochastic demand modeled from section 3.2 is used as one of the inputs to the developed model. The optimal decision, i.e. the alternative at each stage is aircraft acquisition and leasing decision to meet stochastic demand while making decision to sell the aging aircraft. For a particular operating period, although the state variables and the corresponding optimal solutions could be obtained, the optimal decision for the next operating period is unknown due to uncertainty. In fact, the states of the next operating period are uncertain given the current decision because many factors may not be known with certainty in practice (Taha, 2003;

Winston, 2004). In other words, the developed model is probabilistic as its inputs (stochastic demand) and outputs (optimal solutions) are subject to possible occurrence of unexpected events, which is stochastic (probabilistic) in nature.

3.4.1 Constraints

The practical constraints considered for aircraft acquisition and leasing decision model are outlined as follows:

Budget constraint Budget constraint ascertains whether or not the solution is financially feasible for airlines. For this constraint, the sum of aircraft purchase and lease cost should not be more than airline's allocated budget. This constraint could be expressed as follows:

$$\sum_{i=1}^{n} purc_{ti} x_{ti}^{P} + \sum_{i=1}^{n} lease_{ti} x_{ti}^{L} \leq MAX_{budget(t)} \text{ for } t = 1,...,T \tag{3.31}$$

Demand constraint To ensure that stochastic demand could be met desirably at a targeted level of service, the demand constraint could be expressed as follows:

$$\sum_{i=1}^{n} \left(SEAT_i^t \right) \left(f\left(D_t^S, A_t^i \right) \right) \geq (1-\alpha) D_t^S \text{ for } t = 1,...,T; S = s_1,...,s_k \tag{3.32}$$

for which the level of demand could be derived by using the 5-step modeling framework while $1-\alpha$ is the confidence level (targeted service level) to meet stochastic demand. Equation (3.32) assures that the service frequency provided by airlines (with available number of aircraft seats) would be sufficient adequately to meet travel demand satisfactorily.

Parking constraint When an aircraft is not in operation, it has to be parked at the hangar or at the apron of the airport. In such a case, the choice of aircraft would sometimes be constrained by the geometry layout of the hangar or the apron of the airport. As such, parking constraint is ought to be considered feasibly. This constraint could be outlined as follows:

$$\sum_{i=1}^{n}\sum_{y=0}^{m}\left(I_{tiy}^{P}+I_{tiy}^{L}+x_{ti}^{P}+x_{ti}^{L}\right)\left(size_{i}\right)\leq PARK_{t} \text{ for } t=1,\ldots,T \tag{3.33}$$

Sales of aircraft constraint For some airlines, aging aircraft which is less cost-effective might be sold at the beginning of a certain operating period when airlines make the decision to purchase new aircraft. However, the quantity of aircraft sold should not be more than the aircraft owned by airlines. This constraint can be expressed as follows:

$$sold_{tiy}\leq I_{(t-1)i(y-1)}^{P} \text{ for } t=1,\ldots,T; i=1,\ldots,n; y=1,\ldots,m \tag{3.34}$$

Order delivery constraint The delivery of new aircraft depends on the production and the supply of aircraft manufacturers. Sometimes, there might be an availability issue in delivering new aircraft. As such, aircraft to be purchased should not be more than the number of aircraft available in the market. This constraint could be formed as follows:

$$x_{ti}^{P} \le ORDER_t \text{ for } t = 1,...,T; i = 1,...,n \qquad (3.35)$$

For aircraft leasing, it is assumed that order delivery constraint is not relevant due to its possible availability within one year (short-term duration) for some circumstances. In addition, the quantity of leased aircraft is relatively flexible at certain extent (not really limited to manufacturing constraint).

Lead time constraint In practice, airlines would get an agreeable lead time (the period between placing and receiving an order) from aircraft manufacturer when they place an order for new aircraft. This constraint should be considered as it indicates when airlines are supposed to order new aircraft. For *n* types of aircraft, this constraint can be expressed as follows:

$$P\left(RLT_{ti} \ge DLT_{ti}\right) \le \beta \text{ for } t = 1,..., T; i = 1,..., n \qquad (3.36)$$

In real life, there are chances that the targeted lead time would change (say, due to the technical problems of the manufacturer), thus lead time should be a random value that could be represented by a certain distribution. In this research, the lead time is assumed to be normally distributed with mean μ_{LT} and standard deviation σ_{LT}. The constraint could be stated as follows:

$$DLT_{ti} \ge F^{-1}\left(1-\beta\right)\sigma_{LT} + \mu_{LT} \text{ for } t = 1,...,T; i = 1,...,n \qquad (3.37)$$

where $F^{-1}(1-\beta)$ is the inverse cumulative probability of $1-\beta$.

Selling time constraint Aging aircraft which is considered as less economical and effective at some extent might be sold by airlines at a certain operating period. In such a case, airlines need to know the most suitable time to release their aging aircraft for sales particularly to look for prospective buyers in advance. In real practice, the real selling time might be longer than the desired selling time. Therefore, this constraint is formed with the aim to reduce the possibility of this incident as least as possible. This constraint could be defined as follows:

$$P\left(RST_{ti} \geq DST_{ti}\right) \leq \gamma \text{ for } t = 1,...,T; i = 1,...,n \tag{3.38}$$

It is assumed that selling time of aircraft has a normal distribution with mean μ_{ST} and standard deviation σ_{ST}:

$$DST_{ti} \geq F^{-1}\left(1-\gamma\right)\sigma_{ST} + \mu_{ST} \text{ for } t = 1,...,T; i = 1,...,n \tag{3.39}$$

where $F^{-1}(1-\gamma)$ implies the inverse cumulative probability of $1-\gamma$.

3.4.2 Objective Function

The objective of aircraft acquisition and leasing model is to maximize the operational profit of airlines in determining the quantity and type of aircraft that should be purchased or leased to meet stochastic demand. The operational profit of airlines could be derived by considering the subtraction of the total operating cost from the total revenue. For an airline, the total revenue is generated from the operational income (i.e. the sales of flight tickets) and the sales of aging aircraft while the total operating cost is formed by aircraft operational cost, purchase/lease cost, maintenance cost, depreciation expenses, payable deposit of aircraft acquisition and leasing, and fuel expenses.

For operating period t, the total revenue, $TR(I_t^P + I_t^L)$ of airline can be expressed as follows:

$$TR\left(I_t^P + I_t^L\right) = E\left(fare_t^S\right) D_t^S + \sum_{i=1}^{n}\sum_{y=1}^{m} sold_{tiy} resale_{tiy} \text{ for } t = 1,\ldots,T; S = s_1,\ldots,s_k \tag{3.40}$$

The first term on the right-hand side of Equation (3.40) indicates the expected income from the sale of flight tickets by considering stochastic demand, D_t^S while the second term signifies the revenue from the sales of aging aircraft.

The total operating cost, $TC(I_t^P + I_t^L)$ of operating period t can be formed as follows:

$$\begin{aligned} TC\left(I_t^P + I_t^L\right) = {} & E\left(\cos t_t^S\right) D_t^S + \sum_{i=1}^{n} u_{ti} + \left(purc_{ti}\right)\left(x_{ti}^P\right) + \sum_{i=1}^{n} lease_{ti}\left(x_{ti}^L\right) + \sum_{i=1}^{n} hgf\left(D_t^S, A_t^i\right) + \sum_{i=1}^{n}\sum_{y=1}^{m}\left(I_{tiy}^P\right)\left(dep_{tiy}^P\right) + \\ & \sum_{i=1}^{n}\sum_{y=1}^{m}\left(I_{tiy}^L\right)\left(dep_{tiy}^L\right) + \sum_{i=1}^{n} dp_{ti}\left(x_{ti}^P\right) + \sum_{i=1}^{n} dl_{ti}\left(x_{ti}^L\right) + \sum_{i=1}^{n} C\left(fuel_{ti}\right) \text{ for } t = 1,\ldots,T; S = s_1,\ldots,s_k \end{aligned} \tag{3.41}$$

The terms on the right-hand side of Equation (3.41) denote the expected operational cost of airline, aircraft purchase cost, lease cost, maintenance cost, depreciation expenses, payable deposit of aircraft acquisition and leasing, and fuel expenses, respectively.

3.4.3 Problem Formulation

In summary, the aircraft acquisition and leasing decision model can be presented mathematically as follows:

For t = 1, 2,..., T

$$P\left(I_t^P + I_t^L\right) = \max_{X_t} \left(1 + r_t\right)^{-t} \left\{ \begin{array}{l} p_{s_1} \left(\begin{array}{l} E(\,fare_t^{s_1})D_t^{s_1} + \sum_{i=1}^{n}\sum_{y=1}^{m} sold_{tiy} resale_{tiy} - E\left(\cos t_t^{s_1}\right) D_t^{s_1} - \\ \sum_{i=1}^{n} u_{ti} + \left(\,purc_{ti}\right)(x_{ti}^P) - \sum_{i=1}^{n} lease_{ti}\left(x_{ti}^L\right) - \sum_{i=1}^{n} hgf\,(D_t^S, A_t^i) - \\ \sum_{i=1}^{n}\sum_{y=1}^{m} \left(I_{tiy}^P\right)\left(dep_{tiy}^P\right) - \sum_{i=1}^{n}\left(I_{ti}^L\right)\left(dep_{ti}^L\right) - \sum_{i=1}^{n} dp_{ti}\left(x_{ti}^P\right) - \\ \sum_{i=1}^{n} dl_{ti}\left(x_{ti}^L\right) - \sum_{i=1}^{n} C\left(\,fuel_{ti}\right) \end{array} \right) + \ldots + \\ p_{s_k} \left(\begin{array}{l} E(\,fare_t^{s_k})D_t^{s_k} + \sum_{i=1}^{n}\sum_{y=1}^{m} sold_{tiy} resale_{tiy} - E\left(\cos t_t^{s_k}\right) D_t^{s_k} - \\ \sum_{i=1}^{n} u_{ti} + \left(\,purc_{ti}\right)(x_{ti}^P) - \sum_{i=1}^{n} lease_{ti}\left(x_{ti}^L\right) - \sum_{i=1}^{n} hgf\,(D_t^S, A_t^i) - \\ \sum_{i=1}^{n}\sum_{y=1}^{m} \left(I_{tiy}^P\right)\left(dep_{tiy}^P\right) - \sum_{i=1}^{n}\left(I_{ti}^L\right)\left(dep_{ti}^L\right) - \sum_{i=1}^{n} dp_{ti}\left(x_{ti}^P\right) - \\ \sum_{i=1}^{n} dl_{ti}\left(x_{ti}^L\right) - \sum_{i=1}^{n} C\left(\,fuel_{ti}\right) \end{array} \right) + P_{t+1}\left(I_t^P + I_t^L\right) \end{array} \right\} \tag{3.42}$$

subject to (3.31)-(3.35), (3.37) and (3.39) where D_t^S, X_t^P, X_t^L, I_t^P, I_t^L, $SOLD_t$, O_t, $R_t \in Z^+ \cup \{0\}$. The term $\left(1 + r_t\right)^{-t}$ is used for discounted value across the planning horizon while k indicates the k-th probable phenomenon for having I_t^P and I_t^L as initial fleet supply at the beginning of each operating period. The optimal decision (output) of the developed model, i.e. the optimal quantity of aircraft to be purchased and leased, could be used as the inputs in optimizing other operational decisions of airlines, such as optimization of fleet routing, flight scheduling and crew assignment (Barnhart et al., 2003).

3.4.4 Lower Bound and Optimal Solutions

The solution of decision variable in model (3.42) is found to be influenced by demand constraint (Equation (3.32)). In case the change of demand is non-positive (i.e. no increment of demand), the lower bound of the solution is 0. This is because the decision variable defined is nonnegative, i.e. $x_{ti}^P, x_{ti}^L \geq 0$ and total of n types of aircraft to be purchased and leased is also nonnegative, i.e. $\sum_{i=1}^{n} x_{ti}^P + x_{ti}^L \geq 0$ for a particular operating period. In case if the change in demand is positive (i.e. demand increases), the lower bound is governed by demand constraint. It is to ensure that the supply of aircraft (via acquisition or leasing) must meet the level of demand at a certain desired service level. Nevertheless, the upper bound (UB), i.e. the maximum of aircraft that could be purchased (or leased) is subject to aircraft availability in the market, $ORDER_t$, which is expressed in order delivery constraint (Equation (3.35)). To summarize, the lower bound, LB, of the developed model follows the following equation:

$$LB = \begin{cases} X_t^P = 0,\ X_t^L = 0 & \text{if } \Delta D_t^S \leq 0 \\ \left(\sum_{i=1}^{n} \left(SEAT_i^t \right) \left(f\left(D_t^S, A_t^i \right) \right) \geq \left(1-\alpha \right) D_t^S \right) \cap \left(x_{ti}^P \leq ORDER_t \right) & \text{if } \Delta D_t^S > 0 \end{cases} \tag{3.43}$$

where ΔD_t^S indicates the change of demand from year to year, i.e. $\Delta D_t^S = D_t^S - D_{t-1}^S$.

Let $\Omega = \{X_{ti}^{P}, X_{ti}^{L} : LB \leq X_{ti}^{P}, X_{ti}^{L} \leq UB\}$ be the set of decision variable for aircraft acquisition and leasing decision model and the operational profit (i.e. the objective function to be maximized) of the developed model be $P(I_t^P + I_t^L)$ where $\Omega \subseteq I_t^P \cup I_t^L$. The optimal solution of the developed model could be written as $P^*(I_t^{P*} + I_t^{L*})$ where P^* is the optimum (maximum) profit of each operating period t for which I_t^{P*} and I_t^{L*} denote the corresponding total quantity of aircraft (including the aircraft to be purchased and leased) that maximizes $P(I_t^P + I_t^L)$. As such, the optimal solution (i.e. maximum operational profit) of the developed model could be written as follows:

$$P^*\left(I_t^{P*} + I_t^{L*}\right) = \underset{I_t}{Max}\, P\left(I_t^P + I_t^L\right) \tag{3.44}$$

3.4.5 Solution Method

The developed model in the form of probabilistic dynamic programming model can be solved by decomposing it into a series of simpler sub-problems. By using the backward working method, the sub-problem at the last period of the planning horizon, T is solved first. The optimal solution found for the states at the current stage leads to the problem solving at the period of $T-1, T-2, ..., 1$. This procedure continues until all sub-problems have been solved optimally so that the decision policy to purchase and/or lease aircraft can be determined strategically. For the developed optimization model, the type of solution method, i.e. linear programming model or non-linear programming model can be identified clearly based on the function of number of flights, $f\left(D_t^s, A_t^n\right)$; function of traveled mileage, $gf\left(D_t^s, A_t^n\right)$; function of maintenance cost, $hgf\left(D_t^s, A_t^n\right)$; function of fuel expenses, $C\left(fuel_{tn}\right)$ and practical constraints (3.31)-(3.35), (3.37) and (3.39). If they are in the form of linear function in terms of the decision variables, then model (3.42) can be solved as a linear programming model. Otherwise, it is solved as a non-linear programming model. The linearity of these components is primarily based on the operational data of a particular airline. It shall then be validated by using the regression test with the aid of mathematical software. For the illustrative case study as shown in the following section, non-linear relationship was adopted for the above-mentioned components as the regression relationship obtained from the published reports (Malaysia Airlines, 2010a; Air Asia Berhad, 2010a) show non-linearity. Powell (2007) specified that non-linear programming is one of the possible solutions for the dynamic programming model. Nonetheless, it could not be solved directly with any available conventional methods. The spreadsheet functionality of Excel 2007 coupled with own developed algorithm was utilized to compute the optimal solutions.

For a larger size of aircraft acquisition and leasing decision model, the solution method is still feasible in generating computational results. However, the computational efficiency reduces when the problem size gets larger due to additional modeling parameters and variables. As such, more computational effort is necessary for the larger state and stage spaces. Two major concerns that could affect computational efficiency are airline's planning horizon and the type of aircraft. The extension of planning horizon, T would result in an increment ratio of $\frac{1}{T}$, i.e. an additional of 10-20% of computational efforts for each increment (in year). For each additional type of aircraft, there is $(ORDER_t + 1)$ times more computational time required where $ORDER_t$ refers to order delivery constraint. It is estimated that the computational time required to generate an optimal solution is about 50-60 seconds for each operating period.

3.4.6 An Illustrative Case Study: Nonlinear Programming Model

To examine the applicability of the developed model, most of the data input are chosen based on publicly published reports and accessible websites of airlines in order to design a close to reality case study.

3.4.6.1 Inputs for Stochastic Demand Modeling

There are three types of unexpected events, i.e. biological disaster (e.g. flu disease), economic recession and natural disaster (e.g. storm) which are assumed to affect the demand level. The modeling of probability distributions to quantify these unexpected events is carried out based on some published reports. According to the data obtained from the Centre for Research on the

Epidemiology of Disasters (2010), the occurrence of biological disaster was found to follow Poisson distribution and has a mean, μ of 7, i.e. $\text{Prob}(\text{bio-disaster}) \sim Pois(\mu = 7)$. This indicates that the biological disaster happens 7 times in average in a year. Based on the data from International Monetary Fund (Global Recession, 2010; Franke and John, 2011), it was found that the occurrence of economic downturn also follows Poisson distribution in which $\text{Prob}(\text{econ-downturn}) \sim Pois\left(\mu = \frac{1}{9}\right)$. This shows that the economic recession happens once in an average of 9 years. For a natural disaster to occur (Centre for Research on the Epidemiology of Disasters, 2010; Franke and John, 2011), the probability of occurrence has a normal distribution, i.e. $\text{Prob}(\text{natural disaster}) \sim N(64, 8)$.

For the travel growth projection, the historical data shows that the growth percentage ranges from 5% to 9% (International Civil Aviation Organization, 2008; Malaysia Airports Holding Berhad, 2008; Malaysia Airlines, 2010a; International Air Transport Association, 2011). As such, an equal probability for each unit of growth is assumed, i.e. the percentage growth of 5%, 6%, 7%, 8% and 9% has the probability of 0.2 to happen throughout the planning horizon. However, there is no restriction if uneven probability is assumed. Besides, the forecasted demand, D_f is estimated to follow a normal distribution, i.e. $D_f \sim N\left(1.4141\text{x}10^7, 9.04\text{x}10^{12}\right)$ according to the data obtained from the published reports from Malaysia Airlines (2010a). With the aid of the convolution algorithm, the projected demand of base year, D_0 is then determined accordingly.

Based on the above-mentioned data, the level of stochastic demand for each operating period throughout the planning horizon is obtained by applying the 5-step modeling framework of stochastic demand (as discussed in section 3.2). The detailed output of stochastic demand is shown in Table 3.5. Table 3.5 reveals the fact that the possible occurrence of unexpected event and the predicted growth of travel demand could affect the level of stochastic demand at varying degrees. Basically, the SDI value is greater than 1 when unexpected event does not exist. Conversely, the existence of unexpected event produces the SDI with the value of at most 1.

3.4.6.2 Inputs for Aircraft Acquisition and Leasing Decision Model

Two types of aircraft i.e. A320-200 ($n = 1$) and A330-300 ($n = 2$) are considered for a set of OD pairs. Only two types of aircraft are considered as many low-cost carriers operate their business with few varieties of aircraft types, for example: AirAsia (A320-214, A320-216), Jetstar Airways (A320-200, A321-200, A330-200), JAL Express (B737-400, B737-800) and Tiger Airways (A320-200) (more examples could be seen in O'Connell and William (2005)). Furthermore, airlines tend to operate aircraft from the same aircraft manufacturer (mostly Airbus or Boeing). Therefore, the two types of aircraft (both Airbus) considered in the case study are practical. A320-200 and A330-300 were chosen as the example as there is more available information for these types of aircraft. However, the developed methodology is not restricted to the quantity and type of aircraft used. In addition, a planning horizon of eight years is also justified according to Malaysia Airlines (2010a) and AirAsia Berhad (2010a), on average, the acquisition of new aircraft requires a period of five years to be completely delivered. Besides, the desired lead time is assumed to have a normal distribution with an average of three years, and standard deviation of 1.5, i.e. $DLT \sim N(3, 1.5)$. As such, two types of aircraft which are considered for a planning horizon of eight years is reasonably practical to reflect airline's real operations. Tables 3.2 and 3.6 shows the input data used in the model.

Table 3.5: The Output of Stochastic Demand

Operating period	1	2	3	4	5	6	7	8
Occurrence of unexpected event (Y= it exists, N=it does not exist)	N	N	Y (biological disaster)	N	Y (biological disaster, recession)	N	N	N
Probability of unexpected events, [1]	0.00	0.00	-0.40	0.00	-0.07	0.00	0.00	0.00
Probability of the possible increment of forecasted demand, [2]	0.09	0.09	0.08	0.05	0.07	0.08	0.08	0.06
Total of probability, [1]+[2]	0.09	0.09	-0.32	0.05	0.00	0.08	0.08	0.06
Stochastic demand index, SDI	1.09	1.09	0.68	1.05	1.00	1.08	1.08	1.06
Stochastic demand (number of travelers in millions)	17.3	18.9	12.8	13.5	13.5	14.6	15.8	16.7

The capacity of A320-200 and A330-300 is assumed to be 180 (with a total size of $1282m^2$) and 295 (with a total size of $3836m^2$), respectively (Airbus, 2010a, 2010b). As mentioned earlier, the expected flight fare and cost as shown in Table 3.2 are generated based on the available financial reports of Malaysia Airlines (Malaysia Airlines, 2010a). In addition, aircraft purchase cost as shown in Table 3.6 are obtained from the published data of Airbus (Airbus, 2010c). With aircraft purchase price and the estimated useful life of aircraft (i.e. five years), the depreciation values of aircraft are calculated by using straight-line depreciation approach. By considering the residual value of AirAsia (AirAsia Berhad, 2010b), the aircraft resale price and depreciation value (as shown in Table 3.6) are obtained based on the assumed residual value (i.e. salvage cost) of aircraft, which is 10% of aircraft purchase cost. For aircraft leasing, the respective lease cost, residual value and depreciation value are obtained based on the finance lease of MAS (Malaysia Airlines, 2010b).

Table 3.6: Aircraft Resale Price, Depreciation Value, Purchase Cost, Lease Cost and Residual Value ($ millions)

y	1	2	3	4	5	Average
$resale_{t1y}$	67.24	52.48	37.72	22.96	8.2	37.72
$resale_{t2y}$	174.66	136.32	97.98	59.64	21.3	97.98
dep^P_{t1y}	14.76					14.76
dep^P_{t2y}	38.34					38.34
$purc^P_{t1}$	82					82
$purc^P_{t2}$	213					213
dep^L_{tny}	26.66					26.66
$lease_{tn}$	148.09					68.12
Residual value	121.43	94.77	68.12	41.46	14.81	148.09

A benchmark scenario is created to examine the applicability of the developed methodology. The data input can be categorized into three categories, i.e. by definition, by assumption or by assumption based on the real data. They are shown as follows:

By definition:

- Two probable phenomenon are considered, where $k = 2$
- Discount rate, $r_t = 5\%$
- Significance level of demand constraint, $\alpha = 5\%$
- Significance level of lead time constraint, $\beta = 5\%$
- Significance level of selling time constraint, $\gamma = 5\%$
- $D_t^{s_1} = D_t$ and $D_t^{s_2} = (1-\alpha) D_t^{s_1}$ (3.45)

By assumption:

- At $t = 1$, the probability of aircraft possession is $p_{s_1} = 0.5$ and $p_{s_2} = 0.5$
- At $t = 1$, initial quantity of aircraft to be three years old is $I_{113}^P = I_{123}^P = 4$
- Setup cost, $u_{ti} = 0$

By assumption (based on real data):

- At $t = 1$, initial quantity of aircraft is $I_{11}^P = I_{12}^P = 50$ and $I_{11}^L = I_{12}^L = 0$
- Allocated budget, $MAX_{budget(t)} = \$6{,}500{,}000{,}000$
- Area of hangar, $PARK_t = 500{,}000 m^2$
- Order delivery constraint, $ORDER_t = 5$
- Salvage cost of aircraft = 10% of aircraft purchase cost
- Deposit of aircraft acquisition, $DP_t = 10\%$ of aircraft purchase cost
- Deposit of aircraft leasing, $DL_t = 10\%$ of aircraft lease cost
- The function of number of flights is

$$f = 22.57\left(A_t^n\right)^2 - 9.776\text{x}10^2 A_t^n + 7.83\text{x}10^4 \qquad [\text{R}^2 = 0.97] \qquad (3.46)$$

- The function of traveled mileage is

$$g = 2{,}066f - 2{,}875{,}383 \quad [\mathrm{R}^2 = 0.83] \tag{3.47}$$

- The function of maintenance cost is

$$h = 5.177\text{x}10^3 + 7.97\text{x}10^{-3} g \quad [\mathrm{R}^2 = 0.94] \tag{3.48}$$

- The function of fuel expenses is

$$C\left(fuel_{tn}\right) = 7.46f + 8.3\text{x}10^{-5} f^2 - 98{,}572 \quad [\mathrm{R}^2 = 0.88] \tag{3.49}$$

- The number of aircraft is

$$NA = 10^{-5} NP - 73.6 \quad [\mathrm{R}^2 = 0.92] \tag{3.50}$$

  where *NP* is the number of travelers.

Based on the data as reported by Malaysia Airlines (2010a) and AirAsia Berhad (20101b), Equations (3.46)-(3.50) are obtained by conducting polynomial regression analysis (Meyer and Krueger, 2005). Equations (3.46)-(3.50) are anticipated to be correlated with stochastic demand, D_t^S and total operated aircraft, A_t^n. The regression analysis shows that Equations (3.46)-(3.48) are fitted fairly well as non-linear functions in terms of A_t^n. Similarly, the analysis reveals that Equation (3.49) is best fitted as a quadratic function in terms of the number of flights, which could be consequently, expressed as a non-linear function in terms of A_t^n via Equation (3.46). Besides, regression analysis exhibits that Equation (3.50) is best fitted as a linear function in terms of number of travelers.

Equation (3.45) implies the proportion of stochastic demand, which corresponds to the phenomenon of s_1 and s_2. Equation (3.46) indicates that the number of flights is affected by total operated aircraft, which is gained from aircraft acquisition and leasing. Equation (3.47) denotes that a flight flies 2,066 kilometres in average. Equation (3.48) signifies that a unit cost of 0.00797 is charged as maintenance cost for each additional unit of mileage traveled. For this equation, \$5,177 indicates an overall estimated maintenance cost without considering an additional traveled mileage. Equation (3.49) shows that total of fuel expenses depends on number of flights, which are operated during the planning horizon. This implies that fuel expenses associate closely with total operated aircraft, A_t^n which is greatly depending on aircraft acquisition and leasing decision. Equation (3.50) displays that every addition of 100,000 travelers requires one additional aircraft. In other words, one traveler requires 0.00001 aircraft.

According to Meyer and Krueger (2005), the intercept of regression equation carries no practical meaning if the range of independent variable does not include 0. The number of flights, f, in Equation (3.46) falls within the range of $67{,}460 \leq f \leq 79{,}927$ (based on the real data). Accordingly, the constant in Equation (3.46) has no practical interpretation. In addition, it can be shown that the traveled mileage in Equation (3.47) is always positive. Such explanation is also applicable to Equations (3.49)-(3.50).

For $t = T = 8$, the developed optimization model could be simplified to model (3.51)-(3.59) as follows:

$$P(I_8^P + I_8^L)$$

$$= \max_{X_8} \frac{1}{(1.05)^8} \left[\begin{array}{l} p_{s_1} \left(\begin{array}{l} 118D_8^{s_1} + \left(8.2\text{x}10^6 sold_{815} + 2.13\text{x}10^7 sold_{825}\right) - \left(8.2\text{x}10^7 x_{81}^P + 2.13\text{x}10^8 x_{82}^P\right) \\ 2.67\text{x}10^7 \left(x_{81}^L + x_{82}^L\right) - \left(5.177\text{x}10^3 + 7.97\text{x}10^{-3} g\right) - \\ \left(1.476\text{x}10^7 I_{81}^P + 3.834\text{x}10^7 I_{82}^P\right) - 2.67\text{x}10^6 \left(I_{81}^L + I_{82}^L\right) - \\ \left(8.2\text{x}10^6 x_{81}^P + 2.13\text{x}10^7 x_{82}^P\right) - 1.48\text{x}10^7 \left(x_{81}^L + x_{82}^L\right) - \left(7.46 f + 8.3\text{x}10^{-5} f^2 - 98{,}572\right) \end{array} \right) + \\ p_{s_2} \left(\begin{array}{l} 101.65D_8^{s_2} + \left(8.2\text{x}10^6 sold_{815} + 2.13\text{x}10^7 sold_{825}\right) - \left(8.2\text{x}10^7 x_{81}^P + 2.13\text{x}10^8 x_{82}^P\right) \\ 2.67\text{x}10^7 \left(x_{81}^L + x_{82}^L\right) - \left(5.177\text{x}10^3 + 7.97\text{x}10^{-3} g\right) - \\ \left(1.476\text{x}10^7 I_{81}^P + 3.834\text{x}10^7 I_{82}^P\right) - 2.67\text{x}10^6 \left(I_{81}^L + I_{82}^L\right) - \\ \left(8.2\text{x}10^6 x_{81}^P + 2.13\text{x}10^7 x_{82}^P\right) - 1.48\text{x}10^7 \left(x_{81}^L + x_{82}^L\right) - \left(7.46 f + 8.3\text{x}10^{-5} f^2 - 98{,}572\right) \end{array} \right) \end{array} \right] \tag{3.51}$$

subject to

$$82x_{81}^P + 213x_{82}^P + 26.7\left(x_{81}^L + x_{82}^L\right) \le 6{,}500 \tag{3.52}$$

$$22.57\left(A_8^n\right)^2 - 977.6A_8^n + 11{,}321 \ge 0 \tag{3.53}$$

$$D_8^{s_1} = 16{,}744{,}756,\ D_8^{s_2} = 15{,}907{,}518 \tag{3.54}$$

$$\left(I_{81}^P + I_{81}^L + x_{81}^P + x_{81}^L\right)(1{,}282) + \left(I_{82}^P + I_{82}^L + x_{82}^P + x_{82}^L\right)(3{,}836) \le 500{,}000 \tag{3.55}$$

$$sold_{815} \le I_{81}^P,\ sold_{825} \le I_{82}^P \tag{3.56}$$

$$x_{81}^P \le 5,\ x_{82}^P \le 5 \tag{3.57}$$

$$DLT_{81} \ge 32,\ DLT_{82} \ge 32 \tag{3.58}$$

$$DST_{81} \ge 24,\ DST_{82} \ge 24 \tag{3.59}$$

where $D_8^S,\ X_8^P,\ X_8^L,\ I_8^P,\ I_8^L,\ SOLD_8,\ O_8,\ R_8 \in Z^+ \cup \{0\}$ for which $A_t^n = I_{81}^P + I_{82}^P$ $+ I_{81}^L + I_{82}^L + x_{81}^P + x_{82}^P + x_{81}^L + x_{82}^L$. Equation (3.52) takes the budget constraint of $6.5x10^9$ to purchase and/or to lease aircraft. By applying the simulation approach as elaborated earlier, the stochastic demand simulated for $t = 8$ is 16,744,756. With a 95% confidence level, it is found that the total number of aircraft that should be operated for this operating period appears to be a non-linear function, which is indicated in Equation (3.53). Equation (3.54) indicates that the stochastic demand of t = 8 is predicted to be 16,744,756 for the probable phenomenon of s_1 and 15,907,518 for the probable phenomenon of s_2, which is derived by Equation (3.45). Equation (3.55) is parking constraint as a geometry limitation; Equation (3.56) is sales of aircraft constraint, which is derived with the assumption that an aircraft of five years old or more are considered to be sold, thus: $sold_{815} \leq I^P_{714}$ and $sold_{825} \leq I^P_{724}$. Since $I^P_{714} \leq I^P_{81}$ and $I^P_{724} \leq I^P_{82}$, these expressions subsequently result in $sold_{815} \leq I^P_{81}$ and $sold_{825} \leq I^P_{82}$ as could be seen in Equation (3.56). Equation (3.57) indicates order delivery constraint to purchase new aircraft. With the assumed normal distribution of $RLT_{8n} \sim N(2, 0.4)$ and $RST_{8n} \sim N(1.5, 0.3)$, Equation (3.58) and Equation (3.59) represent the lead time and selling time constraints respectively, for which the desired period to order new aircraft is at least 32 months (i.e. 2.66 years $\approx$ 3 years) while the desired period to release aging aircraft for sales is at least 24 months, i.e. 2 years in advance. For model (3.51), the functions of number of flights, traveled mileage, maintenance cost, and fuel expenses as depicted by Equations (3.46)-(3.49) are found to be non-linear functions in terms of total operated aircraft, A^n_t. Hence, the developed model (3.51) is solved as a non-linear programming model. By using working backwards mechanism, the procedure can be repeated to formulate the optimization model for the operating period, $t = 7, 6, 5, 4, 3, 2, 1$.

In order to investigate the impact of changes of the inputs to the computational results, six scenarios with variations to some of the modeling parameters used in the benchmark scenario are developed. The following lists the outlined scenarios.

- Scenarios A and B have confidence level of 90% and 99%, respectively.
- Scenarios C and D have probable phenomena indicator (i.e. probability of aircraft possession) of 0.6:0.4 and 0.4:0.6, respectively.
- Scenarios E and F have order delivery constraint, $ORDER_t = 4$ and $ORDER_t = 6$, respectively.

3.4.7 Results and Discussions

The computational results of benchmark scenario are shown in Table 3.7. Table 3.7 shows a consistently increasing trend on the discounted annual profit of airline except where there is a decrease in stochastic demand or when a cost is charged to purchase new aircraft, lease aircraft, or order new aircraft in advance. In particular, the operating period from 1 to 3, which involves aircraft leasing and higher demand, produce a higher operational profit compared to subsequent operating periods. For the operating period with aircraft acquisition, i.e. operating period from 4 to 8, the profit of airline increases gradually, mainly due to an increment in stochastic demand. This shows that the developed methodology is capable of capturing demand uncertainty in real practice in producing an optimal profit. Certainly, this would provide a better insight for airlines in making profitable decision to manage their fleet supply under stochastic demand.

Table 3.7: The Results of Benchmark Scenario (Aircraft Acquisition and Leasing Decision Model)

Operating period, *t*		1	2	3	4	5	6	7	8
Initial quantity of aircraft owned	A320-200	50	50	46	46	49	52	56	60
	A330-300	50	50	46	46	46	46	47	48
Initial quantity of leased aircraft	A320-200	0	0	5	5	5	5	5	5
	A330-300	0	0	5	5	5	5	5	5
Quantity of aircraft to be ordered	A320-200	3	3	4	4	5	0	0	0
	A330-300	0	0	1	1	1	0	0	0
Quantity of aircraft to be received	A320-200	0	0	0	3	3	4	4	5
	A330-300	0	0	0	0	0	1	1	1
Quantity of aircraft to be leased	A320-200	0	5	0	0	0	0	0	0
	A330-300	0	5	0	0	0	0	0	0
Quantity of aircraft to be released for sales	A320-200	4	0	0	0	0	0	3	3
	A330-300	4	0	0	0	0	0	0	0
Quantity of aircraft to be sold	A320-200	0	0	4	0	0	0	0	0
	A330-300	0	0	4	0	0	0	0	0
Total operated aircraft		100	110	102	105	108	113	118	124
Stochastic demand (million)		17.3	18.9	12.8	13.5	13.5	14.6	15.8	16.7
Discounted annual profit ($ millions)		589	224	411	150	158	123	103	267

The graphical results of Scenarios A-F are illustrated in Figures 3.2-3.4. The results of Scenarios A and B (in Figure 3.2) indicate that when the confidence level changes, there is an impact on the operational profit. The confidence level signifies the service level (i.e. level of demand) targeted by airlines, and hence airline's profit is affected if the targeted service level changes. Apart from this, the results of Scenarios A and B established the fact that a higher profit is gained when the value of confidence level increases i.e. when the level of service rises. The results also show that there is a tendency for airlines to purchase and/or to lease more aircraft to meet a higher level of demand but subject to operational constraints. In particular, for operating periods 5, 6 and 8, the operational profit of the benchmark scenario is higher than Scenario B due to aircraft acquisition decision to meet a higher level of demand. Overall, the findings show that airlines have to make the fleet planning decision wisely as well as to set their target properly in order to maximize operational profit.

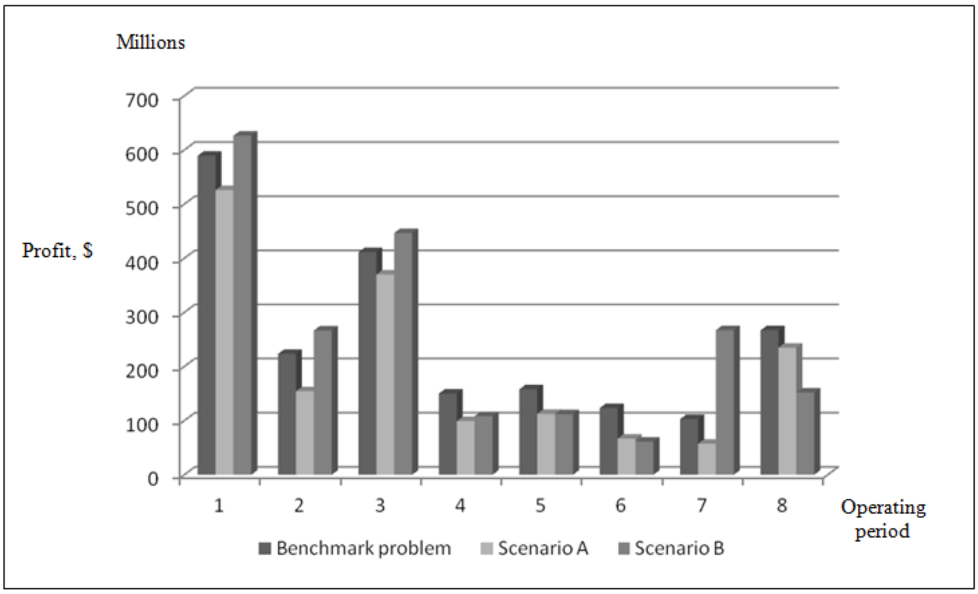

Figure 3.2: The Results of Scenarios A and B

Figure 3.3 shows the results in setting the probability of probable phenomena (aircraft possession) for which Scenario C has the probability of 0.6:0.4, Scenario D has the probability of 0.4:0.6 and the benchmark scenario is 0.5:0.5. The results show that Scenario C which has the highest probability in meeting demand (i.e. highest level of service) could yield the highest operational profit, which is in average 21% more than Scenario D and 11% more compared to the benchmark scenario. Comparatively, the benchmark scenario generates 12% more profit than Scenario D. As such, it is approximated that an increment of 1% of stochastic demand would generate an additional 1% of operational profit. This could be explained by the fact that the service level which is met at a higher chance (probability) is likely to generate more revenue for airlines (from the sales of flight tickets). Hence, it could be seen that the probable phenomena and its probability which associates closely with the level of stochastic demand could greatly affect the operational profit of airlines.

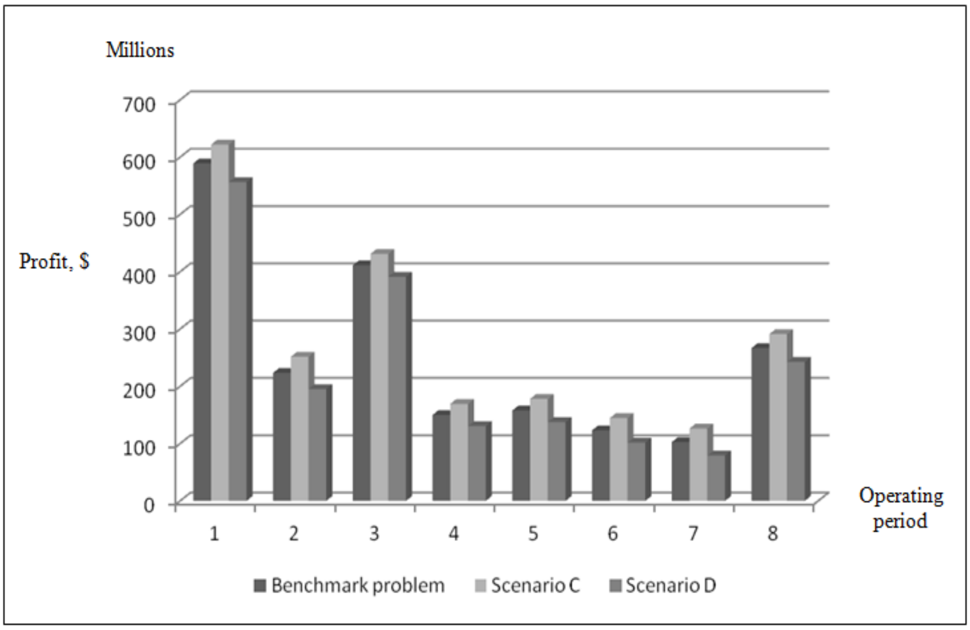

Figure 3.3: The Results of Scenarios C and D

As displayed in Figure 3.4, the results of Scenarios E and F show that the order delivery constraint could affect the optimal decision and operational profit of airlines. The results illustrate that the higher the value of order delivery constraint is, the lower would the profit be. For the operating periods

1, 4, 5 and 6, Scenario E produces the lowest profit due to the aircraft acquisition deposit and cost that are incurred for aircraft acquisition decision-making. Besides, the decision-making to purchase and/or to lease aircraft is also affected by the consideration of airlines in getting the least number of aircraft as long as the total quantity of aircraft is adequate to provide the targeted level of service. Hence, it is important to note that it's not certainly profitable to purchase or lease more aircraft. The decision to purchase (or lease) lesser aircraft probably contributes a higher profit level due to less charged costs.

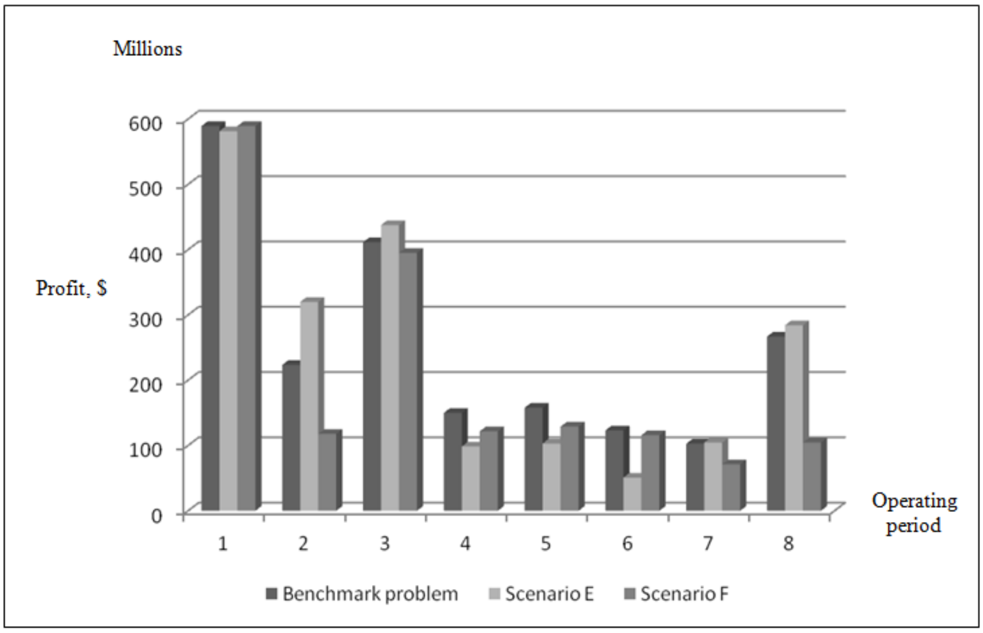

Figure 3.4: The Results of Scenarios E and F

The consistency and stability of results could be empirically confirmed by comparing the findings with the actual operational statistics of airlines (AirAsia Berhad, 2010a; Malaysia Airlines, 2010a). Table 3.8 summarizes the fleet size of airlines (i.e. AirAsia and MAS) as compiled from their annual reports as well as fleet planning decision of each operating period as obtained from the developed model. It could be observed that, the fleet size of AirAsia and MAS during the operating years of 2006 to 2010 falls within the range of two standard deviations from its average. The fleet planning solutions obtained from the benchmark problem and other scenarios exhibit similar pattern, i.e. the fleet size for the operating periods from 1 to 8 falls within the range of two standard deviations from its average. Therefore, the solutions are coherent with the operating performance of airlines. As such, the findings are consistent with the actual practice and hence the stability of the results (as well as the developed model) could be empirically confirmed.

Concisely, it could be seen that the results obtained from the developed model are reasonable and stable when compared empirically with airline's data. The sensitivity analysis shows that the developed model and its solutions are sensitive to the modeling parameters. This implies that the values of these parameters need to be chosen with care. In addition, it is important to note that there is no ideal means to obtain a supreme profit as optimal fleet planning decision is affected decisively by several factors, i.e. management policy of airlines (for instance, as reported by MAS (Malaysia Airlines, 2010c), a 100%-leased structure is not optimal in the long-term, MAS intends to shift to an optimal mix of leased/owned fleet), the desired scenarios to be optimized and the occurrence of unpredictable unexpected event. Therefore, in order to assure an optimal profit in fleet planning, the aspects as discussed earlier should be taken into consideration wisely.

Table 3.8: The Summary of Fleet Planning Decision (Aircraft Acquisition and Leasing Decision Model)

	Fleet size										
	Empirical (from reports)			Model							
					Scenario						
	Year	AirAsia	MAS	*t*	Benchmark	A	B	C	D	E	F
Operating Year	2006	42	97	1	100	100	100	100	100	100	100
	2007	65	102	2	110	110	110	110	110	108	112
	2008	78	109	3	102	102	102	102	102	100	104
	2009	84	112	4	105	105	106	105	105	104	107
	2010	77	117	5	108	108	110	108	108	108	110
				6	113	112	115	113	113	113	115
				7	118	117	120	118	118	118	120
				8	124	122	125	124	124	123	126
Average (AG)		69	107		110	110	111	110	110	110	112
Standard Deviation (SD)		17	8		8	7	9	8	8	8	8
AG + 2SD		103	123		126	124	129	126	126	126	128
AG – 2SD		35	91		94	96	93	94	94	94	96

3.4.8 Summary

A new methodology is developed to solve the fleet planning decision model under uncertainty. To do this, a 5-step modeling framework which is incorporated with the Stochastic Demand Index (SDI) is developed to quantify the demand level under uncertainty for each operating period. To solve the fleet planning problem, a probabilistic dynamic programming model is formulated to determine the optimal quantity and type of aircraft to be purchased and/or leased so that the stochastic demand could be met profitably throughout the planning horizon. Besides, a probable phenomena indicator is defined necessarily to ensure that the aircraft possession of airlines is sufficient adequately to meet stochastic demand at a desired service level. The results obtained from the illustrative case study demonstrated that the developed methodology is well responsive to modeling parameters and it is viable in providing optimal solution for fleet planning decision model.

In overall, the developed approach reflects the actual situation of airline industry, ranging from the challenge of uncertainty to the practical issues in acquiring and leasing aircraft. Subject to the occurrence of unexpected event and operational constraints, the developed methodology could produce viable solutions for long-term aircraft acquisition and leasing decision model. For airlines, this is crucial to ensure economy sustainability (by maximizing profit) as well as management efficiency from the operational aspect (by ensuring adequate fleet supply of aircraft) to meet stochastic demand satisfactorily.

CHAPTER 4

STRATEGIC FLEET PLANNING MODELING FRAMEWORK

4.1 Supply-demand Interaction In Fleet Planning

With the aim to make a strategic fleet planning decision to assure an adequate fleet supply in meeting stochastic demand, this chapter is organized systematically in two major sections. The first section deals with the analysis of traveler's mode choice as an important element in demand management. Specifically, the traveler's mode choice for different trip purpose (leisure and business) is modeled and analyzed specifically based on the type of trip (local and trans-border trips). The resultant mode choice analysis is then incorporated in the Analytic Hierarchy Process (AHP) modeling framework to quantify the probability of probable phenomena in fleet planning. Notably, probable phenomena are the key aspects (determinant) of aircraft possession in the fleet planning decision-making and hence its probability (likelihood) in optimizing the fleet planning decision needs to be quantified properly. To do this, the subjective judgment of airline's management (decision makers of fleet planning) is tackled explicitly. The developed framework enables airlines to capture the supply-demand interaction in greater detail. A numerical example, outlined with airlines' operational data, is demonstrated to examine the applicability of the developed framework in determining the probability of probable phenomena with regard to three key aspects, namely operational, economy and environmental aspects. The resultant probabilities are then applied to solve a realistic fleet planning problem. In terms of managerial and operational practices, the developed methodology, incorporated with mode choice analysis, is useful to assure an adequate fleet supply to meet demand fluctuation. More importantly, stochastic demand could be met satisfactorily with optimal profit.

4.2 Mode Choice Analysis

Since the past few decades, the rapid economy growth in the developed as well as the developing countries has fostered the brisk development of the transport network. As a result, various travel modes are now available conveniently in moving travelers from an origin to a particular destination. Basically, travelers make their choices based on their perceived utility on each travel mode. Air transport was once considered as the most elegant and expensive transport mode. It is used mostly for long distance travel (especially to overseas) while ground transport is commonly used for short distance (local or trans-border) travel.

It is important for transport operators to understand how different transport modes compete with each other in multimode transport network. This is a crucial step to manage travel demand efficiently and to predict the future travel trend precisely. To transport operators, a proper understanding of travelers' mode choice behavior and the underlying contributing factors could help them improve their services continuously. Despite its importance, there are limited studies pertaining to investigate how air transport competes with various transport modes in the multimode network. So far, most of the existing studies focus on the competition among air transport and also between the air transport and the high-speed train. Other travel modes, such as buses, trains, or private vehicles, are not studied. Those are important travel modes of transport especially in the developing countries. Besides, most studies targeted the developed countries. However, there are known differences in travel behavior and choices among the travelers of the developing countries in comparison to the developed countries (Khoo and Ong, 2011; Khoo et al., 2012).

Accordingly, the competition between air transport as well as ground transport (i.e. buses, trains, and private vehicles) in the developing country context should be investigated. Stated preference surveys were conducted in the Klang Valley region of Malaysia and traveler's mode choice are modeled to investigate the factors affecting mode choice decision for both local and trans-border trips by trip purposes (leisure and business). Nine attributes, namely travel time, travel cost, safety, comfort, service frequency, facility, on-time performance, booking/purchase method, and promotional package are studied.

A sensitivity analysis on the travel cost and comfort is carried out to inspect how the demand of transport operators (including airlines) would change if these attributes vary. In addition, it is anticipated that mode choice decision would be influenced by the background of travelers.

4.2.1 Local and Trans-border Trip

A local trip is defined as a trip generated between two cities in the same country. In this research, the cities chosen for local trip are Kuala Lumpur and Penang. Kuala Lumpur, situated in the central region, is the capital city of Malaysia. It is the major governance, financial, and business centre in the country. Penang is a beautiful city in the northern region of Malaysia. It is situated about 330km from Kuala Lumpur. The city is declared by UNESCO as the Heritage City in 2008 (UNESCO, 2008). It is famous among the tourists for its food and historical buildings. A trans-border trip is defined as a trip generated between two cities across nearby country. It requires travelers to show their passport (either with or without visa) when crossing the country's boundary. For this research, Singapore is chosen as the abroad city for trans-border trip. Singapore is situated about 350km, south of Kuala Lumpur. Figure 4.1 shows the geographical locations of these cities. For the case study, these cities are chosen because there are multimode available between these cities. One can choose ground transport (such as train, bus, or private vehicles) or air transport (LCC or FSC) to travel between these cities. In addition, there is considerable demand between these origin-destination (OD) pair. For each of these trips (local and trans-border), two trip purposes, i.e. leisure and business trips, are considered explicitly.

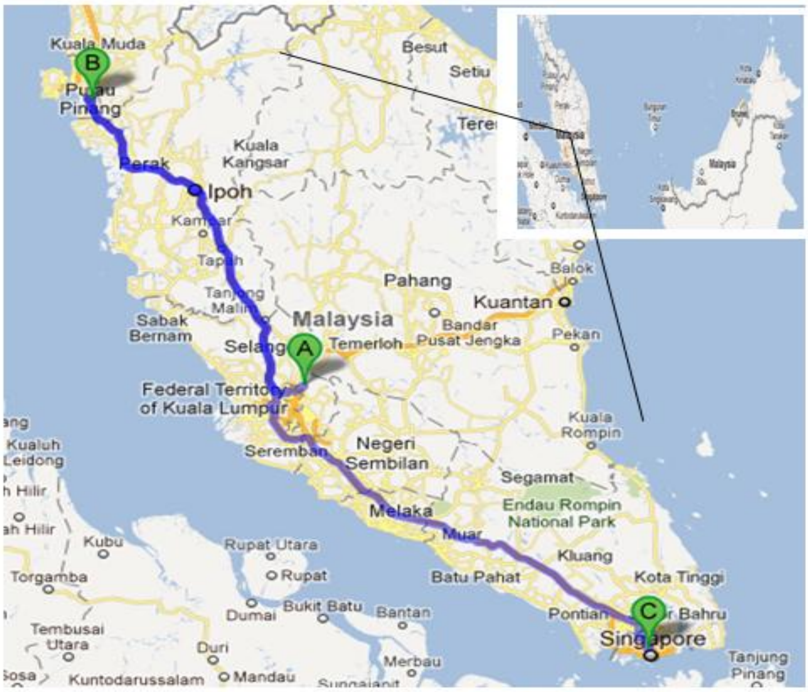

Figure 4.1: The Location of Klang Valley, Penang and Singapore

4.2.2 Stated Preference Survey

In this section, the setting of questionnaire and stated preference survey are explained in detail.

4.2.2.1 Experimental Design

Five types of travel mode, i.e. LCC (AirAsia), FSC (MAS), bus (single-decker and double-decker bus), train, and private car are considered to model traveler’s mode choice. Nine attributes, i.e. travel time (includes access and egress time), travel cost (includes access and egress cost), safety, comfort, service frequency, facility, on-time performance, booking/purchase method and promotional package, were considered in the experimental design of the questionnaire. Two levels (i.e. low and high level) are considered for each attributes. This contributes to a total of 512 (i.e. 2^9) possible sets of choice. However, it is impractical to present all the attributes combination to the respondents in real practice. Therefore, a fractional factorial design is adopted by considering 16 sets of choice to be presented to the travelers. It involves four basic design attributes (i.e. travel time, travel cost, safety, and comfort) and five independent generators (i.e. service frequency, facility, on-time performance, booking/purchase method, and promotional package). The basic designs are selected based on the findings of a pilot survey. Subsequently, the choices are divided into two blocks, each with eight sets of choice, by utilizing blocking approach (confounding factorial design).

4.2.2.2 Traveling Attributes

Tables 4.1 and 4.2 respectively illustrate the traveling attributes, and the levels used (i.e. low and high levels) in designing the stated preference survey for local and trans-border trips. The setting of traveling attributes is described as follows:

Travel time The considered travel time in the survey is the total travel time which takes into account the access time and egress time of travel mode. For air transport, the check-in time is also considered. The values set for travel time are either obtained or estimated from available resources. For example, the average check-in time for LCC and FSC are obtained from the websites of airlines (Malaysia Airlines, 2010a; AirAsia Berhad, 2010a). In-vehicle travel time of buses and cars are estimated based on travel speed. For air transport and train services, expected in-vehicle travel time is obtained from accessible websites (Malaysia Airlines, 2010a; AirAsia Berhad, 2010a; *Keretapi Tanah Melayu Berhad*, 2010) while access and egress time are assumed for all travel modes. A minimum value (such as access or egress time) is estimated for low level while a maximum value is estimated for high level.

Travel cost The total travel cost is the sum of journey cost, access and egress cost. The journey cost of air transport (LCC and FSC), whether by train or bus, is obtained from the respective websites. The travel cost of private vehicles takes into account the petrol price (an average of RM0.15 (USD0.05) per kilometre) and toll charges. The petrol price would change depending on the types of petrol and vehicle. Accordingly, the minimum cost is defined for the low level while the maximum cost is defined for the high level.

Table 4.1: The Attributes of KL-Penang Trip (Local Trip)

Travel mode	MAS	AirAsia	Bus	Private car	Train
Travel time (minute)	120, 200	135, 320	330, 385	300, 360	440, 505
Travel cost (RM)	110, 605	85, 360	35, 130	90, 140	60, 170
Comfort	0, 9	0, 6	0, 13	0, 1440	0, 4
Safety	5, 0	1, 0	129, 0	1692, 0	28, 0
Service frequency	1, 9	1, 6	1, 13	1, 1440	1, 4
Facility	0, 9	0, 6	0, 13	0, 1440	0, 4
On-time performance	0, 9	0, 6	0, 13	0, 1440	0, 4
Booking/purchase method	1, 3	1, 3	1, 2	0, 1	1, 2
Promotional package	0, 9	0, 6	0, 13	0, 1440	0, 4

Table 4.2: The Attributes of KL-Singapore Trip (Trans-border Trip)

Travel mode	MAS	AirAsia	Bus (single-decker)	Bus (double-decker)	Private car	Train
Travel time (minute)	185, 335	200, 395	420, 480	360, 450	300, 420	480, 575
Travel cost (RM)	315, 990	115, 735	45, 215	65, 260	100, 160	95, 190
Comfort	0, 6	0, 10	0, 13	0, 13	0, 1440	0, 4
Safety	5, 0	1, 0	129, 0	129, 0	1692, 0	28, 0
Service frequency	1, 6	1, 10	1, 13	1, 13	1, 1440	1, 4
Facility	0, 6	0, 10	0, 13	0, 13	0, 1440	0, 4
On-time performance	0, 6	0, 10	0, 13	0, 13	0, 1440	0, 4
Booking/purchase method	1, 3	1, 3	1, 2	1, 2	0, 1	1, 2
Promotional package	0, 6	0, 10	0, 13	0, 13	0, 1440	0, 4

Safety   The record of accidents of air transport (LCC and FSC) is extracted from Aviation Safety Network of Flight Safety Foundation (Flight Safety Foundation, 2010). For bus and car, a high level indicates a safe journey with no accident while a low level takes into account the past year's accident records involving each mode (MIROS, 2010). Due to unreadily accessible data for the records of train accidents in the context of Malaysia, the relevant values (as shown in Tables 4.1 and 4.2) were compiled based on the list of train accidents of some developed and developing countries (Wikipedia, 2012).

Service frequency For private cars, service frequency of '1' is used as the low level while '1440' is outlined as the high level with the assumption that private cars are available all the time (24 hours). For other travel modes, the respective service frequency is obtained from accessible websites.

Booking/purchase method For the booking/purchase method, the value of low level (i.e. the value of 1) across the alternatives (travel mode) implies that there is (minimum) one purchase or booking method in getting a place to travel with a particular mode while the value of high level indicates the total number of ways in purchasing/booking a place to travel with selected travel mode. There are three methods for air transport (LCC or FSC) travelers to buy flight ticket, i.e. website booking, booking via travel agent, and during travel fair. For buses, travelers could purchase their tickets from the counter or through travel agent. For trains, travelers could purchase his/her ticket from the website or at the stations. For private cars, travelers drive alone (value of '0') or share with their friends/relatives (value of '1').

Comfort, facility, on-time performance and promotional package Customarily, the comfort level of travel mode associates closely with the provided services (or facilities) in using a particular travel mode. The low level of comfort, which implies unsatisfactory condition, signifies that a traveler feels that the travel with a particular mode is not up to his or her perceived (comfort/satisfactory) level. This may occur due to numerous factors, for instance the condition of the seat (spacious or not), the air-conditioner system (workable or not), check-in and on-board facilities (convenient or not), etc. Conversely, a high level of comfort implies that a particular traveler is satisfied with the existing condition of the provided facilities/services. Similarly, the elements of facility, on-time performance and promotional package could be outlined accordingly to reflect the perception of travelers towards on-board equipments (for facility), delay or rescheduling issue (for on-time performance) and special discount or offer of tickets (for promotional package). Due to unavailable real data from transport operators, the value of high level of comfort, facility, on-time performance and promotional package are considered in accordance to the provided service frequency while the low level considers the value of '0' for an unsatisfactory condition. For instance, '0, 6' for the promotional package of MAS (in Table 4.2) denotes that there is no promotional package for the low level and six promotional packages for the high level. For the values of high level of on-time performance in Table 4.2, the values of 10 for AirAsia and 13 for bus signify that the departure of AirAsia and bus are all on-time (no delay/rescheduling) i.e. 10 times for AirAsia and 13 times for bus in accordance with the frequency of service provided.

4.2.3 Questionnaire and Respondents

The questionnaire is divided into two sections for which the first section examines the socioeconomic characteristics of respondents while the second section requires the respondents to choose their preferred mode choice for local and trans-border trips. A group of five well-trained surveyors were sent out to conduct the questionnaire survey from 11st January to 17th February 2011. The targeted respondents for this research are the residents in the Klang Valley region which is the surrounding area of Kuala Lumpur. All travelers are considered to have the same origin i.e. Kuala Lumpur. A total of 552 respondents (i.e. 273 for local trip and 279 for trans-border trip) were interviewed. The distributions of respondents are displayed in Table 4.3.

Table 4.3: The Characteristics of Respondents

Origin-destination		KL-Penang	KL-Singapore	Origin-destination		KL-Penang	KL-Singapore
Variable	Category	Percentage	Percentage	Variable	Category	Percentage	Percentage
Gender	Male	52	50	Monthly income	≤ RM1500	51	35
	Female	48	50		RM1501 - RM3500	29	45
Race	Malay	21	25		RM3501 - RM5500	11	13
	Chinese	68	62		RM5501 - RM7500	4	4
	Indian	10	12		≥ RM7501	4	3
Age	≤ 20	19	11	Household size	≤ 2	20	20
	21 - 30	48	53		3 - 6	70	68
	31 - 40	18	22		≥ 7	11	11
	41 - 50	9	6	Number of working adults	≤ 2	66	62
	≥ 51	7	8		3 - 6	32	36
Educational level	SPM/STPM	27	33		≥ 7	1	2
	Certificate/ diploma/ advanced diploma	19	30	Number of cars	0	7	8
	Degree	46	29		1	29	35
	Master & above	6	5		2	34	36
	Others	1	3		3	19	15
Occupation	Government servant	8	14		4	11	6
	Executive/ administrator	25	27	Daily travel mode	Private car	60	63
	Professionals	15	23		Public transport	40	37
	Students	41	20				
	Retired	2	7				
	Others	8	9				

4.2.4 Modeling Approach: Multinomial Logit Models

By using the data collected from the stated preference survey, several models were tested with Limdep/Nlogit software to model traveler's mode choice. Multinomial logit model was found to be the best fitted model to reflect the mode choice decision for both local and trans-border trips. The principle of a logit model is that an individual is trying to optimize (i.e. maximize) his or her utility by selecting an option which is the most beneficial for a traveling situation. The higher utility denotes that it is more likely that an alternative will be chosen. Based on the maximum likelihood estimation technique, multinomial logit models (discrete choice models) capture the influence of attributes and characteristics on decision makers' preferences (Train, 2003). For the mode choice modeling of an individual *i*, the regression equations which are the utility functions of all interested alternatives (travel modes), U_{ij} could be modeled in the form as below:

$$\text{Utility function of travel mode } j,\ U_{ij} = \boldsymbol{\beta}\mathbf{x} + \varepsilon_{ij} \qquad (4.1)$$

where $\boldsymbol{\beta}$ is the vector of the estimated parameters (corresponding to each interested attribute of $\mathbf{x}$), $\mathbf{x}$ is the vector of the interested attributes (including traveling attributes and socioeconomic characteristics of travelers) and ε_{ij} is the error term (i.e. the term which is assumed to be Gumbel distributed). The choice probability, P_{ij} of individual *i* is then expressed as follows for a total of *J* alternatives.

$$P_{ij} = \frac{\exp(\beta_j x_{ij})}{\sum_{q=1}^{J} \exp(\beta_q x_{iq})}, \; j = 1,2,\ldots,J \tag{4.2}$$

Note that there are a few limitations of the logit model known in literature, such as the assumption of independence from irrelevant alternatives (IIA), the unobserved factors are unrelated to the choices (McFadden and Train, 2000), and taste variations vary systematically with respect to the observed variable (Train, 1998, 2003).

Specifically for the instance with nine traveling attributes and six socioeconomic characteristics (for which x_1: travel time, x_2: travel cost, x_3: comfort, x_4: safety, x_5: service frequency, x_6: facility, x_7: on-time performance, x_8: booking/purchase method, x_9: promotional package, x_{10}: gender, x_{11}: race, x_{12}: age, x_{13}: income, x_{14}: household size, x_{15}: number of cars), the vectors of $\boldsymbol{\beta}$ and $\mathbf{x}$ could be expressed as follows:

$$\boldsymbol{\beta} = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_{14} \\ \beta_{15} \end{pmatrix}, \mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_{14} \\ x_{15} \end{pmatrix} = \begin{pmatrix} \text{travel time} \\ \text{travel cost} \\ \vdots \\ \text{household size} \\ \text{number of cars} \end{pmatrix} \tag{4.3}$$

Note that the utility function U_{ij} is the dependent variable of the mode choice analysis. By considering all interested attributes (with estimated parameters), the utility function could then be expressed by:

$$U_{ij} = \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{14} x_{14} + \beta_{15} x_{15} + \varepsilon_{ij} \tag{4.4}$$

For the instance to consider five travel modes, i.e. the alternative $j = MAS,\ AirAsia,\ Bus,\ Car,\ Train$ which respectively refers to the travel of a trip with Malaysia Airlines (full service carrier), AirAsia (low-cost carrier), bus, car and train, the utility function of each specific travel mode can be expressed, in general, as follows:

$$U_{iMAS} = Time_{MAS}x_1 + Cost_{MAS}x_2 + \cdots + Size_{MAS}x_{14} + NumCars_{MAS}x_{15} + \varepsilon_{iMAS} \tag{4.5}$$

$$U_{iAirAsia} = Time_{AirAsia}x_1 + Cost_{AirAsia}x_2 + \cdots + Size_{AirAsia}x_{14} + NumCars_{AirAsia}x_{15} + \varepsilon_{iAirAsia} \tag{4.6}$$

$$U_{iBus} = Time_{Bus}x_1 + Cost_{Bus}x_2 + \cdots + Size_{Bus}x_{14} + NumCars_{Bus}x_{15} + \varepsilon_{iBus} \tag{4.7}$$

$$U_{iCar} = Time_{Car}x_1 + Cost_{Car}x_2 + \cdots + Size_{Car}x_{14} + NumCars_{Car}x_{15} + \varepsilon_{iCar} \tag{4.8}$$

$$U_{iTrain} = Time_{Train}x_1 + Cost_{Train}x_2 + \cdots + Size_{Train}x_{14} + NumCars_{Train}x_{15} + \varepsilon_{iTrain} \tag{4.9}$$

Notably, the respective utility function (with significant estimated parameters) could be obtained accordingly by performing mode choice analysis appropriately. In order to perform mode choice analysis, all interested variables (with the respective measurement unit) are described in Table 4.4 and the relevant sources of the modeling variables are presented in Appendix B.

4.2.5 Findings: Mode Share of Trips

The probability of choosing travel mode for local and trans-border trips is presented in Table 4.5. For local leisure trip, the results show that air transport is preferred. About 49% and 24% of travelers choose FSC and LCC, respectively. Private vehicle is the most popular travel mode among ground transport. About 13% of travelers choose to use private vehicle, followed by bus (9%) and train (5%). Local business travelers show similar choice with leisure travelers. Nevertheless, fewer road users (23%) are found for business trip. This demonstrates that air transport gains more interest from business travelers than leisure travelers.

Table 4.4: The Description of the Interested Variables

Variable name	Measurement unit	Description
Dependent variable		
Utility function, U_{ij}	Numerical value (point form)	An indicator which implies how likely an alternative (travel mode) is chosen for traveling purposes. A higher value of utility indicates that it is more likely that a specific travel mode will be chosen.
Traveling attributes		
Travel time, x_1	Hour and/or minute	Total travel time which takes into account the in-vehicle time, access time and egress time of a specific travel mode. For air transport, the check-in time is also considered.
Travel cost, x_2	Ringgit Malaysia (RM)	Total travel cost which takes into account the sum of journey cost, access and egress cost.
Comfort, x_3	Number of times *(associated with service frequency)*	An indicator which depicts the satisfactory level of a traveler towards a specific travel mode.
Safety, x_4	Number of accidents	An indicator which demonstrates how secure (safe) a travel mode is.
Service frequency, x_5	Number of times *(associated with service frequency)*	An indicator which shows how frequent a travel mode is available.
Facility, x_6	Number of times *(associated with service frequency)*	An indicator which indicates the adequacy of the supporting services (in terms of facilities/equipment) provided by the transport operators.
On-time performance, x_7	Number of times *(associated with service frequency)*	An indicator which signifies the punctuality of a travel mode.
Booking/purchase method, x_8	Number of available ways	An indicator which reveals how a traveler purchases/orders a seat in order to travel with a particular travel mode.
Promotional package, x_9	Number of times *(associated with service frequency)*	An indicator which shows the possibility of a traveler to travel with a cheaper cost (e.g. purchase flight ticket during the promotional period).
Socioeconomic characteristics		
Gender, x_{10}	Categorical	Sexual category (male or female).
Race, x_{11}	Categorical	Ethnic group (Malay, Chinese, Indian or others).
Age, x_{12}	Year	The length of living time.
Income, x_{13}	Ringgit Malaysia (RM)	The earnings level (monthly) of a particular traveler.
Household size, x_{14}	Numerical value	The number of family members.
Number of cars, x_{15}	Numerical value	The quantity of private cars possessed by a traveler.

Trans-border leisure travelers are found to have the highest tendency (36%) in using air transport for which LCC (20%) is preferred than FSC (16%). Among the ground transport, private vehicle is the most likely option with the choice probability of 32%, followed by single-decker bus (20%), double-decker bus (5%) and train (4%). Besides, air transport dominates the market of trans-border business trip for which FSC (53%) is favored compared to LCC (15%). The private vehicle again dominates the ground transport with its choice probability of 15%. Bus and train are not preferred by business travelers.

Table 4.5: The Choice Probability of Local and Trans-border Trips (%)

	Local trip (KL-Penang)		Trans-border trip (KL-Singapore)	
Travel mode	Leisure trip	Business trip	Leisure trip	Business trip
FSC (MAS)	49.06	59.57	16.52	53.15
LCC (AirAsia)	24.05	17.06	20.34	15.02
Bus (single-decker)	9.04	8.08	20.66	8.09
Bus (double-decker)	-	-	5.81	5.04
Private car	13.30	10.70	32.31	15.11
Train	5.02	4.60	4.37	3.60

4.2.6 Analysis of LCC's Impacts on Mode Choice Decision

Tables 4.6 and 4.7 present multinomial logit models developed from the stated preference survey of local and trans-border trips, respectively. The models are statistically significant at 95% confidence level from the perspectives of socioeconomic factors as well as the traveling attributes of transport operators. All models are examined with the same socioeconomic backgrounds of travelers and also on nine traveling attributes as described earlier. The results show that the models are statistically significant towards different traveling factors. Based on these models, the impacts of LCC on mode choice decision is investigated and presented in the following sub-sections.

4.2.6.1 Impact of LCC on FSC

The results show that the major factor that encourages trans-border leisure trip makers to choose LCC over FSC is low travel cost. This is similar to the findings of O’Connell and William (2006) and Mohd Suki (2014). However, for local leisure trip, travelers prefer FSC more than LCC (as the utility constant of FSC is higher than LCC). This is because FSC could offer a better comfort level compared to LCC. For trans-border business trip, the travel cost remains as the major factor that encourages travelers to choose LCC. However, most of the trans-border business travelers opt for FSC than LCC most probably owing to the company’s policies (normally larger firms) in taking FSC due to the frequent flyer initiatives. This fact could be supported by the occupation of respondents for which more than 50% of the respondents (as shown in Table 4.3) are holding the position as government servant, executive and professional, which are most likely working in large-scaled companies which prefer FSC than LCC. This finding is in accordance with the results of Evangelho et al. (2005) and O'Connell and Williams (2005, 2006). Besides, it was found that comfort is the major factor for local business trip. The estimated parameter shows that LCC is able to increase their mode share if the comfort level could be improved (more significant than FSC since the value is higher).

For trans-border leisure trip, a sensitivity analysis is performed to investigate the impact of the changes of travel cost on the mode share. The results are displayed in Table 4.8. The results show that if the travel cost of LCC decreases by 10% to 50%, the choice probability of LCC is estimated to increase 2.71%-18.39%, with an average of 10.12%. In addition, this would attract an additional of 2.22% of FSC travelers to LCC. For local business trip, the results of sensitivity analysis as illustrated in Table 4.9 signify that if the comfort level of LCC improves gradually (from 10% to 50%), the market share of LCC could increase at an average of 4.24%. Specifically, the improvement in comfort means that transport operators aim to ensure that their travelers would use and enjoy more facilities/services. In such a case, transport operators may provide some on-board facilities so that travelers could feel more relax and comfortable during their travel. For instance, electric train services (ETS) train is equipped with LCD TV particularly for the informative and relaxation purposes. Accordingly, the higher level of improvement of comfort level refers to more facilities/services that can be enjoyed by travelers during their travel. Similarly, the reduction of travel cost, the adjustment (i.e. improvement) of the comfort level at a higher level (i.e. from 10% to 50%) would increase the market share of the LCC at a greater extent (i.e. from 1.26% to 7.45%). Besides, it could be seen that the improvement of LCC's comfort level attracts an average of 3% of FSC travelers.

Table 4.6: The Modeling Results of KL-Penang Trip (Local Trip)

	Leisure trip		Business trip	
Parameter	Coefficient	t-statistic	Coefficient	t-statistic
$Constant_{MAS}$	2.6159	3.613	2.9045	3.961
$Constant_{AirAsia}$	1.3013	44.657	1.0904	28.490
$Constant_{Bus}$	-0.0645	-9.533	-0.4927	-16.918
$Gender_{MAS}$	-0.0725	-7.690	-0.0943	-15.773
$Gender_{AirAsia}$	-0.0679	-38.375	-	-
$Gender_{Bus}$	-0.2689	-119.756	-0.2171	-11.056
$Gender_{Car}$	0.1007	383.864	0.0946	10.733
$Gender_{Train}$	0.3085	21.484	0.2809	136.089
$Race_{MAS}$	-	-	-0.1190	-548.728
$Race_{Car}$	-	-	-0.0371	-36.963
$Time_{Car}$	-0.0091	-18.411	-0.0103	-1.640
$Comfort_{MAS}$	0.1317	5.941	0.1918	12.643
$Comfort_{AirAsia}$	-	-	0.2570	13.140
$Comfort_{Bus}$	0.0823	55.978	-	-
$Safety_{Bus}$	0.0292	17.039	-	-
Log-likelihood function	-2611.500		-2606.650	
p-value	0.0319		0.0161	
Number of observations	2,216		2,216	

Table 4.7: The Modeling Results of KL-Singapore Trip (Trans-border Trip)

	Leisure trip		Business trip	
Parameter	Coefficient	t-statistic	Coefficient	t-statistic
$Constant_{MAS}$	2.0219	2.281	3.9085	4.387
$Constant_{Single\text{-}decker\ bus}$	2.5810	378.929	3.0808	448.562
$Income_{MAS}$	0.1469	17.355	0.2057	18.668
$Income_{AirAsia}$	0.0343	37.583	-	-
$Income_{Single\text{-}decker\ bus}$	-0.1480	-157.429	-0.0084	-15.949
$Income_{Double\text{-}decker\ bus}$	-0.1969	0.0379	-0.4571	-18.218
$Income_{Car}$	0.0785	118.149	0.1157	172.681
$Income_{Train}$	0.0852	1.956	0.1442	4.602
$Cost_{AirAsia}$	-0.0046	-3.229	-0.0073	-7.190
$Cost_{Double\text{-}decker\ bus}$	-	-	-0.0181	-4.025
$Cost_{Train}$	-0.0206	-16.327	-0.0402	-83.191
$Safety_{AirAsia}$	-	-	0.0124	2.309
$Safety_{Single\text{-}decker\ bus}$	0.0117	5.078	-	-
Log-likelihood function	-3380.697		-2944.421	
p-value	0.0000		0.0000	
Number of observations	2,222		2,224	

Table 4.8: The Sensitivity Analysis of KL-Singapore Trip (Trans-border Leisure Trip)

Travel cost of AirAsia		-10%	-20%	-30%	-40%	-50%	Average
Choice probability (%)	MAS	-0.61	-1.32	-2.13	-3.04	-4.01	-2.22
	AirAsia	+2.71	+5.95	+9.69	+13.88	+18.39	+10.12
	Single-decker bus	-0.41	-0.87	-1.40	-1.98	-2.61	-1.45
	Double-decker bus	-0.20	-0.43	-0.71	-1.02	-1.36	-0.74
	Car	-1.37	-3.02	-4.96	-7.13	-9.47	-5.19
	Train	-0.14	-0.30	-0.49	-0.70	-0.94	-0.51

Table 4.9: The Sensitivity Analysis of KL-Penang Trip (Local Business Trip)

Comfort level of AirAsia		+10%	+20%	+30%	+40%	+50%	Average
Choice probability (%)	MAS	-0.92	-1.92	-3.00	-4.17	-5.42	-3.09
	AirAsia	+1.26	+2.64	+4.13	+5.73	+7.45	+4.24
	Bus	-0.12	-0.26	-0.40	-0.56	-0.73	-0.41
	Car	-0.15	-0.31	-0.48	-0.67	-0.87	-0.50
	Train	-0.07	-0.15	-0.24	-0.33	-0.43	-0.24

4.2.6.2 Impact of LCC on Ground Transport

For local business trip, the comfort of LCC is found to be significant. This reveals that local business travelers tend to fly with LCC, which is anticipated to have a better comfort level (probably due to shorter travel time) compared to the ground transport (i.e. private car, bus, train). For local trip (both leisure and business purposes), the fact that LCC is preferred is also supported by the constant of LCC which has a higher value compared to the constant of bus. For trans-border trip (both leisure and business purposes), travel cost emerges as the major cause that encourages travelers to travel with LCC. In addition to travel cost, safety appears as the significant determinant for trans-border business travelers in choosing LCC. LCC is preferred most possibly owing to the least accident occurrence compared to ground transport (as shown in Table 4.2). Furthermore, there might be a negative perception of travelers towards the safety of group transport, especially car and bus due to increasingly road accidents from year to year (MIROS, 2012). This supports the decision-making of business travelers who have a concern for safety.

The findings of sensitivity analysis for trans-border leisure trip and local business trip (as displayed in Tables 4.8 and 4.9), respectively show that the adjustment of travel cost and comfort level could increase the mode share of LCC. If the travel cost of LCC decreases (10%-50%), the choice probability of LCC is estimated to increase gradually with an average of 10.12%, by shifting about 8% of the users of ground transport (i.e. 5% of car users, 2% of bus users and about 1% of train users). Besides, the findings show that if the comfort level of LCC improves gradually (10%-50%), the market share of LCC could increase at an average of 4.24% for which the improvement of the comfort level at a higher level would increase the market share of the LCC with a greater proportion. However, the impact of the improvement of comfort level in mode shifting is lesser compared to the reduction of travel cost, i.e. this strategy (improvement of comfort level) would only attract about 1.15% of the users of ground transport.

4.2.6.3 Effect of Socioeconomic Background

From the mode choice analysis, it was found that one of the significant factors that could influence travelers' mode choice is their socioeconomic background. Table 4.6 shows that gender is a significant factor that affect leisure and business travelers of local trips. The results show that male travelers prefer to travel with air transport and bus while car and train are the likely options among female travelers. Besides, mode choice decision is also affected by the race factor. Malay and Chinese travelers show a high tendency in traveling with FSC and car. From Table 4.6, it could be seen that respondents' income level is another significant factor for leisure and business trips. It shows that those with higher income tend to travel with air transport or private vehicles. On the other hand, those with lower income show a tendency to travel with bus, most probably due to cheaper travel cost.

4.2.7 Implications for Managerial Practices

For airlines, mode choice analysis is particularly crucial from three major managerial perspectives, i.e. demand, supply and sustainability as listed as follows:

From the aspect of demand:

- to manage travel demand properly
- to predict future travel trend precisely
- to develop and implement appropriate marketing strategy considerably
- to attract new travelers (to increase mode share) effectively

From the aspect of supply:

- for operations and performance enhancement (to improve existing services and systems)
- for services planning (to meet travelers' demand and expectations)
- for fleet planning decision-making (to support operating networks)

From the aspect of sustainability:

- to retain the loyalty of travelers
- to outperform competitors (under multimode transportation system)
- to assure profitable operations and market shares

4.2.8 Summary

A proper understanding of travelers' mode choice decision in multimode transport network is important for an efficient planning. It is a crucial step to predict the usage of transport facilities and to manage travel demand effectively. While most of the studies focus on the analysis for the developed countries, this research investigates travelers' mode choice decision in the developing countries. Besides studying the choices between LCC and FSC, this research also aims to deliberate the competition between LCC and ground transport. A stated preference survey is carried out to investigate travelers' choice for local and trans-border trips. Multinomial logit models are developed to identify the underlying factors that contribute to mode choice. It was found that a few influential factors that could affect mode choice decision are trip purpose, traveling destination, travel cost, comfort, safety, and travelers' background. It was also found that LCC is only preferred by those on trans-border leisure trip. For those who choose LCC, low travel cost is their main concern. Other travelers choose FSC due to its excellent comfort level. Most of the travelers who choose to use ground transport prefer to travel with their own private vehicles for more flexibility and comfort. However, for those who choose to use buses, travel safety has become their main concern. A sensitivity analysis is carried out to study the impact of changes of travel cost and comfort level on LCC. The results show that the LCC is able to attract a substantial amount of travelers from FSC and ground transport if the ticket price is reduced while the comfort level is increased. As such, it could be seen that mode choice analysis could provide informative highlights to airlines for services enhancement (including how to provide a strategic fleet planning as discussed in the following section). Therefore, in order to capture the mode choice of travelers properly, those aspects as discussed earlier should be handled wisely.

4.3 Analytic Hierarchy Process (AHP) Modeling Framework

4.3.1 The Role of Analytic Hierarchy Process (AHP) In Fleet Planning Decision-Making

While providing an adequate fleet supply, it is important to capture mode choice analysis (traveler’s response) in view of the fact that air travelers (passengers) are the main users of airline's services which constitutes the market share and main income to airlines. Furthermore, traveler’s behavior was changing with extensive growth of multimode transportation networks. As such, how airlines make an optimal fleet planning decision, i.e. a multiple criteria decision-making, throughout the planning horizon is important to meet travel demand profitably at a desired service level. Therefore, the fleet planning decision-making of airlines which is, in fact, uncertain (primarily due to stochastic demand) and greatly governed by various key aspects (multi-criteria) could be solved strategically with the aid of the AHP.

By allowing the respective judgments to vary over the values of a fundamental scale of 1-9, AHP possess the capability to capture the fuzziness (uncertainty) in making a multi-criteria decision (Saaty and Tran, 2007). Specifically, the judgments made with AHP, in the form of pair-wise comparison, by using judgment scale 1-9 are fuzzy (uncertain). As such, the fleet planning decision-making of airlines which is, in fact, uncertain could be solved by making use AHP suitably. Comparatively, AHP is widely used due to its ease of use as well as its straightforward scalable and understandable manner than any other multi-criteria decision making methods (Velasquez and Hester, 2013). More importantly, AHP which is able to capture the fuzziness and vagueness (uncertainty) explicitly could reflect realistically the fleet planning problem of airlines in a better manner. To the best of the authors' knowledge, this research is the first that integrates AHP and mode choice modeling in solving the fleet planning problem explicitly. The developed methodology is capable to show how various key aspects affect fleet planning decision-making, i.e. how fleet planning (a multi-criteria decision) is made to meet stochastic demand.

4.3.2 Modeling Framework

The proposed modeling framework of AHP basically involves three major stages as displayed in Figure 4.2. Stage 1 involves the judgment and comparison among decisional criteria while Stage 2 focuses on the judgment and comparison among the key aspects for each decisional criteria. Finally, Stage 3 computes the end result which is the probability of the key aspect that influence the fleet planning decision-making. For Stage 1, the modeling framework commences by evaluating the relative comparison of n decisional criteria with a comparison scale of 1-9 (Saaty, 1980, 1994). Typically, the relative comparison is presented in the form of a matrix, i.e. a square matrix with a size of n x n. In other words, the matrix is playing the role to reflect the subjective judgment of decision makers towards the relative comparison of n decisional criteria. For n x n matrix, the diagonal element which is the comparison of n decisional criteria against itself is always equal to 1 while other elements in the matrix signify the relative comparison of n decisional criteria. For n x n matrix, it is observable that $a_{ij} = \frac{1}{a_{ji}}$ for which a_{ij} defines the element at row i and column j of the matrix. This shows that the element a_{ij} and a_{ji} are the reciprocal of each other. As such, the n x n matrix is also known as reciprocal matrix.

It is important to note that some degree of inconsistency is expected due to the fact that the decision-making is made based on the subjective judgment of decision makers. Therefore, the consistency of the matrix needs to be examined accordingly. This can be done by conducting a consistency test. Mathematically, the matrix is said to be consistent if a_{ij} x $a_{jk} = a_{ik}$ $\forall i,\ j,\ k$. Generally, there are three components, namely consistency ratio (*CR*), consistency index (*CI*) and random consistency index (*RI*) that are required to carry out the consistency test. Basically, *CR* evaluates the ratio of *CI* and *RI* of the matrix in such a way that *CI* measures the consistency of the matrix by making use of the deviation of the eigenvalue and matrix size while *RI* is the average *CI* of a large sample of randomly generated matrices. The matrix is said to be consistent if *CR* < 0.1. To examine the consistency, the largest eigenvalue of the matrix, $\lambda_{\max}$ also acts as a consistency indicator for which the matrix is said to be more consistent if the value of $\lambda_{\max}$ is getting closer to matrix size (Saaty, 1990).

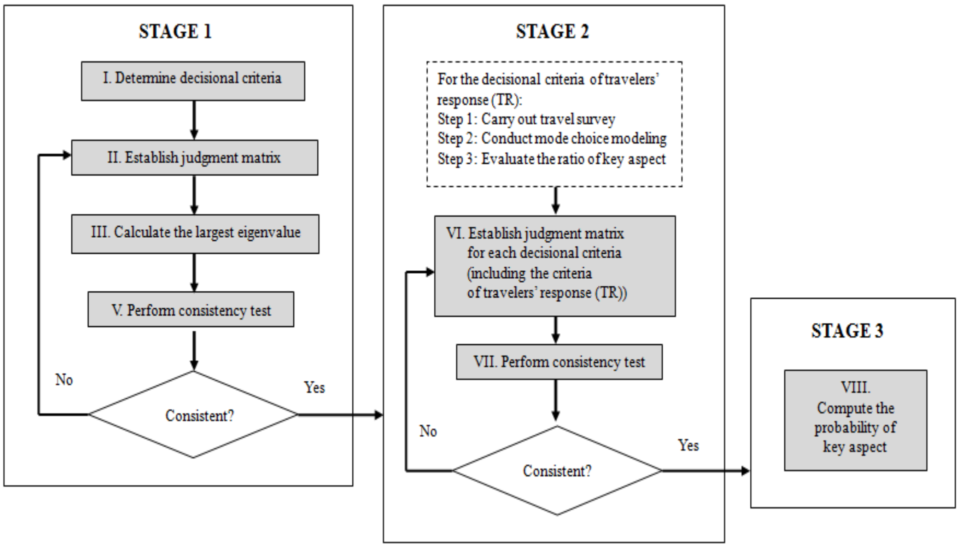

Figure 4.2: The Modeling Framework to Quantify the Probability of Key Aspect

At stage 2, a similar procedure (as in stage 1) is carried out to form the judgment matrix that reflects the relative comparison among the key aspect for each decisional criteria. As addressed earlier, the key aspect refers to a particular perspective (concern) that could affect the fleet planning decision-making. By validating the consistency of matrix, subsequently the output of AHP approach is computed (at stage 3) to quantify the probability of the respective key aspect. The aspect with a higher probability is interpreted to be more essential than other aspect with a lower value. Note that the total of probability is one, i.e. 100% as the full decision of airlines. The decision-making in fleet planning shall then be driven by the resultant probability of key aspects.

The modeling framework of AHP (embedded with mode choice modeling) as outlined in Figure 4.2 can be carried out as follows:

For **stage 1**:

I. Determine decisional criteria, C_i

To make fleet planning decision, decisional criteria, $C_i, i = 1,...,n$ can be identified appropriately by identifying the relevant element that could affect the decision-making of airlines. Generally, the elements that are found to affect airlines are decision policy of airlines, consultancy of experts/consultants, past performance of airlines and travelers' response in view of their influential impacts in fleet planning (AirAsia Berhad, 2004; KPMG, 2007; Lessard, 2012; Malaysia Airlines, 2010a; Ryanair, 2012).

II. Establish judgment matrix (for n decisional criteria)

A pair-wise comparison matrix, A involving n decisional criteria (as determined from step I) can be expressed as follows (Saaty, 1980):

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix}_{nxn} \tag{4.10}$$

Generally, matrix A is governed by a_{ij}>0, $a_{ii} = 1$, $a_{ij} = \dfrac{1}{a_{ji}}$ for $\forall i, j$. To assure consistency, note that a_{ij} x $a_{jk} = a_{ik}$ $\forall i, j, k$. Specifically, a_{ij} implies the relative comparison of criteria *i* over *j* based on judgment scale 1-9 (for which 1:equal importance, 3:weak importance of one over the other; 5:strong importance; 7:demonstrated importance; 9:absolute importance while 2, 4, 6 and 8 signify the corresponding intermediate values between two adjacent judgment (Saaty, 1977, 1980, 1990)).

In real practice, decision makers are likely to make an inconsistent comparison (judgment). To handle this issue, the following actions could be done (Saaty and Tran, 2007):

(1) Identify the most inconsistent judgment in the matrix and determine the range of values for which the inconsistency could be improved.

(2) Request the decision maker to consider if he/she can alter his/her judgment to a possible value in that range. Otherwise, the decision is postponed until a better understanding is obtained.

(3) Same procedure could be repeated by examining the second most inconsistent judgment and so on.

III. Calculate the largest eigenvalue

As an indicator for consistency, the largest eigenvalue, λ_{max} of matrix *A* can be determined as follows (Saaty, 1990):

$$\lambda_{max} = \sum_{j=1}^{n} a_{ij} \frac{w_j}{w_i} \qquad (4.11)$$

for which a_{ij} is the element of matrix A while w_i and w_j respectively represent the average of row i and j of matrix A. Note that a matrix is said to be more consistent if the value of the largest eigenvalue is getting closer to matrix size.

IV. Perform consistency test (for matrix A)

Consistency test is needed to assure the consistency of matrix A (with size n). This test can be conducted based on the consistency index, CI and random consistency index, RI which are outlined as follows (Saaty, 1977):

$$CI = \frac{\lambda_{\max} - n}{n-1},\ RI = \frac{1.98(n-2)}{n} \tag{4.12}$$

Saaty (1977) showed that $\lambda_{\max} = n$ if the matrix does not include any inconsistency. This implies that the closer the value of $\lambda_{\max}$ to n, the matrix is more consistent.

By using the measurement of CI and RI, the consistency ratio, CR can be evaluated as follows:

$$CR = \frac{CI}{RI} \tag{4.13}$$

As shown in Equation (4.13), CR compares the consistency index, CI of the matrix and a purely random matrix, RI. The judgment matrix is said to be consistent if $CR < 0.1$.

For **stage 2**:

V. Establish judgment matrix of key aspect (for each decisional criteria)

For airlines, key aspect s_k signifies the relevant aspect (concern) that could affect fleet planning decision-making. Specifically, the probability of key aspect reflects the likelihood or degree of each perspective in making an optimal fleet planning decision. As such, how to capture these key aspects for decision-making is vital. It is important to note that the number of key aspect to be captured may vary among airlines. For instance, some airlines claim that the aspects of operational and economy are two major determinants in fleet planning (AirAsia Berhad, 2010a; Malaysia Airlines, 2010a). In addition, the environmental aspect should be taken inconsideration due to its increasing concern and impacts on airline's operations. In such a case, three key aspects namely s_1, s_2 and s_3 could be defined accordingly to capture the aspect of operational, economy and environmental, respectively. For airlines, operational aspect (s_1) particularly refers to relevant perspectives such as the ability to secure traffic rights and operating difficulties of aircraft type while the economy aspect (s_2) covers the financial benefits of shareholders, economic benefits of new aircraft and so on. For the environmental aspect (s_3), the fuel efficiency of airlines is included in view of the fact that lesser fuel consumption produces fewer emission (Williams et al., 2002). In fact, these aspects (operational, economy and environmental) are closely related to one another owing to the fact that aircraft operations of airlines in supporting the operating networks would greatly affect not only the financial gains of airlines but also their green (environmental) performance in terms of fuel efficiency, aircraft emission and noise.

By considering k key aspects, i.e. $s_1,...,s_k$ and decisional criteria C_i, the pair-wise comparison matrix of the key aspect (for each decisional criteria), B_{C_i} can be formed as follows:

$$B_{C_i} = \begin{bmatrix} 1 & s_{12} & \cdots & s_{1n} \\ 1/s_{12} & 1 & \cdots & s_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/s_{1n} & 1/s_{2n} & \cdots & 1 \end{bmatrix}_{kxk} \tag{4.14}$$

for which matrix B_{C_i} is a square matrix with size *k* x *k* while s_{ij} reflects the relative comparison of key aspect s_i over s_j.

In order to obtain the pair-wise comparison matrix of the key aspect $s_1,...,s_k$ for the decisional criteria of travelers' response, travel survey and mode choice analysis can be done as follows:

Step 1: Conduct travel survey

Travel survey can be undertaken necessarily by airlines to examine the preference of travelers as well as its impacts in fleet planning. Specifically, travel survey for different trip purpose (e.g. leisure or business) can be carried out for different destination (e.g. local or trans-border). Traveler's response via survey could reveal their preferences and travel behavior in a better manner.

Step 2: Conduct mode choice analysis

The response of travelers via travel surveys (input) could be utilized to generate the mode choice modeling models (output). The estimated parameters of respective trip (e.g. local leisure trip, local business trip, trans-border leisure trip and trans-border business trip) which constitute the mode share of respective operating network can be obtained accordingly from the mode choice modeling analysis.

Step 3: Evaluate the ratio of key aspect to form judgment matrix, B_{C_i}

For the decisional criteria of travelers' response, the pair-wise comparison matrix of key aspect $s_1,...,s_k$ can be evaluated by taking into account the mode share analysis (from step 2). Subsequently, the mode share of operating network which corresponds to the respective key aspect can be evaluated accordingly to obtain the relative comparison of key aspect. To do this, the relevant components of each key aspect, $F_{s_k}^w$ are taken into account to assess the relationship of the operating network, Net_d and corresponding key aspect, s_k. This is necessary to examine the impacts between operating network and key aspect (to work out the ratio of key aspect). The detail framework to evaluate the ratio of key aspect is shown in Figure 4.3.

By considering W relevant components of key aspect and also P operating networks, the respective ratio of key aspect (to form judgment matrix

B_{C_i}) can be computed as follows:

$$s_i : s_j = \left| \frac{\sum Net_d F_{S_i}^w}{\sum Net_d F_{S_j}^w} \right|, i,\ j = 1,\dots,k; w = 1,\dots,\ W; d = 1,\dots,\ P \qquad (4.15)$$

where Net_d refers to operating network and $F_{S_k}^w$ denotes the relevant component of key aspect, s_k .

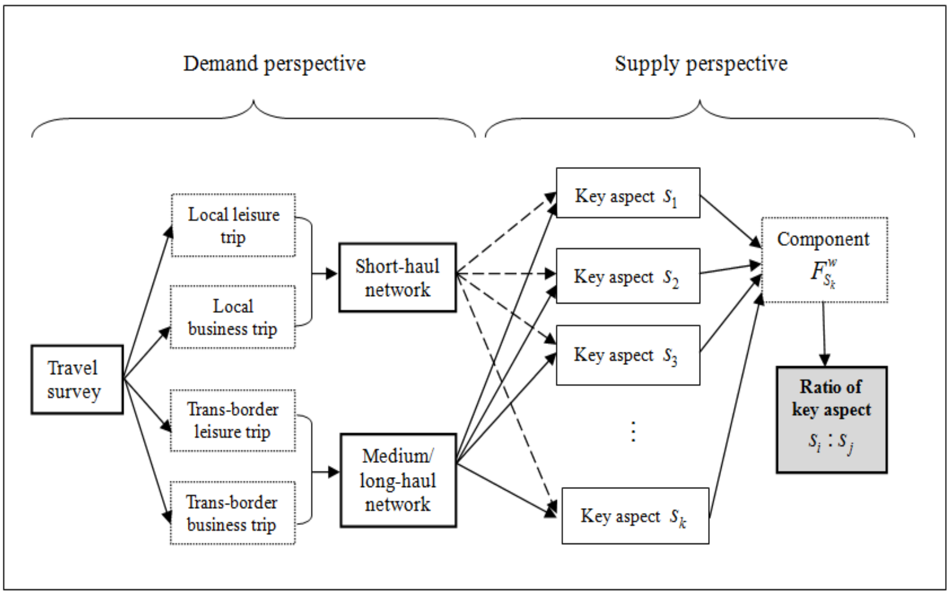

Figure 4.3: The Evaluation of the Ratio of Key Aspect

VI. Perform consistency test (for matrix B_{C_i})

The consistency of matrix, B_{C_i} can be confirmed by adopting a similar procedure as described in stage 1, i.e. the matrix is said to be consistent if $CR < 0.1$.

For **stage 3**:

VII. Compute the probability of key aspect

The probability of key aspect can be evaluated as follows (Saaty, 1980):

$$\text{Probability} = \sum A_i^* B_r^* \qquad (4.16)$$

where A_i^* represents the average of row $i = 1, 2, ..., n$ (i.e. decisional criteria) of normalized matrix *A* while B_r^* denotes the average of row $r = 1, 2, ..., k$ (i.e. key aspect with regard to each decisional criteria) of normalized matrix B_{C_i}.

4.3.3 Numerical Example

This section illustrates the applicability of the developed framework (with mode choice modeling) to quantify the probability of the respective key aspect in making an optimal fleet planning decision.

I. Determine decisional criteria, C_i

Based on publicly accessible published reports (AirAsia Berhad, 2004; KPMG, 2007; Lessard, 2012; Malaysia Airlines, 2010a; Ryanair 2012), four decisional criteria, namely the decision policy of airline (*DP*), consultancy of experts (*CE*), past performance of airline (*PP*) and travelers' response (*TR*) are identified as the major key aspect that could affect the fleet planning decision of airlines. The elements of *DP*, *CE*, *PP* and *TR* are denoted as criteria

C_1, C_2, C_3 and C_4 respectively. Specifically, the decision policy of airlines (*DP*), C_1 refers to a particular course of action for airlines to make operational and managerial decision (including fleet planning decision). For instance, airlines may standardize their fleet choice in terms of aircraft type primarily due to financial and operational concerns. For airlines, the consultancy of experts (*CE*), C_2 refers to advices or judgments of consultants/panels towards airline's operating performance, financial management as well as decision-making. In supporting the servicing networks, the past performance of airline (*PP*), C_3 includes the perspectives of demand and supply for which demand perspective takes into account the travel trend while the perspective of supply considers the fleet performance in servicing available operating networks. From the perspective of the users of air transport system, the travelers' response (*TR*), C_4 focuses on the mode choice modeling of travelers which reveals the behavior and perception of travelers towards the services of airlines.

II. Establish judgment matrix (for n decisional criteria)

Based on the decisional criteria of C_1, C_2, C_3 and C_4 as identified in Step I, judgment matrix A can be formed as follows:

$$A = \begin{bmatrix} 1 & 0.75 & 0.57 & 1.00 \\ 1.33 & 1 & 0.77 & 1.32 \\ 1.74 & 1.29 & 1 & 1.68 \\ 1.00 & 0.76 & 0.60 & 1 \end{bmatrix}_{4x4}$$

To obtain matrix A, accessible published information is compiled with the aid of a simulation approach for which the simulated data (in Table 4.10) represents the relative comparison of 10 managerial experts towards the decisional criteria C_i over C_j. As shown in Table 4.10, the judgments of experts are compiled suitably as geometric mean (Aczel and Saaty, 1983).

III. Calculate the largest eigenvalue

The largest eigenvalue, $\lambda_{\max}$ of matrix *A* can be determined as follows:

$$\lambda_{\max} = \sum_{j=1}^{n} a_{ij} \frac{w_j}{w_i} = 4.0001$$

The value of the largest eigenvalue is coherent with the fact of Saaty (1977) for which $\lambda_{\max} \geq n$.

IV. Perform consistency test (for matrix A)

Since $n = 4$ (i.e. size of matrix *A*), the element of *CR* is computed as follows:

$$CR = \frac{CI}{RI} = \frac{4.1 \text{ x } 10^{-5}}{0.99} = 4.2 \text{ x } 10^{-5}$$

Thus, the consistency is acceptable because $CR < 0.1$. This signifies that the matrix *A* is consistent (reliable) in terms of the judgment (evaluation) of decision makers.

Table 4.10: The Evaluation of Relative Comparison

Expert, k	1	2	3	4	5	6	7	8	9	10	Geometric mean
a_{12}	0.71	0.6	0.76	0.75	1.02	0.69	0.79	0.81	0.93	0.57	0.75
a_{13}	0.63	0.67	0.56	0.51	0.44	0.62	0.63	0.8	0.51	0.47	0.57
a_{14}	1.03	0.94	0.96	0.92	1.01	0.96	1.07	0.97	1.01	1.15	1.00
a_{23}	0.81	0.86	1.01	0.75	0.69	0.76	0.83	0.54	0.9	0.69	0.77
a_{24}	1.26	1.33	1.23	1.27	1.46	1.25	1.36	1.36	1.37	1.35	1.32
a_{34}	1.7	1.51	1.61	1.63	1.86	1.72	1.81	1.77	1.46	1.75	1.68

V. Establish judgment matrix of key aspect (for each decisional criteria)

To form the matrix of traveler's response (*TR*), the following procedure can be conducted:

Step 1: Conduct travel survey

Four stated preference travel surveys had been undertaken in 2011 (as discussed earlier) in order to model the mode choice decision of travelers. These surveys aim to identify and analyze the preference of travelers towards the ground transport (bus, car and train) and air transport (FSC and LCC). These surveys are denoted as y_1, y_2, y_3 and y_4 for local leisure trip, local business trip, trans-border leisure trip and trans-border business trip, respectively. Generally, the operating networks of airlines can be categorized as short-haul and medium/long-haul networks. In such a case, local leisure trip (y_1) and local business trip (y_2) as domestic flights are classified as short-haul network (Net_1) while trans-border leisure trip (y_3) and trans-border business trip (y_4) are included for medium/long-haul network (Net_2). These networks are then utilized to evaluate the ratio of key aspect, s_k (as described further in

Step 3).

Step 2: Conduct mode choice modeling

The response of travelers via travel surveys (input) are then adopted to generate the mode choice modeling models (output). The results of mode choice analysis are summarized in Table 4.11.

Table 4.11: The Modeling Results of Travel Survey

Network	Short-haul network, Net_1		Medium/long-haul network, Net_2	
Attribute	Local leisure trip, y_1	Local business trip, y_2	Trans-border leisure trip, y_3	Trans-border business trip, y_4
Mode choice of trip	36.5550	38.3150	18.4300	34.0850
Average mode choice	37.4350		26.2575	

Step 3: Evaluate the ratio of key aspect to form judgment matrix, B_{TR}

As shown in Table 4.12, the mode share of respective network which correspond to the aspect of operational (s_1), economy (s_2) and environmental (s_3) of airlines are evaluated accordingly to compare with the respective key aspect. To do this, the relevant components of each key aspect, $F_{s_k}^{w}$ are taken into account to assess the relationship of the operating networks, Net_d and corresponding aspect, s_k. As mentioned earlier, the relevant components of operational aspect (s_1) of airlines may refer to several perspectives, including the number of passengers carried and the load factor in servicing operating networks. On the other hand, the economy aspect of airlines (s_2) may cover numerous components, including the operating revenue and available capacity (seats) while the environmental aspect (s_3) captures the fuel consumption of airline in response to fuel efficiency of the operating networks. The data of these aspects are compiled based on the operating performance of Malaysia Airlines (Malaysia Airlines, 2010a). The evaluation of the ratio of respective key aspect is shown in Table 4.12.

Table 4.12: The Evaluation of the Ratio of Key Aspect (For Traveler's Response)

		Key aspect s_1 (operational)		Key aspect s_2 (economy)		Key aspect s_3 (environmental)
Operating network	Average mode choice	Load factor, $F_{S_1}^1$	Passengers carried, $F_{S_1}^2$	Revenue passenger kilometers (RPK), $F_{S_2}^1$	Available seats kilometers (ASK), $F_{S_2}^2$	Fuel efficiency, $F_{S_3}^1$
Short-haul, Net_1	37.4350	50%	45%	10%	10%	68%
Medium/long-haul, Net_2	26.2575	50%	55%	90%	90%	32%
$\sum Net_d F_{S_k}^w$		63.1336		54.7505		33.8582
Ratio of key aspect		$s_1 : s_2 = 1.15,\ s_1 : s_3 = 1.86,\ s_2 : s_3 = 1.62$				

By having the ratio of key aspect, the judgment matrix of travelers' response, B_{TR} could be formed as follows:

$$B_{TR} = \begin{bmatrix} 1 & 1.15 & 1.86 \\ 0.87 & 1 & 1.62 \\ 0.54 & 0.62 & 1 \end{bmatrix}_{3\text{x}3}$$

As mentioned earlier, there are three more decisional criteria, i.e. decision policy of airline (*DP*), consultancy of experts (*CE*) and past performance of airline (*PP*). The judgment matrices of these decisional criteria are assumed to be as follows (due to the lack of accessible data):

$$B_{DP} = \begin{bmatrix} 1 & 1 & 3 \\ 1 & 1 & 2 \\ 1/3 & 1/2 & 1 \end{bmatrix}_{3x3}, B_{CE} = \begin{bmatrix} 1 & 1 & 3 \\ 1 & 1 & 2 \\ 1/3 & 1/2 & 1 \end{bmatrix}_{3x3}, B_{PP} = \begin{bmatrix} 1 & 1 & 3 \\ 1 & 1 & 2 \\ 1/3 & 1/2 & 1 \end{bmatrix}_{3x3}$$

By carrying out consistency test, the consistency of these matrices were confirmed because $CR < 0.1$ for all matrices.

At the final stage (stage 3), the respective probability of key aspect is summarized in Table 4.13. Table 4.13 shows that the probability of the key aspect are $p_{s_1} = 0.4374$, $p_{s_2} = 0.3821$ and $p_{s_3} = 0.1805$ for the aspects of operational, economy and environmental, respectively. Practically, $p_{s_1} = 44\%$ signifies the likelihood of aircraft possession (via acquisition or leasing) in accordance to the operational aspect of airlines (s_1) while its complement, i.e. $p_{s_2} = 38\%$ and $p_{s_3} = 18\%$ refer to the probability of aircraft possession by taking into account the aspect of economy (s_2) and environmental (s_3). Note that $\sum_{\forall i} p_{S_i} = 1$ and this implies 100% of the full (complete) decision-making of airlines in fleet planning.

Table 4.13: The Evaluation of Key Aspect in Fleet Planning

Key aspect	Decisional criteria				Probability
	DP (0.1977)	*CE* (0.2630)	*PP* (0.3396)	*TR* (0.1997)	
Operational, s_1	0.4429	0.4429	0.4429	0.4154	0.4374
Economy, s_2	0.3873	0.3873	0.3873	0.3614	0.3821
Environmental, s_3	0.1698	0.1698	0.1698	0.2232	0.1805

4.3.4 An Application in Solving Fleet Planning Problem

In such a complicated air transportation system, airlines encounter many challenging unexpected events which are unpredictable in nature. In accordance to the occurrence of unexpected events (risks), an efficient fleet planning is necessary. As such, the probable phenomena, $s_1,...,s_k$ for a total of k phenomena are defined to describe the possible key aspect of aircraft possession in meeting stochastic demand under uncertainty. The probability of probable phenomena, $p_{s_1},...,p_{s_k}$ quantifies the likelihood (probability) of respective key aspect (determinant) in making fleet planning decision via aircraft acquisition/leasing. In other words, they define how the fleet supply (aircraft composition) is made to meet travel demand. Preferably, the quantity of aircraft should be available adequately (at a right time) for a strategic fleet planning decision. If probable phenomena and its probability are not defined, it means that airlines only deals with one possible aspect to meet stochastic demand, i.e. they have perfect confidence that a certain level of stochastic demand will be met by considering a single aspect only. However, this should not be the case because the actual decision-making process is subject to multiple criteria (aspects). Furthermore, the decision-making may vary from time to time under uncertainty. As such, this indicator is necessary in fleet planning. The number of probable phenomenon varies depending on the perception and consideration of airlines. In this research, three key aspects (probable phenomena), namely operational, economy and environmental are considered.

4.3.5 Fleet Planning Decision Model

In general, the airline's profit is contributed by the total revenue and the total operating cost. For operating period *t*, the total revenue, $TR(I_t^P + I_t^L)$ can be expressed as follows:

$$TR\left(I_t^P + I_t^L\right) = E\left(fare_t^S\right)D_t^S + \sum_{i=1}^{n}\sum_{y=1}^{m} sold_{tiy} resale_{tiy} \text{ for } t = 1,\dots,T; S = s_1,\dots,s_k \tag{4.17}$$

For Equation (4.17), the first term on the right-hand side indicates the expected income from the sales of flight tickets while the second term denotes the revenue from the sales of aging aircraft.

On the other hand, the total operating cost, $TC(I_t^P + I_t^L)$ of airlines can be formed as follows:

$$\begin{aligned} TC\left(I_t^P + I_t^L\right) = {} & E\left(\cos t_t^S\right)D_t^S + \sum_{i=1}^{n} u_{ti} + \left(purc_{ti}\right)\left(x_{ti}^P\right) + \sum_{i=1}^{n} lease_{ti}\left(x_{ti}^L\right) + \sum_{i=1}^{n} hgf\left(D_t^S, A_t^i\right) + \sum_{i=1}^{n}\sum_{y=1}^{m}\left(I_{tiy}^P\right)\left(dep_{tiy}^P\right) + \\ & \sum_{i=1}^{n}\sum_{y=1}^{m}\left(I_{tiy}^L\right)\left(dep_{tiy}^L\right) + \sum_{i=1}^{n} dp_{ti}\left(x_{ti}^P\right) + \sum_{i=1}^{n} dl_{ti}\left(x_{ti}^L\right) + \sum_{i=1}^{n} C\left(fuel_{ti}\right) \text{ for } t = 1,\dots,T; S = s_1,\dots,s_k \end{aligned} \tag{4.18}$$

The terms on the right-hand side of Equation (4.18) signify the expected cost of flight, aircraft purchase cost, lease cost, maintenance cost, depreciation expenses, payable deposit of aircraft acquisition/leasing and fuel expenses, respectively.

In summary, fleet planning model of airlines of operating period $t=1,\ldots,\ T$ can be presented as follows:

$$P\left(I_t^P+I_t^L\right)=\max_{X_t}\frac{1}{\left(1+r_t\right)^t}\left\{\begin{array}{l} p_{s_1}\left(TR\left(I_t^P+I_t^L\right)-TC\left(I_t^P+I_t^L\right)\right)+\ldots \\ +p_{s_k}\left(TR\left(I_t^P+I_t^L\right)-TC\left(I_t^P+I_t^L\right)\right)+P_{t+1}\left(I_t^P+I_t^L\right)\end{array}\right\} \tag{4.19}$$

subject to:

Budget constraint: $\sum_{i=1}^{n} purc_{ti}x_{ti}^P+\sum_{i=1}^{n} lease_{ti}x_{ti}^L\leq MAX_{budget(t)}$ (4.20)

Demand constraint: $\sum_{i=1}^{n}\left(SEAT_i^t\right)\left(f\left(D_t^S,A_t^i\right)\right)\geq\left(1-\alpha\right)D_t^S$ (4.21)

Sales of aircraft constraint: $sold_{tiy}\leq I_{(t-1)i(y-1)}^P$ (4.22)

Lead time constraint: $DLT_{ti}\geq F^{-1}\left(1-\beta\right)\sigma_{LT}+\mu_{LT}$ (4.23)

Selling time constraint: $DST_{ti}\geq F^{-1}\left(1-\gamma\right)\sigma_{ST}+\mu_{ST}$ (4.24)

where $D_t^S,X_t^P,X_t^L,I_t^P,I_t^L,SOLD_t,O_t,R_t\in Z^+\cup\left\{0\right\}$. For model (4.19), budget constraint ascertains whether if the solution is financially feasible for airlines while demand constraint ensures that travelers' demand could be met satisfactorily. The constraint of sales of aircraft ensures that the quantity of aircraft sold is not more than the aircraft owned by airlines. Lead time constraint and selling time constraint respectively indicate when airlines are supposed to order new aircraft and release aging aircraft for sales. The term $\left(1+r_t\right)^{-t}$ is used for discounted value across the planning horizon while p_{s_k} indicates the probability of *k*-th probable phenomenon for having I_t^P and I_t^L as initial fleet supply (aircraft possession). Specifically, the element of p_{s_1}, p_{s_2} and p_{s_3} respectively signifies the probability of operational, economy and environmental aspect of airlines in making strategic fleet planning decision.

Mathematically, the developed optimization model, in the form of probabilistic dynamic programming model, can be solved by decomposing it into a series of simpler sub-problems by using backward workings mechanism.

4.3.6 Data Description

A case study consisting of three types of aircraft, i.e. A320-200, A330-300 and B737-800 are considered for a set of OD pairs for a planning horizon of eight years. Most of the data are compiled based on the available reports (AirAsia Berhad, 2010a; Malaysia Airlines, 2010a; Airbus, 2010a, 2010b, 2010c; Boeing, 2012). For each operating period, the level of stochastic demand is obtained by applying the 5-step modeling framework of stochastic demand. Based on the AHP modeling framework, the probability of key aspects (for the benchmark scenario) are $p_{s_1} = 0.4374$, $p_{s_2} = 0.3821$ and $p_{s_3} = 0.1805$ for the aspect of operational, economy and environmental, respectively. The data input of benchmark scenario are listed as follows:

- Three probable phenomena are considered, i.e. $k = 3$
- At t = 1, quantity of aircraft is $I_{11}^{P} = I_{12}^{P} = I_{13}^{P} = 35$ and $I_{11}^{L} = I_{12}^{L} = I_{13}^{L} = 0$
- At t = 1, quantity of aircraft to be three years old is $I_{113}^{P} = I_{123}^{P} = I_{133}^{P} = 3$
- Budget, $MAX_{budget(t)} = \$6,500$ million
- Discount rate, $r_t = 5\%$
- Significance level of demand constraint, $\alpha = 5\%$

- Significance level of lead time constraint, $\beta = 5\%$
- Significance level of selling time constraint, $\gamma = 5\%$
- Deposit of aircraft acquisition, $DP_t = 10\%\left(purc_{tn}\right)$
- Deposit of aircraft leasing, $DL_t = 10\%\left(lease_{tn}\right)$
- Setup cost, $u_{ti} = 0$
- $D_t^{s_1} = D_t,\ D_t^{s_i} = \left(1-\alpha\right)D_t^{s_{i-1}},\ i = 2,\ 3,..,\ k$ (4.25)
- The function of number of flights is

$$f = 22.57\left(A_t^n\right)^2 - 9.776\text{x}10^2 A_t^n + 7.83\text{x}10^4 \ [\text{R}^2 = 0.97] \quad (4.26)$$

- The function of traveled mileage is

$$g = 2{,}066 f - 2{,}875{,}383 \ [\text{R}^2 = 0.83] \quad (4.27)$$

- The function of maintenance cost is

$$h = 5.177\text{x}10^3 + 7.97\text{x}10^{-3} g \ [\text{R}^2 = 0.94] \quad (4.28)$$

- The function of fuel expenses is

$$C\left(fuel_{tn}\right) = 7.46 f + 8.3\text{x}10^{-5} f^2 - 98{,}572 \quad [\text{R}^2 = 0.88] \quad (4.29)$$

- The quantity of aircraft is

$$NA = 10^{-5} NP - 73.6 \ [\text{R}^2 = 0.92] \quad (4.30)$$

where *NP* is the number of travelers.

In addition to benchmark scenario, two more scenario (as shown in Table 4.14) are examined for further analysis to inspect relevant influential input in generating strategic fleet planning decision.

Table 4.14: Further Analysis in Solving Fleet Planning Problem

Scenario	Decisional criteria	Description	Judgment matrix
P	Decision policy (*DP*)	The adjustment on the relative comparison of key aspect is done in the form as follows: environmental $\geq$ operational $\geq$ economy	$B_{DP} = \begin{bmatrix} 1 & 2 & 1 \\ 1/2 & 1 & 1/3 \\ 1 & 3 & 1 \end{bmatrix}_{3x3}$
Q	Travelers' response (*TR*)	The change of travelers' response is investigated towards travel cost reduction strategy. According to mode choice analysis, the mode share was found to increase 18.39% in response to the strategy of airline (AirAsia) in reducing 50% of travel cost (airfare).	$B_{TR} = \begin{bmatrix} 1 & 1.02 & 1.98 \\ 0.98 & 1 & 1.94 \\ 0.51 & 0.52 & 1 \end{bmatrix}_{3x3}$
Note: For the relative comparison of key aspect, the benchmark scenario is outlined in such a way as follows: operational $\geq$ economy $\geq$ environmental			

Specifically, scenario P focuses on the changes of decision policy (DP) of airline, i.e. from the aspect of supply. By allocating different weight (priority) on operational, economy and environmental aspect in such a way that the environmental aspect gains the highest concern (priority) in terms of the decision policy of airline, followed by operational and economy aspects, scenario P inspects not only the possible variation on the probability of the respective key aspect (operational, economy and environmental) but also the possible changes of decision-making in fleet planning. It is anticipated that the resultant outputs are driven by the weight allocation of airline based on the relevant decision policy (i.e. an influential decisional criteria in fleet planning). Scenario Q inspects the perspective of demand in terms of the changes of travelers' response (TR). By capturing the possible changes of mode choice decision of travelers towards the services of airlines (i.e. travel cost reduction), scenario Q inspects the impacts of demand level (in terms of choice probability) in fleet planning, i.e. by quantifying the possible probability of operational, economy and environmental aspects that could affect fleet planning decision greatly. Specifically, traveler's response could be compiled by undertaking various travel survey on the respective operating networks (short-haul and medium/long-haul). It is anticipated that scenarios P and Q would capture the supply-demand interaction in a greater and better manner.

4.3.7 Results and Discussion

4.3.7.1 Benchmark Problem versus Scenario P

The results of the case study are shown in Table 4.15 and 4.16 (with the graphical results as displayed in Figure 4.4). The results imply that the decisional criteria could affect the probability of the key aspects (operational, economy and environmental), optimal profit of airline as well as fleet planning decision-making. From the results of the benchmark scenario, it could be seen that the relative comparison of key aspect for decisional criteria tends to produce the probability of key aspect in about the same way. This could be seen in Tables 4.14 and 4.15 for which the judgment matrix of benchmark scenario which has the relative comparison of the key aspect in the form of operational $\geq$ economy $\geq$ environmental would produce the probability of key aspect in similar way, i.e. probability of operational aspect $\geq$ probability of economy aspect $\geq$ probability of environmental aspect. Some changes to the probability of key aspect could be seen in scenario P for which the adjustment of the relative comparison of key aspect has been done with regard to the decision policy of airline (while other decisional criteria remain unchanged). Scenario P was outlined by putting more weight (relative comparison) on environmental aspect instead of operational and economy aspect. Subsequently, the results in Table 4.15 show that the probability of environmental aspect increases about 30% while the probability of operational and economy aspects decreases (compared to benchmark scenario). However, the probabilities of operational and economy aspects are still higher compared to environmental aspect. This happens because the resultant probability of key aspect is affected not only by the decision policy of airlines but also other decisional criteria. This signifies that the decisional criteria of fleet planning have a direct and influential impact on the resultant probability of the key aspect which would subsequently constitute an optimal solution of airline. Generally, the results confirm that there's a linkage between the decisional criteria and the probability of key aspect as well as the optimal solution of the fleet planning model. Therefore, the key aspect in fleet planning has to be quantified wisely.

Table 4.15: The Results of Fleet Planning Model

Scenario	Probability of key aspect			Average profit ($ millions)
	Operational	Economy	Environmental	
Benchmark	0.4374	0.3821	0.1805	309
P	0.4264 (-3%)	0.3391 (-11%)	0.2345 (+30%)	302 (-2.3%)
Q	0.4348 (-1%)	0.3887 (+2%)	0.1765 (-2%)	395 (+27.8%)

Note: The value in bracket denotes the improvement level compared to the benchmark scenario.

Table 4.16: The Results of Fleet Size

Aircraft	Purchase/lease	Benchmark scenario	Scenario P	Scenario Q
A320 -200	Purchase	37	37	38
	Lease	6	6	8
A330 -300	Purchase	34	34	34
	Lease	7	6	8
B747 -800	Purchase	33	32	35
	Lease	5	7	7
Total fleet size (by year 8)		122 (purchase:104, lease:18)	122 (purchase:103, lease:19)	130 (purchase:107, lease:23)

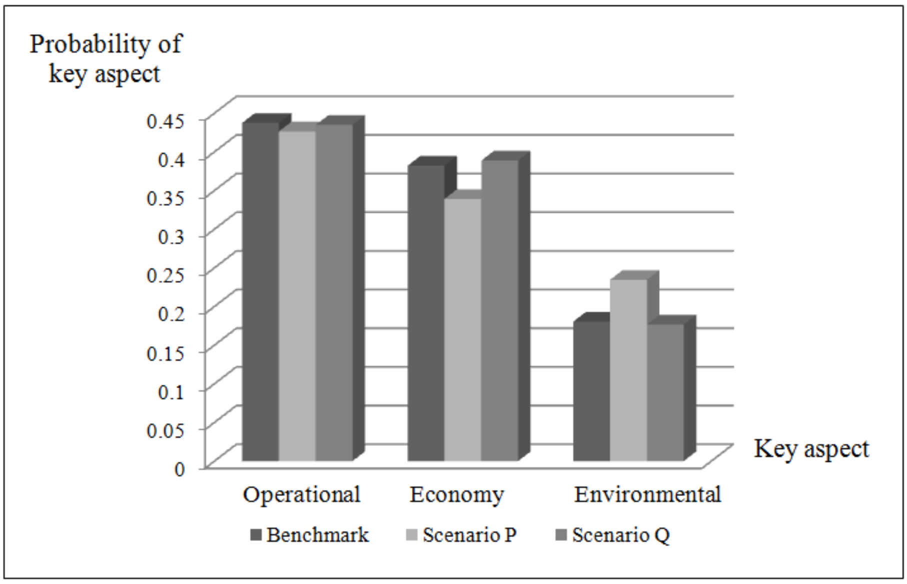

Figure 4.4: The Graphical Results of the Probability of Key Aspects

In terms of the profit level of airline, Table 4.15 shows that the benchmark scenario produces a higher profit than scenario P (in average). It could be seen that the average profit of airline decreases 2.3% (about $7 millions) when the probability of operational and economy aspects decreases (for scenario P). Thus, it could be deduced that a higher concern (or relative comparison) on operational and economy aspects tends to produce a higher profit. This could be explained by the fact that the operational aspect of airline plays a vital role to generate income and optimal profit in meeting travel demand. Therefore, this aspect is more revenue-sensitive (from the economy aspect) and hence it would impact the average profit level at a larger scale (compared to the environmental aspect). Generally, the findings show that instead of the environmental aspect, the operational and economy aspects should be the two major considerations in fleet planning. This is in line with the practice of airlines (AirAsia Berhad, 2010a; Malaysia Airlines, 2010a). In overall, the findings suggest the airline to allocate more weight (probability) on operational aspect to assure optimal profit. At the same time, the aspect of economy and environmental should be weighted appropriately for a better financial performance. Desirably, the relative comparison of the key aspect should assign the highest concern on the operational aspect, followed by economy and environmental aspect.

In terms of the fleet size as displayed in Table 4.16, it could be seen that the resultant probability of the key aspect would affect the decision-making of aircraft acquisition and leasing. Although with similar fleet size, Table 4.16 shows that benchmark scenario tends to acquire (purchase) new aircraft to meet travel demand while scenario P shows a tendency to lease aircraft rather than purchasing new aircraft. This could be explained by the average profit of scenario P which tends to be lower. In such a case, airline would opt to lease aircraft rather than purchasing new aircraft (with a much higher acquisition cost). This shows that the decisional criteria which associate closely with the probability of key aspect could make a difference in fleet planning.

4.3.7.2 Benchmark Problem versus Scenario Q

For scenario Q, the results in Table 4.15 show that travelers' response towards the strategy of travel cost reduction could affect the probability of key aspect in making the fleet planning decision. With this strategy, the probability of economy aspect was found to increase approximately 2% while the probability of operational and environmental aspects decrease 1% and 2%, respectively. This signifies that the travel cost reduction strategy is more sensitive to the economy aspect of airline. This happens primarily due to the monetary concern in terms of the financial management of airlines. In such a case, the probability of economy aspect increases. Correspondingly, the operational and environmental aspect in accordance to the travel cost reduction strategy would also be impacted. The change of probability on operational aspect was found to be minimal while the probability of environmental aspect decreases 2%. This could be justified by the fact that the mode share increment of airline (due to the travel cost reduction strategy) would require more necessary operational and economical adjustments (i.e. both are vital elements) instead of environmental aspect and hence the operational aspect retains about the same probability (with such a minimal change) compared to the environmental aspect. Comparatively, the operational aspect still emerges with the highest probability and hence its significance in scenario Q could be empirically confirmed. This finding is coherent with the practice of airlines for which Malaysia Airlines (2013) revealed that to increase mode share (i.e. to meet more sales target) effectively, there is a need to manage operational costs better by improving airline's productivity in both people and processes (which could be directly or indirectly related to aircraft operations). Some of the operative efforts that have been implemented by airlines to increase mode share are effective delay reduction, boarding management, baggage handling and upgrading of internet booking system (Malaysia Airlines, 2013; AirAsia Berhad, 2013).

In terms of the profit level of scenario Q, the results as displayed in Table 4.15 show that the strategy of travel cost reduction would increase the average profit by 28% compared to the benchmark scenario. Approximately, this would contribute about $86 millions for each operating year. This shows that travelers' response towards the travel cost reduction which contributed to a higher mode share would subsequently produce a higher profit for airline. Besides, the results in Table 4.16 reveal that a higher profit of airline generates a greater flexibility for them in acquiring and leasing new aircraft. This explains the fleet size of scenario Q which comprises about 7% more aircraft compared to the benchmark scenario. All in all, it could be deduced that travelers' response as one of the decisional criteria has influential impacts in making the fleet planning decision. Therefore, the probability of key aspect which is greatly affected by the decisional criteria in fleet planning has to be quantified appropriately.

4.3.8 Summary

This research developed a novel methodology to integrate the Analytic Hierarchy Process and mode choice modeling to quantify the likelihood of key aspect in making the optimal fleet planning decision. The developed methodology is very useful in solving fleet planning problem by assuring an adequate supply to meet stochastic demand. The results of an illustrative case study, focusing on the key aspect of operational, economy and environmental, demonstrated that the developed methodology (embedded with mode choice analysis) is practically viable in providing an optimal profit in fleet planning. Besides, the findings reveal that the optimal profit and fleet planning decision are influenced greatly by influential decisional criteria which associates closely with the probability of key aspects (i.e. operational, economy and environmental). By properly incorporating the mode choice analysis in fleet planning model, the developed approach enables airlines to capture the supply-demand interaction in a better manner as well as in greater detail.

CHAPTER 5

OPTIMAL FLEET PLANNING WITH SLOT PURCHASE

5.1 Slot Purchase and Fleet Planning Decision-Making

In order to attain a desired service frequency particularly to meet increasing demand, airlines need to purchase new slots under certain circumstances. This happens mainly due to the strictly regulated aircraft operations at some airports. In view of a closed relation between the service frequency and fleet supply of airlines, the slot purchase decision-making needs to be incorporated necessarily in solving the fleet planning problem of airlines. To do this, two-stage fleet planning decision model (as shown in Figure 5.1) is formulated for which the first stage (stage 1), i.e. slot purchase decision model (SPDM) plays the role to select the operating route (flight) that qualifies for slot purchases while the subsequent stage (stage 2), i.e. fleet planning decision model (FPDM) solves the fleet planning problem of airlines optimally in the form of probabilistic dynamic programming model. Specifically, SPDM in stage 1 selects the qualified operating route optimally based on the maximum revenue which is contributed directly by the airfare of specific passenger's class (business and economy). The resultant service frequency and revenue from SPDM in stage 1 is captured subsequently in making optimal fleet planning decision in the next stage (stage 2). To solve FPDM in stage 2, aircraft acquisition and leasing decision is made based on optimal profit produced by the current operating networks (under stochastic demand). The decision variables of FPDM (in stage 2) are optimal quantity of respective aircraft type that is to be purchased/leased given that slot purchase of a particular operating route is selected optimally (in stage 1). In stage 2, although the state variables and the corresponding optimal solutions (including service frequency of each operating route) of a particular operating period could be obtained, the optimal decision for the next operating period is unknown due to uncertainty, i.e. many factors may not be known with certainty in practice (Taha, 2003; Winston, 2004).

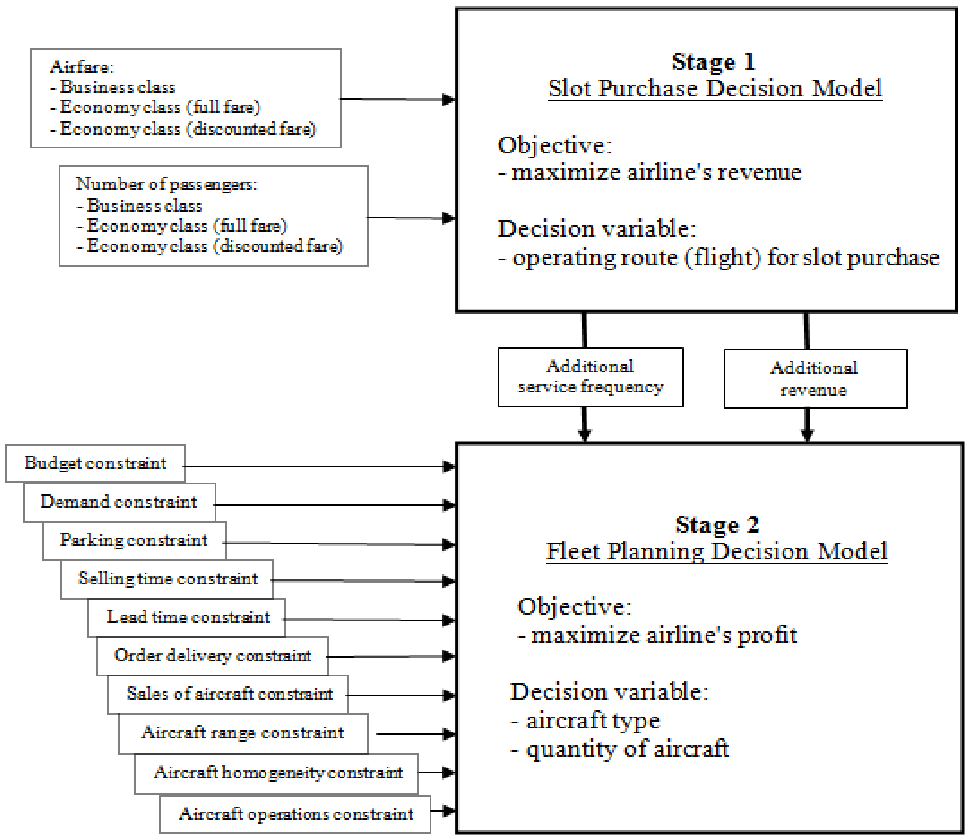

Figure 5.1: Two-stage Fleet Planning Decision Model

5.2 Stage 1: Slot Purchase Decision Model (SPDM)

5.2.1 Constraints

Three practical constraints that are required to be considered necessarily in making an optimal slot purchase decision are listed as follows:

Slot purchase budget constraint In order to ensure that slot purchase is financially feasible for airlines, the slot price of a particular operating route (flight) should not be more than the willingness to pay of airlines. Slot price as well as airline's willingness to pay are greatly affected by numerous factors, including aircraft operation time (for arrival/departure), airline regulation, demand level, etc. (Gillen, 2006). Depending on airline's allocated budget, this constraint can be formed as follows:

$$C_{F_i} \leq W_{F_i} \text{ for } F_i \in F_{ex} \tag{5.1}$$

Slot determination constraint In view that slot purchase is needed primarily to support increasing demand which is stochastic in nature, the respective operating route that qualifies as slot purchase (to be decided for slot purchase decision) should be taken into consideration not only based on the level of increasing demand but also on airline's current fleet supply in order to meet stochastic demand desirably. Thus, slot determination constraint could be formed as follows:

$$F_i = \begin{cases} 1, \left(D_{t,F_i} > D_{t-1,F_i}\right) \cap \left(D_{t,F_i} \geq \sum_{i=1}^{n} \left(LF_{n,F_i}^{t-1}\right)\left(SEAT_{n,F_i}^{t-1}\right)\left(f_{n,F_i}\left(D_{t-1}^{S}, A_{t-1}^{i}\right)\right)\right) \\ 0, \text{otherwise} \end{cases}, \text{ for } F_i \in F_{ex} \tag{5.2}$$

for which $F_i = 1$ implies that operating route, F_i qualifies for slot purchase in view of the demand level of the current operating period, t is higher than the demand level of the previous operating period, $t-1$, i.e. demand increases in the current operating period. Comparatively, the current demand level must also exceed the airline's fleet supply (from previous operating period) to be qualified for slot purchase.

Aircraft execution constraint To ensure that the qualified operating route for slot purchase would be operated during airport working hours, the aircraft execution constraint could be formed as follows:

$$open \leq TUN_{n,F_i,k}^{t} + BLK_{n,F_i}^{t} + TUN_{n,F_i,m}^{t} + BLK_{n,F_i}^{t} + TUN_{n,F_i,k}^{t} \leq close \text{ for } \forall n, k, m, F_i \in F_{ex} \tag{5.3}$$

This constraint is important mainly due to prior approval (permission) of aircraft operations at some airports, especially when the aircraft arrival or departure needs to be made before or after standard operation hours at the airport.

5.2.2 Problem Formulation

To make an optimal slot purchase decision, the airfare of each passenger’s class (i.e. business class, economy class with full fare and discounted fare) is considered specifically with the aim to maximize the operational revenue of a particular operating route under stochastic demand. For airlines, slot purchase is required particularly to meet demand increment. Therefore, the objective of slot purchase decision model (SPDM) in maximizing airline's operational revenue could be formed as follows:

$$R_{t,F_i} = \underset{F_i \in F_{ex}}{Max} \frac{1}{\left(1+r_t\right)^t} \left\{ c_{biz,F_i} \left(\Delta p^*_{biz,F_i}\right) + c_{fec,F_i} \left(\Delta p^*_{fec,F_i}\right) + c_{dec,F_i} \left(\Delta p^*_{dec,F_i}\right) \right\} \quad (5.4)$$

for which it is estimated that $\Delta p^*_{biz,F_i} = Biz_{\%} \left(D^*_{t,F_i}\right)$, $\Delta p^*_{fec,F_i} = Fec_{\%} \left(D^*_{t,F_i}\right)$ and $\Delta p^*_{dec,F_i} = Dec_{\%} \left(D^*_{t,F_i}\right)$ to be the respective demand level of each passenger's class (business class, economy class with full fare and discounted fare) that to be met by making optimal slot purchase decision (with discount rate r_t). For different passenger's class, demand increment that to be supported by new slot (via optimal slot purchase decision) is estimated to be $D^*_{t,F_i} = D_{t,F_i} - D_{t-1,F_i}$ by considering the demand level of two consecutive operating periods. Specifically, the demand level of a particular operating period *t* could be obtained accordingly based on the 5-step stochastic demand modeling framework.

In overall, the developed slot purchase decision model (SPDM) could be formed as follows:

$$R_{t,F_i} = \underset{F_i \in F_{ex}}{Max} \frac{1}{\left(1+r_t\right)^t} \left\{ c_{biz,F_i} \left(\Delta p^*_{biz,F_i} \right) + c_{fec,F_i} \left(\Delta p^*_{fec,F_i} \right) + c_{dec,F_i} \left(\Delta p^*_{dec,F_i} \right) \right\} \tag{5.5}$$

Subject to:

$$C_{F_i} \le W_{F_i} \text{ for } F_i \in F_{ex} \tag{5.6}$$

$$F_i = \begin{cases} 1, \left(D_{t,F_i} > D_{t-1,F_i} \right) \cap \left(D_{t,F_i} \ge \sum_{i=1}^{n} \left(LF^{t-1}_{n,F_i} \right) \left(SEAT^{t-1}_{n,F_i} \right) \left(f_{n,F_i} \left(D^S_{t-1}, A^i_{t-1} \right) \right) \right), & \text{for } F_i \in F_{ex} \\ 0, \text{otherwise} & \end{cases} \tag{5.7}$$

$$open \le TUN^t_{n,F_i,k} + BLK^t_{n,F_i} + TUN^t_{n,F_i,m} + BLK^t_{n,F_i} + TUN^t_{n,F_i,k} \le close \text{ for } \forall n,k,m,F_i \in F_{ex} \tag{5.8}$$

By solving model (5.5), the airline would be able to select the optimal operating route that requires slot purchase to meet demand increment. Correspondingly, the optimal revenue and additional service frequency produced by the optimal operating route (via slot purchase decision) could be obtained.

Specifcally, the kind of slot purchase decision model that should be used for fleet planning is the one that should assure that the increment of stochastic demand could be met by the airline by having an adequate fleet composition (with the corresponding service frequency). In view of the fact that supply and demand emerge to be the central elements in fleet planning, this kind of slot purchase decision model should relate demand-supply perspective closely by fully utilizing the fleet composition of the airline (to meet demand increment). Besides, this kind of slot purchase decision model should assure the operational and economic sustainability of the airline (via the formulation of the objective function and practical constraints). This could assist the airline to make optimal fleet planning profitably and hence lead it to a greater flexibility in providing more service frequency to meet demand increment. Furthermore, the developed slot purchase decision model is of the kind that should relate aircraft-airport interaction to a great extent for which all servicing airports (including hub airports) which operate directly with the airline (with the respective aircraft type) are considered completely. In other words, the developed model should be applied flexibly to obtain more slots at desired airports (not limited to hub airports) so that the demand increment of the respective operating route could be met desirably. By having this in place, the developed slot purchase decision model would ensure that the fleet planning of the airline is to be made feasibly to serve the optimal operating route.

Therefore, the slot purchase decision model (5.1)-(5.8) developed is suitable for fleet planning because it could:

- assure that the increment of stochastic demand could be met by the airline by having an adequate fleet composition (with optimal fleet planning decision)
- relate demand-supply perspective closely by fully utilizing the fleet composition of the airline (to meet demand increment)
- assure the operational and economic sustainability of the airline (via the formulation of the objective function and practical constraints)

- relate aircraft-airport interaction to a great extent for which all servicing airports (including hub airports) which operate directly with the airline (with the respective aircraft type) are considered completely, i.e. the developed model could be applied flexibly to obtain more slots at desired airports (not limited to hub airports) so that the demand increment of the respective operating route could be met desirably.

By having these characteristics in place, it can be deduced that the developed slot purchase decision model is suitable to support the fleet planning analysis (in comparison to the existing studies) in view of the crucial elements to make an optimal fleet planning, i.e. demand, supply and sustainability, have been capture explicitly.

5.3 Stage 2: Fleet Planning Decision Model (FPDM)

5.3.1 Constraints

Ten practical constraints are considered necessarily to solve the fleet planning problem. These constraints are listed as follows:

Aircraft operations constraint In compliance to regulated traffic rights/approvals particularly at some airports, the aircraft operations of airlines are strictly under control, i.e. the service frequency of airlines cannot exceed a certain limit. Under this circumstance, the actual aircraft utilization of airlines (subject to maximum utilization) of each operating route can be expressed as follows:

$$\left\lfloor \frac{AVT_{n,F_i}^{t}}{BLK_{n,F_i}^{t} + TUN_{n,F_i,k}^{t}} \right\rfloor \text{ x } EFF_t \leq MXU_{n,F_i}^{t} + Af_{n,F_i}^{t} \text{ for } \forall t, n, k, F_i \in F_{ex} \qquad (5.9)$$

Note that the sum of block time, BLK_{n,F_i}^{t} and turn round time, $TUN_{n,F_i,k}^{t}$ is also known as elapsed time. For Equation (5.9), the left-hand side denotes the actual aircraft utilization within a particular duration (e.g. one year) which is greatly affected by aircraft availability, AVT_{n,F_i}^{t} (i.e. total number of operating days in a given period) and also network efficiency factor, EFF_t which comprises numerous operating factors, including traffic rights, arrival/departure slot restriction, etc. Generally, the actual aircraft utilization would be higher if the elapsed time could be reduced or network efficiency factor and aircraft availability increases. The right-hand side shows that additional service frequency resulted from slot purchase decision, Af_{n,F_i}^{t} provides a greater control for airlines to provide more service frequency to meet stochastic demand. In case if slot purchase is not made, the total aircraft operations of airlines to service each operating route is not more than the permitted maximum service frequency, MXU_{n,F_i}^{t} for which $Af_{n,F_i}^{t} = 0$ in Equation (5.9).

Budget constraint Budget constraint ascertains whether if the solution is financially feasible for airlines for which the sum of purchase and lease cost of aircraft should not be more than the allocated budget for aircraft acquisition and leasing. This constraint could be expressed as follows:

$$\sum_{i=1}^{n} purc_{ti} x_{ti}^{P} + \sum_{i=1}^{n} lease_{ti} x_{ti}^{L} \leq MAX_{budget(t)} \text{ for } \forall t \tag{5.10}$$

Demand constraint In order to ensure that travel demand could be met satisfactorily at a desired level of service, the demand constraint could be expressed as follows:

$$\sum_{i=1}^{n} LF_{i,F_i}^{t} \left(SEAT_{i,F_i}^{t} \right) \left(f_{i,F_i} \left(D_t^S, A_t^i \right) \right) \geq \left(1-\alpha \right) D_t^S \text{ for } \forall t, s_k \in S, F_i \in F_{ex} \tag{5.11}$$

where $1-\alpha$ is airline's confidence level to meet stochastic demand, D_t^S (to be modeled by using 5-step demand modeling framework). Practically, Equation (5.11) assures that the service frequency of individual operating route, $f_{n,F_i}\left(D_t^S, A_t^i \right)$ that offers respective aircraft capacity (number of seats), $SEAT_{n,F_i}^{t}$ at load factor, LF_{n,F_i}^{t} is adequate sufficiently to support the current demand level.

Parking constraint When an aircraft is not in operation, it has to be parked at the hangar or apron of airport and hence the choice of aircraft would sometimes be constrained by the geometry layout of hangar/apron at the airport. In such a case, parking constraint is ought to be considered feasibly. This constraint is outlined as follows:

$$\sum_{i=1}^{n}\sum_{y=0}^{m}\left(I_{tiy}^{P}+I_{tiy}^{L}+x_{ti}^{P}+x_{ti}^{L}\right)\left(size_{i}\right)\leq PARK_{t}\ \text{for}\ \forall t \qquad (5.12)$$

Sales of aircraft constraint For some airlines, aging aircraft which is less cost-effective might be sold at the beginning of a certain operating period when airlines make decision to purchase new aircraft. However, the quantity of aircraft sold should not be more than the aircraft owned by airlines. This constraint can be expressed as follows:

$$sold_{tiy}\leq I_{(t-1)i(y-1)}^{P}\ \text{for}\ \forall t,y,i\in n \qquad (5.13)$$

Order delivery constraint The delivery of new aircraft relatively depends on the production and supply of aircraft manufacturers. Sometimes, there might be an issue on the availability and delivery of the new aircraft. As such, the aircraft to be purchased should not be more than the quantity of aircraft available in the market. This constraint can be expressed as follows:

$$x_{ti}^{P}\leq ORDER_{t}\ \text{for}\ \forall t,i\in n \qquad (5.14)$$

Aircraft range constraint For airlines, aircraft range refers to the maximum distance flown by the respective aircraft type. Aircraft range is crucial for consideration in view that the mileage (distance) of each operating route might vary differently. To assure operational feasibility is in practice, the aircraft range constraint could be formed as follows:

$$RG_i > DIS_{F_i} \text{ for } i \in n, F_i \in F_{ex} \tag{5.15}$$

Equation (5.15) signifies that the type of aircraft chosen by airlines must be practically feasible for which the choice of aircraft for operations must possess aircraft range which is greater than the distance of a particular operating route.

Aircraft homogeneity constraint In order to support the current operating networks, airlines tend to acquire/lease aircraft type based on aircraft homogeneity (standardization) in fleet composition, mainly due to various issues including aircraft maintenance, pilot employment, etc. There is a variety of aircraft type (with particular specification) which may practically be suitable to support airline's operating networks. By considering aircraft homogeneity in the fleet composition, the constraint to operate possible aircraft type can be formed as follows:

$$X_{ti}^{P}, X_{ti}^{L} \in FV_{ti} \text{ for } t, i \in n \tag{5.16}$$

where FV_{ti} is the existing variety of airline's fleet composition (with *n* types aircraft type) of operating period *t*.

Lead time constraint In practice, airlines would get an agreeable lead time (the period between placing and receiving order) from aircraft manufacturer when they place an order for a new aircraft. This constraint should be considered as it indicates when airlines are supposed to order new aircraft. For *n* types of aircraft, this constraint can be expressed as follows:

$$P\left(RLT_{ti} \geq DLT_{ti}\right) \leq \beta \text{ for } \forall t, i \in n \tag{5.17}$$

It is important to note that there are chances that the targeted lead time may vary and hence the lead time should be a random value that could be represented by a certain distribution. By assuming lead time is normally distributed with mean μ_{LT} and standard deviation σ_{LT}, the lead time constraint could be stated as follows:

$$DLT_{ti} \geq F^{-1}\left(1-\beta\right)\sigma_{LT} + \mu_{LT} \text{ for } \forall t, i \in n \tag{5.18}$$

where $F^{-1}(1-\beta)$ is the inverse cumulative probability of $1-\beta$.

Selling time constraint An aging aircraft which is considered as less economical might be sold by airlines in a particular operating period. In such a case, airlines need to know the most suitable time to release aging aircraft for sales particularly to look for prospective buyers in advance. However, real selling time might be longer than desired selling time. Therefore, the selling time constraint is formed with the aim to reduce the possibility of this incident as least as possible. This constraint can be outlined as follows:

$$P\left(RST_{ti} \geq DST_{ti}\right) \leq \gamma \text{ for } \forall t, i \in n \tag{5.19}$$

By assuming that selling time has a normal distribution with mean μ_{ST} and standard deviation σ_{ST}, selling time constraint could be formed by:

$$DST_{ti} \geq F^{-1}\left(1-\gamma\right)\sigma_{ST} + \mu_{ST} \text{ for } \forall t, i \in n \tag{5.20}$$

where $F^{-1}(1-\gamma)$ implies the inverse cumulative probability of $1-\gamma$.

5.3.2 Objective Function

The objective of the fleet planning decision model (FDPM) is to maximize airline's operational profit by determining the optimal quantity and type of aircraft that should be purchased/leased to meet stochastic demand. The operational profit of airline could be derived by considering the difference in the total operating cost and total revenue. For an airline, the total revenue is generated from operational income (i.e. the sales of flight tickets) and the sales of aging aircraft while the total operating cost is formed by operational cost, aircraft purchase/lease cost, maintenance cost, depreciation expenses, payable deposit of aircraft acquisition/leasing, fuel expenses and total slot price.

For operating period *t*, the total revenue, $TR\left(I_t^P + I_t^L\right)$ of airlines can be expressed as follows:

$$\begin{aligned} TR\left(I_t^P + I_t^L\right) = & \sum_{\forall F_i, \phi \in \Phi} c_{\phi,F_i}\left(\Delta p^*_{\phi,F_i}\right) f_{n,F_i}\left(D^S_{t,F_i}, A_t^i\right) + \\ & \sum_{i=1}^{n}\sum_{y=1}^{m} sold_{tiy} resale_{tiy} \ \text{ for } t, i \in n, F_i \in F_{ex}, s_k \in S \end{aligned} \tag{5.21}$$

The first term on the right-hand side of Equation (5.21) indicates the expected income from the sales of flight tickets by considering the service frequency of the respective route and the corresponding passenger's classification (business, economy with full fare and discounted fare). The second term signifies the revenue from the sales of aging aircraft. Note that if there is any slot purchase decision (at stage 1), the expected income of airline from the sales of flight tickets would increase due to additional service frequency permitted (via slot purchase).

The total operating cost, $TC\left(I_t^P + I_t^L\right)$ for operating period t, can be formed as follows:

$$TC\left(I_t^P + I_t^L\right) = \sum_{\forall F_i,\phi\in\Phi} v_{\phi,F_i}\left(\Delta p^*_{\phi,F_i}\right) f_{n,F_i}\left(D^S_{t,F_i}, A^n_t\right) + \sum_{i=1}^{n} u_{ti} + \left(purc_{ti}\right)\left(x^P_{ti}\right) + \sum_{i=1}^{n} lease_{ti}\left(x^L_{ti}\right) +$$
$$\sum_{i=1}^{n} hgf\left(D^S_t, A^i_t\right) + \sum_{i=1}^{n}\sum_{y=1}^{m}\left(I^P_{tiy}\right)\left(dep^P_{tiy}\right) + \sum_{i=1}^{n}\sum_{y=1}^{m}\left(I^L_{tiy}\right)\left(dep^L_{tiy}\right) + \sum_{i=1}^{n} dp_{ti}\left(x^P_{ti}\right) +$$
$$\sum_{i=1}^{n} dl_{ti}\left(x^L_{ti}\right) + \sum_{i=1}^{n} C\left(fuel_{ti}\right) + \sum_{F_i\in F_{ex}} C_{F_i} \text{ for } t, i \in n, F_i \in F_{ex}, s_k \in S \tag{5.22}$$

The terms on the right-hand side of Equation (5.22) denote the expected operational cost, aircraft purchase cost, lease cost, maintenance cost, depreciation expenses, payable deposit of aircraft acquisition/leasing, fuel expenses and total slot price, respectively.

5.3.3 Problem Formulation

Mathematically, the developed fleet planning decision model (FPDM) which is in the form of probabilistic dynamic programming model can be presented as follows:

$$
P\left(I_t^P+I_t^L\right)=\max_{X_t}\left(1+r_t\right)^{-t}\left\{
\begin{array}{l}
p_{s_1}\left(\begin{array}{l}
\sum_{\forall F_i,\phi\in\Phi} c_{\phi,F_i}\left(\Delta p^*_{\phi,F_i}\right)f_{n,F_i}\left(D^{s_1}_{t,F_i},A^n_t\right)+\sum_{i=1}^{n}\sum_{y=1}^{m} sold_{tiy}resale_{tiy}-\\
\sum_{\forall F_i,\phi\in\Phi} v_{\phi,F_i}\left(\Delta p^*_{\phi,F_i}\right)f_{n,F_i}\left(D^{s_1}_{t,F_i},A^n_t\right)-\sum_{i=1}^{n}u_{ti}+\left(purc_{ti}\right)\left(x^P_{ti}\right)-\\
\sum_{i=1}^{n}lease_{ti}\left(x^L_{ti}\right)-\sum_{i=1}^{n}hgf\left(D^{s_1}_t,A^i_t\right)-\sum_{i=1}^{n}\sum_{y=1}^{m}\left(I^P_{tiy}\right)\left(dep^P_{tiy}\right)-\\
\sum_{i=1}^{n}\sum_{y=1}^{m}\left(I^L_{tiy}\right)\left(dep^L_{tiy}\right)-\sum_{i=1}^{n}dp_{ti}\left(x^P_{ti}\right)-\sum_{i=1}^{n}dl_{ti}\left(x^L_{ti}\right)-\\
\sum_{i=1}^{n}C\left(fuel_{ti}\right)-\sum_{F_i\in F_{ex}}C_{F_i}
\end{array}\right)+\ldots+\\
p_{s_k}\left(\begin{array}{l}
\sum_{\forall F_i,\phi\in\Phi} c_{\phi,F_i}\left(\Delta p^*_{\phi,F_i}\right)f_{n,F_i}\left(D^{s_1}_{t,F_i},A^n_t\right)+\sum_{i=1}^{n}\sum_{y=1}^{m} sold_{tiy}resale_{tiy}-\\
\sum_{\forall F_i,\phi\in\Phi} v_{\phi,F_i}\left(\Delta p^*_{\phi,F_i}\right)f_{n,F_i}\left(D^{s_k}_{t,F_i},A^n_t\right)-\sum_{i=1}^{n}u_{ti}+\left(purc_{ti}\right)\left(x^P_{ti}\right)-\\
\sum_{i=1}^{n}lease_{ti}\left(x^L_{ti}\right)-\sum_{i=1}^{n}hgf\left(D^{s_k}_t,A^i_t\right)-\sum_{i=1}^{n}\sum_{y=1}^{m}\left(I^P_{tiy}\right)\left(dep^P_{tiy}\right)-\\
\sum_{i=1}^{n}\sum_{y=1}^{m}\left(I^L_{tiy}\right)\left(dep^L_{tiy}\right)-\sum_{i=1}^{n}dp_{ti}\left(x^P_{ti}\right)-\sum_{i=1}^{n}dl_{ti}\left(x^L_{ti}\right)-\\
\sum_{i=1}^{n}C\left(fuel_{ti}\right)-\sum_{F_i\in F_{ex}}C_{F_i}
\end{array}\right)+P_{t+1}\left(I_t^P+I_t^L\right)
\end{array}\right\}
\tag{5.23}
$$

The developed model is optimized subject to the practical constraints (5.9)-(5.16), (5.18) and (5.20) where D_t^S, X_t^P, X_t^L, I_t^P, I_t^L, $SOLD_t$, O_t, $R_t \in Z^+ \cup \{0\}$. The term $(1+r_t)^{-t}$ is used for the discounted value across the planning horizon while p_{s_k} indicates the probability of *k*-th probable phenomenon for having $I_t^P,\, I_t^L \in I_t$ as fleet supply (aircraft possession) in operation at the beginning of each operating period, i.e. this component is playing a vital role to ensure the adequacy of aircraft to service the current operating networks. The optimal decision (output) of the model are optimal quantity of the respective aircraft type to be acquired (via aircraft acquisition/leasing) to service each operating route. By solving this model optimally, the service frequency of each operating route (under stochastic demand) could also be determined strategically.

5.4 Solution Method

5.4.1 Stage 1: Slot Purchase Decision Model (SPDM)

With the aim to increase service frequency to meet stochastic demand, slot purchase decision model (SPDM), i.e. model (5.5) can be solved optimally based on the maximum revenue generated by individual operating route. In other words, among the potential operating routes that require slot purchase, the one which produces utmost revenue is selected optimally in making slot purchase decision (subject to practical constraints). It is important to note that the revenue of respective operating route (for slot purchase consideration) is greatly influenced by the airfare of business and economy (either full fare or discounted fare) class. In making optimal slot purchase decision, the level of travel demand, which behaves fluctuating, also has a significant impact in generating total revenue of each operating route.

With the aim to increase service frequency by making optimal slot purchase decision, let $\omega = \left\{ R_{F_i}, \forall F_i \in F_{ex} \right\}$ be the set of revenues generated by operating route, $F_i \in F_{ex}$ in the current operating networks. Mathematically, the optimal solution of SPDM could be written as $R^*_{F_i}$, i.e. the optimum (maximum) revenue of selected operating route, $F^*_i \in F_{ex}$. This implies that operating route F^*_i generates the greatest revenue compared to other operating routes, i.e. $R^*_{F_i} > R_{F_i}$ for $F_i \in F_{ex}$. The optimal revenue, $R^*_{F_i}$ is subsequently included in stage 2 (i.e. fleet planning decision model) as parts of airline's expected income. This signifies that optimal slot purchase decision would contribute and increase the operational income of airlines (in stage 2). Correspondingly, additional service frequency, Af^{t}_{n,F_i} that is available from slot purchase decision-making is incorporated necessarily in aircraft operations constraint (Equation (5.9) in stage 2) to optimize fleet planning decision.

5.4.2 Stage 2: Fleet Planning Decision Model (FPDM)

The developed fleet planning decision model (FPDM) can be solved by decomposing it into a series of simpler sub-problems. By using backward working mechanism, the sub-problem of the last operating period, T is solved first. The optimal solution obtained for the states at the current operating period subsequently leads to the problem solving at the period of $T-1, T-2, ..., 1$. This procedure continues until all sub-problems have been solved optimally so that the decision policy to purchase and/or lease aircraft can be determined strategically. For the developed model, the type of solution method, i.e. linear programming model or non-linear programming model can be identified clearly based on the objective function and practical constraints. If they are in the form of linear function in terms of decision variables, then the developed model can be solved as a linear programming model. Otherwise, it is solved as a non-linear programming model. The linearity of these components is primarily driven by the operational data of a particular airline. It shall then be validated by using regression test with the aid of mathematical software. For the illustrative case study in the next section, non-linear relationship was adopted in view that the regression relationship obtained from the published reports (Malaysia Airlines, 2010a; AirAsia Berhad, 2010a) show non-linearity. Powell (2007) specified that non-linear programming approach is a possible solution for dynamic programming model.

To solve FPDM, the decision variable in model (5.23) is found to be influenced by demand constraint (Equation (5.11)) as well as order delivery constraint (Equation (5.14)) which refers to aircraft availability that could be purchased/leased in the market. To summarize, the lower bound, LB, of fleet planning model can be outlined as follows:

$$LB = \begin{cases} X_t^P = 0,\ X_t^L = 0 & \text{if } \Delta D_t^S \leq 0 \\ \left(\sum_{i=1}^{n} LF_{i,F_i}^t \left(SEAT_{i,F_i}^t \right) \left(f_{i,F_i} \left(D_t^S, A_t^i \right) \right) \geq \left(1-\alpha\right) D_t^S \right) \cap \left(x_{ti}^P \leq ORDER_t \right) & \text{if } \Delta D_t^S > 0 \end{cases} \tag{5.24}$$

where ΔD_t^S indicates the change of demand from year to year, i.e. $\Delta D_t^S = D_t^S - D_{t-1}^S$. Equation (5.24) clearly shows that the lower bound, LB, is relatively affected by the service frequency of respective operating route, which might include additional service frequency generated from SPDM (from stage 1). Basically, a strategic FPDM would make optimal decision-making to ensure that airline's fleet supply (with corresponding service frequency) is adequate to meet a desired demand level.

5.5 An Illustrative Case Study

5.5.1 Data Description

Five types of aircraft, i.e. B737-400, B737-800, B777-200, A330-300 and A380 are considered for a set of OD pairs for a planning horizon of eight years. These aircraft are chosen based on the fleet composition of Malaysia Airlines (Malaysia Airlines, 2013) in servicing 38 international routes. According to Malaysia Airlines (2010a) and AirAsia Berhad (2010a), in average, the acquisition of new aircraft requires a period of five years to be delivered completely. Besides, the desired lead time is assumed to have a normal distribution with an average of three years and standard deviation of 1.5, i.e. $DLT \sim N(3, 1.5)$. As such, five types of aircraft which are considered for a planning horizon of eight years are reasonably practical to reflect the actual practice of airlines.

Tables 5.1-5.8 show the input data of the developed model. The specifications of aircraft as well as the initial fleet size of airline are shown in Table 5.1. In Table 5.2, the demand level of airline is obtained from the 5-step demand modeling framework. Besides, it is assumed that an airline which is based in Kuala Lumpur International Airport (KLIA) is operating a total of 38 routes (as shown in Table 5.3). The expected value of flight fare and flight cost per passenger are displayed in Table 5.4 while the purchase cost, lease cost, depreciation cost, resale price and residual value of the respective aircraft could be seen in Tables 5.5 and 5.6, respectively. Table 5.7 shows the standard operation hours of aircraft at the respective airports for which the slot purchase decision was taken into consideration. Only four airports (i.e. Amsterdam, Frankurt, London and Paris) were considered for slot purchase due to the fact that slot control is commonly applied in Europe and the United States (Mehndiratta et al., 2003).

Table 5.1: Aircraft Specifications (AirAsia Berhad, 2013; Malaysia Airlines, 2013; Airbus, 2013; Boeing, 2013)

Aircraft	B737-400	B737-800	B777-200	A330-300	A380
Category	Small		Large		Jumbo
Flight type	Short-haul		Medium-haul		Long-haul
Size (m^2)	1,221	1,600	4,352	4,288	6,424
Maximum take-off weight (kg)	68,050	79,010	247,200	230,000	560,000
Range (km)	4,204	5,665	12,200	11,300	15,700
Seating configuration (in terms of number of seats)					
Business/first class	16	16	39	42	79
Economy class	130	144	275	258	446
Capacity (number of seats)	146	160	314	300	525
Initial fleet size (for year 1)	13	17	8	8	2

Table 5.2: The Travel Demand of Airline

Year	Travel demand	Year	Travel demand
1	10,080,858	5	7,845,529
2	10,988,135	6	8,473,171
3	7,471,932	7	9,151,025
4	7,845,529	8	9,700,086

Table 5.3: The Operational Data of International Routes (Malaysia Airlines, 2013)

Route	Destination	Daily frequency	Aircraft	Distance (km)	Block time	Airfare (business class), $	Economy class (full fare), $	Economy class (discounted fare), $
1	Adelaide (ADL)	1	A330-300	5682	7hr 10mins	1,599	742	415
2	Amsterdam (AMS)	1	B777-200	10235	12hr 55mins	2,828	1,040	495
3	Auckland (AKL)	1	B777-200	8704	13hr	2,009	996	587
4	Bandar Seri Begawan (BWN)	1	B737-400	1491	10hr	382	204	90
5	Bangalore (BLR)	1	B737-800	2875	2hr 30mins	675	468	268
6	Bangkok (BKK)	4	B737-800	1251	2hr 20mins	255	175	84
	Bangkok (BKK)	1	B737-400	1251	4hr	255	175	84
7	Beijing (PEK)	1	A330-300	4413	2hr 5mins	996	456	302
	Beijing (PEK)	1	B777-200	4413	2hr 5mins	996	425	274
8	Brisbane (BNE)	1	A330-300	6438	6hr 10mins	1,600	769	415
9	Chennai (MAA)	2	B737-800	2626	6hr 10mins	718	445	208
10	Colombo (CMB)	1	B737-800	2465	8hr 5mins	471	410	219
11	New Delhi (DEL)	1	B737-800	3875	13hr 45mins	798	561	307
	New Delhi (DEL)	1	A330-300	3875	5hr 10mins	798	561	307
12	Denpasar Bali (DPS)	2	B777-200	1966	6hr 25mins	437	119	239
	Denpasar Bali (DPS)	2	B737-800	1966	3hr 40mins	437	119	239
13	Dhaka (DAC)	1	B777-200	2636	8hr 50mins	468	335	200
	Dhaka (DAC)	1	A330-300	2636	3hr 20mins	468	335	200
14	Frankfurt (FRA)	1	B777-200	9996	2hr 30mins	2,645	893	511
15	Guangzhou (CAN)	5	B737-800	2592	5hr 30mins	705	418	200
16	Hanoi (HAN)	2	B737-800	2085	5hr 30mins	444	252	132
17	Ho Chi Minh City (SGN)	3	B737-800	1053	3hr	406	204	84

Table 5.3 continued: The Operational Data of International Routes (Malaysia Airlines, 2013)

Route	Destination	Daily frequency	Aircraft	Distance (km)	Block time	Airfare (business class), $	Economy class (full fare), $	Economy class (discounted fare), $
18	Hong Kong (HKG)	1	A380	2562	3hr	692	316	170
	Hong Kong (HKG)	2	B737-800	2562	3hr 50mins	692	316	170
19	Hyderabad (HYD)	1	B737-800	3009	3hr 50mins	745	508	308
20	Jakarta (CGK)	6	B737-800	1141	12hr 41mins	697	455	64
21	Jeddah (JED)	1	B777-200	7055	9hr 10mins	971	762	489
22	Tribhuvan (KTM)	1	B737-800	3275	14hr 45mins	486	349	288
23	Kunming (KMG)	1	B737-800	2476	14hr 30mins	683	369	151
24	London (LHR)	2	A380	10603	4hr 5mins	2,911	1,248	549
25	Male (MLE)	1	B737-800	3133	5hr 15mins	959	463	318
26	Manila (MNL)	4	B737-800	2496	3hr 25mins	455	335	172
27	Melbourne (MEL)	1	A330-300	6329	15hr 30mins	1,462	583	283
28	Mumbai (BOM)	1	B737-800	3623	15hr 30mins	798	561	307
29	Osaka Kansai (KIX)	1	A330-300	4983	1hr 55mins	1,288	592	265
30	Paris (CDG)	1	A380	10439	3hr 50mins	2,518	924	460
31	Perth (PER)	1	A330-300	4139	3hr 50mins	1,267	636	254
32	Phnom Penh (PNH)	2	B737-800	1040	4hr 10mins	419	192	70
33	Seoul Incheon (ICN)	1	A330-300	4606	2hr	1,127	267	558
34	Shanghai Pu Dong (PVG)	2	A330-300	3798	9hr 15mins	774	439	267
35	Taipei (TPE)	4	B737-800	3268	4hr 50mins	518	389	226
36	Tokyo Narita (NRT)	2	B777-200	5406	3hr 40mins	1,328	642	387
37	Xiamen (XME)	1	B737-800	2991	2hr 45mins	603	439	248
38	Yangon (RGN)	2	B737-800	1682	2hr 45mins	437	235	61

Table 5.4: The Expected Value of Flight Fare and Cost per Flight

Fare & Cost, $	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8
$E\left(fare_t^{S_1} \right)$	124,122	136,534	150,188	165,207	181,727	199,900	219,890	241,879
$E\left(fare_t^{S_2} \right)$	117,916	129,708	142,678	156,946	172,641	189,905	208,895	229,785
$E\left(fare_t^{S_3} \right)$	111,710	122,881	135,169	148,686	163,554	179,910	197,901	217,691
$E\left(\cos t_t^{S_1} \right)$	74,473	81,921	90,113	99,124	109,036	119,940	131,934	145,127
$E\left(\cos t_t^{S_2} \right)$	70,750	77,825	85,607	94,168	103,585	113,943	125,337	137,871
$E\left(\cos t_t^{S_3} \right)$	67,026	73,729	81,101	89,212	98,133	107,946	118,741	130,615

Table 5.5: The Purchase Cost, Lease Cost and Depreciation Cost of Aircraft ($ million)

Aircraft	B737-400	B737-800	B777-200	A330-300	A380
Purchase cost	4.5	90.5	278.8	239.4	403.9
Lease cost	4.1	81.45	250.9	215.5	363.5
Depreciation cost					
- purchased aircraft	0.8	16.3	50.2	43.1	72.7
- leased aircraft	0.7	14.7	45.2	38.8	65.4

Table 5.6: The Resale Price and Residual Value of Aircraft ($ million)

Year, *y*	B737-400	B737-800	B777-200	A330-300	A380
1	3.7	74.2	228.6	196.3	331.2
2	2.9	57.9	178.4	153.2	258.5
3	2.1	41.6	128.2	110.1	185.8
4	1.3	25.3	78.1	67.0	113.1
5	0.5	9.1	27.9	23.9	40.4

Table 5.7: The Standard Operations Hour of Aircraft at Airport (Boeing, 2013)

Airport	Start of working hours	End of working hours
Amsterdam (AMS)	6.00am	10.00pm
Frankurt (FRA)	6.00am	10.00pm
London (LHR)	6.00am	11.30pm
Paris (CDG)	6.00am	11.30pm
Kuala Lumpur (KLIA)	6.00am	11.30pm

In addition to the aforementioned data, other data input of the case study are listed as follows:

By definition:

- Three probable phenomenon, i.e. $k=3$ are considered
- Discount rate, $r_t = 5\%$
- Load factor, $LF_{n,F_i}^{t} = 70\%$
- Significance level of demand constraint, $\alpha = 10\%$
- Significance level of lead time constraint, $\beta = 5\%$
- Significance level of selling time constraint, $\gamma = 5\%$
- Annual aircraft availability, AVT_{n,F_i}^{t} = 340 days
- Portion of passenger in business class, $Biz_{\%} = 12\%$
- Portion of passenger in economy class (full fare), $Fec_{\%} = 20\%$
- Portion of passenger in economy class (discounted fare), $Dec_{\%} = 80\%$
- $D_t^{s_1} = D_t$ and $D_t^{s_k} = (1-\alpha) D_t^{s_{k-1}}$ for $t = 1,...,T;\ k > 1$ (5.25)

By assumption:

- The probability to possess aircraft is $p_{s_1} = 0.50$, $p_{s_2} = 0.36$ and $p_{s_3} = 0.14$
- At $t=1$, initial quantity of aircraft to be four years old is $I_{1i4}^{P} = 2$ for $i = 1,2,3,4$
- Setup cost, $u_{ti} = 0$
- Maximum utilization of aircraft, $MXU_{t,F_i} = 1.05(\text{actual aircraft utilization})$
- Airline's willingness to pay, $W_{F_i} = \$6$ million

By assumption (based on real data):

- Slot price, $C_{F_i} = \$5$ million

- Allocated budget, $MAX_{budget(t)} = \$6,500$ million
- Area of parking space, $PARK_t = 500{,}000 m^2$
- Order delivery constraint, $ORDER_t = 5$
- Salvage cost of aircraft = 10% x $PURC_t$
- Deposit of aircraft acquisition, $DP_t = 10\%$ x $PURC_t$
- Deposit of aircraft leasing, $DL_t = 10\%$ x $LEASE_t$
- Network efficiency factor, $EFF_t = 60\%$
- Turn round time, $TUN^t_{n,F_i,k}$ = 40 minutes
- The function of maintenance cost is

$$h = 5177 + 7.97\text{x}10^{-3} g \quad [\mathrm{R}^2 = 0.94] \tag{5.26}$$

where g is the traveled mileage.

- The quantity of aircraft is

$$NA = 10^{-5} NP - 73.6 \quad [\mathrm{R}^2 = 0.92] \tag{5.27}$$

where NP is the number of travelers.

- The function of fuel expenses is

$$C\left(fuel_{tn}\right) = 7.46 f + 8.3\text{x}10^{-5} f^2 - 98{,}572 \quad [\mathrm{R}^2 = 0.88] \tag{5.28}$$

In order to assure an adequate fleet supply, three probable phenomena, i.e. $k = 3$ are considered to account for the operational, economy and environmental aspects. As reported by Malaysia Airlines (2010a) and AirAsia Berhad (2010a), the operational and economy aspects are two major concerns in fleet planning decision-making. Additionally, the environmental aspect is included necessarily due to its increasing concern and crucial impacts on airline’s operations. Without these elements in place, fleet planning decision-making may not be suitable to support the operating networks under uncertainty. Based on the reports of Malaysia Airlines (2010a) and AirAsia Berhad (2010a), Equations (5.26)-(5.28) are obtained by conducting polynomial regression analysis (Meyer and Krueger, 2005). Equation (5.26) signifies that a unit cost of 0.00797 is charged as maintenance cost for each additional unit of mileage traveled. For this equation, $5177 indicates an overall estimated maintenance cost without considering additional traveled mileage. Besides, the regression analysis exhibits that Equation (5.27) is best fitted as a linear function in terms of the number of travelers. Equation (5.27) displays that every addition of 100,000 travelers requires one additional aircraft for which the constant in Equation (5.27) has no practical interpretation. Similarly, the analysis reveals that fuel expenses (Equation (5.28)) is best fitted as a quadratic function in terms of the number of flights.

In order to investigate the impact of changes of the inputs to the computational results, an additional scenario (without slot purchase), i.e. scenario A is tested. By doing this, some differences compared to benchmark scenario (with slot purchase) in making the optimal fleet planning decision could be observed. The benefits of considering slot purchase could also be identified. Besides, the connections of slot purchase, service frequency and fleet planning of airlines could be captured. In addition, scenario B is examined to inspect the impacts of optimal slot purchase decision in providing the desired service frequency for new operating network (instead of adding service frequency for existing operating networks). Specifically, scenario B is outlined for airline's consideration to operate a new operating network for short-haul route (labeled as #1), medium-haul rote (denoted as #2) and long-haul route (indicated as #3). For new network expansion, the estimated demand level and expected airfare of each operating route are shown in Table 5.8.

Table 5.8: The Estimated Demand Level and Average Fare for New Network Expansion

Route	Flight type	Estimated demand level (per annum)	Airfare ($)		
			Business class	Economy class (full fare)	Economy class (discounted fare)
#1	Short-haul	84,539	737	369	208
#2	Medium-haul	77,228	1680	840	474
#3	Long-haul	131,636	2,426	1,213	685

Note: The data input for new network expansion was compiled accordingly based on the average value of existing operating networks (38 operating routes).

5.6 Results and Discussions

As mentioned earlier, slot purchase decision-making is determined based on the optimal revenue of the individual operating period. It was found that the long-haul flight from KL to London (KL-London) emerges as the most gainful operating route (with maximum revenue). By making slot purchase decision for this route (KL-London), the results of the developed two-stage fleet planning decision model are displayed in Table 5.9. Table 5.9 also shows the results of scenario A which excludes the slot purchase in fleet planning and scenario B for new network expansion. The relevant graphical results are displayed in Figure 5.2.

Table 5.9: The Computational Results of Respective Scenario

	Benchmark scenario	Scenario A	Scenario B
Slot purchase consideration	Yes	No	Yes
Slot purchase decision for existing networks *(Yes implies slot purchase is made;* *No indicates no slot purchase)*	Yes: Year 1,2,4,6,7,8 No: Year 3,5	Nil	Yes: Year 2,4,6,7,8 No: Year 3,5
Slot purchase decision for new network	Nil	Nil	Yes: Year 1 No: Year 2-8
Revenue and profit			
Annual revenue (contributed by slot purchase), $ - existing network - new network	 33,912,947 Nil	 Nil Nil	 33,912,947 129,917,782
Annual profit of airline, $	579,890,573	555,565,392	784,890,573
Demand			
Annual demand (met by slot purchase) - existing network - new network	 29,045 Nil	 Nil Nil	 29,045 131,636
Average demand level of airline	8,944,533	8,934,261	9,076,169
Service frequency			
Annual service frequency (provided by slot purchase) - existing network - new network	 42 Nil	 Nil Nil	 42 251
Average service frequency of airline (per annum)	27,864	27,832	28,115
Fleet Planning Decision			
Fleet size (at the end of the planning horizon)	55	54	57
B737-400	18	18	18
B737-800	16	16	16
B777-200	6	6	6
A330-300	12	12	12
A380	3	2	5
Quantity of purchased aircraft: leased aircraft	48:7	50:4	48:9
Ratio of purchased aircraft: leased aircraft	87%:13%	93%:7%	84%:16%

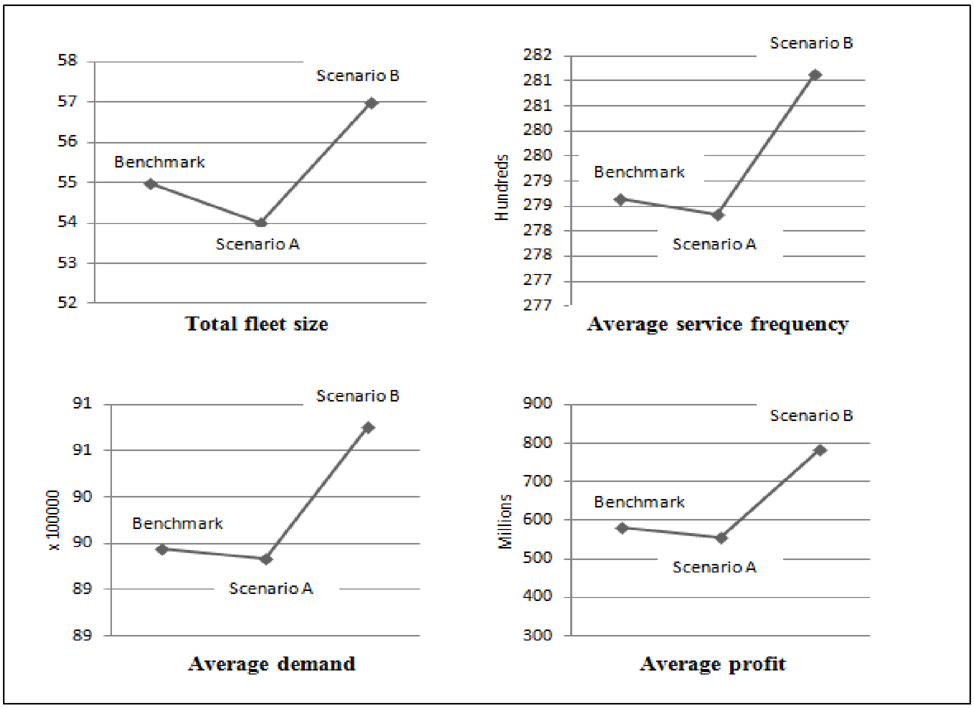

Figure 5.2: The Graphical Results of Two-Stage Fleet Planning Decision Model

As shown in Table 5.9, the benchmark scenario (with slot purchase decision) provides a higher service frequency, i.e. 27,864 which is 42 times more than scenario A (without slot purchase). Correspondingly, the demand level met by the benchmark scenario appears to be higher in average, i.e. it is approximately to be 10,272 more than scenario A (per annum). This signifies that the airline could meet a higher level of stochastic demand by providing more service frequency via optimal slot purchase decision. This finding is in line with the facts as revealed by Brueckner (2009), Fukui (2010) and Babic and Kalic (2011, 2012). Consequently, more profit could be obtained by airline due to the contribution of a higher level of revenue which is mainly generated by additional flights (resulted from slot purchase decision of KL-London). This shows that by making an optimal slot purchase decision, a higher demand level could be met by airlines at a more profitable level. On average, it is approximated that an additional 1% of demand increment that is met via slot purchase decision would constitute about 0.97% of service frequency (flight). This is coherent with the findings of Pitfield et al. (2009) who revealed that the demand increment would increase service frequency. Such increment would then result in additional revenue at $2.88 million (average value per annum), which consequently contributes about $6.15 million of profit (per annum). Similar fact also shows that slot purchase is useful for airlines to assure that more profit could be seen in Babic and Kalic (2011, 2012).

Specifically, Table 5.9 shows that airline did not make any slot purchase decision for operating year 3 and 5 (for benchmark scenario). This could be explained by the level of stochastic demand that is estimated to drop about 32% in year 3 (see Table 5.2). For year 5, there is no demand increment (compared to previous year, i.e. year 4) and hence slot purchase decision did not apply for these operating periods. Under these circumstances, the airline may consider to sell or lease the slot to other airlines for additional income (Fukui, 2010). This shows that the developed model is able to provide insightful information to airlines at the right time to make relevant slot purchase decision throughout long-term planning horizon.

In order to provide a higher service frequency (via slot purchase decision) to meet demand increment, the results (in Table 5.9) show that airline would tend to acquire/lease more aircraft to support the current operating network. As shown in Table 5.9, benchmark scenario, which includes slot purchase decision, possesses one more aircraft, i.e. A380, compared to scenario A which does not account for slot purchase decision. In accordance to slot purchase decision to service the KL-London route, A380 is leased mainly due to their availability in supporting long-haul flight (KL-London) at a more economical aircraft acquisition/lease cost per seat. This signifies that there is a positive relation between the slot purchase decision and fleet planning decision of airlines for which the slot purchase decision-making that basically aims to provide a higher service frequency to meet more demand would practically require more aircraft (via acquisition/leasing) for services. Yet, the optimal quantity of respective aircraft type that is needed for additional operations is very much dependent on the operating route and corresponding demand level that is to be serviced via slot purchase, e.g. the KL-London route would require jumbo aircraft (A380). Conversely, it could be inferred that there is a tendency for airlines to acquire/lease fewer aircraft if the slot purchase decision is not taken into consideration (as shown by the fleet size of scenario A). Besides, the results show that airline tends to lease aircraft rather than purchase new aircraft when slot purchase is incorporated in fleet planning. This could be justified by the cost of aircraft leasing which is much lower than aircraft purchase cost and hence aircraft leasing is preferred in fleet planning in order to assure a higher profit of airline. This explains that the portion of leased aircraft of benchmark scenario (with slot purchase) which appears to be much higher than scenario A (in Table 5.9).

Apparently, it could be empirically deduced that demand increment influences the slot purchase decision positively and it is observable that slot purchase has a positive impact on service frequency, fleet supply as well as profit level. This shows that slot purchase has a direct and closed linkage not only with the demand aspect but also the supply aspect, which are relatively vital for the supply-demand management. More importantly, the results show that the incorporation of slot purchase in fleet planning is beneficial to airlines in achieving social and economic sustainability. This is practically viable for airlines by providing a better service quality via a higher service frequency to meet more demand (social aspect) as well as obtaining a higher revenue and profit (economic aspect) by making optimal slot purchase and fleet planning decision.

5.6.1 Further Application: New Network Expansion

In view of the benefits of optimal slot purchase decision in meeting more demand via a higher service frequency (as discussed earlier), the developed model could also be adopted suitably to expand new network (see Appendix C for more details about the model modification). It is anticipated that the new network expansion which would provide additional (new) service frequency would generate additional revenue and profit to airlines. By considering three new networks (for scenario B), i.e. #1 (short-haul), #2 (medium-haul) and #3 (long-haul), the developed SPDM (stage 1) shows that long-haul route (#3) generates the highest revenue compared to other routes. This suggests to the airline to operate new operating network, i.e. #3 (at the beginning of operating period 1) and this would contribute a total of 39 operating routes, in overall, throughout the planning horizon. Besides, the results of scenario B show that new network expansion (via optimal slot purchase and fleet planning decision) would be able to meet a higher level of demand which is approximately 131,636 more than the benchmark scenario (per annum). Correspondingly, scenario B would provide an additional of 251 flights (service frequency) per annum to meet increasing demand (for new network #3). This would then contribute more revenue to airline, i.e. $130 millions (from new network) and consequently generate more annual profit, i.e. approximately to be $785 million per annum.

In terms of the fleet size (compared to benchmark scenario), the findings in Table 5.9 show that airline would possess more aircraft (via aircraft leasing) for new network expansion. For aircraft leasing, two A380 is chosen optimally not only due to its technical specification in supporting the long-haul network (#3), but also to assure optimal profit of airline. In overall, the findings produced by the developed model show that new network expansion (with optimal slot purchase and fleet planning decision) yields beneficial returns to airlines in meeting more demand (with a larger fleet composition for desired service frequency) as well as producing higher profit margin.

5.6.2 Results Verification

The consistency and stability of computational results could be empirically confirmed by comparing the findings with actual operational statistics of airline (Malaysia Airlines, 2013). Table 5.10 summarizes the fleet size of airline (i.e. MAS) as compiled from accessible annual reports and optimal fleet planning decision of each operating period as obtained from the developed model. It could be observed that the fleet size of MAS during operating years of 2006 to 2012 falls within the range of two standard deviations from its average. The optimal solutions obtained from the benchmark problem, scenarios A and B show similar pattern, i.e. the fleet size of operating periods 1 to 8 falls within the range of two standard deviations from its average. Similar pattern could be observed from Table 5.11 for service frequency determination of airline. Therefore, it is apparent that the solutions obtained from the developed model are coherent with the operating performance of airline. As such, the findings are consistent with the actual practice and hence the stability of the results (as well as the developed model) could be empirically confirmed.

Table 5.10: The Summary of Fleet Planning Decision

	Empirical report		Scenario			
	Year	MAS*	*t*	Benchmark	A	B
Operating period *(Note for *: The fleet size of MAS are computed only for international network, which is approximated to be 35% of total operating networks (Malaysia Airlines, 2013))*	2005	39	1	48	48	50
	2006	34	2	44	43	45
	2007	36	3	44	43	45
	2008	38	4	46	44	47
	2009	39	5	46	44	47
	2010	41	6	49	46	50
	2011	45	7	52	48	53
	2012	50	8	55	49	57
Average (AG)		40.3		48.0	45.6	49.3
Standard Deviation (SD)		5.1		3.9	2.4	4.2
AG + 2SD		50.5		55.8	50.5	57.6
AG – 2SD		30.0		40.2	40.7	40.9

Table 5.11: The Summary of Service Frequency of Airline

	Empirical report		Scenario			
	Year	MAS*		Benchmark	A	B
Operating period *(Note for *: The service frequency of MAS are computed only for international network, which is approximated to be 35% of total operating networks (Malaysia Airlines, 2013))*	2005	51,634	1	30,175	30,123	30,426
	2006	53,719	2	31,635	31,583	31,886
	2007	43,021	3	24,556	24,556	24,807
	2008	39,640	4	26,191	26,166	26,442
	2009	37,486	5	26,091	26,091	26,342
	2010	42,795	6	26,971	26,929	27,222
	2011	38,071	7	27,814	27,768	28,065
	2012	36,777	8	29,482	29,445	29,733
Average (AG)		42,893		27,864	27,833	28,115
Standard Deviation (SD)		6,482		2,386	2,369	2,386
AG + 2SD		55,857		32,637	32,570	32,888
AG – 2SD		29,929		23,092	23,095	23,343

5.7 Summary

This research developed a novel methodology to solve the long-term fleet planning problem under stochastic demand. A two-stage fleet planning decision model is formulated for which the aim of the first stage is to select individual operating route (at optimal revenue) that necessitates the slot purchase to meet demand increment while the second stage aims to maximize the operational profit of airlines, by determining the optimal quantity of respective aircraft type (with corresponding service frequency) that is to be purchased and/or leased. The results of a realistic case study with 38 international routes demonstrated that the developed methodology is sensitive to the modeling parameters and it is feasible in providing optimal solutions for fleet planning problem. Concisely, the findings revealed that slot purchase is beneficial to airlines in assuring a higher profit level. This could be achieved when a higher level of travel demand is met by providing more service frequency (with optimal slot purchase decision). By incorporating slot purchase in fleet planning, it was also found that airline would tend to lease aircraft rather than purchase new aircraft, yet the quantity and aircraft type is dependent on specific operating route that requires slot purchase. The developed methodology, in fact, reflects realistically the actual situation of airline industry, ranging from the challenges of providing the desired service frequency (by incorporating slot purchase) to meet stochastic demand under uncertainty to the practical issues in acquiring/leasing adequate fleet supply under numerous practical constraints.

CHAPTER 6

ENVIRONMENTAL PERFORMANCE ASSESSMENT FOR FLEET PLANNING

6.1 The Role of Environmental Performance Assessment

In response to environmental concern which is receiving greater attention nowadays by the airlines industry, airlines play a vital role in conserving the environment. Ideally, airlines should reduce the amount of pollutants emitted from their operating networks. Specifically, three major environmental factors of airlines, namely aircraft emission, noise and fuel consumption, could be decreased at a larger scale by having a well-defined monitoring system. As such, a modeling framework of green index is formulated to assess the environmental (green) performance of airlines. The developed framework is able to quantify airline's green level of aircraft emission, noise and fuel efficiency specifically based on the aircraft operations of airlines in supporting the current operating networks. Subsequently, the overall green performance of airlines in terms of Green Fleet Index (GFI) could then be compiled systematically. The resultant GFI, as a green indicator, is capable to reveal not only the green performance of airlines at present, but also provide some constructive improvement strategies to yield a greener performance. The effectiveness of the respective improvement strategy could also be identified accordingly for airline's further action. The formulations of the respective green level (for aircraft emission, noise and fuel efficiency) as well as the GFI of airlines are outlined in following sections. The applicability of the developed modeling framework is tested with an illustrative case study. The results show that the developed methodology is practically feasible to assist airlines to achieve a greener performance.

6.2 Quantify Green Index: Gini Coefficient

Basically, Green Index (GI) measures the degree of environmental performance, i.e. it is an environmental indicator which signifies the scale of green performance based on the aircraft operations of airlines. The GI is derived borrowing the concept of Gini coefficient (Gini, 1912), which is originally created to reflect the income distribution of a nation's residents. It is a measure of statistical dispersion which indicates the inequality among the values of a frequency distribution. The coefficient that ranges from zero (minimum) to one (maximum) indicates the equality degree from perfect equality to imperfect equality. Geometrically, the Gini coefficient is expressed as a ratio of two regions defined by a 45 degrees line (i.e. the line of perfect equality) and a Lorenz curve. The area of region under the Lorenz curve can be evaluated based on the properties of trapezoid whereas the area under the line of perfect equality is exactly half in a unit box. Gini coefficient can also be computed using the mean difference formula, covariance approach and matrix form. Despite different formulations with its own appeal in a specific context, the formulations are mathematically equivalent (Xu, 2004).

In view of the fact that Gini coefficient measures the equality degree (with the scale from zero to one), this signifies that a data set that is closer to each other (by having a narrower gap) would tend to have a lower Gini coefficient, and vice versa. In other words, a data set with a higher equality would tend to have a smaller variance or standard deviation (due to a narrower gap among the data). This reveals that a smaller variance or standard variance, in fact, could reflect a greener performance. As such, if airlines could reduce their aircraft emission, noise and fuel consumption effectively (especially for specific operating route with critical pollutants or fuel consumption), the resultant operating networks would produce a lesser amount of pollutants and hence a smaller variance or standard deviation could be obtained (by having a smaller average too). Equivalently, a greener performance by airlines would have a lower Gini coefficient, average, variance as well as standard deviation. As such, Gini coefficient is adopted to quantify the green level of airlines. Practically, a greener performance could be achieved if airlines could implement some improvement strategies effectively.

In this research, the GI is computed by using the geometrical approach as shown in Equations (6.1) and (6.2):

$$GI = 2\Delta A \tag{6.1}$$

where the component of ΔA indicates the area in between the Lorenz curve and the line of perfect equality. It is evaluated as follows:

$$\Delta A = \frac{1}{2} - \sum_{\forall c} \frac{1}{2}\left(W_c + W_{c-1}\right)\left(Cat_c - Cat_{c-1}\right) \tag{6.2}$$

for which W_c indicates the cumulative percentage of environmental factor W (for the vertical axis) while Cat_c denotes the cumulative percentage of operating routes (for the horizontal axis) in category c. Category, c, refers to the group of environmental factor (with the corresponding operating routes) ranked in ascending order. Fellman (2012) pointed out that the simplest way is to define five quintiles or 10 deciles for Lorenz curve, i.e. $c = 1, 2, 3, 4, 5$ for five quintiles and $c = 1, 2, ..., 10$ for 10 deciles. For the right hand side of Equation (6.2), the constant of half refers to the area under the line of perfect equality while second component denotes the total area under the Lorenz curve (based on the properties of trapezoid). Alternatively, the GI can be simplified as follows:

$$GI = 1 - \sum_{\forall c} \left(W_c + W_{c-1}\right)\left(Cat_c - Cat_{c-1}\right) \tag{6.3}$$

Mathematically, $GI \to 0$ indicates that the environmental performance of airlines, in overall, is greener while $GI \to 1$ implies that the green performance of airlines is getting poorer and exhibits a greater tendency to be not green for the current operating networks. Specifically, greener performance implies that there is a lesser amount of emission, noise and/or fuel consumption produced from aircraft operations of a particular operating year (in comparison to previous year). In order to quantify the overall environmental performance of airlines of a particular operating period, three indices are derived specifically for aircraft emission, noise, and fuel consumption (as explained below).

6.2.1 Green Emission Index

The relevant contributing factors to aircraft emission are load factor, aircraft status (new or aging), emission rate and service frequency. Aircraft emission is computed during landing and take-off (LTO) cycle as well as cruising stage. In fact, emission produced from LTO and cruising stages are reported to be different. According to Givoni and Rietveld (2010), the resultant emission from LTO stage is found to be harmful as local air pollution while aircraft emission from the cruising stage would result in climate change issues. The aircraft emission rate, which is contributed by hydrocarbon (HC), carbon monoxide (CO), particular matter (PM), nitrogen oxides (NO_x) and sulphur oxides (SO_2), i.e. major elements produced from LTO and cruising stages, measured for each aircraft in kilogram. Miyoshi and Mason (2009) and Chao (2014) revealed that both LTO and cruising stages have to be considered to capture aircraft emission completely. As such, the total aircraft emission of airlines of a particular operating year t, EX_t, can be expressed in general form as follows:

$$
\begin{aligned}
EX_t = {} & LF_{i,F_i}^t \left(\sum_{\forall F_i} ER_t^i f_{i,F_i}^2 \left(D_t^S, A_t^i \right) OLD \right) + \\
& LF_{i,F_i}^t \left(\sum_{\forall F_i} ER_t^i \theta f_{i,F_i}^1 \left(D_t^S, A_t^i \right) NEW \right), t = 1, \dots, T; i = 1, \dots, n; S = s_1, \dots, s_k
\end{aligned}
\tag{6.4}
$$

where LF_{n,F_i}^t refers to load factor, ER_t^n is the emission rate of individual flight (depending on aircraft type), $f_{n,F_i}^m \left(D_t^S, A_t^n \right)$ is the service frequency of operating route (depending on the level of travel demand, D_t and total quantity of aircraft, A_l of airline which may vary for different status of aircraft, m for which $m=1$ refers to new aircraft while $m=2$ implies aging aircraft, θ is the parameter of environmental sustainability while OLD and NEW respectively indicates the proportion of aging (more than 1 year old) and new (up to 1 year old) aircraft that servicing route *OD*. Particularly, total quantity of aircraft refers to total number of fleet (aircraft) in operation for which airline's fleet supply is obtained by making optimal aircraft acquisition/leasing decision.

According to Grampella et al. (2013), the respective aircraft type with different engines was found to emit pollutants differently and hence they used engine-weighted pollutants to compute aircraft emission level. In order to compute the total emission level of airlines of a particular operating period, in fact the developed Equation (6.4) could be applied similarly to capture engine-weighted pollutants for which a particular amount of pollutants (engine-weighted) can be compiled in terms of the emission rate of a specific aircraft type. Specifically, Equation (6.4) is formulated to compute the total aircraft emission of the landing and take-off (LTO) and cruising stages, i.e. the entire aircraft operation (with weighted-amount of pollutants) is taken into consideration completely. Particularly for the LTO stage, the engine-weighted emission rate of hydrocarbon (HC), carbon monoxide (CO), particular matter (PM), nitrogen oxides (NO_x) and sulphur oxides (SO_2) can be compiled accordingly to determine the total amount of emission level of each pollutant (for the respective aircraft type).

The GI_E is then computed by using the following equation:

$$GI_E = 1 - \sum_{\forall c} \left(EX_{t,c} + EX_{t,c-1} \right) \left(Cat_c - Cat_{c-1} \right),\ t = 1, \ldots, T \tag{6.5}$$

for which $EX_{t,c}$ and Cat_c respectively denotes cumulative percentage of emission level (for vertical axis) and operating routes (for horizontal axis) in category c. Mathematically, $GI_E \to 0$ signifies that the environmental performance of airlines in terms of aircraft emission appears to be better and greener for which, in overall, the servicing routes in current operating network produce a lesser amount of emission. On the other hand, $GI_E \to 1$ implies that the green performance of airlines is getting poorer and exhibits a greater tendency to be not green for current operating networks. This could happen when the operating routes emit exceptional high amount of aircraft emission. Such a substantial aircraft emission from the operating networks would negatively affect the overall green performance of airlines.

6.2.2 Green Noise Index

Generally, the level of aircraft noise of a particular flight can be computed based on three reference points, namely stage of lateral (f_L), approach (f_A) and flyover (f_F) (ICAO, 2011). According to ICAO (2011), aircraft noise level during these stages is greatly affected by aircraft weight (closely related to load factor) and number of engines of aircraft. Accordingly, the cumulative noise level, EXN_t, of a particular operating year, t of airlines can be generalized as follows:

$$EXN_t = LF_{i,F_i}^t \left(\sum_{\forall F_i} \left(f_L(M) + f_A(M) + f_F(M,\ E) \right) f_{i,F_i}^2 \left(D_t^S, A_t^i \right) OLD \right) +$$
$$LF_{i,F_i}^t \left(\sum_{\forall F_i} \left(f_L(M) + f_A(M) + f_F(M,\ E) \right) \theta f_{i,F_i}^1 \left(D_t^S, A_t^i \right) NEW \right), t = 1,...,T; i = 1,...,n; S = s_1,...,s_k$$

(6.6)

where $f_L(M)$, $f_A(M)$ and $f_F(M,E)$ respectively represents aircraft noise level at lateral, approach and flyover stages which greatly depends on aircraft weight, M and number of engines, E. Note that annual cumulative noise level of airlines is contributed by all servicing flights and hence the service frequency of respective route, $f_{n,F_i}^m \left(D_t^S, A_t^n \right)$ is included in Equation (6.6). Besides, it is important to note that aging and new aircraft might emit different noise level (mainly due to their technical specifications) and hence the status of aircraft, m (i.e. $m=1$ for new aircraft and $m=2$ for aging aircraft) is considered to compute cumulative noise level.

Specifically, Equation (6.6) is formulated to compute the cumulative noise level of a particular operating year. The formulation of this equation is guided by the three noise certification values (at the stages of lateral, approach and flyover) of aircraft (ICAO, 2011). In practice, some airports are relatively concern on the sum of the noise certification levels of aircraft (which consequently determine the noise charges) and hence the sum of these stages (at lateral, approach and flyover) is formulated accordingly in Equation (6.6). Some of the examples of airport that impose noise charges by referring to the sum of the noise certification levels of aircraft are Tokyo-Haneda airport, Amsterdam-Schiphol airport and Sydney airport (Hsu and Lin, 2005). The relevant study which make uses the sum of the three noise certification values could be seen in Givoni and Rietveld (2010) for which they obtained the sum value (of lateral, approach and flyover stages) and subsequently determine the corresponding average in order to assess aircraft noise exposure level. This shows that the three noise certification values can be summed up for further computation. However, they considered only one aircraft type in their formulation. In view of the fact that noise charges are airport-specific, it is important to note that there are various formulas to determine the aircraft noise level (with corresponding charges). The formula of energetic mean, which could be seen in Adler et al. (2013), Martini et al. (2013) and Grampella et al. (2013), was also found to be a useful approach and it is mainly used to determine airport noise charges (for different noise level).

The GI_N is then computed by using the following equation:

$$GI_N = 1 - \sum_{\forall c} \left(EXN_{t,c} + EXN_{t,c-1} \right) \left(Cat_c - Cat_{c-1} \right), \ t = 1, \ldots, T \qquad (6.7)$$

for which $EXN_{t,c}$ and Cat_c respectively indicates cumulative percentage of noise level (for vertical axis) and operating routes (for horizontal axis) in category *c*. Basically, $GI_N \to 0$ implies that in terms of the environmental performance of airlines, the green level of aircraft noise is getting better (with a tendency to be quieter or greener) by producing lesser aircraft noise throughout the planning horizon. Conversely, $GI_N \to 1$ signifies that the green level of aircraft noise is getting worst (poorer or not green). This reveals that aircraft noise is emitted substantially by servicing routes in the current operating networks. Under this circumstance, an extensive level of aircraft noise would affect and worsen the overall green performance of airlines.

6.2.3 Green Fuel Efficiency Index

An aircraft that is more fuel-efficient utilizes less fuel in servicing the operating networks of airlines. Less fuel consumption by a particular fleet (e.g. new aircraft) is relatively beneficial to airlines to travel further as well as to meet a higher level of demand. Therefore, the total traveled mileage, travel demand and fuel consumption are considered simultaneously to quantify the green level of fuel efficiency. For a particular operating period *t*, the fuel efficiency level, FEL_t of airlines can be expressed as follows:

$$FEL_t = LF^t_{i,F_i t}\left(\frac{\sum_{\forall F_i} FC^2_{i,F_i}\left(D^S_t, A^i_t\right)OLD}{\sum_{\forall F_i} gf^2_{i,F_i}\left(D^S_t, A^i_t\right)\sum_{\forall F_i} NP^2_{i,F_i}\left(D^S_t, A^i_t\right)}\right)+$$
$$LF^t_{i,F_i}\left(\frac{\sum_{\forall F_i} FC^1_{i,F_i}\left(D^S_t, A^i_t\right)NEW}{\sum_{\forall F_i} gf^1_{i,F_i}\left(D^S_t, A^i_t\right)\sum_{\forall F_i} NP^1_{i,F_i}\left(D^S_t, A^i_t\right)}\right), t = 1,...,T; i = 1,...,n; S = s_1,...,s_k \tag{6.8}$$

where $FC^m_{n,F_i}\left(D^S_t, A^i_t\right)$, $gf^m_{n,F_i}\left(D^S_t, A^i_t\right)$ and $NP^m_{n,F_i}\left(D^S_t, A^i_t\right)$ respectively denotes the fuel consumption, traveled mileage and total of passenger of operating route F_i. Note that $\sum_{\forall F_i} FC^1_{i,F_i}\left(D^S_t, A^i_t\right) = \theta \sum_{\forall F_i} FC^2_{i,F_i}\left(D^S_t, A^i_t\right)$.

The GI_{FE} is then computed by using the following equation:

$$GI_{FE} = 1 - \sum_{\forall c} \left(FEL_{t,c} + FEL_{t,c} \right) \left(Cat_c - Cat_c \right), \; t = 1, \ldots, T \tag{6.9}$$

for which $FEL_{t,c}$ and Cat_c respectively refers to cumulative percentage of fuel efficiency level (for vertical axis) and operating routes (for horizontal axis) in category *c*. Similar to the concept of the green level of aircraft emission and noise, $GI_{FE} \to 0$ signifies that the environmental performance of airlines from the aspect of fuel efficiency is getting better (and greener) with less fuel consumption in overall to service the current operating networks. Conversely, $GI_{FE} \to 1$ denotes that the green level of airlines in terms of fuel efficiency tends to be poorer and not green due to extensive fuel consumption in the current operating networks. Such an operating system (with substantial fuel consumption) would subsequently affect the green performance of airlines.

Compared to Equation (6.4) which calculates the total aircraft emission of airlines, Equation (6.8) computes the total amount of fuel consumed by airlines to support the entire operating networks. Note that in the case when more fuels are consumed by airlines, there are more aircraft emissions emitted to the environment. In other words, there is a direct linkage between fuel consumption and aircraft emission as fuel consumption determines the amount of emission proportionally. Contrary to aircraft emission, aircraft fuel does not have direct impacts to the environment but aircraft emission emitted through fuel burning would produce some harmful pollutants (e.g. carbon dioxide).

6.3 Quantify Green Fleet Index: Analytic Hierarchy Process

As displayed in Figure 6.1, by taking into consideration the Green Index (GI) of *W* environmental factors (e.g., aircraft emission, noise and fuel efficiency), the overall environmental performance of airlines in terms of Green Fleet Index (GFI) can be quantified systematically by making use Analytic Hierarchy Process (AHP) (Zadeh, 1965; Saaty, 1980). Owing to the fact that the environmental performance of airlines is relatively influenced by the occurrence of unexpected event which may affect the green performance of airline, AHP which is capable to capture fuzziness or uncertainty (Zhü, 2014) is adopted to quantify the GFI. For instance, heavy air traffic congestion (due to demand increment) may affect the aircraft landing process at a particular airport and this may result in more fuel consumption (and emission) due to the unavailability of airport for landing. In such a case, fuel consumption (and emission) of airlines may appear to be more significant relative to aircraft noise. This highlights that by capturing the occurrence of unexpected event, the resultant output of GFI would reflect the actual operations closely and the green performance of airlines could be monitored in a better manner. Recognizing the need to capture fuzziness in practice, AHP which is originated from the fuzzy set theory was first introduced by Zadeh (1965) with the attempt to select and prioritize a number of actions by evaluating a group of predetermined criteria. The AHP is widely applied in other sectors, including resource management and corporate strategy (Velasquez and Hester, 2013). However, none of the literatures apply AHP to solve the environmental issue in the air transport sector.

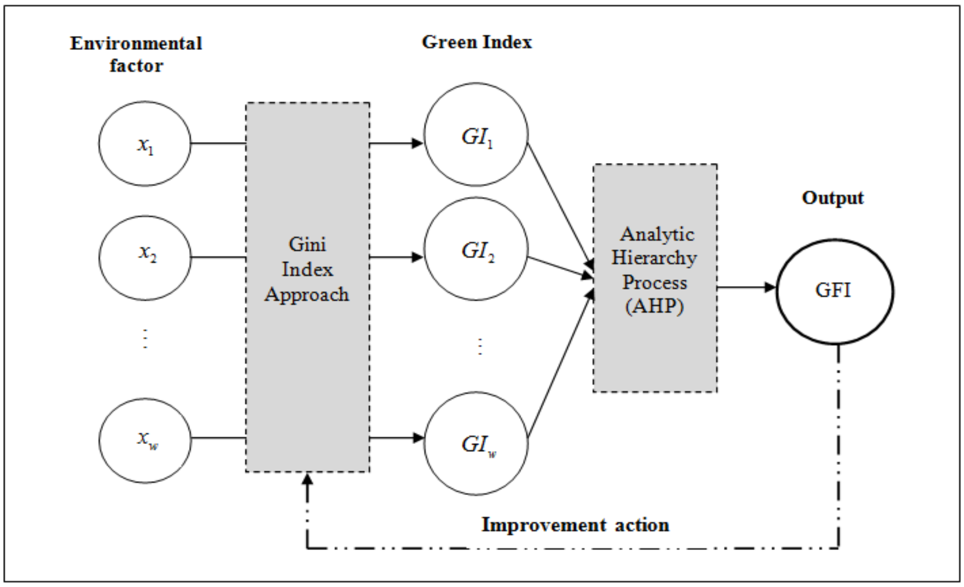

Figure 6.1: The Modeling Framework to Quantify Green Fleet Index

In general, the modeling framework to quantify the green performance of airlines, in terms of GFI, can be carried out as follows:

Step 1: Obtain Green Index

The relevant Green Index (GI) which would constitute the GFI can be obtained accordingly based on the procedure as explained in the previous section. Generally, the major GI of airlines consists of Green Emission Index (GI_E), Green Noise Index (GI_N) and Green Fuel Efficiency Index (GI_{FE}). However, the element of GI may vary for other sectors.

Step 2: Establish judgment matrix (for the relative comparison of GI)

A pair-wise comparison matrix, A involving the relative comparison of GI (as obtained in step 1) can be expressed as follows (Saaty, 1980):

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix}_{nxn} \tag{6.10}$$

for which a_{ij} indicates relative comparison of green index GI_i over GI_j. Generally, matrix A is governed by a_{ij} x $a_{jk} = a_{ik}$ $\forall i,\ j,\ k$ to assure consistency. Specifically, a_{ij} implies the subjective judgment (relative comparison) of criteria *i* over *j* based on judgment scale 1-9 (Saaty, 1977, 1980, 1990).

Step 3: Calculate the largest eigenvalue

As an indicator for consistency, the largest eigenvalue, $\lambda_{\max}$ of a matrix can be determined as follows (Saaty, 1990):

$$\lambda_{\max} = \sum_{i,j=1}^{n} a_{ij} \frac{w_j}{w_i} \tag{6.11}$$

for which a_{ij} is the element of matrix A while w_i and w_j respectively represent the average of row *i* and *j* of matrix *A*. Note that a matrix is said to be more consistent if the value of the largest eigenvalue is getting closer to matrix size.

Step 4: Perform consistency test

A consistency test is needed to assure the consistency of matrix *A* (with size *n*). This test can be conducted based on the consistency index, *CI* and random consistency index, *RI* which are outlined as follows (Saaty, 1977).

$$CI = \frac{\lambda_{\max} - n}{n-1}, \ RI = \frac{1.98(n-2)}{n} \tag{6.12}$$

Saaty (1977) showed that $\lambda_{\max} = n$ if the matrix does not include any inconsistency. This implies that the closer the value of $\lambda_{\max}$ to *n*, the matrix is more consistent. By using the measurement of *CI* and *RI*, the consistency ratio, *CR* can be evaluated as follows:

$$CR = \frac{CI}{RI} \tag{6.13}$$

The judgment matrix is said to be consistent if *CR* < 0.1.

Step 5: Establish judgment matrix of green status (for each GI)

To capture the possible green status of GI that might be green or not green, a pair-wise comparison matrix of each GI, B_{GI_W} can be formed as follows:

$$B_{GI_W} = \begin{bmatrix} 1 & s_{ij} \\ s_{ji} & 1 \end{bmatrix}_{2x2} \tag{6.14}$$

for which matrix B_{GI_W} is a square matrix with a size 2 x 2 while s_{ij} reflects the relative comparison of green status s_i over s_j. Green status basically comprises two possible conditions (categories or status), i.e. green or not green. In fact, there is no restriction for the number of status, Equation (6.14) could be applied appropriately for more categories as desired by airlines.

Step 6: Perform consistency test

The consistency of matrix, B_{GI_W} can be confirmed directly by checking a_{ij} x $a_{jk} = a_{ik}$ $\forall i, j, k$. In fact, matrix of size 2 x 2 is indeed consistent in view of the fact that a_{12} x $a_{21} = a_{11}$=1 .

Step 7: Compute the Green Fleet Index (GFI)

The resultant GFI can be evaluated as follows:

$$GFI = \sum A_i^* B_r^* \tag{6.15}$$

where A_i^* represents the average of row $i = 1, 2, \ldots, n$ of normalized matrix A while B_r^* denotes the average of row $r = 1, 2, \ldots, a$ of normalized matrix B_{GI_W} . Note that a lower GFI value implies a greener performance.

6.4 An Illustrative Case Study

A realistic example is set up to evaluate the applicability of the developed methodology. In order to get closer to reality, most of the data used for evaluation were obtained from accessible published reports. The data resources include the websites of AirAsia Berhad (2013), Malaysia Airlines (2013), Airbus (2013) and Boeing (2013).

6.4.1 Data Description

It is assumed that an airline that is based at the Kuala Lumpur International Airport (KLIA) is operating a total of 38 routes (as shown in Table 6.1) with five types of aircraft, namely B737-400, B737-800, B777-200, A330-300 and A380. These aircraft are chosen based on the fleet composition operated by Malaysia Airlines (Malaysia Airlines, 2013) in servicing international routes at 70% load factor (in average). In order to examine the green performance of airline for a planning horizon of one year, the operations of these aircraft are considered accordingly. The specification of aircraft (including the fleet size of airline) and the environmental performance of aircraft are shown in Tables 6.2 and 6.3, respectively while the annual travel demand of airline, which is estimated to be 10,080,858 is obtained from the 5-step demand modeling framework. Besides, the service frequency of airline, i.e. 35,672 flights is compiled from the annual reports of airline (AirAsia Berhad, 2013).

A do-nothing scenario is assessed by using the aforementioned data input (without implementing any improvement action). In addition, four improvement strategies, namely increase load factor (strategy A), operate new aircraft (strategy B), reduce service frequency (strategy C), and reduce fuel consumption (strategy D), as shown in Table 6.4, were evaluated to examine their impact on the green performance of airlines. Although these improvement strategies might be related to one another to a certain extent, it is important to note that each strategy would be planned and implemented by airlines at a different stage. Increasing load factor (strategy A) could be categorized as pre-operational strategy for which airlines would need to carry out effective actions to keep the load factor high. This could be done in numerous ways, including implementing attractive marketing strategies to boost up flight ticket sales and perform joint-efforts or alliances (if necessary) among airlines. Besides, operating new aircraft (strategy B) could be considered as operational strategy towards aircraft activities in servicing the current operating networks. For strategy C, service frequency reduction refers to the strategy of airlines to retain the same capacity of passengers by reducing the number of flights. This is particularly required especially when airlines are controlled strictly under capacity/runway constraints. One of the ways for airlines to retain the same number of passengers is to operate a larger size of aircraft. For strategy D, fuel consumption reduction could be done in several ways, especially during aircraft operations. It is anticipated that airlines would have a greener performance by consuming less fuel which produce fewer pollutants.

Table 6.1: The Operating Information of International Routes (Malaysia Airlines, 2013)

Route	Destination	Frequency (daily)	Servicing aircraft	Distance (km)	Annual emission level (kg)	Annual noise level (EPNdB)	Annual fuel efficiency (kg/km/passenger)
1	Adelaide (ADL)	1	A330-300	5682	36,675,591	101,431	7.25
2	Amsterdam (AMS)	1	B777-200	10235	66,060,159	101,431	7.25
3	Auckland (AKL)	1	B777-200	8704	76,509,876	101,667	9.87
4	Bandar Seri Begawan (BWN)	1	B737-400	1491	13,111,721	101,667	9.88
5	Bangalore (BLR)	1	B737-800	2875	9,017,764	96,160	3.52
6	Bangkok (BKK)	4	B737-800	1251	15,705,974	384,640	14.10
	Bangkok (BKK)	1	B737-400	1251	3,926,821	96,650	3.53
7	Beijing (PEK)	1	A330-300	4413	13,235,117	96,405	3.37
	Beijing (PEK)	1	B777-200	4413	32,775,323	101,549	8.34
8	Brisbane (BNE)	1	A330-300	6438	41,554,733	101,431	7.25
9	Chennai (MAA)	2	B737-800	2626	46,175,447	203,334	19.75
10	Colombo (CMB)	1	B737-800	2465	7,733,437	96,650	3.52
11	New Delhi (DEL)	1	B737-800	3875	12,154,630	96,650	3.52
	New Delhi (DEL)	1	A330-300	3875	12,154,630	96,650	3.52
12	Denpasar Bali (DPS)	2	B777-200	1966	34,573,400	203,334	19.76
	Denpasar Bali (DPS)	2	B737-800	1966	24,204,375	193,299	13.83
13	Dhaka (DAC)	1	B777-200	2636	23,175,618	101,667	9.88
	Dhaka (DAC)	1	A330-300	2636	8,673,757	99,040	3.70
14	Frankfurt (FRA)	1	B777-200	9996	74,690,753	99,158	8.39
15	Guangzhou (CAN)	5	B737-800	2592	100,756,528	495,792	43.67
16	Hanoi (HAN)	2	B737-800	2085	36,665,284	203,334	19.75
17	Ho Chi Minh City (SGN)	3	B737-800	1053	27,785,853	305,002	29.64
18	Hong Kong (HKG)	1	A380	2562	22,525,200	101,667	9.88
	Hong Kong (HKG)	2	B737-800	2562	45,050,400	203,334	19.75
19	Hyderabad (HYD)	1	B737-800	3009	9,439,202	96,650	3.52
20	Jakarta (CGK)	6	B737-800	1141	21,491,430	579,898	21.16
21	Jeddah (JED)	1	B777-200	7055	22,125,833	96,650	3.52
22	Tribhuvan (KTM)	1	B737-800	3275	10,452,681	93,676	3.75
23	Kunming (KMG)	1	B737-800	2476	7,767,929	189,917	3.52
24	London (LHR)	2	A380	10603	84,433,764	176,877	6.73
25	Male (MLE)	1	B737-800	3133	9,828,017	96,650	3.52
26	Manila (MNL)	4	B737-800	2496	31,322,562	386,599	14.10
27	Melbourne (MEL)	1	A330-300	6329	55,634,981	101,667	9.87
28	Mumbai (BOM)	1	B737-800	3623	11,364,460	96,650	3.52
29	Osaka Kansai (KIX)	1	A330-300	4983	15,628,873	96,650	3.52
30	Paris (CDG)	1	A380	10439	31,301,824	96,405	3.37
31	Perth (PER)	1	A330-300	4139	32,157,778	80,227	10.53
32	Phnom Penh (PNH)	2	B737-800	1040	18,295,377	203,334	19.76
33	Seoul Incheon (ICN)	1	A330-300	4606	14,446,753	96,650	3.52
34	Shanghai Pu Dong (PVG)	2	A330-300	3798	24,966,320	193,299	7.38
35	Taipei (TPE)	4	B737-800	3268	64,849,023	385,619	22.29
36	Tokyo Narita (NRT)	2	B777-200	5406	69,788,633	202,861	14.50
37	Xiamen (XME)	1	B737-800	2991	6,701,239	202,861	2.52
38	Yangon (RGN)	2	B737-800	1682	29,581,004	203,334	19.76

Note: Distance (in kilometer) of each operating route is compiled based on the estimated miles of flight as detailed by Malaysia Airlines (2013).

Table 6.2: The Specification of Aircraft (AirAsia Berhad, 2013; Malaysia Airlines, 2013; Airbus, 2013; Boeing, 2013)

Aircraft	B737-400	B737-800	B777-200	A330-300	A380
Capacity (seats)	146	160	314	300	525
Size (m^2)	1,221	1,600	4,352	4,288	6,424
Number of engines	2	2	2	2	4
Maximum take-off weight (kg)	68,050	79,010	247,200	230,000	560,000
Range (km)	4,204	5,665	12,200	11,300	15,700
Category	Small		Large		Jumbo
Flight type	Short-haul		Medium-haul		Long-haul
Initial fleet size	13	17	8	8	2
Note: The parameter of environmental sustainability is $\theta = 96.5\%$.					

Table 6.3: The Emission Rate, Noise Level and Fuel Consumption of Aircraft (AirAsia Berhad, 2013; Malaysia Airlines, 2013; Airbus, 2013; Boeing, 2013; ICAO, 2011; Scheelhaase, 2010; Givoni and Rietveld, 2010)

Aircraft	Emission rate of LTO stage (kg/seat)	Emission rate of cruising stage (kg/kg of fuel)	Cumulative noise level (EPNdB/aircraft)	Fuel consumption of LTO cycle (kg/seat)	Fuel consumption/km during cruising stage (kg/seat)
B737-400	0.1482	3.16	376.36	5.65	0.02668
B737-800	0.1352	3.16	378.28	5.16	0.02435
B777-200	0.4477	3.16	397.91	8.16	0.03478
A330-300	0.2156	3.16	396.99	5.62	0.02673
A380	0.1789	3.16	314.00	4.66	0.02219

Table 6.4: The Strategy for Improvement Actions

Strategy	Description
A (increase load factor)	Increase load factor up to 80% for entire operating network.
B (operate new aircraft)	Operate new aircraft for operating route which exceeds 10 kg/km/passenger in terms of fuel efficiency (annually).
C (reduce service frequency)	Reduce 50% service frequency of operating route which exceeds 10 kg/km/passenger in terms of fuel efficiency (annually).
D (reduce fuel consumption)	Reduce 20% fuel consumption for entire operating network.

6.4.2 Results and Discussions

The graphical results of the respective Lorenz curve are illustrated in Figure 6.2 and the numerical results of green level are presented in Table 6.5. In terms of the overall green performance of airline, the results in Table 6.5

show that fuel efficiency is the worst performing factor, followed by aircraft emission and noise. This could be confirmed from Figure 6.2 where the Lorenz curve of fuel efficiency is the furthest from the line of perfect equality (comparing to the Lorenz curve of emission and noise). From the overall results in terms of the GFI in Table 6.5, it could be inferred that airline (under do-nothing scenario) is still relatively far from the desired green performance if there is no improvement strategy in action. Therefore, some improvement actions should be taken in accordance to current environmental performance of airline. This could be done by focusing on fuel efficiency enhancement, not only because of fuel efficiency was found to be the worst performing factor, but also to reduce pollutants as well as the operational cost of airlines via fuel savings. Four improvement strategies as listed in Table 6.4 are carried out accordingly to yield a greener performance.

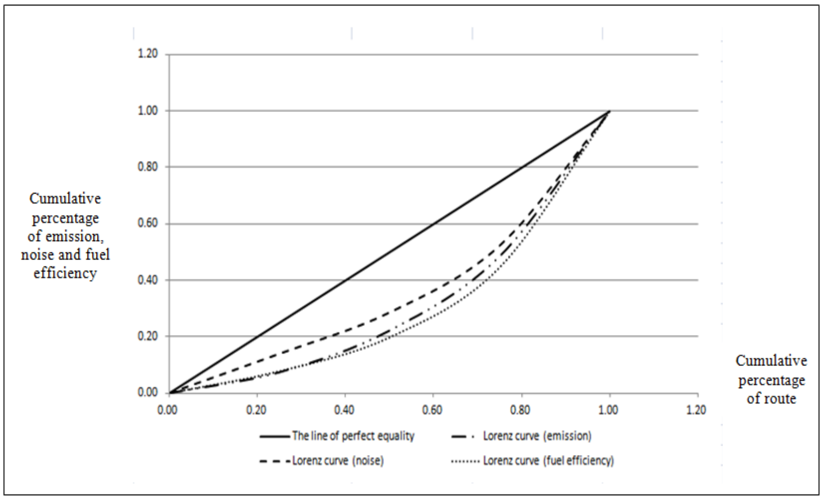

Figure 6.2: The Graphical Results of Green Index

Table 6.5: The Results of Strategy A-D

	Do-nothing	Strategy A	Strategy B	Strategy C	Strategy D
Green Emission Index	0.5130	0.4489 (+12.5%)	0.5077 (+1.0%)	0.3441 (+32.9%)	0.5102 (+0.5%)
Green Noise Index	0.3932	0.3440 (+12.5%)	0.3847 (+2.2%)	0.2860 (+27.3%)	0.3932 (+0%)
Green Fuel Efficiency Index	0.5562	0.4867 (+12.5%)	0.5477 (+1.5%)	0.3446 (+38.0%)	0.5500 (+1.1%)
Green Fleet Index (GFI)	0.4972	0.4351 (+12.5%)	0.4901 (+1.4%)	0.3938 (+20.8%)	0.4936 (+0.7%)

6.4.2.1 Strategy A: Increase Load Factor

The results show that an increasing load factor (strategy A) is an effective strategy to improve the environmental performance of airline. This strategy improves all green indices significantly, approximately to be 12.5% for all green indices (as shown in Table 6.5). These findings are in line with the results reported by Miyoshi and Mason (2009) and Morrell (2009). In addition, the results revealed that in average, 1% increment of load factor would improve the green performance of airline (in terms of the GFI) up to 1.3%. Generally, a higher load factor would generate a lower proportion of pollutants (emission, noise and fuel consumption) per unit load factor. In other words, increasing the load factor is more environmentally beneficial compared to a lower load factor. Empirically, the relation in the change of emission level and load factor could be deduced as $\Delta EX_t < \Delta LF_t$ where ΔEX_t and ΔLF_t respectively indicate the change of aircraft emission and load factor. This relation signifies that the change in the emission level is relatively lower than the increment in the load factor. Empirically, the results show that aircraft noise and fuel consumption exhibit similar pattern of changes. This explains for the greener performance of airline in overall (by increasing load factor).

6.4.2.2 Strategy B: Operate New Aircraft

As shown in Table 6.5, operating new aircraft (strategy B) with the latest technology would improve the green performance of airline effectively. The results indicate that if more routes are operated with new aircraft, the aircraft noise level could be improved, i.e. 2.2% for scenario B (by operating 20 routes with new aircraft). This is then followed by the improvement of fuel efficiency and aircraft emission. In average, operating new aircraft on every 10 routes would contribute 0.7% improvement of green performance.

The improvement of fuel efficiency system of aircraft could be the major reason to yield a better performance of fuel efficiency and aircraft emission level. Under this strategy, it was found that about 48% of the operating networks is operated with new B737-800 and 7% is supported by new A380. These aircraft are claimed to be fuel-efficient (Morrell, 2009; Airbus, 2013) and their operations in supporting the operating networks of airline explains the promising improvement of fuel efficiency as well as aircraft emission. Specifically, B737-800 produces the least emission rate and A380 was claimed to consume 17% lesser fuel (per passenger). As such, the contribution of new aircraft of B737-800 and A380 may justify a comparable performance of fuel efficiency and aircraft emission.

Besides, the results show that aircraft noise level has the largest green improvement, i.e. about 2.2% which appears to be slightly higher (better) than fuel efficiency and aircraft emission. This could be explained by the noise level which is emitted only from the landing and take-off (LTO) stage. Aircraft noise during cruising stage is not considered because the noise level generated from LTO stage was found to have more critical social impacts (noise annoyances) on neighboring communities. Therefore, the performance of aircraft emission and fuel efficiency which involve both LTO and cruising stages appears to emit more pollutants compared to aircraft noise level.

6.4.2.3 Strategy C: Reduce Service Frequency

The results, as shown in Table 6.5, empirically confirmed that a reduction of service frequency (strategy C) is one of the constructive strategies to improve green performance. Excluding operating route with single service frequency, scenario C reduces a total of 22 flights on 13 routes (i.e. Bali, Tokyo, Manila, Bangkok, Chennai, Hong Kong, Hanoi, Yangon, Taipei, Phnom Penh, Jakarta, Ho Chi Minh and Guangzhou). As shown in Table 6.5, the greatest improvement (about 38%) is fuel efficiency, followed by aircraft emission and noise. These findings are coherent with the findings from

McGovern (1998) and Monbiot (2006). In average, green level improves approximately 9.5% for every reduction of 10 flights.

The strategy to reduce service frequency implies that a particular aircraft would fly less. This strategy was found to be the simplest way to reduce environmental impact (Lijesen, 2010). By flying less, the current operating networks of airline is constrained under a limited capacity (number of flights). Under this circumstance, the level of aircraft emission, noise and fuel consumption generated by constrained capacity would be controlled under a certain level. Comparatively, a lower quantity of flights (by reducing service frequency) would produce lesser amount of pollutants and hence the environmental impacts would be reduced proportionally. Nevertheless, it is important to note that a reduction of service frequency might not be a desirable strategy in view of profit consideration. This strategy would affect not only airline’s revenue, but also its competitiveness on the global market. Note that service frequency reduction may retain the existing capacity of passengers (before reduction) by operating larger aircraft. This highlights the fact that green performance of airlines (by reducing service frequency) is also closely related to the fleet planning of airlines.

6.4.2.4 Strategy D: Reduce Fuel Consumption

Airlines could reduce fuel consumption (strategy D) in many ways. For example, to operate a new aircraft for a better fuel efficiency (Janic, 1999; Morrell, 2009), to implement strategic fuel management strategy (Abdelghany et al., 2005; Tsai et al., 2014) and to practice optimal aircraft operations (Williams et al., 2002; Nikoleris et al., 2011). In this research, fuel consumption is reduced by assuming that any of these strategies could be applied. The results in Table 6.5 indicate that the green improvement with this strategy is relatively minimal for which there is no impact on green noise index.

In terms of fuel efficiency which is greatly affected by the amount of fuel consumption by the airlines, ICAO (2010) pointed out that an improvement of 2% over a medium planning horizon is promising and this has been set as a global target (for the year 2010-2020) to preserve the environment. With this target, it is approximated that a gradual improvement would equivalently be 0.2% per annum. Besides, ICAO (2010) revealed that a better improvement of 0.8% (per annum) is achievable with more enthusiastic actions. From Table 6.5, it could be seen that the findings on the green performance of airline (under the strategy to reduce fuel consumption) is practically viable as the results are very much closer to the global target, i.e. 0.2%-0.8% per annum. Therefore, it could be empirically confirmed that this strategy is indeed environmental beneficial for airlines and the results, in fact, reflect a valid outcome (although the numerical findings appears to be relatively minimal).

6.5 Advantages of the Proposed Framework

As discussed earlier, it could be observed clearly that among the proposed strategies, the service frequency reduction (strategy C) yields the largest improvement in green level for which the improvement is up to 21%. This is followed by the strategy to increase load factor (with an average improvement of 13%), operating new aircraft (1.4%), and fuel consumption reduction (0.7%). Airlines could carry out strategic planning based on this insightful information by capturing environmental sustainability or green concern in fleet planning. In addition, this framework also revealed the effectiveness of each strategy. For example, it is not necessary that acquiring new aircraft (strategy B) would be the best option to mitigate environmental problems. The developed framework also allows the users to analyse in detail towards the improvement contributed by each strategy. For instance, by implementing strategy A (increase load factor), the green level on emission, noise and fuel efficiency exhibits a similar improvement level while the fuel efficiency of airlines could be greatly improved if service frequency is reduced. In addition, airlines should not consider fuel consumption reduction as one of the strategies to reduce noise level (see Table 6.5). Such conclusion could be made as the developed framework allows the contribution of each component to be evaluated specifically. Besides, it could be seen that the developed framework offers great flexibility to airlines to incorporate any other relevant factor that may affect the green performance of airlines. It is not only restricted to three environmental factors as discussed in this research. Instead of a single improvement strategy, the framework also highlights that the evaluation of multiple strategies at one time may yield a greener performance.

6.6 Summary

In compliance to stricter environmental rules and regulations on aircraft operations, nowadays airlines have to capture their green performance particularly to avoid paying tremendous fines. This could be done if airlines knows their current green status and identify some effective strategies for improvement. The developed framework in quantifying the Green Fleet Index (GFI) could assist airlines not only to quantify explicitly the respective green index (on aircraft emission, noise and fuel efficiency) but also evaluate the effectiveness of specific mitigation strategies. In this research, three major environmental factors (emission, noise and fuel efficiency) are considered but the developed methodology is not restricted to these factors. Other relevant factors could be incorporated appropriately in the developed framework. From the proposed strategies, it can be observed that each improvement strategy has different impacts on individual environmental factor. In order to yield a greener performance, airlines may integrate numerous strategies necessarily or incorporate green issue at the planning stage, e.g. include green concern in the fleet planning model. Besides, it is anticipated that green improvement would also contribute a higher profit level to airlines (as discussed in next chapter).

CHAPTER 7

GREEN FLEET PLANNING DECISION MODEL

7.1 Bi-objective Green Fleet Planning

This chapter presents the formulation of the green fleet planning decision model to optimize airline's profit and green performance. Ideally, the developed model aims to maximize the operational profit of airline while minimizing the green fleet index (GFI) for each operating period throughout the planning horizon in order to yield a better environmental performance (i.e. a lower value of GFI implies a greener performance). As such, the developed model is formulated as a bi-objective green fleet planning model. By analyzing a realistic case study, the resultant findings show that the developed methodology is beneficial to airlines not only in assuring a higher profit level but also reducing pollutants at a greater scale. Besides, the results empirically reveal the importance of incorporating green concern in fleet planning. Concisely, the developed model is feasible for airlines to sustain profitably and environmentally.

7.2 Problem Formulation

To operate a set of origin-destination (OD) pairs in the current operating networks, assume that there is a selection of *n* types of aircraft that could be purchased or leased. The decision variables of the developed green fleet planning decision model are the quantity and type of aircraft to be purchased or leased in order to optimize the environmental performance and operational profit of airlines. For a particular operating period, although the optimal solutions could be obtained, the optimal decision for the next operating period is unknown due to uncertainty (Taha, 2003; Winston, 2004).

7.2.1 Constraints

The practical constraints in optimizing the green fleet planning decision model are listed below:

Budget constraint Budget constraint ascertains whether or not the solution is financially feasible for airlines. For this constraint, the sum of aircraft purchase and lease cost should not be more than the airline's allocated budget. This constraint could be expressed as follows:

$$\sum_{i=1}^{n} purc_{ti} x_{ti}^{P} + \sum_{i=1}^{n} lease_{ti} x_{ti}^{L} \leq MAX_{budget(t)} \text{ for } t = 1, \ldots, T \qquad (7.1)$$

Demand constraint To meet travel demand satisfactorily at a desired service level, demand constraint could be formed as follows:

$$\sum_{i=1}^{n}\left(SEAT_{i,F_i}^{t}\right)\left(f_{i,F_i}\left(D_t^S, A_t^i\right)\right)\geq\left(1-\alpha\right)D_t^S \text{ for } t=1,\ldots,T; S=s_1,\ldots,s_k \quad (7.2)$$

where $1-\alpha$ is the confidence level (service level) of airlines to meet stochastic demand for which the level of demand could be modeled by using the 5-step modeling framework. Specifically, Equation (7.2) assures that the service frequency of each operating route, $f_{n,F_i}\left(D_t^S, A_t^i\right)$ that is offered with the aircraft capacity (number of seat), $SEAT_{n,F_i}^{t}$ would meet stochastic demand desirably.

Parking constraint When an aircraft is not in operation, it has to be parked at the hangar or apron at the airport. In such a case, the choice of aircraft would be constrained by the geometry layout of the hangar/apron at airport. As such, parking constraint is ought to be considered feasibly. This constraint could be formed as follows:

$$\sum_{i=1}^{n}\sum_{y=0}^{m}\left(I_{tiy}^{P}+I_{tiy}^{L}+x_{ti}^{P}+x_{ti}^{L}\right)\left(size_i\right)\leq PARK_t \text{ for } t=1,\ldots,T \quad (7.3)$$

Sales of aircraft constraint For some airlines, aging aircraft which is less cost-effective might be sold at the beginning of a certain operating period when airlines make the decision to purchase new aircraft. However, the quantity of aircraft sold should not be more than the aircraft owned by airlines. This constraint could be outlined as follows:

$$sold_{tiy} \leq I^{P}_{(t-1)i(y-1)} \text{ for } t = 1,...,T,; i = 1,...,n; y = 1,...,m \tag{7.4}$$

Order delivery constraint The delivery of new aircraft depends on the production and the supply of aircraft manufacturers. Sometimes, there might be an availability issue in delivering new aircraft. As such, the aircraft to be purchased by airlines should not be more than the quantity of aircraft available in the market. This constraint can be expressed as follows:

$$x^{P}_{ti} \leq ORDER_{t} \text{ for } t = 1,...,T; i = 1,...,n \tag{7.5}$$

Aircraft range constraint For airlines, aircraft range refers to the maximum distance flown by the respective aircraft type. The aircraft range is crucial for consideration in view that the mileage (distance) of each operating route might vary differently. To assure operational feasibility in practice, the constraint to operate possible aircraft type in terms of range (maximum distance flown) could be formed as follows:

$$RG_{i} > DIS_{F_{i}} \text{ for } i = 1,..., n \tag{7.6}$$

Equation (7.6) signifies that the type of aircraft chosen by airlines must be practically feasible for which the choice of aircraft for operations must possess an aircraft range which is greater than the distance of a particular operating route.

Aircraft homogeneity constraint In order to support the current operating networks, airlines tend to acquire/lease aircraft type based on aircraft homogeneity (standardization) in fleet composition, mainly due to various issues including aircraft maintenance, pilot employment, etc. There is a variety of aircraft type (with particular specification) which may practically be suitable to support airline’s operating networks. By considering aircraft homogeneity in the fleet composition, the constraint to operate possible aircraft type can be formed as follows:

$$X_{ti}^{P}, X_{ti}^{L} \in FV_{ti} \text{ for } t = 1, \ldots, T; i = 1, \ldots, n \tag{7.7}$$

where FV_{ti} is the existing variety of airline's fleet composition (with *n* types aircraft type) of operating period *t*.

Lead time constraint In practice, airlines would get an agreeable lead time (the period between placing and receiving an order) from the aircraft manufacturer when they place an order for new aircraft. This constraint should be considered as it indicates when airlines are supposed to order new aircraft. For *n* types of aircraft, this constraint can be expressed as follows:

$$P\left(RLT_{ti} \geq DLT_{ti}\right) \leq \beta \text{ for } t = 1, \ldots, T; i = 1, \ldots, n \tag{7.8}$$

Since in real life, there are chances that the targeted lead time may vary (say, due to the technical issues of the manufacturer), the lead time should be a random value that could be represented by a certain distribution. In this research, the lead time is assumed to be normally distributed with mean μ_{LT} and standard deviation σ_{LT}. The lead time constraint could be stated by,

$$DLT_{ti} \geq F^{-1}\left(1-\beta\right)\sigma_{LT} + \mu_{LT} \text{ for } t = 1,...,T; i = 1,...,n \qquad (7.9)$$

where $F^{-1}(1-\beta)$ is the inverse cumulative probability of $1-\beta$.

Selling time constraint An aging aircraft which is considered as less economical might be sold by airlines at a particular operating period. In such a case, airlines need to know the most suitable time to release their aging aircraft for sales particularly to look for prospective buyers in advance. In real practice, the real selling time might be longer than the desired selling time. Therefore, this constraint is formed with the aim to reduce the possibility of this incident as least as possible. The selling time constraint could be defined as follows:

$$P\left(RST_{ti} \geq DST_{ti}\right) \leq \gamma \text{ for } t = 1,...,T; i = 1,...,n \qquad (7.10)$$

It is assumed that selling time has a normal distribution with mean μ_{ST} and standard deviation σ_{ST}, selling time constraint could be formed as follows:

$$DST_{ti} \geq F^{-1}\left(1-\gamma\right)\sigma_{ST} + \mu_{ST} \text{ for } t = 1,...,T; i = 1,...,n \qquad (7.11)$$

where $F^{-1}(1-\gamma)$ implies the inverse cumulative probability of $1-\gamma$.

7.2.2 Objective Function

The objective of green fleet planning decision model is to maximize the environmental performance and operational profit of airlines by determining the optimal quantity and type of aircraft that should be purchased and/or leased to meet stochastic demand. The operational profit of airline could be derived by considering the subtraction of the total operating cost from the total revenue. For an airline, the total revenue is basically generated from the operational income (i.e. the sales of the flight tickets) and the sales of aging aircraft while the total operating cost is formed by operational cost, aircraft purchase and lease cost, maintenance cost, depreciation expenses and payable deposit of aircraft acquisition and leasing.

For the operating year *t*, the total revenue, $TR(I_t^P + I_t^L)$ is expressed as follows:

$$
\begin{aligned}
TR\left(I_t^P + I_t^L\right) = E\left(fare_{tn}^S\right) E\left(seat_{tn}^S\right) f_{i,F_i}^m\left(D_t^S, A_t^i\right) + \\
\sum_{i=1}^{n}\sum_{y=1}^{m} sold_{tiy} resale_{tiy} \text{ for } t = 1,\ldots,T; i = 1,\ldots,n; S = s_1,\ldots,s_k
\end{aligned}
\tag{7.12}
$$

For Equation (7.12), the first term on the right-hand side indicates the expected income from the sales of flight tickets by considering the service frequency of airlines. The second term signifies the revenue from the sales of aging aircraft.

The total operating cost for the operating year t, $TC(I_t^P + I_t^L)$ is formed as follows:

$$
\begin{aligned}
TC\left(I_t^P + I_t^L\right) = E\left(\cos t_{tn}^S\right) E\left(seat_{tn}^S\right) f_{i,F_i}^m\left(D_t^S, A_t^i\right) + \sum_{i=1}^{n} u_{ti} + \left(purc_{ti}\right)\left(x_{ti}^P\right) + \sum_{i=1}^{n} lease_{ti}\left(x_{ti}^L\right) + \\
\sum_{i=1}^{n} hgf\left(D_t^S, A_t^i\right) + \sum_{i=1}^{n}\sum_{y=1}^{m}\left(I_{tiy}^P\right)\left(dep_{tiy}^P\right) + \sum_{i=1}^{n}\sum_{y=1}^{m}\left(I_{tiy}^L\right)\left(dep_{tiy}^L\right) + \sum_{i=1}^{n} dp_{ti}\left(x_{ti}^P\right) + \\
\sum_{i=1}^{n} dl_{ti}\left(x_{ti}^L\right) \text{ for } t = 1,\ldots,T; i = 1,\ldots,n; S = s_1,\ldots,s_k
\end{aligned}
$$

(7.13)

The terms on the right-hand side of Equation (7.13) respectively denote the expected operational cost, aircraft purchase cost (with setup cost if there is any), lease cost, maintenance cost, depreciation expenses and payable deposit of aircraft acquisition and leasing.

While attaining the operational profit (by considering the difference of operating cost and revenue), the green performance of airlines should be monitored closely to preserve the environment. As discussed earlier, a greener performance could be achieved by minimizing the GFI. The function of GFI of airlines could be defined as follows:

$$GFI\left(I_t^P + I_t^L\right) = f\left(GI_E, GI_N, GI_{FE}\right) \tag{7.14}$$

for which the GFI is constituted by the respective green index (GI) as discussed in the previous chapter.

7.2.3 Green Fleet Planning Decision Model

In summary, the bi-objective green fleet planning decision model of airlines can be presented as follows:

$$\mathrm{Opt}\left(OBJ_1,\ OBJ_2\right) \tag{7.15}$$

where OBJ_1, OBJ_2 respectively indicates the first objective and second objective to be optimized (i.e. Opt represents maximization or minimization) for which the objective functions are outlined as below:

Objective 1: Maximize operational profit, $P\left(I_t^P + I_t^L\right)$

$$P\left(I_t^P + I_t^L\right) = \max\left(1+r_t\right)^{-t} \left\{ \begin{array}{l} p_{S_1}\left(TR\left(I_t^P + I_t^L\right) - TC\left(I_t^P + I_t^L\right)\right) + \ldots + \\ p_{S_k}\left(TR\left(I_t^P + I_t^L\right) - TC\left(I_t^P + I_t^L\right)\right) + P_{t+1}\left(I_t^P + I_t^L\right) \end{array} \right\} \quad (7.16)$$

Objective 2: Minimize the Green Fleet Index, GFI

$$GFI\left(I_t^P + I_t^L\right) = \min f\left(GI_E, GI_N, GI_{FE}\right) \quad (7.17)$$

The proposed model is optimized subject to the practical constraints (7.1)-(7.7), (7.9) and (7.11) where D_t^S, X_t^P, X_t^L, I_t^P, I_t^L, $SOLD_t$, O_t, $R_t \in Z^+ \cup \{0\}$ and $0 \le GFI \le 1$. The term $\left(1+r_t\right)^{-t}$ is used for the discounted value across the planning horizon while p_{s_k} indicates the probability of k-th probable phenomenon for having I_t^P, $I_t^L \in I_t$ as the initial aircraft in operation at the beginning of each operating period, i.e. this component is playing a vital role to ensure the adequacy of aircraft to support the current operating networks. The optimal decision (output) of the developed model is the optimal quantity and type of aircraft to be purchased or leased.

7.2.4 Solution Method

The developed bi-objective fleet planning decision model, as displayed in Figure 7.1, can be solved with the aid of lexicographic optimization approach (Collette and Siarry, 2004). This approach has the advantage of explicitly prioritizing the optimization objectives, which could reflect the realistic concerns of airlines. Basically, lexicographic optimality approach deals with a hierarchical order among all objectives for which the objective function is optimized one by one starting from the highest prioritized objective. The optimal solution of the optimization model is obtained after optimizing all objective functions. In other words, it permits the decision makers to rank the priority (or concern) on different optimization objective according to its relative importance and solves the optimization problem systematically without the need to specify exact weight value. Generally, the procedure of the solution method could be conducted in two stages as outlined below:

Stage 1: Lexicographic optimization

Step 1: Rank J objectives from the highest to the lowest priority level. By having objective ranking, the optimization problem could be presented (as follows) where OBJ_i has the highest priority while OBJ_J has the lowest priority, i.e. OBJ_i has a higher priority than OBJ_j for $i < j$.

$$\text{Opt}\left(OBJ_i, OBJ_{i+1}, OBJ_{i+2}, ..., OBJ_{J-1}, OBJ_J\right)$$

Step 2: Starting from the objective with the highest priority level (objective OBJ_i), optimize green fleet planning decision model subject to all constraints. Determine the optimal value of this objective that can be attained, i.e. $OBJ_i^* = \text{Opt}(OBJ_i)$.

Step 3: For remaining objectives, i.e. from OBJ_{i+1} to OBJ_J, optimize green fleet planning decision model accordingly and obtain the optimal objective as follows:

$$OBJ_k^* = \text{Opt}\left(OBJ_k \mid OBJ_L = OBJ_L^*\right),\ k = i+1, ..., J;\ L = i, ..., k-1$$

Step 4: Stop when all objectives are optimized. The solutions obtained are those satisfy all objective optimally.

Stage 2: Improve and finalize green fleet planning decision-making

Step 5: If the solution from Step 4 is unsatisfactorily, implement improvement strategy to obtain a desired optimal solution. Otherwise, proceed to Step 7. (Note: It is decisively depending on airlines to justify whether if the solution is satisfied or not, i.e. the satisfactory condition is airline-specific. For instance, the solutions obtained based on 70% load factor may not be satisfactory for a particular airline and hence a desired solution for a better operating performance (e.g. with a higher load factor at 80%) could be generated by airlines if increasing load factor is to be implemented as an achievable improvement strategy. Conversely, if airline satisfies with the current solution (from Step 4), there is no improvement action needed.)

Step 6: Repeat step 1-4 for optimization.

Step 7: Finalize green fleet planning decision-making.

The lexicographic optimization approach is adopted as it allows the decision makers to rank the priority (concern) on different optimization objective according to its relative importance and solves the optimization problem systematically. This, in fact, reflects the actual situation of airlines for which the decision makers have to consider multiple aspects and various concerns (e.g. operational, economy and environmental factors) in making profitable fleet planning decision (AirAsia Berhad, 2010a; Malaysia Airlines, 2010a). Unlike other solution approaches (for instance, the weighted-sum approach and hybrid method), lexicographic optimization approach does not require the decision maker to quantify the exact weight value (among the optimization objectives) as it is often not trivial to obtain the objective weight precisely, especially for large-scale problems (Prats et al., 2011).

In overall, the unsuitability of other possible solution approaches (due to their characteristics and requirements) is summarized in Table 7.1. Comparatively, the decision makers are merely required to perform objective ranking (without quantifying the exact weight) which is relatively straightforward for the lexicographic optimization approach. This approach is becoming a widely used technique due to its beneficial simplicity and straightforwardly manner with marginal implementation effort.

Table 7.1: The Summary of the Possible Solution Methods (Collette and Siarry, 2004)

Approach	Remarks
Weighted-sum method, Keeney-Raiffa method, distance-to-a-reference approach	Require to transform multi-objective problem into mono-objective. However, some objective functions may not be able to combine due to varying unit measurements.
Jahn method, Geoffrion method	Need to transform multi-objective problem into mono-objective and each objective function is limited under a specific value (as an additional constraint).
Goal attainment/goal programming, Fandel method, STEP method	Limit all objective function under an ideal value (goal) for which the setting of an ideal value may not be realistic and troublesome for some problems.
Proper-equality-constraints (strict-equality-constraints) method	Need to assign a constraint bound (equality form) to each objective function.
Proper-inequality-constraints method, Lin-Tabak algorithm, Lin-Giesy algorithm	Need to assign a constraint bound (inequality form) to each objective function.
Compromise (epsilon constraint) method, hybrid method	Require an additional constraint with epsilon.

Specifically, some of the possible solution methods as summarized in Table 7.1 (e.g. weighted-sum method, Keeney-Raiffa method, distance-to-a-reference approach, Jahn method and Geoffrion method) are less appropriate because the weight value of airline's profit and green level is not known in the literature and hence the transformation of the bi-objective problem into mono-objective appears to be not possible. In addition, both objectives have different unit measurements, i.e. the profit is measured in terms of dollars while the green level is measured in terms of points (0 to 1). As such, a monetary conversion factor of these points to dollars is needed. However, such conversion factor is unknown in the literature. By adopting lexicographic optimization approach as the solution method, this problem can be avoided because the decision makers only need to specify the objective ranking (without quantifying the exact weight) which is much more straightforward.

Besides, some other possible solution methods as listed in Table 7.1 (e.g. goal attainment/goal programming approach, Fandel method, STEP method, proper equality/inequality constraints method, Lin-Tabak algorithm, Lin-Giesy algorithm, compromise method, hybrid method) are not appropriate. These methods require airlines to set a particular target (ideal value or goal) to be achieved for each operating period throughout the planning horizon. The targeted values are required not only for profit level but also green level of airline. However, these approaches do not provide any proper mechanism in determining a desired value of airline's profit and green performance. As such, the setting of a specific goal for the objective functions (i.e. profit and green level) in solving fleet planning model seems not straightforward. Furthermore, an improper determination of targeted goal may not be realistic and the resultant outputs might be questionable at certain extent. Comparatively, lexicographic optimization approach does not require the decision makers to set particular goal to any objective function and this certainly offers a greater flexibility to airlines to optimize fleet planning decision (without specific goal/limit).

However, Collette and Siarry (2004) commented that the lexicographic optimization approach has a drawback with its requirement to rank the importance (or priority) of the objective functions to be optimized. They highlighted that the importance ranking among the objective functions is arbitrary for which two distinct orders of objective functions generate different solutions. Prats et al. (2010) added that there is a difficulty of choosing the priority among the objectives for some applications.

As mentioned beforehand, lexicographic optimization approach establishes a hierarchical order among all optimization objectives. Kerrigan and Maciejowski (2002) revealed than if such a priority exists, a unique solution exists on the Pareto hyper-surface. For the developed model, the optimal solutions (subject to numerous practical constraints) are generally governed by following definitions (Winston, 2004):

Definition 1 (Pareto optimality): *A solution (let it be* Ω^**) of a multi-objective problem is Pareto optimal if no other feasible solution is at least as good as* Ω^* *with respect to every objective and strictly better than* Ω^* *with respect to at least one objective.*

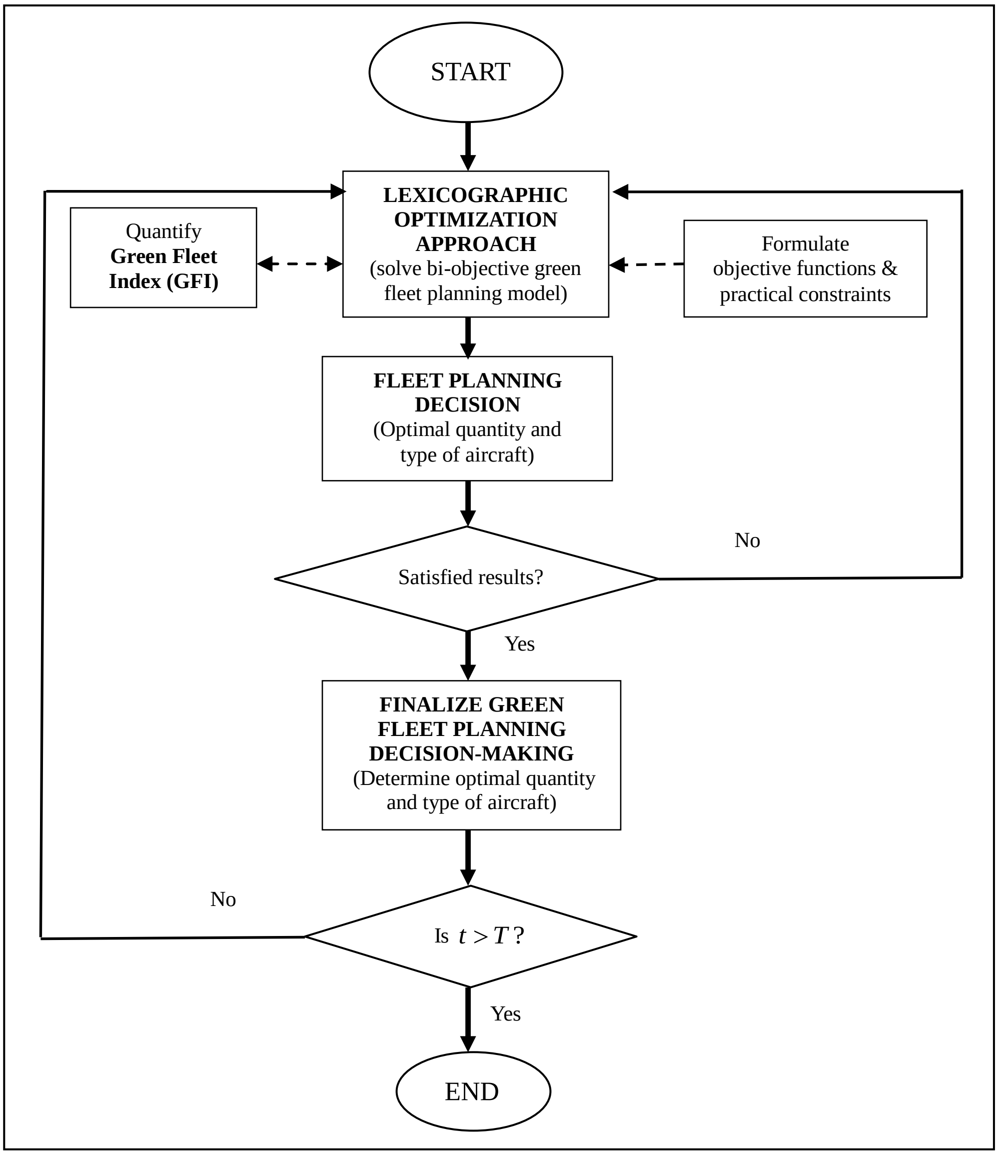

Figure 7.1: The Flow Chart of the Optimization Approach

In solving bi-objective fleet planning problem of airlines (under numerous practical constraints), let the feasible objective function be $\Omega(P, GFI)$ and Pareto-optimal solution could then be expressed as $\Omega^*(P^*, GFI^*)$ for which P^* and GFI^* are the Pareto-optimal solution of airline's profit (maximal) and the GFI (minimal) in terms of optimal quantity of the respective aircraft type. Note that $P^* \geq P$ and $GFI^* \leq GFI$ for which $P^* \in P$ and $GFI^* \in GFI$.

Definition 2 (Pareto dominance): *A feasible solution* Ω_A *dominates a feasible solution* Ω_B *of a multi-objective problem if it is at least as good as* Ω_B *with respect to every objective and is strictly better than* Ω_B *with respect to at least one objective.*

With regard to the total quantity of aircraft composition, I_t, let the feasible decision variable of fleet planning decision model be $I_t \in \Lambda$ of a particular operating period *t*. The feasible solution I_t^* is said to be non-dominated if and only if there is no solution in Λ which dominates I_t^*. In other words, the feasible solution I_t^* is a Pareto dominance solution if and only if I_t^* is non-dominated with regard to the entire solution space of Λ. Mathematically, $P^*(I_t^*) \geq P(I_t)$ and $GFI^*(I_t^*) \leq GFI(I_t)$ applies reasonably for the developed bi-objective green fleet planning decision model.

It is anticipated that the green performance of airline is inversely proportional to the operational profit for which a greener performance that requires more new aircraft would bring down the optimal profit of airline. This reveals that the operational profit and green performance of airline, in fact, have a conflicting (contradictory) relation. Thus, this implies that there would be a compromise solution (Pareto-optimal solution) generated by lexicographic optimization approach for which it is impossible to make any one of the objective functions better off without making the other one worse off, i.e. a greener performance produces a lower profit margin or vice versa. However, the developed model is able to make a substantial environmental cost savings (as discussed more later) by achieving a greener performance.

7.3 An Illustrative Case Study

Five types of aircraft, i.e. B737-400, B737-800, B777-200, A330-300 and A380 are considered for a set of 38 OD pairs for a planning horizon of eight years. These aircraft are chosen based on the fleet composition of Malaysia Airlines (Malaysia Airlines, 2013) in servicing international operating routes. According to Malaysia Airlines (2010a) and AirAsia Berhad (2010a), the acquisition of new aircraft requires, in average, a period of five years to be completely delivered. Besides, the desired lead time is assumed to have a normal distribution with an average of three years and standard deviation of 1.5, i.e. $DLT \sim N(3, 1.5)$. As such, five types of aircraft which are considered for a planning horizon of eight years are reasonably practical to reflect airline's actual practice. The purchase cost, lease cost, depreciation cost, resale price and residual value of the respective aircraft could be seen in Tables 5.5 and 5.6, respectively (as displayed in chapter 5). The 38 operating routes and their relevant environmental data are presented in Table 6.1. The specification and initial fleet size of each aircraft type is shown in Table 6.2 while the environmental performance of aircraft is shown in Table 6.3 (note: Tables 6.1-6.3 are displayed in chapter 6). Annual travel demand of airline, as shown in Table 7.2, is obtained from 5-step modeling framework of stochastic demand while the service frequency of each operating period is compiled from the annual reports of airline (AirAsia Berhad, 2013). Table 7.3 shows the expected value of flight fare and flight cost per passenger.

Table 7.2: The Travel Demand and Service Frequency of Airline

Period, t	Travel demand (number of passenger)	Service frequency (number of flight)
1	10,080,858	39,055
2	10,988,135	42,570
3	7,471,932	28,948
4	7,845,529	30,395
5	7,845,529	30,395
6	8,473,171	32,827
7	9,151,025	35,453
8	9,700,086	37,580

Table 7.3: The Expected Value of Flight Fare and Cost per Passenger

Operating period, t	1	2	3	4	5	6	7	8
$E\left(fare_t^{s_1}\right)$, \$	525	612	673	740	814	896	985	1084
$E\left(fare_t^{s_2}\right)$, \$	528	581	639	703	774	851	936	1030
$E\left(fare_t^{s_3}\right)$, \$	501	551	606	666	733	806	887	975
$E\left(\cos t_t^{s_1}\right)$, \$	309	340	374	411	452	498	547	602
$E\left(\cos t_t^{s_2}\right)$, \$	294	323	355	391	430	473	520	572
$E\left(\cos t_t^{s_3}\right)$, \$	278	306	337	370	407	448	493	542

In addition to the aforementioned data, other data input are listed as follows:

By definition:

- Three probable phenomena are considered, where $k = 3$
- Discount rate, $r_t = 5\%$ for $t = 1, 2, ..., T$
- Significance level of demand constraint, $\alpha = 5\%$
- Significance level of lead time constraint, $\beta = 5\%$
- Significance level of selling time constraint, $\gamma = 5\%$
- $D_t^{s_1} = D_t$ and $D_t^{s_k} = (1-\alpha) D_t^{s_{k-1}}$ for $t = 1, ..., T;\ k > 1$ (7.18)

By assumption:

- The probability of aircraft possession (probable phenomena) is $p_{s_1} = 0.50,\ p_{s_2} = 0.36$ and $p_{s_3} = 0.14$
- At $t = 1$, initial quantity of aircraft to be four years old is $I_{1i4}^P = 2$ for $i = 1, 2, 3, 4$
- Setup cost, $u_{ti} = 0$ for $t = 1, ..., T;\ i = 1, ..., n$

By assumption (based on real data):

- The parameter of environmental sustainability is $\theta = 96.5\%$
- Allocated budget, $MAX_{budget(t)} = \$6,500$ million
- Area of parking space (hangar and/or apron), $PARK_t = 500,000 m^2$
- Order delivery constraint, $ORDER_t = 5$
- Load factor, $LF_{n,F_i}^t = 70\%$

- Salvage cost of aircraft $= 10\%$ x $PURC_t$ for $t = 1, \ldots, T$
- Deposit of aircraft acquisition, $DP_t = 10\%$ x $PURC_t$ for $t = 1, \ldots, T$
- Deposit of aircraft leasing, $DL_t = 10\%$ x $LEASE_t$ for $t = 1, \ldots, T$
- Unit cost of emission, $UEC^t_{n,F_i} = \$27 / \text{ton}$
- Noise charge, $UNC^t_{n,F_i} = \$90$ per unit of noise
- Fuel cost, $UFS_t = \$100 / \text{barrel}$
- The function of maintenance cost is

$$h = 5177 + 7.97\text{x}10^{-3} g \quad [\text{R}^2 = 0.94] \tag{7.19}$$

where g is the traveled mileage.

- The quantity of aircraft is

$$NA = 10^{-5} NP - 73.6 \quad [\text{R}^2 = 0.92] \tag{7.20}$$

where NP is the number of travelers.

Based on the reports of Malaysia Airlines (2010a) and AirAsia Berhad (2010a), Equations (7.19) and (7.20) are obtained by conducting polynomial regression analysis (Meyer and Krueger, 2005). Equation (7.19) signifies that a unit cost of 0.00797 is charged as maintenance cost for each additional unit of mileage traveled. For this equation, \$5177 indicates an overall estimated maintenance cost without considering an additional traveled mileage. Besides, the regression analysis exhibits that Equation (7.20) is best fitted as a linear function in terms of number of travelers. Equation (7.20) displays that every addition of 100,000 travelers requires one additional aircraft for which the constant in Equation (7.20) has no practical interpretation.

A benchmark scenario, which is formed by the aforementioned data input, is examined by using the developed model. Profit maximization is chosen as the main (first) objective while GFI minimization is selected as the second objective. This order of objective ranking is chosen merely due to the utmost concern of airlines from the aspect of financial sustainability in attaining optimal profit. In addition, Scenario A is created with the reverse order of objective ranking compared to the benchmark scenario. This aims to investigate the impact of objective ranking on the developed methodology. Scenario B is developed by considering a single objective, i.e. profit maximization, particularly to reveal the advantage of the developed methodology in tackling environmental problem. Scenario C and D inspect the benefits of having improvement in operational strategies, i.e. increasing load factor and reducing service frequency. Scenario D has reduced eight flights (daily) for six routes (Hong Kong, Chennai, Taipei, Tokyo, Guangzhou and London) throughout the planning horizon. A total reduction of 2738 flights per annum is simulated in Scenario D compared to the benchmark scenario. Note that service frequency reduction excludes all routes with single service frequency. Table 7.4 shows the summary of all outlined scenarios.

Table 7.4: Additional Scenario for Further Analysis

<table>
<tr><th>Scenario</th><th>Objective ranking</th><th>Load factor</th><th>Service frequency</th></tr>
<tr><td>Benchmark</td><td>1st: maximize profit, 2nd: minimize GFI</td><td rowspan="3">70%</td><td rowspan="4">Default
service frequency
(as shown in Table 6.1)</td></tr>
<tr><td>A</td><td>1st: minimize GFI, 2nd: maximize profit</td></tr>
<tr><td>B</td><td>Single objective (profit maximization)</td></tr>
<tr><td>C</td><td>1st: maximize profit, 2nd: minimize GFI</td><td>80%</td></tr>
<tr><td>D</td><td>1st: maximize profit, 2nd: minimize GFI</td><td>70%</td><td>50% reduction</td></tr>
</table>

7.4 Results and Discussions

The results of case study are displayed in Tables 7.5-7.8. Specifically, Tables 7.5 and 7.6 present the results of the benchmark scenario while Tables 7.7 and 7.8 respectively displays the green performance and fleet planning decision for all scenarios.

Table 7.5: The Green Performance of Airline (Benchmark Scenario)

Operating period	Green Emission Index	Green Noise Index	Green Fuel Efficiency Index	Green Fleet Index (GFI)	Fleet size (*purchased fleet: leased fleet*)	Stochastic demand (millions)
1	0.5403	0.3923	0.5383	0.5001	48 (*0:0*)	10.08
2	0.5820	0.4278	0.5752	0.5379	44 (*0:4*)	10.99
3	0.5761	0.4279	0.5872	0.5403	44 (*0:0*)	7.47
4	0.5518	0.4094	0.5607	0.5168	46 (*0:2*)	7.85
5	0.5536	0.4094	0.5617	0.5179	46 (*0:0*)	7.85
6	0.5067	0.3763	0.5136	0.4741	50 (*0:4*)	8.47
7	0.4787	0.3554	0.4863	0.4483	53 (*1:2*)	9.15
8	0.4550	0.3363	0.4604	0.4251	56 (*1:2*)	9.70
Average	0.5305	0.3918	0.5354	0.4951	48.4	8.9

7.4.1 The Results of Benchmark Scenario

The results of the GFI as shown in Table 7.5 indicate that the green performance of airline is improving at 2% per annum for the planning horizon of eight years. The trend of gradual improvement is mainly contributed by the incorporation of new aircraft (via acquisition and leasing) as detailed in Table 7.6. Generally, new aircraft is found to be greener than the aging aircraft by incorporating advanced technology and fuel-efficient system that produce less pollutant (Janic, 1999; Miyoshi and Mason, 2009). As there are more new aircraft that is incorporated in airline's fleet composition, i.e. approximately 4.2% in average throughout the planning horizon, the value of the GFI depicts a decline trend, i.e. GFI is improving and getting greener from year to year.

Table 7.6: The Fleet Planning Decision of Airline (Benchmark Scenario)

Operating period		1	2	3	4	5	6	7	8	Average
Initial quantity of aircraft owned	B737-400	13	11	11	11	11	11	11	12	11.4
	B737-800	17	15	15	15	15	15	15	15	15.3
	B777-200	8	6	6	6	6	6	6	6	6.3
	A330-300	8	6	6	6	6	6	6	6	6.3
	A380	2	2	2	2	2	2	2	2	2.0
Initial quantity of leased aircraft	B737-400	0	0	0	0	1	1	2	2	0.8
	B737-800	0	0	1	1	1	1	2	2	1.0
	B777-200	0	0	0	0	0	0	1	1	0.3
	A330-300	0	0	2	2	3	3	4	6	2.5
	A380	0	0	1	1	1	1	1	1	0.8
Quantity of aircraft to be ordered	B737-400	0	0	0	1	1	0	0	0	0.3
	B737-800	0	0	0	0	0	0	0	0	0.0
	B777-200	0	0	0	0	0	0	0	0	0.0
	A330-300	0	0	0	0	0	0	0	0	0.0
	A380	0	0	0	0	0	0	0	0	0.0
Quantity of aircraft to be received	B737-400	0	0	0	0	0	0	1	1	0.3
	B737-800	0	0	0	0	0	0	0	0	0.0
	B777-200	0	0	0	0	0	0	0	0	0.0
	A330-300	0	0	0	0	0	0	0	0	0.0
	A380	0	0	0	0	0	0	0	0	0.0
Quantity of aircraft to be leased	B737-400	0	0	0	1	0	1	0	0	0.3
	B737-800	0	1	0	0	0	1	0	0	0.3
	B777-200	0	0	0	0	0	1	0	0	0.1
	A330-300	0	2	0	1	0	1	2	2	1.0
	A380	0	1	0	0	0	0	0	0	0.1
Quantity of aircraft to be released for sales	B737-400	0	0	0	0	0	0	0	0	0.0
	B737-800	0	0	0	0	0	0	0	0	0.0
	B777-200	0	0	0	0	0	0	0	0	0.0
	A330-300	0	0	0	0	0	0	0	0	0.0
	A380	0	0	0	0	0	0	0	0	0.0
Quantity of aircraft to be sold	B737-400	0	2	0	0	0	0	0	0	0.3
	B737-800	0	2	0	0	0	0	0	0	0.3
	B777-200	0	2	0	0	0	0	0	0	0.3
	A330-300	0	2	0	0	0	0	0	0	0.3
	A380	0	0	0	0	0	0	0	0	0.0
Total operated aircraft		48	44	44	46	46	50	53	56	48.4
Stochastic demand (millions)		10.08	10.99	7.47	7.85	7.85	8.47	9.15	9.70	8.9
Operational profit ($ millions)		664	1,087	611	525	747	495	725	863	715

Throughout the planning horizon of eight years, a total of 16 new aircraft (as shown in Table 7.6) which comprises eight A330-300, four B737-400, two B737-800, one A380 and one B777-200 are acquired. In average, two new aircraft are acquired or leased every year. New A330-300 is preferred in serving medium-haul flights compared to B777-200 as A330-300 is more environmental friendly and cost saving. A330-300 supports about 89% of medium-haul flights while B777-200 only supports about 11% of these flights. For short-haul flights, B737-400 is more favorable compared to B737-800. It was found that B737-400 is used in 67% of short-haul flights while B737-800 only takes about 33%. This is because both types of aircraft have approximated relatively equivalent green performance, but B737-800 is much more expensive. Therefore, B737-400 which is more economical is preferred by the airline. Besides, the results revealed that A380 supports long-haul flights with 6% of total operating networks. The jumbo aircraft A380 was chosen primarily due to the greenest performance in terms of fuel efficiency, noise and emission during cruising stage. This deduced that there is a strong linkage between the green performance of airline and the incorporation of new aircraft into the fleet composition, i.e. new aircraft has a positive impact on green performance. In other words, new aircraft is environmentally beneficial (greener), yet depending on aircraft type.

Furthermore, Table 7.5 shows that fuel consumption is the most critical factor (followed by emission and noise) that contributes to pollution as it has the highest GI value. This means that if airline could tackle the fuel consumption issue, it would greatly improve airline's green performance. This shows another advantage of the developed methodology in which individual contributing factor could be evaluated separately. This allows airlines to understand in a better manner and prioritize their mitigation strategies accordingly.

While improving green performance, it is important for airline to retain an optimal profit. From Table 7.6, it could be seen that there is a fluctuating trend of profit level in response to demand fluctuation throughout the planning horizon. Generally, the profit of airline tends to increase when stochastic demand is getting higher. Conversely, the profit would drop when demand level falls. This could be justified by the adjusted service frequency of airline to meet demand fluctuation, i.e. airline would basically obtain more income and hence results to a higher profit level (in meeting increasing demand with a higher service frequency). As deduced earlier, operating more new aircraft (compared to aging aircraft) would assure a greener performance. While getting more aircraft into the fleet composition to meet a higher demand level, it is interesting to see that the profit level of airline may appear to be lower. This happens mainly due to costly aircraft acquisition/leasing cost. The green performance of airline is inversely proportional to the operational profit for which a greener performance that requires more new aircraft would bring down the optimal profit of airline. This reveals that the operational profit and green performance of airline, in fact, have a conflicting (contradictory) relation. Thus, it implies that there would be a compromise solution for which the airline could make green fleet planning decision desirably based on their utmost preference, either towards the maximization of green performance (via the minimization of the GFI) or profit optimization.

Besides, the results in Table 7.5 show that the resultant GFI tend to be higher (i.e. not green) for a higher level of demand. In others words, the green performance of airline is inversely proportional to travel demand for which a lower demand level would results in a greener performance. This could be explained by the aircraft operations for which a higher demand level that requires more flights would consequently produce more emission, noise and fuel consumption. As such, the GFI of airline is found to be higher owing to more pollutants from increasing flight operations (or more aircraft activities to meet demand increment). Therefore, it could also be inferred that the green performance of airline is inversely proportional not only to the demand level but also to the profit level of airline (note: demand level is positively proportional to profit level). However, in terms of the operational profit, the highest demand level may not assure the highest profit level owing to aircraft acquisition/leasing decision which involve costly expenses including the payable deposit for the respective fleet planning decision in a particular operating period throughout the planning horizon. This shows that the developed methodology is not only sensitive to the green performance of airline but also well responsive to demand uncertainty to attain optimal profit. Certainly, it is relatively useful for airlines to manage their fleet planning decision environmentally and profitably.

7.4.2 Impact of Objective Ranking

Lexicographic optimization approach requires the specification of priority ranking for the objectives that need to be optimized. Scenario A has the minimization of GFI as the first objective and profit maximization as the second objective. Such priority orientation is in reverse to the objective ranking of the benchmark scenario. Table 7.7 shows that the average GFI of Scenario A is 0.4863 which is approximated to be 1.8% lower compared to the GFI of the benchmark scenario. This shows that if environmental concern is given first priority in optimization, a slightly greener fleet could be obtained comparing to the profit maximization as priority. By inspecting the profit level as shown in Table 7.8, Scenario A has the average profit of $644 million which is about 10% lesser than the benchmark scenario ($715 million). This is because Scenario A suggested a larger fleet size (additional of three aircraft) compared to the benchmark scenario in which greener aircraft, i.e. A380 and B737-800 is acquired. When more new aircraft is acquired, the green level of airline improves (Janic, 1999; Miyoshi and Mason, 2009; Morrell, 2009). Nevertheless, more money has to be spent for aircraft acquisition which brings to a lower profit level. A trade-off of $71 million of profit for a marginal improvement in green performance (1.8%) would cause the airline to favor the benchmark scenario compared to Scenario A. In such a case, the results suggested that airlines could retain profit maximization as the main priority, and consider green performance as the subsidiary (second) objective. This yields a win-win situation between the airline and the environment.

7.4.3 Impact of Green Consideration

It could be seen that the GFI for the benchmark scenario is lower than those in Scenario B. The difference in GFI for both scenarios for each operating year throughout the planning horizon is 0%, 4.4%, 4.8%, 4.5%, 4.6%, 8.9%, 10.4% and 11.9% respectively (refer to Table 7.7). This shows that the green performance of airlines improves year-by-year if it is given due consideration. In average, the proposed fleet composition in the benchmark scenario is 6% greener compared to those in Scenario B. By inspecting the fleet planning decision in Table 7.7, it is observed that Scenario B has a smaller fleet size compared to the benchmark scenario. Its fleet consists of more not green aircraft, i.e. B777-200, and lesser green aircraft, i.e. A380 and B737-800. This shows that if only a single objective is considered, the fleet composition of airline is not green in overall.

In terms of the profit level of airline, Table 7.8 displays that the benchmark scenario shows an average of 17% lesser profit compared to those in Scenario B. Equivalently, airline would forego about $20.7 million for each additional 1% of green improvement in terms of the GFI, i.e. the profit level of benchmark scenario is about 2.8% lower than scenario B to achieve each increment (1%) of greener performance. Nevertheless, airline could make a possible saving in the environmental cost by achieving a greener performance. Besides, the forfeit could be further reduced by airlines if additional strategies, such as increasing load factor or service frequency reduction, are incorporated. In overall, the resultant findings show that fleet planning decision and operational profit are greatly influenced by the green concern of airlines.

Table 7.7: The Green Fleet Index (GFI) for All Scenarios

Operating period	1	2	3	4	5	6	7	8	**Average**
Benchmark scenario									
Green Emission Index	0.5403	0.5820	0.5761	0.5518	0.5536	0.5067	0.4787	0.4550	**0.5305**
Green Noise Index	0.3923	0.4278	0.4279	0.4094	0.4094	0.3763	0.3554	0.3363	**0.3918**
Green Fuel Efficiency Index	0.5383	0.5752	0.5872	0.5607	0.5617	0.5136	0.4863	0.4604	**0.5354**
Green Fleet Index (GFI)	0.5001	0.5379	0.5403	0.5168	0.5179	0.4741	0.4483	0.4251	**0.4951**
Scenario A									
Green Emission Index	0.5403	0.5820	0.5761	0.5411	0.5419	0.4967	0.4592	0.4365	**0.5217**
Green Noise Index	0.3923	0.4278	0.4279	0.4009	0.4006	0.3689	0.3420	0.3194	**0.3850**
Green Fuel Efficiency Index	0.5383	0.5752	0.5872	0.5477	0.5497	0.5036	0.4676	0.4338	**0.5254**
Green Fleet Index (GFI)	0.5001	0.5379	0.5403	0.5058	0.5068	0.4648	0.4307	0.4041	**0.4863 (+1.8%)**
Scenario B									
Green Emission Index	0.5403	0.6018	0.6035	0.5767	0.5788	0.5510	0.5284	0.5095	**0.5612**
Green Noise Index	0.3923	0.4479	0.4483	0.4280	0.4279	0.4089	0.3919	0.3762	**0.4152**
Green Fuel Efficiency Index	0.5383	0.6053	0.6152	0.5861	0.5872	0.5601	0.5369	0.5156	**0.5681**
Green Fleet Index (GFI)	0.5001	0.5614	0.5661	0.5401	0.5414	0.5161	0.4948	0.4759	**0.5245 (-5.9%)**
Scenario C									
Green Emission Index	0.4728	0.4972	0.4929	0.4722	0.4741	0.4492	0.4066	0.3876	**0.4566**
Green Noise Index	0.3432	0.3655	0.3661	0.3506	0.3505	0.3297	0.2997	0.2842	**0.3362**
Green Fuel Efficiency Index	0.4710	0.4920	0.5024	0.4800	0.4810	0.4480	0.4072	0.3872	**0.4586**
Green Fleet Index (GFI)	0.4376	0.4598	0.4623	0.4423	0.4435	0.4167	0.3781	0.3597	**0.4250 (+14.2%)**
Scenario D									
Green Emission Index	0.4661	0.4994	0.5257	0.5087	0.5108	0.4838	0.4489	0.4311	**0.4843**
Green Noise Index	0.3449	0.3910	0.3843	0.3744	0.3742	0.3563	0.3405	0.3256	**0.3614**
Green Fuel Efficiency Index	0.4868	0.5286	0.5434	0.5439	0.5450	0.5206	0.4782	0.4580	**0.5131**
Green Fleet Index (GFI)	0.4417	0.4804	0.5005	0.4868	0.4881	0.4645	0.4308	0.4130	**0.4632 (+6.4%)**

Note: The value in bracket (at last column) indicates the improvement level of the GFI compared to benchmark scenario.

7.4.4 Impact of Increasing Load Factor

The results as shown in Table 7.7 indicate that the green level of airline (for Scenario C) improves by increasing aircraft load factor. Approximately, it is about 14% greener compared to the benchmark scenario. This finding is consistent with the finding of Miyoshi and Mason (2009) who revealed that aircraft emission could be reduced effectively by increasing load factor while the positive effect of load factor on fuel efficiency could be seen in Morrell (2009). Greener performance of airline in accordance to increasing load factor could be explained by the fleet size of airline which is relatively contributed by the quantity of purchased/leased aircraft. As shown in Table 7.8, an additional of two aircraft is acquired in Scenario C (compared to the benchmark scenario) in order to meet a higher demand level. In addition, the results show that there is a higher tendency for airline to operate large or jumbo aircraft in response to increasing load factor. This is possible because Scenario C tends to obtain higher revenue (with a higher load factor) and this provides a greater opportunity to airline to acquire more aircraft to support the current operating network. More importantly, the acquisition of more jumbo aircraft (A380) would improve the overall environmental performance because A380 exhibits the best green performance compared to other types of aircraft. Therefore, the overall environmental performance of airline is greener by increasing load factor.

While Scenario C showed an improved green level, it has achieved a greater profit level compared to the benchmark scenario. The profit obtained in Scenario C is 84% greater than the benchmark scenario. In fact, the profit level is higher than those obtained with a single objective (profit maximization) at 80% load factor. The profit level for the scenario with a single objective (profit maximization) at 80% load factor is about $880 million which is about 50% lesser than those earned in Scenario C. As such, the findings revealed that increasing load factor is a cost effective strategy to airline not only in assuring a greener performance but also in maintaining a high profit level.

Table 7.8: The Fleet Planning Decision (In Average) for Various Scenarios

Scenario		**Benchmark**	**A**	**B**	**C**	**D**
Quantity of purchased aircraft	B737-400	11.4	11.4	12.1	11.6	12.1
	B737-800	15.3	15.3	15.3	15.3	15.3
	B777-200	6.3	6.3	6.6	6.3	6.3
	A330-300	6.3	6.3	6.8	6.3	7.1
	A380	2.0	2.0	2.0	2.1	2.0
Quantity of leased aircraft	B737-400	0.8	0.8	0.0	1.4	0.0
	B737-800	1.0	1.5	0.8	0.8	0.8
	B777-200	0.3	0.4	0.0	1.5	0.0
	A330-300	2.5	2.5	0.8	1.0	0.8
	A380	0.8	0.8	0.0	1.0	0.8
Total quantity of operated aircraft	B737-400	12.6	12.6	12.6	13.8	12.6
	B737-800	16.5	17.1	16.1	16.1	16.1
	B777-200	6.6	6.9	7.0	8.0	6.3
	A330-300	9.8	9.8	7.8	7.9	8.5
	A380	2.9	3.0	2.0	3.6	2.9
Quantity of aircraft to be received	B737-400	0.3	0.3	0.5	0.4	0.5
	B737-800	0.0	0.0	0.0	0.0	0.0
	B777-200	0.0	0.0	0.4	0.0	0.0
	A330-300	0.0	0.1	0.1	0.0	0.5
	A380	0.0	0.0	0.0	0.1	0.0
Quantity of aircraft to be leased	B737-400	0.3	0.3	0.0	0.4	0.0
	B737-800	0.3	0.4	0.1	0.1	0.1
	B777-200	0.1	0.3	0.0	0.3	0.0
	A330-300	1.0	0.9	0.1	0.6	0.1
	A380	0.1	0.3	0.0	0.4	0.1
Quantity of aircraft to be sold	B737-400	0.3	0.3	0.3	0.3	0.3
	B737-800	0.3	0.3	0.3	0.3	0.3
	B777-200	0.3	0.3	0.3	0.3	0.3
	A330-300	0.3	0.3	0.3	0.3	0.3
	A380	0.0	0.0	0.0	0.0	0.0
Fleet size (by year 8)		56	59	50	58	51
Average profit ($ millions)		715	644	839	1,317	640
Profit improvement		-	-10%	+17%	+84%	-10%

7.4.5 Impact of Reducing Service Frequency

The results as shown in Table 7.7 indicate that the overall performance in Scenario D is greener by about 7%, in average, compared to the benchmark scenario. This is in line with the findings of Lijesen (2010) who pointed out that the reduction of service frequency is beneficial to reduce environmental impacts. Generally, a lower service frequency would produce lesser pollutants due to fewer flight operations. From Table 7.7, it was found that aircraft emission has the greatest improvement, followed by aircraft noise and fuel consumption when service frequency is reduced. For fleet planning decision, the results show that lesser A330-300 and B777-200 is acquired as these aircraft are found to emit substantial emission if compared to other aircraft type. With this fleet composition, aircraft noise could also be reduced effectively. However, the improvement scale of fuel efficiency is not as much as emission and noise.

By reducing service frequency, it could be seen that Scenario D produces a lower profit level, i.e. about 10% lower than the benchmark scenario (as displayed in Table 7.8). This happens mainly due to lesser aircraft operations in which about 12% flights (yearly) are canceled. Equivalently, each reduction of 1% service frequency (or 228 flights per annum) would reduce 0.8% profit level. As such, service frequency reduction would be a less popular strategy in tackling the environmental issues. This is because reducing service frequency would not only affect airline's profit level but also impairs its competitiveness.

7.4.6 Potential Cost Savings for Greener Fleet

As mentioned earlier, the GFI is derived as an indicator to quantify the green performance of airline. Basically, a lower GFI value signifies that airline has a greener fleet and vice versa. Besides functioning as an indicator, the GFI could be converted into a cost function to compute the cost savings with regards to a greener performance by airlines. The environmental cost function could be determined by performing regression analysis of the GFI with regard to the expected penalty cost (i.e. emission cost, noise charges and fuel expenses) based on the relevant input data throughout the planning horizon. For regression analysis, the total environmental cost is the dependent variable (at vertical axis) while the GFI is the independent variable (at horizontal axis). Specifically, the total environmental cost is contributed by total emission cost, total noise charges and total fuel expenses of each individual operating route. Note that the unit emission cost and unit noise charges are airport-specific and unit fuel cost may fluctuate from time to time.

Table 7.9 shows that if an exponential function, which is the best fitted function, is adopted to reflect the relationship between the GFI and environmental cost, each additional 10% improvement in green performance (i.e. an additional 10% reduction in GFI value) would contribute to a possible savings of $43 million in average for each operating period. Throughout the planning horizon of eight years, this would contribute to a possible savings up to $344 million (which is equivalently to be 76 new B737-400s!). Certainly, this potential savings could be achieved by having a well-defined green fleet planning model, which could be adjusted in a relatively flexible manner, by implementing some improvement strategies to yield a potential cost savings in a larger scale.

Table 7.9: The Environmental Cost

Best fitted function		Exponential function, $EC^{t}_{GFI} = 7\text{x}10^{7} e^{3.3357GFI}$ $[R^2 = 0.79]$	
Scenario	Green Fleet Index (GFI)	Environmental cost, $	Annual savings (*for 10% improvement*)
Benchmark	0.4951	300,635,395	46,430,351
A	0.4863	293,584,611	44,810,483
B	0.5245	329,006,271	53,246,395
C	0.4250	237,388,800	31,833,775
D	0.4632	267,743,315	38,646,059
Average	**0.4788**	**285,671,679**	**42,993,412**

Undeniably, the green fleet planning possesses 'double effect' (by making green aircraft acquisition/leasing decision), i.e. it is anticipated to improve green performance of airline at certain extent, yet it will also lead to some financial impacts, especially from the perspective of environmental cost (which is constituted by aircraft emission and noise charges as well as the relevant fuel expenses in supporting the operating networks of the airline). As displayed in Table 7.9, the improvement strategies (green strategies) of Scenario C and D both yield a greener performance (with a lower GFI) and also generate a lower environmental cost in comparison to the benchmark scenario (without any green strategy). This could be explained by the inclusion of more new aircraft which is greener (for scenario C) and also due to fewer aircraft operations with less fuel and pollutants (for scenario D). Approximately, the airline could lower about 1.5% environmental cost by improving 1% GFI with Scenario C while Scenario D could lower about 1.8% environmental cost by improving 1% GFI. Therefore, Scenario D seems to be more 'efficient' in lowering the environmental cost in comparison to Scenario C. However, scenario D may not be the most desirable strategy for the airline in view of the fact that the reduction of service frequency may result in a loss of market share in such a competitive airline industry. This highlights that there are many crucial aspects (concerns) to be taken into consideration by the airline to finalize the 'best' strategy for green fleet planning. Notably, the 'best' strategy may also vary among airlines with different business structures.

In brief, it can be deduced that the resultant double-effect (green and financial impact in terms of environmental cost), which depict positive results, is in fact beneficial to the airline. Yet, it is decisively depending on the airlines to carry out the 'most desirable' green strategy in supporting their operating networks, profitably and environmentally.

7.5 Summary

Nowadays, with the enforcement of stringent policies to preserve the environment, commercial airlines are encountering increasing financial burden in paying pollution fines. Correspondingly, a novel methodology is developed to optimize airline's green fleet planning decision by taking into account the environmental concern and operational aspects explicitly. The methodology comes in two-fold. Firstly, a framework of Green Fleet Index (GFI) is developed to quantify airline's green performance by capturing three major environmental components, i.e. aircraft emission, noise and fuel efficiency. This framework is also able to reveal the potential savings of environmental cost. Secondly, a bi-objective green fleet planning decision model is formulated to determine optimal quantity and type of aircraft to be purchased and/or leased at a desired green performance and optimal profit level. The developed model also allows the evaluation of various operational improvement strategies to yield a better operating performance (to be greener or profitable).

In overall, the results of a realistic case study show that the developed methodology is sensible to provide viable solutions in making green fleet planning decision under stochastic demand. The findings show that airlines could maintain the objective to maximize profit during fleet optimization, but there is a beneficial advantage to capture the green fleet index as a second objective. It was found that when an environmental issue is considered, the fleet composition of airlines demonstrates a significant difference. Specifically, more green aircraft are preferred if the methodology takes into account the green performance of aircraft. Although airline's profit level might be affected, this could be recovered from potential environmental cost savings.

Between the two operational improvement strategies investigated, it was found that increasing load factor is a promising strategy. As such, various attractive marketing strategies to boost up flight ticket sales might be necessary to increase the load factor. The joint-efforts or alliances among airlines could also be implemented (if necessary) to yield a greater profit level at a higher load factor. In addition, it is airlines' corporate and social responsibility to ensure that their business is operated in a sustainable manner by minimizing the impact to the environment and society. Thus, the integration of numerous operational improvement strategies may further improve airline's green performance as well as profit level.

CHAPTER 8

CONCLUSIONS

This chapter concludes the research with a comprehensive summary. Besides, some future works are suggested and research accomplishment is presented.

8.1 Summary

The stochastic nature of the world has posed significant challenges to such a competitive airline industry. As such, how airlines forecast the level of demand accurately and realistically under uncertainty is crucial to assure that the fleet planning decision-making of airlines could be made optimally to meet demand fluctuation. Furthermore, travel demand forecasting could influence the robustness of the results in overall. To capture demand uncertainty, a novel 5-step modeling framework of stochastic demand is developed to determine the level of stochastic demand realistically by capturing the occurrence of unexpected events and airline's projected demand under uncertainty. The probability of the possible occurrence of stochastic demand (subject to unexpected events and projected demand) is termed as Stochastic Demand Index (SDI). Contrary to past studies, the developed 5-step modeling framework of stochastic demand is not limited to any type of probability distribution (i.e. distribution-free) and hence it could be applied flexibly in solving the long-term fleet planning problem under uncertainty.

To meet stochastic demand at a desired service level, how airlines make a profitable fleet planning decision, by making optimal aircraft acquisition and leasing decision is of utmost importance. In order to optimize long-term fleet planning decision that generates maximum profit, several fleet planning decision models, including aircraft acquisition decision model, aircraft acquisition and leasing decision model, strategic fleet planning modeling framework, two-stage fleet planning decision model and bi-objective green fleet planning model, are developed mathematically to determine the optimal quantity and aircraft type to be purchased/leased for each operating period throughout the planning horizon. By having the respective fleet planning decision model in place, the optimal fleet planning decision could be made by airlines by providing adequate fleet supply (aircraft composition) to meet stochastic demand desirably. In comparison to past studies, numerous practical constraints that realistically capture various technical and operational considerations of airlines are included necessarily in the developed models. This is vital to assure that the aircraft operations of airlines are practically viable to support the current operating networks at a desired and profitable service level.

While providing an adequate fleet supply, it is vital for airlines to capture the mode choice analysis (traveler's response) in view of the fact that air travelers (passengers) are the main users of airline's services which constitutes the market share and also is the main income for the airlines. Furthermore, the needs and expectation of passengers nowadays might be changing from time to time under competitive multimodal transportation system. To capture the traveler's response realistically, stated preference surveys of different operating networks of airline (including short-haul and medium/long-haul networks) had been carried out for different trip purpose (leisure and business) and destination (local and trans-border). Based on the collected data, mode choice analysis had been performed accordingly to inspect the influential factors that significantly affect the market share of airline. The resultant market share is then incorporated necessarily into the developed strategic fleet planning modeling framework to quantify the probability of the respective key aspect (probable phenomena) of fleet planning decision-making so that the supply-demand interaction could be captured in a better manner. To quantify the probability of probable phenomena (i.e. key aspect of operational, economy and environmental) that affecting the fleet planning decision-making, Analytic Hierarchy Process (AHP) which possess the ability to capture uncertainty is adopted. By incorporating mode choice analysis and subjective evaluation of airline's management (with the aid of AHP), the developed approach assures that an adequate fleet supply could be possessed (via aircraft acquisition/leasing) by airlines to meet demand fluctuation desirably. However, none of the past studies capture the supply-demand interaction explicitly, in such a way, in solving the fleet planning problem.

Pertaining to the issue of the regulated limits of aircraft operations (in terms of flight frequency) at some particular airports, the developed two-stage fleet planning decision model plays the role to offer greater flexibility to airlines in order to provide appropriate service frequency (including additional service frequency if necessary) in supporting the operating networks. The developed two-stage fleet planning decision model comprises the slot purchase decision model (stage 1) and fleet planning decision model (stage 2). In particular, the optimal slot purchase decision would assure that increasing demand could be met satisfactorily (with a higher service frequency) under uncertainty while optimal fleet planning decision assures that airline's operating networks could be supported profitably with an adequate fleet supply (with appropriate aircraft composition and corresponding service frequency). By incorporating the airfare of specific passenger's class in optimizing the developed model, airlines would obtain utmost revenue and profit, not only to support the existing operating networks but also to expand new network.

In view of the increasing concerns to preserve the environment, the environmental (green) performance of airlines should not be compromised while making profitable fleet planning decision to meet stochastic demand. To do this, an environmental performance assessment framework is developed to examine the environmental factors (i.e. aircraft emission, noise and fuel efficiency) that could affect airline's green performance to a great extent. The green (environmental) performance of airline for each operating period throughout the planning horizon could be assessed specifically towards different environmental factor, i.e. in the form of Green Emission Index, Green Noise Index and Green Fuel Efficiency Index. The overall green performance is compiled as Green Fleet Index (GFI) as the green indicator of airline's performance. To solve the fleet planning problem of airline, a bi-objective green fleet planning decision model is formulated to minimize the environmental impacts while maximizing the operational profit of airline. To achieve a greener performance, some improvement strategies could also be implemented accordingly by airlines. Besides, airlines would also make a substantial amount of environmental cost savings by incorporating green concern in fleet planning. In brief, it could be empirically deduced that the developed approaches are practically viable to assure airline's sustainability in terms of economy, social and environment.

In overall, the contributions of this research could be listed as follows:

1. Formulation of optimal fleet planning decision model in generating utmost profit for airlines while assuring adequate fleet supply and service frequency to meet stochastic demand under numerous practical constraints.

2. Development of a novel modeling framework to model and determine the level of stochastic demand realistically under uncertainty.

3. Identification and verification of a closed linkage (interaction) between supply and demand that is required to be captured explicitly in solving fleet planning problem.

4. Incorporation of mode choice analysis and subjective judgments of airline's management that possesses significant impacts in fleet planning.

5. Suggestion on various improvement strategies to achieve airline’s greener performance by reducing the amount of pollutants via optimal fleet planning decision.

Apparently, it could be concluded that all research objectives, as listed in chapter 1, are achieved successfully by developing and optimizing the relevant fleet planning decision models (as discussed above). Briefly, the characteristics and uniqueness of the respective model to solve the fleet planning problem under stochastic demand are summarized in Table 8.1.

Table 8.1: Fleet Planning Decision Model

Model	Aircraft acquisition decision model	Aircraft acquisition and leasing decision model	Two-stage fleet planning decision model	Green fleet planning decision model
Objective function	Maximize profit	Maximize profit	Maximize revenue (stage 1) Maximize profit (stage 2)	• Maximize profit • Minimize Green Fleet Index
Practical constraints	• Budget constraint • Demand constraint • Parking constraint • Sales of aircraft constraint • Order delivery constraint • Lead time constraint • Selling time constraint	• Budget constraint • Demand constraint • Parking constraint • Sales of aircraft constraint • Order delivery constraint • Lead time constraint • Selling time constraint	Slot purchase decision model (stage 1): • Slot purchase budget constraint • Slot determination constraint • Aircraft execution constraint Fleet planning decision model (stage 2): • Budget constraint • Demand constraint • Parking constraint • Sales of aircraft constraint • Order delivery constraint • Lead time constraint • Selling time constraint • Aircraft homogeneity constraint • Aircraft range constraint • Aircraft operations constraint	• Budget constraint • Demand constraint • Parking constraint • Sales of aircraft constraint • Order delivery constraint • Lead time constraint • Selling time constraint • Aircraft homogeneity constraint • Aircraft range constraint
Type of decision-making	• Aircraft acquisition	• Aircraft acquisition • Aircraft leasing	• Aircraft acquisition • Aircraft leasing	• Aircraft acquisition • Aircraft leasing
Decision variables	• Aircraft quantity • Aircraft type	• Aircraft quantity • Aircraft type	• Operating route with slot purchase • Aircraft quantity • Aircraft type	• Aircraft quantity • Aircraft type
Probable phenomena	• Operational • Economy	• Operational • Economy	• Operational • Economy • Environmental	• Operational • Economy • Environmental
Type of airfare	Average airfare	Average airfare	• Business class • Economy class (full & discounted)	Average airfare
Stochastic demand	Yes	Yes	Yes	Yes
Individual operating route	Nil	Nil	Yes	Yes
Mode choice modeling	Nil	Nil	Yes	Yes

8.2 Future Works

In order to capture the perception of airline's management in a better manner to solve the strategic fleet planning modeling framework, the evaluation of airline's management in comparison with the key aspects (probable phenomena) for specific decisional criteria of fleet planning could be obtained by approaching the relevant authority or managerial executives of airlines. Alternatively, more publicly accessible data could be compiled if it is obtainable.

In order to solve the strategic fleet planning modeling framework (Chapter 4), the largest eigenvalue is determined according to the adopted procedure of Analytic Hierarchy Process (AHP). In fact, the procedure can be applied for any dimension of judgment matrix, i.e. it is not limited to matrix size. Yet, the computational time will increase when the dimension of the judgment matrix gets larger. Therefore, the computational procedure to determine the largest eigenvalue can be modified appropriately to increase the computational efficiency.

While having green fleet in operations could help address the environmental issue (as discussed in chapter 7), the integration of several improvement strategies is anticipated to improve airline's green performance and profit margin with a larger scale. As such, the effects of implementing multiple approaches simultaneously (e.g. increasing load factor and reducing fuel consumption) could be examined further to yield a greener performance while attaining a desired profit level under stochastic demand.

To optimize the green performance of airline, the concept of 'tradable credit' may be incorporated. This could be done by adding the element of environmental quota, for instance emission allowance and trading permit, in the objective function of fleet planning decision model (in order to maximize airline's green performance) or modifying the computation of environmental cost savings accordingly.

In view of the air transportation system being a complicated inter-correlated system, the developed methodologies to optimize the fleet planning decision of airlines could be incorporated into other operational decision-making of airlines (e.g. flight scheduling, crews assignment, aircraft maintenance, etc.) in order to assure a higher operating efficiency of airlines which would benefit air travelers in return.

8.3 Research Accomplishment

Based on the findings of this research, the following papers had been submitted to some well-known journals and conferences. The publication status of submitted papers is listed as below:

No.	Title of Paper	Journal	Status
1	Acquisition of New Aircraft with Probabilistic Dynamic Programming	Journal of Eastern Asia Society for Transportation Studies (EASTS), 9, 2022-2037 (2011)	Published
2	An Aircraft Acquisition Decision Model Under Stochastic Demand	Journal of King Saud University – Science, 23, 323-330 (2011)	Published (*ISI journal*)
3	An Optimal Aircraft Fleet Management Decision Model under Uncertainty	Journal of Advanced Transportation, 48, 798-820 (2014)	Published (*ISI journal*)
4	A Bi-objective Dynamic Programming Approach for Airline Green Fleet Planning	Transportation Research Part D, 33, 166-185 (2014)	Published (*ISI journal*)
No.	**Title of Paper**	**Conference**	**Status**
1	Application of Probabilistic Dynamic Programming In Formulating An Aircraft Acquisition Decision Model	The Malaysian Universities Transportation Research Forum and Conferences 2010, December 2010, Malaysia	Presented and published
2	Acquisition of New Aircraft with Probabilistic Dynamic Programming	The 9th International Conference of Eastern Asia Society for Transportation Studies (EASTS), June 2011, Korea	Presented and published
3	Impacts of Budget Airlines in Modelling the Mode Choice of Leisure Travellers: A Case Study of Klang Valley, Malaysia	The 2012 World Conference of Air Transport Research Society, June 2012, Taiwan	Presented and published
4	Mode Choice Decision Model and Its Application for Aircraft Fleet Management	The First International Conference on Behavioural and Social Science Research, November 2012, Malaysia	Presented and published
5	Investigating the Impacts of Budget Airlines towards the Mode Choice Decision of Business Travellers: A Case Study of Klang Valley, Malaysia	The IEEE Student Conference 2012, October 2012, Malaysia	Presented and published (*IEEE Xplore, pp. 46-51*)
6	Integration of Fuzzy Analytic Hierarchy Process and Probabilistic Dynamic Programming in Optimizing Fleet Management	The International Conference on Mathematical Sciences and Statistics, February 2013, Malaysia	Presented and published (*American Institute of Physics proceedings, pp. 539-544*)
7	An Environmentally Sustainable Fleet Management Model under Uncertainty	The 2013 World Conference of Air Transport Research Society, June 2013, Italy	Presented and published

8	Quantifying Environmental Green Index For Fleet Management Model	The 10th International Conference of Eastern Asian Society for Transportation Studies (EASTS), September 2013, Taiwan	Presented and published
9	Green Fleet Planning Framework: Assessment and Improvement Strategies	The 9th International Conference of Urban Regeneration and Sustainability, September 2014, Italy	Presented and published (*WIT Transactions on Ecology and the Environment Transactions, 191, pp. 735-747*)

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APPENDIX A

Convolution Algorithm (Winston, 2004)

According to the Central Limit Theorem, the total (sum) Y of n independent and identically distributed random variables (e.g., $Y_1, Y_2, ..., Y_n$) for which each with mean μ and variance σ^2, is approximately to have a normal distribution with mean $n\mu$ and variance $n\sigma^2$. This implies that the random variable Y could be expressed as follows.

$$Y \sim N\left(n\mu, n\sigma^2\right) \quad \text{(A.1)}$$

for which $Y = Y_1 + Y_2 + ... + Y_n = \sum_{i=1}^{n} Y_i$. With this fact, the normal distribution of random number R is formed as follows.

$$R \sim N\left(\frac{n}{2}, \frac{n}{12}\right) \quad \text{(A.2)}$$

for which $R = R_1 + R_2 + ... + R_n = \sum_{r=1}^{n} R_r$ is the sum of n random numbers. (Note: each random number has a uniform distribution $U(0,1)$ with mean $\frac{1}{2}$ and variance $\frac{1}{12}$).

Correspondingly to Equation (A.2), in order to generate the standard normal variates for the origin distribution of random number i.e. uniform distribution, the following expression could be formed.

$$z = \frac{\sum_{r=1}^{n} R_r - \frac{n}{2}}{\sqrt{\frac{n}{12}}} \tag{A.3}$$

where $z \sim (0,1)$. To simplify the computational procedure, $n = 12$ is used for Equation (A.3) and this results in the term as follows.

$$z = \sum_{r=1}^{12} R_r - 6 \tag{A.4}$$

for which $\sum_{r=1}^{12} R_r$ is the sum of 12 random numbers. Based on the standard relation of $z = \frac{X - \mu}{\sigma}$ for normal distribution, $X = \mu + \sigma z$ is obtained subsequently. As such, the projected demand, D_0 could be formed as follows.

$$D_0 = \mu_f + \sigma_f \left(\sum_{r=1}^{12} R_r - 6 \right) \tag{A.5}$$

for which the forecasted demand, D_f^t has mean μ_f and standard deviation σ_f.

Note: According to Winston (2004), $n = 12$ has the advantage to simplify the computational procedure especially the time consumption on a computer. However, it has no problem to use any other value of *n*. In other words, other than $n = 12$, the usage of any other value of n would increase the computational difficulty and hence to avoid the difficulty from this aspect, $n = 12$ is chosen particularly to simplify the computational (by reducing computational difficulty).

APPENDIX B

The Relevant Sources of the Mode Choice Modeling Variables

The sources of the mode choice modeling variables are summarized as below:

Variable name	Variable sources
Travel time	• Access time, egress time: obtained by assumption (depends on the departure point, i.e. traveler's home and his/her final destination) • In-vehicle time: obtained from the airlines, bus & train operators' websites(Malaysia Airlines, 2010d; AirAsia Berhad, 2010c; journeymalaysia.com, 2010; *Keretapi Tanah Melayu Berhad*, 2010);estimation based on the driving speed & distance (for private car) • Check-in time (for air transport): obtained from the websites of the airlines
Travel cost	• Access cost, egress cost: obtained by assumption (depends on the departure point, i.e. traveler's home and his/her final destination) • In-vehicle cost: obtained from the airlines, bus &train operators' websites(Malaysia Airlines, 2010d; AirAsia Berhad, 2010c; journeymalaysia.com, 2010; *Keretapi Tanah Melayu Berhad*, 2010); estimation based on the toll charges, petrol price, driving speed & distance (for private car)
Safety	To compile the record of accidents: • air transport: obtained from Aviation Safety Network of Flight Safety Foundation (Flight Safety Foundation, 2010) • bus, car: obtained the record of road accidents from MIROS (2010) • train: compiled relevant values based on Wikipedia (2012)
Service frequency	• Car: assumed • Bus, train, airlines: obtained from the respective website of the transport operators (Malaysia Airlines, 2010d; AirAsia Berhad, 2010c; journeymalaysia.com, 2010; *Keretapi Tanah Melayu Berhad*, 2010)
Booking/purchase method	Based on the available methods in the market: • Airlines: booking/purchase via website, travel agent or travel fair • Train: booking/purchase via website or train station • Bus: booking/purchase via counter or travel agent • Car: by assumption
Comfort, facility, on-time performance, promotional package	Due to unavailable data from the transport operators, these variables are compiled in accordance to the provided service frequency(please refer to service frequency as stated above)

APPENDIX C

Model Modification for New Network Expansion

With the aim to maximize airline's operational revenue (via new network expansion), the developed slot purchase decision model (stage 1) could be modified as follows:

$$R_{t,F_i} = \underset{F_i \in F_{nw}}{Max} \frac{1}{\left(1+r_t\right)^t} \left\{ E\left(c_{biz,F_i}\right) E\left(p^*_{biz,F_i}\right) + E\left(c_{fec,F_i}\right) E\left(p^*_{fec,F_i}\right) + E\left(c_{dec,F_i}\right) E\left(p^*_{dec,F_i}\right) \right\} \tag{C.1}$$

Subject to:

$$C_{F_i} \leq W_{F_i} \text{ for } F_i \in F_{nw} \tag{C.2}$$

$$open \leq TUN^t_{n,F_i,k} + BLK^t_{n,F_i} + TUN^t_{n,F_i,m} + BLK^t_{n,F_i} + TUN^t_{n,F_i,k} \leq close \text{ for } \forall n,k,m,F_i \in F_{nw} \tag{C.3}$$

where the expected airfare of operating route F_i (in new network, F_{nw}) could be estimated as $E\left(c_{biz,F_i}\right)$, $E\left(c_{fec,F_i}\right)$ and $E\left(c_{dec,F_i}\right)$ respectively for business class, economy class with full fare and discouted fare. In overall, the expected demand level of new operating route is approximately to be $E\left(D^{F_i}_t\right) = E\left(p^*_{biz,F_i}\right) + E\left(p^*_{fec,F_i}\right) + E\left(p^*_{dec,F_i}\right)$ for $F_i \in F_{nw}$. Specifically, the objective function, i.e. Equation (C.1) assures that optimal operating route for new network expansion would generate maximum revenue for airlines for which the resultant optimal solution is subject to slot purchase budget constraint (Equation (C.2)) and aircraft execution constraint (Equation (C.3)) to assure financial and operational feasibility (note: slot determination constraint in stage 1 could be omitted for airlines to choose optimal new network for expansion). By making optimal slot purchase decision (at stage 1) for new network expansion, optimal operating route F_i^* would generate the greatest revenue compared to other operating routes. Mathematically, $R_{F_i}^* > R_{F_i}$ for $F_i \in F_{nw}$. For stage 2, the developed fleet planning decision model applies similarly for new network expansion.