Investigating Hong Kong's Role as the Main Air Transport Hub in the Asia-Pacific Region

A thesis presented in partial fulfilment of the requirements for the degree of

Doctorate of Philosophy

in

Aviation

at Massey University, Manawatu Campus,

New Zealand

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2012

ABSTRACT

Hong Kong International Airport (HKIA) has experienced growth in air traffic volumes since its opening in 1998, and has established itself as one of the main international hub airports in the Asia-Pacific region and China's primary gateway. However, it is concerned about losing this position due to increased competition from alternative international gateway hub airports in Mainland China and around the Asia-Pacific region. In particular, HKIA's growth in passenger numbers started to show a declining trend and was smaller relative to other regional airports.

The objective of this research was to investigate HKIA's relative operational efficiency and network position and forecast its ability to maintain its role as the main air transport hub in the Asia-Pacific region and the primary passenger gateway to Mainland China. The research in this thesis undertook three separate but related empirical studies to answer several questions that contribute to addressing the overall research objective. The first study used Data Envelopment Analysis (DEA) to assess the operational efficiency of HKIA compared to other major Asia-Pacific airports. HKIA was found to reside on the efficiency frontier as one of the most efficient airports in the Asia-Pacific region. In the second study, the NetScan Connectivity Units (CNU) model measured and compared the direct, indirect, and hub connectivity of the major Asia-Pacific airports. HKIA was found to have a competitive position offering larger direct and hub connectivity to other international regions relative to other airports. Furthermore, the market share analysis showed that HKIA maintained its role as China's primary passenger gateway handling a significant share of China's inbound international visitors from several regions around the world. In the third study, the Box−Jenkins Seasonal Autoregressive Integrated Moving Average (SARIMA) and ARIMAX models were modelled to forecast Hong Kong airport's future passenger throughput, and its future passenger throughput were projected to grow.

The findings of the research suggested that HKIA has maintained its position as the main air transport hub in the Asia-Pacific region and China's primary passenger

gateway with the support of efficient operations and competitive international flight connectivity networks. Given that HKIA maintains this relative position, its airport passenger throughput is forecasted to grow in the future.

ACKNOWLEDGMENTS

It is my pleasure to express my gratitude to my loved ones and many people for their part in supporting the completion of this thesis.

I dedicate this thesis to my wife (Iris), my little son (Ian), and my mum for their patience and unwavering supports throughout the long PhD journey. Their support has always given me the impetus and motivation to complete this endeavour within three years.

I must also express sincere appreciation to my main supervisor, Professor Hamish Gow, for giving me this opportunity to continue research under his supervision, and for providing a new research direction through the reorganisation of my thesis structure. Most importantly, his recommendation letter was the key input to support my successful scholarship application (Massey University's Doctoral Completion Bursary); the funding have been very important for my family and me during the final stage of my PhD journey.

I would also like to express thanks to my co-supervisor, Dr. Ozer-Balli Hatice, who has been very supportive in offering constructive comments and guidance throughout my research in terms of econometric techniques. In addition, I must say thanks to another co-supervisor, Dr. Andrew Gilbey, who has been very kind in helping me during the toughest period of supervisor change, as well as editing my rough draft very patiently. More importantly, he recommended me to the Head of the Aviation School to lecture three undergraduate papers as a tutor, giving me invaluable lecturing experience during the PhD programme.

Finally, lot of thanks also go to Dr. Kelvin Heagney, who has been a good listener and my buddy for the last three years.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 : INTRODUCTION

1.1 INTRODUCTION

Although Hong Kong International Airport (HKIA) is one of the busiest aviation hubs in the Asia-Pacific region and the primary gateway to Mainland China, intense competition has resulted in smaller growth of air traffic volumes relative to other international gateway hub airports in Asia. This is a major threat to HKIA. However, the government of Hong Kong has developed HKIA as a long-term strategic asset to drive the continued long-term growth of Hong Kong, so the slower growth of HKIA relative to its peers is concerning and requires further investigation. This thesis investigates the role of HKIA as the main air transport hub in the Asia-Pacific region and the primary passenger gateway to Mainland China, as well as projecting its future growth.

The new HKIA was built in 1998 to replace the old congested Hong Kong Kai Tak Airport, aiming to meet the expected growth in airport traffic volumes (Zhang *et al*., 2004; Williams, 2006; Ishutkina & Hansman, 2009). Over the past 15 years, HKIA has shown a steady growth in air traffic volumes, except following the events of September 11 terrorist attack in the US, the Severe Acute Respiratory Syndrome (SARS) outbreak, the Asian financial crisis, and the global economic downturn (e.g. Wong, 2002; Grais, Ellis & Glass, 2003; McKercher & Hui, 2004; Pine & Mckercher, 2004; Siu & Wong, 2004; Kozak, Crotts & Law, 2007; Martin, 2007; Ishutkina & Hansman, 2009). To secure HKIA's status as one of the most important aviation hubs in the Asia-Pacific region, a third runway will be built which could accommodate the forecasted airport traffic up to 2030 and possibly beyond, giving a substantial boost to Hong Kong's economy (HKAA, 2011).

The liberalisation of China's air transport policy began in the 1990s, and the rapid network expansions among the major Asian international gateway hub airports have brought intensified competition to HKIA (e.g. Park, 2003; Seabrooke *et al*., 2003; Zhang, 2003; Zhang *et al*., 2004; Zhang & Round, 2008; Shaw *et al*., 2009). In essence, these developments created immediate challenges and threats to HKIA's operations, and also undermined its competitiveness to transport international passengers across the regions. The figures showed that HKIA only achieved an average of single-digit growth in air passenger numbers between 2005 and 2010 compared to double-digit growth elsewhere (ACI, 2002−2010). This growth rate was far behind those of international gateway hub airports in the Asia-Pacific region during the same period, especially three Chinese international gateway hub airports (i.e. Beijing, Shanghai Pudong, and Guangzhou airports). This issue has raised a critical question about Hong Kong's leadership as the key international passenger hub in the Asia-Pacific region.

Despite the declining passenger numbers travelling through HKIA, it was still the busiest air cargo hub in the Asia-Pacific region between 2000 and 2010 in terms of tonnes of air cargo being handled (ACI, 2000−2010). In 2010, it achieved the landmark of becoming the world's busiest airport in handling 4.1 million tonnes of air cargo (ACI, 2010). With respect to its economic value for Hong Kong, air cargo traffic is an engine for Hong Kong's economic growth (HKAA, 2011).

HKIA's role as the primary passenger gateway to Mainland China becomes another important concern in respect of increasing pressure from three emerging Chinese international gateway hub airports in Mainland China and other Asian international gateway hub airports competing China's international passenger traffic (e.g. O'Connor, 1995; Chin, 1997; Li, 1998; Mok, 1998; Bowen, 2000; Chan, 2000; Chang, Cheng & Wang, 2003; Park, 2003; Rimmer, 2003; Hui, Hui & Zhang, 2004; Matsumoto, 2004, 2005, 2007; Zhang *et al*., 2004; Ngo, 2005; Williams, 2006; Wang & Jin, 2007; Winston & Rus, 2008; Chow & Fung, 2009). There was a growing trend of international visitors via HKIA to visit Mainland China, visitor numbers increased from 1.10 to 1.63 million between 2006 and 2010 (HKTB, 2010). However, there have also been significant falls in some regions: for instance, fewer Taiwanese travellers went through HKIA to Mainland China after the signing of direct air link agreement across the Taiwan Strait in 2008. This alarming situation suggested that HKIA may possibly lose its leading position as the main transit point for interchanging and connecting air travellers to Mainland China in respect of some of its key markets (Chang, Hsu & Lin, 2011; Lau *et al*., 2012).

HKIA has had a close relationship with the development of Hong Kong's tourism industry and exerts a significant impact on Hong Kong's economy. Every year, HKIA handles millions of international tourists to visit Hong Kong – the shopping paradise – for shopping and sightseeing. For example, there were around 10.18 million international visitors by air transport visited Hong Kong in 2010 (HKTB, 2010). The economic contribution generated by Hong Kong's tourism industry was 4.4% of Hong Kong's gross domestic product (GDP) (HKCSD, 2012). Concerning the increasing role of toursim in Hong Kong's economy, this thesis also highlights the challenges for airport management and policy makers to meet future tourist arrivals at Hong Kong, and therefore, this research is of critical importance.

There were three key questions that this thesis aimed to answer for investigating the role of HKIA as the main air transport hub in the Asia-Pacific region and the primary gateway to Mainland China. First, the operational efficiency of HKIA compared to other Asia-Pacific airports will be assessed. Second, the competitive position of HKIA's flight connectivity network and its role as China's primary passenger gateway compared to other Asia-Pacific airports will be analysed. Lastly, the future passenger throughput of HKIA will be forecasted.

The format of this chapter is organised as follows. Section 1.2 outlines the historical development of the new HKIA. Section 1.3 presents prior analyses related to HKIA. Section 1.4 presents the research objective and questions. Section 1.5 outlines the research layout and methodologies. Section 1.6 presents the data used in the research. This chapter concludes with an outline of the thesis organisation in Section 1.7.

1.2 HISTORICAL DEVELOPMENT OF THE NEW HONG KONG INTERNATIONAL AIRPORT

After 30 years of isolation, in 1984, the Chinese government initiated an 'open door policy' to develop its economy. Also, the Chinese government intended to develop the Pearl River Delta (PRD) region in the Guangzhou Province of China, which provided opportunity and impetus for Hong Kong's economic growth (e.g. Yun, 1991; Sun 1994; Hoyle *et al*., 1998; Mok, 1998; Sit, 2004). The rapid economic development in the PRD region led to a situation where Hong Kong's logistics industry and air transport industry became very crucial for the import and export of time-constrained and high-value finished products (Enright, Scoot & Chang, 2005). The PRD region has been considered as one of the busiest manufacturing regions in the world (Wang *et al*., 2006). Also, the US Consulate General of Hong Kong was quoted as saying "In 2002 Hong Kong and the PRD region together already comprised a US$250 billion economic powerhouse, even some forecasts predicts that figure may be doubling in 10 years" (Keith, 2002, p.10). [sic]

In the 1980s, the commencement and success of China's opening up as well as its rapid economic development has enabled Hong Kong to play an important role of being the intermediary, middleman or transhipment centre, and the gateway between Mainland China and the rest of the world. In particular, the rapid development in the PRD region boosted the demand for air transport services at the old Hong Kong Kai Tak Airport due to its geographic proximity to the PRD region and its available airport infrastructure (e.g. Yun, 1991; Rimmer, 1992; Sung, 1995; Cheng, Lu & Findlay, 1998; Ash 2003; Zhang *et al*., 2004). Also, Hong Kong's labour-intensive manufacturers were troubled by rising wages and land rents, whereas the attractive low-cost operations offered in the PRD region lured most Hong Kong manufacturers to relocate their factories to the region (up to 80% of the factories in Hong Kong have been closed), but Hong Kong still provided producer services to the factories that had been relocated (Yam & Tang, 1996; Ash, 2003; Seabrooke *et al*., 2003). With this 'Front Shop, Back Factory' – (FSBF) model,[1] Hong Kong acted as a management and controlling centre of the global supply chain for the PRD region, while nearly all of the actual manufacturing processes took places within the PRD region (e.g. Sit & Yang, 1997; Wong, 2002; Yang, 2006; Yeung & Shen, 2008; Schiller *et al*., 2012).

Hong Kong became a Special Administrative Region within the People's Republic of China (PRC) on July 1, 1997. The Hong Kong Special Administrative Region (HKSAR) is governed and operated as 'One Country, Two Systems' – (OCTS) (e.g. Yeung, 1997; Zhang *et al*., 2004; Yang, 2006; Yeung & Shen, 2008). Prior to the handing back of Hong Kong to Chinese sovereignty, the former British government invested a significant proportion of its accumulated financial resources into Hong Kong's transport infrastructure. A new airport was part of this as the old Kai Tak Airport was thought to be approaching its capacity limits during the 1980s when it was facing rapid air transport growth in Hong Kong and in Mainland China, as well as meeting an increase in international tourist demand in Asia and air traffic volumes between Mainland China and Taiwan. For instance, the Hong Kong Civil Aviation Department (HKCAD) turned away 6,700 flights flying to Hong Kong in 1993. Some of the lost traffic was diverted to the nearby airports in Mainland China. Arguably, any further delay in opening a new airport that would have a knock-on effect upon Hong Kong's tourism industry by losing millions of visitors, and more importantly, the lack of airport capacity of the old Kai Tak Airport would bring substantial disadvantage to Hong Kong's future economic development – an economic loss in excess of HK$168 billion by 2026 (e.g. Findlay & Forsyth, 1992; Rimmer, 1992; Hobson & Ko, 1994; Hobson, 1995; Weisel, 1997; Mok & Dewald, 1999; Chan, 2000; Zhang *et al*., 2004). Given the importance of the air transport sector to Hong Kong's future economy, the HKSAR government launched the Port and Airport Development Strategy (PADS) to ensure Hong Kong's future as 'the international hub for the rest of Southeast Asia' and 'an Asian travel hub', or 'the international gateway to China' (Rimmer, 1992; Yeung, 1997).

[1] The FSBF model merged as a result of the early Chinese reform and opening process and considerable differences in capabilities and institutions between Hong Kong and the PRD region in the 1980s.

As part of this strategy it was recognised that it would be necessary to replace the old congested Kai Tak Airport. The new HKIA was built at Chep Lak Kok Island. Construction started in 1991, with airport operation commencing in July 1998. The new HKIA was expected to meet air traffic growth for next decade after its opening (Oum & Yu, 2000). The airport's construction costs amounted to HK$21 billion; its initial capacity was to handle 35 million passengers and 3 million tonnes of cargo per year after first opening, as well as reaching the annual ultimate capacity of 87 million air passengers and 9 million tonnes of air cargo with two runways in operation (e.g. Yeung, 1997; Mok, 1998; Dempsey, 2000; Winston & Rus, 2008). In addition, two passenger terminals currently occupy a total of 690,000 m^2 for handling air passenger movements; Terminal 1 is currently the second largest passenger terminal in the world (HKAA, 2011). To meet future air passenger and cargo traffic demand, the HKSAR government and the airport authority decided to build the third runway, additional passenger terminal areas, aircraft parking spaces, and apron areas at the airport which based on the recommendations of public inquiries from the HKIA's Master Plan 2030 (HKAA, 2011).

HKIA has already become one of the key air transport hubs in the Asia-Pacific region and around the world, and it has frequently been ranked within the world's top 30 busiest airports for handling air passengers and air cargo between 2002 and 2010 (ACI, 2002−2010). In 2010, it was ranked as the 11th world's busiest passenger airport handling 50.9 million passengers (only Beijing Capital International Airport and Tokyo Narita International Airport were ahead of HKIA in the Asia-Pacific region). In terms of air cargo throughput, it was the busiest airport worldwide transporting a total of 4.1 million tonnes of air cargo during the same year. Furthermore, it attracted about 160 international airlines worldwide, operating more than 852 flight movements per day (HKAA, 2011). In addition to its outstanding airport traffic statistics, HKIA has also been honoured many times as the 'World Best Airport' based on air traveller surveys of airports' service standards and quality. For example, Skytrax ranked HKIA as 'the Number 1 airport' during the World Airports Awards in 2011.[2] Moreover, HKIA is the

[2] See Skytrax-Airport Star Ranking. Retrieved December 30, 2011 from http://www.airlinequality.com/news/awards_APR2011.htm

home hub for Cathay Pacific Airways, DragonAir, Hong Kong Airlines, Hong Kong Express Airways, Air Hong Kong, and the private jet operator Metrojet.

Given its important role in Hong Kong's economic development, and its reputation of being the 'World's Best Airport', Hong Kong airport has become one of the hot topics in the air transport industry for the research community to investigate. In addition, it can be seen that HKIA has been well-researched in many aspects, including the airport's and airlines' levels of service (LOS) standards provided to air travellers, the tourist arrival demand for Hong Kong, its status as the leading international air cargo hub, and the level of airport competition Hong Kong airport faces.

1.3 PREVIOUS RESEARCH ON HKIA

Over the past two decades, Hong Kong airport's operations and other related issues have been the subject of much research. For example, three studies (Gilbert & Wong, 2003; Lam *et al*., 2003; Tam & Lam, 2004) investigated the LOS standards and service quality of HKIA and airlines provided to air travellers. These studies concluded that HKIA and the airlines in operation could offer good quality services to secure and attract existing and potential air travellers using Hong Kong to destinations around the world.

Studies have also investigated tourist arrival demand for Hong Kong, and its impact on Hong Kong's economy and the aviation industry (e.g. Mok, 1985; Hobson & Ko, 1994; Hobson, 1995; Qu & Lam, 1997; Choi, Chan & Wu, 1999; Mok & Dewald, 1999; Lew & McKercher, 2002; Cho, 2003; Song, Wong & Chon 2003; Zhang, Jenkins & Qu, 2003; Zhang, Jenkins & Qu, 2006; Choi *et al*., 2008; Doong, Wang & Law, 2008; Wong, Bauer & Wong, 2008; Cheng, 2011). Common to all of these studies, Hong Kong's tourism industry is one of the key business activities facilitating the growth of Hong Kong's economy and its aviation sector. Also, annual tourist arrivals to Hong Kong have a significant impact on Hong Kong airport's passenger throughput.

Furthermore, tourist arrivals and demand patterns for Hong Kong largely depends on factors such as seasonality, country of origin's GDP, relative consumer price, the exchange rate, the interest rate, and the sovereignty changeover.

Research on Hong Kong's aviation industry has also investigated the air cargo industry, especially the international air cargo hub status of Hong Kong airport (e.g. Rimmer, 1992; Schwieterman, 1993; Waters, 1997; Hiemstra & Wong, 2003; Seabrooke *et al*., 2003; Zhang, 2003; Hui, Hui & Zhang, 2004; Zhang *et al*., 2004; Williams, 2006; Wang & Cheng, 2010). All of the research concluded that Hong Kong airport can maintain its leading position as the leading international air cargo hub in the Asia-Pacific region, reflecting the fact that its ability to handle air cargo with well-designed facilities and extensive cargo networks, the rapid growth of China's economy and China's vast hinterland, its excellent strategic position in the Asia-Pacific region, and Hong Kong's liberalised air transport policy. However, its long-term success depends on the development processes of other international cargo hub airports in Mainland China and around the Asia-Pacific region.

Studies have also investigated airport development processes and airport competition in the Asia-Pacific region and explored their impact on HKIA's performance and future development. These studies (e.g. Findlay & Goldstein, 1992; Hobson & Ko, 1994; O'Connor, 1995; Chin, 1997; Mok, 1998; Hooper, 2002; Park, 2003; Robinson, 2006; Wang *et al*., 2006; Williams, 2006; Ishutkina & Hansman, 2009) highlighted serious concerns about HKIA's future as the leading air transport hub in the Asia-Pacific region and China's primary gateway arising from the deregulation of air transportation, the privatisation of airports, and the building and expansion of airport infrastructure around the Asia-Pacific region. These developments have made HKIA face increased competition from the nearby international airports in the Multi-Airport System (MAS) in Southern China (i.e. the PRD region), three major Chinese international gateway hub airports (i.e. Beijing, Shanghai Pudong, and Guangzhou airports), and other international gateway hub airports around the Asia-Pacific region (i.e. Tokyo, Seoul, Taipei, Bangkok, Kuala Lumpur, and Singapore airports). In fact, most Asian international gateway hub airports have already posed significant threats to HKIA with their extensive flight connectivity networks to different regions around the globe, with each airport aiming to become the major air transport centres of the region to capture and transport more air passenger numbers and air cargo traffic (e.g. O'Connor, 1995; Park, 2003; Williams, 2006; Ishutkina & Hansman, 2009).

Although a substantial body of literature has investigated Hong Kong airport, this raises the following question: 'What other important issues could enhance our existing knowledge to understand HKIA's performance and future growth?' This thesis was also motivated by the fact that several important aspects related to HKIA have still not gained much attention from the researchers, such as airport efficiency, the airport's network and connectivity, and future airport passenger throughput.

1.4 RESEARCH OBJECTIVE AND QUESTIONS

The objective of this thesis was to investigate HKIA's ability to maintain and strengthen its role as the main air transport hub in the Asia-Pacific region and the primary passenger gateway to Mainland China. To achieve the research objective, this thesis was developed as an analysis of HKIA within which the aspects of airport efficiency, the airport's network and connectivity, and future airport passenger throughput can be investigated. More importantly, it is critical for the government of Hong Kong and the airport authority to know what HKIA's role is, and to consider the implications of HKIA's role upon Hong Kong's economic development and future policy making.

Three research questions address the research objective:

- How efficient are HKIA's operations compared to those of other Asia-Pacific airports and what factors explain the variations in airport efficiency?

- How does HKIA's flight connectivity network and its role as China's primary passenger gateway compare to other Asia-Pacific airports, and has this changed over times?
- Will HKIA's future passenger throughput continue to grow?

Each research question is addressed in separate empirical studies. In addition, some internal and external factors that might affect HKIA were also identified in the course of the research.

1.5 RESEARCH LAYOUT AND METHODOLOGIES

This thesis was structured to include three separate but related empirical studies which seek to address each of the research questions separately, with the aim of providing evidence to address the research objective through the investigation of three specific areas with respect to HKIA's performance and future growth. Answering these questions required three different empirical models, datasets, and estimation methods. Most importantly, the airport's hub status and/or flight connectivity networks were the thread that linked these three empirical studies.

Airport efficiency is always one of the key indicators to show the performance of an airport (Park, 2003; Graham, 2005). In the first empirical study, the operational efficiency of HKIA was assessed relative to a panel of 29 Asia-Pacific airports, followed by the identification of key determinants which explain the variations in airport efficiency. A two-stage method was used. First: Data Envelopment Analysis (DEA) was applied to investigate the operational efficiency of each Asia-Pacific airport relative to the others in the group, followed by econometric analysis (i.e. the Ordinary Least Squares (OLS) and Tobit models) to determine the significant factors affecting airport efficiency.

To explore an airport's hub position and network competitiveness, its flight connectivity network needs to be analysed. An airport's hub position in the network is largely dependent upon its flight connectivity network to connect air travellers to different regions around the globe. In the second empirical study, the NetScan Connectivity Units (CNU) model was utilised to measure and compare direct, indirect, and hub connectivity among 13 Asia-Pacific airports, aiming to determine HKIA's competitive position relative to its peers in respect to its flight connectivity network to different regions. Furthermore, for the investigation of HKIA's role as China's primary passenger gateway, market share analysis was employed to examine the share of China's total inbound international passengers captured by HKIA or travelling through the airport.

Future air passenger traffic for HKIA was forecasted using the time series forecasting method. An accurate airport traffic demand forecast allows for short- and long-term planning and decision making for the development of airport facilities and flight networks. The forecast needs to cautiously consider the impacts of external forces, particularly airport competition and the dynamics of the airport industry around the Asia-Pacific region. Again, this highlights the fact that the level of competition between HKIA and the major Asian international gateway hub airports has become intense with the rapid expansions of their respective flight connectivity networks as the airports compete to capture increasing regional air travel demand so as to enhance their hub status in the region. In the third empirical study, the Box–Jenkins Autoregressive Integrated Moving Average (ARIMA) methodology was used to build and estimate the Seasonal ARIMA model (SARIMA) and the ARIMAX model with explanatory variables for forecasting HKIA's passenger throughput, as well as projecting its future growth.

1.6 DATA FOR THE RESEARCH

To answer each of the research questions in this thesis, relevant data for analysis was collected from different entities over different periods. Because of the limited available data for the research, the research periods for each of the empirical studies spanned different periods. The following periods were investigated:

- Annual data from 2002−2008 for empirical study 1 (the airport efficiency study)
- Monthly data from December of 2002−2010 for empirical study 2 (the airport's network and connectivity study)
- Monthly data from January 1993−August 2011 for empirical study 3 (the airport passenger throughput forecasting study)

Data was mainly collected from Hong Kong Civil Aviation Department (HKCAD), Hong Kong Airport Authority (HKAA), Hong Kong Tourism Board (HKTB), and Hong Kong Census and Statistics Department (HKCSD). In addition, relevant information also gathered from the International Civil Aviation Organisation (ICAO), the International Air Transport Association (IATA), the Air Transport Research Society (ATRS) - Airport Benchmarking Reports, Airport Council International (ACI), the Official Airline Guide (OAG), China National Tourism Administration (CNTA), the International Monetary Fund (IMF), and that civil aviation authorities and the statistics departments of the study countries, as well as the airports' annual reports and websites. Once again, the data used for each of the empirical studies was specifically drawn from the aforementioned organisations dependent upon the research questions as discussed in the Data Description sections in the thesis.

1.7 ORGANISATION OF THE THESIS

The format of this thesis is structured as follows. Chapter 2 reviews prior literature to identify the key drivers that prompted HKIA's growth and the factors which are likely to affect HKIA's future development. Chapter 3, 4, and 5 report the empirical studies of the thesis. Chapter 3 assesses the operational efficiency of HKIA compared to other Asia-Pacific airports, and then identifies the significant factors for explaining the variations in airport efficiency (Study 1). Chapter 4 measures and compares HKIA's flight connectivity network and hub status relative to other Asia-Pacific airports, as well as investigating its role as China's primary passenger gateway (Study 2). Chapter 5 forecasts HKIA's future passenger throughput (Study 3). Chapter 6 is the conclusion which summarises the key findings and contributions that this thesis makes towards the collective understanding of HKIA's role as the main air transport hub in the Asia-Pacific region and China's primary passenger gateway. Finally, the implications of the research, the limitations of the research and potential areas for future research are discussed.

CHAPTER 2 : LITERATURE REVIEW

2.1 INTRODUCTION

This chapter commences by reviewing the key drivers leading to the past growth of Hong Kong airport (which includes the old Hong Kong Kai Tak Airport and the new HKIA) and the significant factors which are likely to affect the potential for HKIA's future development. The summary section briefly discusses the prior literature reviewed concerning HKIA and indicates its implication for the research objective set out for the thesis. In addition, attention will be drawn to the gaps in the prior research which this thesis aimed to investigate, thereby proving the basis for further investigation concerning HKIA's role as the main air transport hub in the Asia-Pacific region and the primary passenger gateway to Mainland China through three separate but related empirical studies. The literature review related to each specific methodology employed in each of the empirical studies (i.e. the assessment of HKIA's operational efficiency, the analysis of HKIA's flight connectivity network and China's primary passenger gateway role, and the forecasting of HKIA's future passenger throughput) will be addressed in each of the empirical studies.

This chapter is organised as follows. Section 2.2 outlines the key drivers prompting HKIA's past growth and success. Section 2.3 discusses other important factors influencing the potential of HKIA's future growth. A determination of which aspects of HKIA would be investigated to justify its role as the main air transport hub in the Asia-Pacific region and the primary passenger gateway to Mainland China is presented in Section 2.4.

2.2 KEY DRIVERS FOR THE GROWTH OF HKIA

HKIA has already become one of the key aviation hubs for air passenger and cargo transport in the Asia-Pacific region and around the world (Williams, 2006; Ishutkina & Hansman, 2009). The broad context in which HKIA has developed could be explained by the four key drivers outlined below.

1. Large hinterland and/or catchment areas:

60% of the world's population is within six hours flying time of HKIA, especially the large hinterland population size of Mainland China and from around the Asia-Pacific region (O'Connor, 1995; Law & Yeung, 2000; Williams, 2006).

2. Excellent strategic location:

Its location is ideal to serve Mainland China and the Asia-Pacific region, which makes Hong Kong airport a strategically important gateway to Mainland China and the countries in the Asia-Pacific region (Yulong & Hamnet, 2002; Zhang, 2003; Winston & Rus, 2008).

3. Good quality airport attributes:

Foreign airlines were attracted by the attributes offered by Hong Kong airport to operate flight services to Hong Kong, such as the good-quality airport infrastructure and services, and Hong Kong's liberalised air transport policy (Gardiner, Ison & Humphreys, 2005; Robinson, 2006; Ishutkina & Hansman, 2009).

4. Openness to competing airports:

Hong Kong airport's willingness to be far more open to foreign competition than other airports in the Asia-Pacific region, such as the Chinese international gateway hub airports (Robinson, 2006). This forces the airport authority to improve airport infrastructure and services to provide to air passengers and airlines in operation.

2.3 FACTORS AFFECTING HKIA'S FUTURE DEVELOPMENT

While four key drivers of HKIA's past growth have been discussed, a further range of factors will determine how far the potential for HKIA's future development have been realised as follows.

2.3.1 Competition from international airports in Southern China

HKIA has been linked with a cluster of airports in Southern China or the PRD region, collectively identified as the A5 group (i.e. Hong Kong, Guangzhou, Shenzhen, Zhuhai, and Macau airports). Five airports operate within the dynamic PRD region within a 200 kilometres radius. This region has one of the highest airport densities in the world. This also makes HKIA sensitive to airport competition in Southern China (e.g. Yam & Tang, 1996; Mok, 1998; Starkie, 2002; Zhang, 2003; Zhang *et al*., 2004; Wang *et al*., 2006; Williams, 2006; Winston & Rus, 2008; Yeung & Shen, 2008).

2.3.2 Competition from major international gateway hub airports in Mainland China

China's major international gateway hub airports have become significant competitors to HKIA. The Chinese government's intention and policy is to make Guangzhou airport as the third international gateway to Mainland China after Beijing and Shanghai Pudong airports. These three main Chinese airports are commonly regarded as the major international gateway hub airports in Mainland China, and they can generate and concentrate a high level of air passenger travel with their strong political, economic, and social statuses. They are also the hubs for 'Big Three' Chinese airlines, respectively (i.e. Air China, China Eastern Airlines, and China Southern Airlines). These three major Chinese airlines accounted for about 80% of flight operations in Mainland China. Most importantly, these three Chinese airports share the largest proportion of international passenger traffic travelling to Chinese cities through their respective flight connectivity networks instead of passing through HKIA (e.g. Robinson & Bamford, 1978; Hui, Hui & Zhang, 2004; Zhang *et al*., 2004; Ngo, 2005; Williams, 2006; Wang & Jin, 2007; Winston & Rus, 2008; Chow & Fung, 2009).

2.3.3 Competition from major international gateway hub airports in the Asia-Pacific region

Several issues have led to a huge potential increase in air transport demand in the Asia-Pacific region: the Asian's high population density, strong economic growth, improving political stability, and the widespread adoption of 'open-skies' policies (Winston & Rus, 2008). Increasing demand is having the effect of increased competition between the major Asian international gateway hub airports, notably Hong Kong, Bangkok, Singapore, Kuala Lumpur, Seoul, and Tokyo airports (e.g. Hobson & Ko, 1994; O'Connor, 1995; Chin, 1997; Li, 1998; Mok, 1998; Bowen, 2000; Chan, 2000; Chang, Cheng & Wang, 2003; Park, 2003; Rimmer, 2003; Matsumoto, 2004, 2005, 2007; Williams, 2006; Winston & Rus, 2008). Many Asian governments have undertaken airport development and expansion projects aiming to accommodate increasing regional air traffic demand as well as achieving the status of a regional air transport hub (O'Connor, 1995; Park, 2003). In terms of airport competition to HKIA, Williams (2006, p.57) argued that "the market competition is promised for East Asia, with Hong Kong, Singapore, Seoul, and Guangzhou airport, [and] such air transport activities might create significant impacts on HKIA's future". More importantly, increased competition from the Asian international gateway hub airports may have significant negative impacts on HKIA's passenger traffic in two ways: (i) gateway traffic into the PRD region and Mainland China, and (ii) hub traffic for Asian destinations.

2.3.4 The implications of changeover on Hong Kong's air transport industry

The sovereignty changeover was expected to affect the future operations of Hong Kong's local airlines to different levels (Hobson, 1995). In particular, air routes between Hong Kong and Mainland China are no longer being considered as 'international routes', but are categorised as 'regional routes' (Rimmer & Comtois, 2002; Zhang *et al*., 2004). It means that from 1997, air routes between Hong Kong and Mainland China have become 'cabotage routes'[3] (Zhang, 2003). Consequently, those routes have been reserved for incorporated airlines that have their principal place of business in the HKSAR and other airlines of the People's Republic of China. In addition, the Joint Declaration 1984 and Basic Law 1991 also specify that the HKSAR government must agree on the granting of air traffic rights and bilateral air service agreements (ASAs) with the Chinese government. All air service agreements providing air services between Mainland China and other countries with stopovers at Hong Kong shall be concluded by the Chinese government except point-to-point services (e.g. Joint Declaration, 1984, Annex I; Basic Law, 1991, Article 132; Huang, Yung & Huang, 1996; Dorsworth & Mihaljek, 1997; Zhang, 2003; Zhang *et al*., 2004). Furthermore, Chinese airlines are entitled to the fifth freedom air traffic right[4] out of Hong Kong, in such a way that more Chinese airlines can operate in Hong Kong's aviation market. In this respect, either home-based Hong Kong airlines or Chinese airlines can provide flight services to which Hong Kong freely, and that will have positive effects upon HKIA's future passenger traffic volumes.

2.3.5 China's regulatory changes in air transport policy

The growth of the airline industry in Mainland China and the increase in direct international flights between Mainland China and other countries is likely to affect

[3] Cabotage is to carry air passengers within a country by an airline of another country on a route with the origin/destination in its home country.

[4] Fifth freedom air traffic right means that the right to fly between two foreign countries during flights while the flight originates or ends in one's own country.

Hong Kong's future status as a gateway to Mainland China and Southeast Asia. The deregulation of China's air transport industry in 1979 and the consolidation of airlines in 2002 triggered the consolidation of Chinese airlines into the 'Big Three' airlines (i.e. Air China, China Southern Airlines, and China Eastern Airlines). In addition, Mainland China is also pursuing a gradual approach to open its aviation market as well as entering a more liberal international aviation regime (e.g. Zhang, 1998; Lew & McKercher, 2002; Rimmer & Comotois, 2002; Chung, 2003; Mak, 2003; Tanger, 2007; Winston & Rus, 2008; Zhang & Round, 2008; Ishutkina & Hansman, 2009; Shaw *et al*., 2009).

2.3.6 China's airport developments and improvements

China's increasing demand for air travel has prompted the Chinese government to examine airport efficiency and productivity (Yam & Tang, 1996). Improving their airports' productivity and profitability has resulted in more foreign airlines operating flight services to Chinese airports. Depending on the actual number of foreign airlines operating to Mainland China, this may reduce air passenger volumes using HKIA as a stopover to visit Chinese cities. Already, China's airport infrastructure has seen remarkable improvements since the 1990s. For instance, the Chinese government invested ¥17.1 billion to construct and upgrade 45 airports as well as to rebuild more than 90 airports. Under the Eleventh Five-Year-Plan (2006-2010), ¥20 billion would be invested to expand and upgrade Beijing, Shanghai Pudong, and Guangzhou airports, 24 medium-sized hubs (e.g. Chengdu, Haikou, and Xi'an airports), and 28 smaller airports. In addition, the Chinese government has also planned to build an additional 56 new airports by the end of 2015 (e.g. Zhang & Chen, 2003; Zhang *et al*., 2004; Yang, Tok & Su, 2008; Yao & Yang, 2008; Yeung & Kee, 2008; The Economist, 2011). Airport construction is being given priority to support economic development which relies on good air transport infrastructure (Ishutkina & Hansman, 2009).

2.3.7 The growth in China’s air passenger market

Mainland China is now becoming a major air transport player in the Asia-Pacific region as well as the fastest growing air transport market in the world (e.g. Graham, 1998a; Matsumoto, 2005; Ishutkina & Hansman, 2009; Shaw *et al*., 2009). China’s air passenger traffic has achieved a 16.3% increase between 1980 and 2004, and it has already become the world’s third-largest passenger market and is likely to become the largest commercial aviation market outside the US by 2020 (Fung *et al*., 2008). Some international aviation organisations (e.g. International Air Transport Association (IATA) and Boeing) share similar perspectives relating to the future growth of the Chinese airline market (IATA, 1997; Boeing, 2005). The dramatic growth of the Chinese air transport market can be attributed to several factors, including airline reform, strong economic development, increased disposable income, large population size and density, improved ground transport, and the development of the trade and tourism industry (e.g. Zhang, 1998; Hooper, 2002; Ye, Li & Li, 2005; Ishutkina & Hansman, 2009). Given China’s growing international passenger traffic, Hong Kong’s airline industry may gain benefits as Hong Kong’s strategic location to serve Mainland China and the merit emerging from the new air transport policy after the changeover of sovereignty.

2.3.8 Hong Kong’s tourism industry

Hong Kong is a major tourist destination in the Asia-Pacific region and more than 80% of the tourists arrived by air transport (Weiser, 1997; Choi, Chan & Wu, 1999; Doong, Wang & Law, 2008). Hong Kong’s tourism industry has a significant influence on HKIA’s passenger throughput. Concerning Hong Kong as a travel gateway to a destination or region, five major destination types of tourist itinerary pass through Hong Kong airport during their journey: single destination, gateway destination, egress destination, hub destination, and touring destination, as shown in Table 2.1.

Table 2.1. ***Five major destinations served by Hong Kong***

Destination type	Single destination	Gateway destination	Egress destination	Hub Destination	Touring Destination
Origin of travellers	Taiwan and Singapore	US and Australia	Mainland China	International travellers	US and Australia
Purposes	Short break, shopping holiday, business trip	Gateway to destinations in Mainland China, East and Southeast Asia	Southeast Asia and overseas trips	Transit to different destinations worldwide	Gateway to destinations in Mainland China, East and Southeast Asia

Remarks: Adapted from Lew & Mckercher (2002).

2.3.9 China's tourism development

China's rapid economic development has brought a growth of outbound and inbound tourism. Increased openness to the outside world has encouraged more cross-border travel for Chinese citizens (Yu & Lew, 1997; Arlt, 2006). For outbound tourism, Mainland China is expected to become the world's biggest source of outbound tourism, with 115 million of its nationals travelling abroad annually by 2020 (Lew, 2000; Wong, Bauer & Wong, 2008). The ability of Chinese residents to travel outside of Mainland China depends largely on two factors: (i) adequate income to afford international travel, and (ii) official permission to do so (Zhang, Jenkins & Qu, 2003). For inbound tourism, according to the World Trade Organisation (WTO), Mainland China will be the top international destination country in the world, with about 137 million international arrivals by 2020 (Zhang & Lew, 2003).

The tourism industry has a close relationship with the airline industry (Bowen, 2000). The growth of the Chinese tourism market is believed to have a significant impact on Hong Kong's airline industry. Although there are more direct air link and flight connections between Chinese cities and other countries, more Chinese travellers still used Hong Kong airport as a gateway to the destinations taking advantage of its extensive flight connectivity network (e.g. Yu & Lew, 1997; Mak, 2003; Zhang, Jenkins & Qu, 2003; Zhang, Jenkins & Qu, 2006). In addition, the Hong Kong Tourist Association (1999) reported that 57% of Mainland Chinese travellers used air transport to travel to Hong Kong in 1999. Another figure also showed that 75% of all Chinese tourists go to Hong Kong and Macau during their overseas trips. Two-thirds of Mainland visitors travelled to Hong Kong coming from Guangdong, Shanghai, and Beijing areas (Zhang, Jenkins & Qu, 2003; Ryan & Gu, 2009). Moreover, the 'Individual Visit Scheme (IVS)' policy was introduced in July 2003,[5] aiming to simplify travel applications for Mainland Chinese visitors to Hong Kong. Among the 49 IVS cities, Chinese residents from Guangdong, Shenzhen, Shanghai, and Beijing were the major visitors travelling Hong Kong for shopping and sightseeing (e.g. Martin, 2007; Choi *et al*., 2008; Yeung & Shen, 2008; Hong Kong Tourism Commission, 2012).

2.3.10 Direct air link across the Taiwan Strait

Direct air transport links were prohibited between Mainland China and Taiwan as the result of political tension and a direct trade ban that was in place since 1949 (Seabrooke *et al*., 2003; Hui, Hui & Zhang, 2004; Zhang *et al*., 2004). In the past, the cross-strait air traffic was routed through a third nation or intermediary as a transit point prior to entering the border on either side. Hong Kong airport is seen as a convenient place for air passenger transit and air cargo transhipment due to its excellent strategic location and geographic proximity to Mainland China. Earlier rigid air travel restrictions between Mainland China and Taiwan assisted Hong Kong airlines' growth and the airport's expansion, as these restrictions ensured that Taiwan was the second-largest source market for Hong Kong airport after Mainland China (Oum & Yu, 2000). The implementation of cross-strait (direct air link) agreement or '*sang tong*'[6] between Mainland China and Taiwan will have a negative effect on the number of Taiwanese tourists travelling through HKIA (e.g. Hobson & Ko, 1994; Mok & Dewald, 1999; Oum & Yu, 2000; Shon, Chang & Lin, 2001; Clark, 2002; Lin & Chen, 2003; Seabrooke *et*

[5] The policy of the IVS was first introduced on July 28, 2003. The policy allows residents of designated cities in Mainland China to visit Hong Kong in an individual capacity.

[6] Zhang (2003) stated that '*sang tong*' implies the lifting of direct link restrictions in mail, transportation, and trading between Mainland China and Taiwan. At the initial stage of agreement, the majority of direct flight services will mainly involve charter flights during the main festivals and holidays, but more direct scheduled flights operating across the Taiwan Strait will gradually be allowed.

al., 2003; Zhang, 2003; Hui, Hui & Zhang, 2004; Zhang *et al*., 2004; Robinson, 2006; Guo *et al*., 2006; Chang, Hsu & Lin, 2011; Lau *et al*., 2012).

2.3.11 China's WTO accession

Since December 2001, China's WTO accession has attracted considerable attention concerning its short- and long-term implications on Hong Kong's air transport industry. China's WTO accession was expected to create a mixture of opportunities and threats for Hong Kong's role as China's primary gateway to the global market (e.g. Cheong, 2000; Sung, 2002; Seabrooke *et al*., 2003; Zhang, 2003; Zhang & Li, 2003; Hui, Hui & Zhang, 2004; Sit, 2004; Sung, 2004). For air passenger travel, in particular, China's WTO membership may translate into more business visitor arrivals to Mainland China due to more opportunities for foreign direct investment with more liberal ownership restrictions. It also provides other opportunities for Chinese tourism developments that will attract more overseas visitors (Mak, 2003; Tanger, 2007; Zou & Simpson, 2008).

2.3.12 Economic integration with Southern China and Mainland China

Economic integration[7] with Southern China (i.e. the PRD region) and Mainland China might significantly influence Hong Kong's economy and even affect the future development of HKIA (e.g. Kwok & So, 1995; Overbolt, 1995; Sung, 1995; Yeung, 1997; Yulong & Hamnet, 2002; Ash, 2003). The Closer Economic Partnership Arrangement (CEPA) was signed between Hong Kong and the Guangdong province in 2003. The CEPA agreement provides Hong Kong with better-than-WTO-entry terms for 18 service sectors, including transport and tourism (Sit, 2004). The agreement reflects the view that Hong Kong has little future without the Guangdong province (Yeung &

[7] Sung (1995) claimed that economic integration implies the lowering of barriers to economic interactions across countries or regions, thereby facilitating trade and investment. Economic integration can occur through institutional channels, or by granting mutual discriminatory preferences to the parties involved.

Shen, 2008). For example, the former HKSAR Chief Executive Tung Chee-hwa, was quoted by Sit (2004, p.834) as saying that "Hong Kong's economic future will lie in an increased integration and co-development with Guangdong hinterland". Intensive economic integration between Hong Kong and Southern China and Mainland China might bring two important benefits for HKIA. First, Southern China is set to become one of the passenger transport hubs of Asia due to new road connections between Hong Kong and the cities in Southern China and its economic integration (Hobson & Ko, 1994). Second, economic integration might have potential significant implications for Hong Kong's air transport industry such as Hong Kong's PRD-related export and tourism (Sung, 2004).

2.3.13 Exogenous shocks

Exogenous shocks or disruptive events can adversely affect air passenger travel. Such undesirable events cannot be predicted in advance, but they have the potential for dramatic negative impacts on air travel demand for an airport. A number of studies found that the impacts of terrorism and the outbreak of infectious disease on air travel demand, tourism, business, and economy was enormous. For example, the 9/11 terrorist attacks in the US and the SARS outbreak was found to have the significant negative impacts on HKIA's passenger traffic volumes (e.g. Grais, Ellis & Glass, 2003; Lam, Zhong & Tan, 2003; McKercher & Hui, 2004; Pine & Mckercher, 2004; Siu & Wong, 2004; Robinson, 2006; Kozak, Crotts & Law, 2007). Furthermore, Hong Kong's economy is very sensitive to general economic contraction and can easily be hit by negative macroeconomic demand shocks and external shocks such as the Asian Financial Crisis in 1997 and the global economic downturn in 2001 (Wong, 2002; Martin, 2007). Ishutkina and Hansman (2009, p.106) also claimed that "Macroeconomic instability may suppress both the economic and air transport system. Asian financial crisis was identified … in deteriorating economic conditions among the Asian countries as well as decreasing the number of inbound air passengers through Hong Kong International Airport, in particular, affecting the flows of business passengers and investors". However, air passenger traffic usually returns to its long-term trend following exogenous shocks (Njegovan, 2006).

2.4 SUMMARY

A substantial body of literature adds to our understanding of the key drivers that have prompted Hong Kong airport's past growth, and the significant factors that are likely to affect the potential for HKIA's future development, HKIA's role as the main air transport hub in the Asia-Pacific region and the primary passenger gateway to Mainland China are still unclear and are, nevertheless, subject to future investigation. First, previous literature has investigated Hong Kong airport in such a way that the research could not provide a clear understanding of HKIA's ability to maintain and strengthen its role as the main air transport hub in the Asia-Pacific region and as China's primary passenger gateway. Second, the prior research did not address some important aspects related to HKIA such as airport efficiency, the airport's network and connectivity, and future airport passenger throughput − aspects that are critical to understand HKIA's performance relative to other Asia-Pacific airports and its future growth. To shed light on this issue, these three specific aspects of HKIA were investigated in separate empirical studies to address the research objective outlined in the Introduction.

CHAPTER 3 : OPERATIONAL EFFICIENCY OF ASIA-PACIFIC AIRPORTS

3.1 INTRODUCTION

Several factors have stimulated the growth in air transport demand and airport development, such as the rapid economic development, the privatisation of the airport industry, and the liberalisation of aviation policy in the Asia-Pacific region (e.g. Chin, 1997; Bowen, 2000; Oum & Yu, 2000; Hooper, 2002; Oum, Yu & Fu, 2003; Park, 2003; Zhang, 2003; Williams, 2006; Yang, Tok & Yu, 2008). This is reflected by the increasing air traffic volumes handled by the Asia-Pacific airports. Airport Council International (ACI) indicates that several major Asia-Pacific airports have been frequently ranked inside the world's top 30 busiest airports between 2002 and 2008 (ACI, 2002−2008). Moreover, ACI also projects that the announced growth rates for air cargo and aircraft movements in the Asia-Pacific region will reach 6.3% and 4.5%, respectively, by 2025 (ACI, 2007). The International Civil Aviation Organisation (ICAO) also projects that the Asia-Pacific region will become the busiest and fastest growing air transportation market for international passenger traffic by 2025 (ICAO, 2008). Governments in the Asia-Pacific region have therefore invested and constructed airport infrastructure and facilities to meet future air transport demand (O'Connor, 1995). More importantly, airports are now under pressure from emerging competitors competing for air traffic demand. To respond to this pressure, airport efficiency becomes a critical issue for airport management to address (Talley, 1983; Chin & Siong, 2001; Forsyth, 2003).

To investigate airport efficiency, Data Envelopment Analysis (DEA) has become the recognised method for efficiency evaluation due to its simplicity in constructing an efficiency frontier for identifying efficient or inefficient airports. Also, the DEA model requires no assumptions for specifying production functions between airport inputs and outputs. Additionally, the DEA model can handle multiple airport inputs and outputs within a single analysis without any difficulties of aggregation, and can assess an airport's relative efficiency in a single period or in a sequence of periods as well as requiring less information for analysis (e.g. Gillen & Lall, 1997; Pels, Nijkamp & Rietveld, 2001, 2003; Cooper, Seiford & Zhu, 2004; Graham, 2005; Cooper, Seiford & Tone, 2006). Therefore this study used the DEA model to assess the operational efficiencies of the major international airports in the Asia-Pacific region. Three main reasons make this study meaningful: (i) airports operating in the Asia-Pacific region seem to be less researched compared with their counterparts in the US, Europe, and South America, (ii) this study contributes to the existing literature by analysing the efficiency of a large group of Asia-Pacific airports (30 airports) with a longer study period − the size of sampled airports in this study is a good reflection and representation of the airport industry in the Asia-Pacific region due to their roles as the international or regional hub airports in their countries, and (iii) this study extends the work of Lam, Low and Tang (2009), Yang (2010a and b)[8] in assessing the relative operational efficiency of Asia-Pacific airports and seeking to identify the causes of variations in airport efficiency.

The format of this chapter is structured as follows. Section 3.2 presents the literature review with regard to the DEA models for airport efficiency evaluations. Section 3.3 outlines the DEA methodology, the Ordinary Least Squares (OLS) model, and the Tobit model. Section 3.4 presents the dataset of sampled airports, and airport input and output variables for the DEA analysis as well as the key determinants for the OLS and Tobit regression analysis. Section 3.5 presents the results of DEA analysis, the OLS and the Tobit models. Section 3.6 discusses and summarises the key findings of this chapter.

3.2 LITERATURE REVIEW OF DATA ENVELOPMENT ANALYSIS

[8] Three recent studies (Lam, Low & Tang, 2009; Yang, 2010a and b) analysed the efficiency of major international airports operating in the Asia-Pacific region, without identifying any factors which might cause variations in airport efficiency.

3.2.1 Studies using DEA

DEA has become a popular method of investigating airport efficiency. A summary of recent studies using DEA may be seen in Table 3.1. Fewer DEA studies have evaluated airport efficiency in the Asia-Pacific region compared with airports in the US, Europe, and South America. In addition, the DEA studies also showed considerable differences in the airport input and output variables used for the analysis. Three specific forms of DEA analysis were identified from the literature and are discussed in the following subsections: (i) DEA analysis with operational variables, (ii) DEA analysis with financial variables, and (iii) DEA analysis with the second-stage analysis.

3.2.2 DEA models with operational variables

Studies adopting DEA models with operational variables mainly used the operational variables as the inputs and airport traffic as the outputs to evaluate airport efficiency in DEA models. For example, Fernandes and Pacheco (2002) employed DEA models to evaluate the capacity efficiency of 35 domestic airports in Brazil during 1998 in order to find their efficiency in providing passenger services. One of the limitations of this study was that it did not incorporate any airport facilities within the input variables, even though including these would obtain a better representation of airport capacity. Another limitation was that the shorter period of panel data cannot be used to draw a generalised conclusion about the efficiency of Brazilian airports. Yoshida and Fujimoto (2004) used DEA model and the endogenous-weight Total Factor Productivity (TFP) method to assess the relative efficiency of 67 Japanese airports (mostly international airports and small regional airports) during 2000 and to discuss whether any over-investments in Japanese regional airports had been made. The study indicated that the smaller regional airports in Japan have lower efficiency levels compared to others in the group, and the airports constructed in the 1990s are relatively inefficient. However, more meaningful results could be achieved if the study conducted an international comparison of overseas airports with the sampled Japanese airports.

Table 3.1. ***Airport efficiency studies using Data Envelopment Analysis (DEA)***

Authors and date	**Methodology**	**DEA model's orientation**	**Airports studied**	**Airport input variables**	**Airport output variables**
Gillen & Lall (1997)	DEA-BCC model, Tobit model	Output	21 US airports	Number of runways; gates; employees; collection belts; parking spaces; runway length; airport and passenger terminal area	Number of passengers; carrier movements; cargo volume
Parker (1999)	DEA-CCR and -BCC models	Input	32 UK airports	Number of employees; capital stock; other capital inputs	Number of passengers; cargo volume
Murillo-Melchor (1999)	DEA-BCC model, Malmquist Productivity Index (MPI)	Output	33 Spanish airports	Number of workers; value of accumulated capital stock; value of intermediate expenses	Number of passengers
Sarkis (2000)	DEA-CCR and -BCC models	Output	44 US airports	Airport operational costs; number of airport employees; gateways; runways	Operational revenue; passenger flows; commercial and general aviation movements; total cargo transportation
Martin & Roman (2001)	DEA-CCR and -BCC models	Output	37 Italian airports	Labour costs; capital and material costs	Number of passengers; air traffic movements; cargo volume
Pels, Nijkamp & Rietveld (2001)	DEA-BCC model, Stochastic Frontier Analysis (SFA)	Input	34 European airports	Number of runways; aircraft parking (at the terminal and remote area); check-in counters; luggage claims	Number of passengers; aircraft movements
Abbott & Wu (2002)	DEA-CCR and -BCC models, Malmquist Total Factor Productivity, Tobit model	Input	12 Australian airports	Total runway length; number of staff; capital stock	Number of passengers; cargo volume
Fernandes & Pacheco (2002)	DEA-BCC model	Output	35 Brazilian airports	Apron area; departure lounges and luggage claims; number of check-in counters; car parking spaces; length of curb footage	Number of passengers

Continued on next page

Authors and date	**Methodology**	**DEA model's orientation**	**Airports studied**	**Airport input variables**	**Airport output variables**
Bazargan & Vasigh (2003)	DEA-CCR model	Input	45 US airports	Average total operating expenses; average total non-operating expenses; average runways; average gates	Total passengers; air carriers annual operations; other annual operations; aeronautical operating revenue; non-aeronautical operating revenue; percentage of operations in time
Pels, Nijkamp & Rietveld (2003)	DEA-CCR model	Input	33 European airports	Air Traffic Movement (ATM): airport area; aircraft parking positions; number of runways; Air Passenger Movement (APM): aircraft operations; load factor; number of check-in desks; baggage belts	ATM; APM
Pacheco & Fernandes (2003)	DEA-BCC model	Input	35 domestic Brazilian airports	Average number of employees; payroll; operating expenses	Number of domestic passengers; cargo volume; operating revenue; commercial revenue; other revenue
Barros & Sampaio (2004)	DEA-CCR and -BCC models	Input	14 Portuguese airports	Number of employees; capital; price of labour; price of capital	Number of planes; number of passengers; general cargo; mail cargo; sales to planes; sales to passengers
Sarkis & Talluri (2004)	DEA-CCR model, cross-efficiency model, clustering analysis	Input	44 US airports	Operating costs; number of employees; gates; runways	Operating revenue; number of passengers; aircraft movements; general aviation; total freight handled
Yoshida & Fujimoto (2004)	DEA-CCR model	Input	67 Japanese airports	Total runway length; terminal area; access costs; labour	Number of passengers; aircraft operations; cargo volume
Lin & Hong (2006)	DEA-CCR and -BCC models, SFA, cross-efficiency model	Output	20 major international airports worldwide	Number of employees; check-in counters; runways; parking spaces; aprons; boarding gates; terminal area	Number of passengers; aircraft movements; cargo volume

Continued on next page

Authors and date	**Methodology**	**DEA model's orientation**	**Airports studied**	**Airport input variables**	**Airport output variables**
Pathomsiri *et al*. (2006)	DEA-BCC model, Tobit model	Output	14 Multiple Airport Systems (MAS) in the US	Land areas; number of runways; runway area	Number of passengers; aircraft movements
Barros & Dieke (2007)	DEA-CCR and -BCC models	Output	31 Italian airports	Labour costs; capital; operational costs excluding labour costs	Number of passengers; aircraft movements; cargo volume; aeronautical receipts; handling receipts; commercial receipts
Malighetti *et al*. (2007)	DEA-CCR model, Tobit model	Output	34 Italian airports	ATM: airport area; total length of runways; total aircraft parkings; APM: aircraft movements; terminal surface; number of check-in desks; aircraft parking positions; baggage claims	ATM; APM
Li & Liu (2007)	DEA-CCR and -BCC models, MPI, Tobit model	Output	41 Chinese airports	Passenger terminal area; total runway length; airport fuel tank capacity	Number of passengers; cargo volume; aircraft movements
Barros & Dieke (2008)	DEA-CCR and -BCC models, Simar &Wilson regression analysis	Output	31 Italian airports	Labour costs; capital invested; operating costs excluding labour costs	Number of air passengers; number of planes; general cargo; handling receipts; aeronautical sales; commercial sales
Fung *et al*. (2008)	DEA-CCR model, MPI	Output	35 Chinese airports	Total runway length; terminal size	Number of passengers; aircraft movements; cargo volume
Lam, Low & Tang (2009)	DEA-CCR and -BCC models	Input	11 Asia-Pacific airports	Number of employees; capital; soft input; trade value	Number of passenger; aircraft movements; cargo volume

Continued on next page

Authors and date	Methodology	DEA model's orientation	Airports studied	Airport input variables	Airport output variables
Malighetti *et al*., (2009)	DEA-CCR and -BCC models, Simar &Wilson methodology	Output	57 European airports	Total surface area of airport; total runway length; number of aircraft parking positions; check-in desks; baggage claims; aircraft movements; total terminal area	Number of passengers; aircraft movements
Lozano & Gutierrez (2009)	DEA-BCC model	Output	41 Spanish airports	Total runway area; apron capacity; passenger throughput capacity; number. of baggage belts; check-in counters; boarding gates	Air traffic movements; air passengers movements; cargo volume
Muller, Ulku & Zivanovic (2009)	Partial Factor Productivity (PFP), DEA-BCC model; SFA, Tobit model	Output	7 UK and 6 German airports	Terminal area; number of check-in counters; number of gateways	Number of passengers
Yuen & Zhang (2009)	DEA-BCC model, OLS model	Output	25 Chinese airports	Runway length; terminal size	Passenger numbers; cargo volume; aircraft movements
Yang (2010a)	DEA-CCR and -BCC models, MPI	Output	12 Asia-Pacific airports	Number of employees; runways; operating costs	Number of passengers; cargo volume; operating revenue
Yang (2010b)	DEA-CCR and -BCC models, SFA	Output	12 Asia-Pacific airports	Number of employees; runways; operating costs	Number of passengers; cargo volume; operating revenue
Roghanian & Foroughi (2010)	DEA-BCC model	Input	21 Iranian airports	Number of employees; terminal area; length of runway	Aircraft movements; number of passengers; cargo volume

Continued on next page

Authors and date	**Methodology**	**DEA model's orientation**	**Airports studied**	**Airport input variables**	**Airport output variables**
Perelman & Serebrisky (2010)	DEA-CCR and -BCC models, Tobit model	Output	22 Latin American airports, 23 Asia-Pacific airports, 40 European airports, 63 Canadian and US airports	Number of employees; runways; boarding gates	Number of passengers; tonnes of freight; aircraft movements

Remarks: Summarised from the literature and tabled by authors and date. CCR, Charnes, Cooper & Rhodes; BCC, Banker, Charnes & Cooper;

Furthermore, Lozano and Gutierrez (2009) measured the efficiency of 41 Spanish airports during 2006 through the DEA analysis, and half of the airports were found to be technically efficient. Roghanian and Foroughi (2010) also performed a DEA analysis to assess the relative efficiency of 21 Iranian airports during 2009. The study revealed that most airports are practically inefficient and suggested that the Iranian government can significantly increase the efficiency of their airports by setting new regulations and rules.

In the global perspective, the operational efficiency of 20 international airports worldwide in 2003 were studied by Lin and Hong (2006), which used DEA models and Stochastic Frontier Analysis (SFA) for hypothesis testing to examine whether five airport characteristics (i.e. airport ownership, airport size, hub airport, airport location, and the economic growth rate of the country where the airport is located) influence the operational efficiency. The conclusion of the research was that three factors (i.e. hub airport, airport location, and the economic growth rate of airport's home country) are related to the operational performance of airports.

Different dimensions of the operational efficiency of Asia-Pacific airports across different periods were analysed by Lam, Low and Tang (2009) with different DEA models. Their study was the first analysis to apply the DEA analysis to evaluate the Asia-Pacific international airports that took the factor price differential and economic inequalities among countries within the region into consideration. The study showed that the international Asian airports are technical-, scale-, and mix-efficient. However, the presence of country-specific effects and differences in allocative efficiency led to a significant disparity in cost efficiency. In addition, Fung *et al*. (2008) employed DEA models and the Malmquist Productivity Index (MPI) to evaluate the productivity changes of 35 Chinese airports between 1995 and 2004, and also used several factors such as airport location, airport status, and airport ownership to explain the variations in airport efficiency. The study concluded that Chinese airports have experienced more than an average of >3% growth in airport productivity due to technical advancement. More importantly, the airports act as international hub airports and the listed airports are more efficient than other sampled airports.

In practice, it may be far more complicated to explore the possible reasons for using DEA studies with the operational variables for benchmarking airport efficiency but not incorporating any financial variables in the DEA analysis. One of the possible reasons for doing so could be that there is a lack of available financial data related to airport operations or because it is extremely difficult to gather relevant financial data for each airport analysed. As with different airport characteristics and operations, this becomes one of the limitations to studies incorporating the operational variables in the DEA analysis. In addition, most airports are currently operated as commercial organisations to maximise the profitability from aeronautical and non-aeronautical activities. Therefore the financial variables or indicators were used in this present study as airport input and/or output variables in the DEA analysis in order to achieve a fair evaluation of airport efficiency.

3.2.3 DEA models with financial variables

Financial variables or indicators are often used as airport input or output variables during the DEA analysis, coupled with the operational variables. For example, Parker (1999) utilised DEA models to analyse the efficiency of 32 UK airports controlled by the British Airport Authority (BAA) before and after privatization using data retrieved from the financial reports during the periods of 1978−1980 and 1995−1996, respectively. The inputs included the number of employees, capital stock, and other capital inputs; the outputs consisted of the number of passengers and cargo volume. It was revealed that there was no strong evidence of an improvement in the performance of BAA after privatisation. Heathrow Airport was the best performer among the sampled airports over the study periods.

Murillo-Melchor (1999) used DEA models and MPI to analyse the productivity changes of 33 Spanish airports between 1992 and 1994, incorporating accumulated capital stock and intermediate expenses as airport input variables. The study showed a considerable decrease in the total productivity of Spanish airports during the study periods, and the short analysis period was not suitable for a comprehensive conclusion. Sarkis (2000) also employed various DEA models (i.e. the DEA-CCR and -BCC models, simple cross-efficiency, aggressive cross-efficiency, ranked efficiency, and radii of classification ranking) to assess the efficiency of 44 major US airports between 1990 and 1994. Airport operational costs, the number of airport employees, the number of gateways, and the number of runways were the input variables; operational revenue, passenger flows, commercial and general aviation movements, and total cargo transportation were the output variables. The main drawback of this study was that there was a bias toward larger airports during data collection.

Unlike Parker (1999), Martin and Roman (2001) used DEA methodology to combine labour costs, capital costs, and material costs as the airport inputs, and air passengers, aircraft movements, and air cargo as airport outputs to evaluate whether airport privatisation had affected the efficiency of 37 Italian airports during 1997 as well as performing a sensitivity analysis using two approaches of Constant Return to Scale (CRS) and Variable Return to Scale (VRS). The study concluded that airport privatisation will improve the performance of airports, but these measures need to be combined with an adequate process of economic regulation in order to be effective. Furthermore, Pacheco and Fernandes (2003) adopted DEA models to evaluate the managerial and physical efficiency of 35 domestic Brazilian airports during 1998, which used payroll, operating expenses, and employee numbers as airport inputs against airport outputs such as domestic passengers, air cargo, operating and commercial revenue, and other revenue. The conclusions from the study revealed that the airports with higher managerial efficiency and lower physical efficiency enjoy idle capacity to maintain service quality levels without immediate airport infrastructure investment. Sarkis and Talluri (2004) also evaluated the efficiency of 44 US airports between 1990 and 1994 applying DEA models and clustering analysis. Operating costs and operating revenue were used as airport inputs and outputs during the DEA analysis, respectively. One of the main problems of this study was a bias toward larger airports in the dataset, and different outcomes may have been obtained if different parameters of airport inputs and outputs were collected for different airports to perform efficiency evaluation.

More recently, the efficiency of 31 Italian airports was studied by Barros and Dieke (2007) using DEA models with the panel data of 2001 to 2003, using the financial variables as some of the airport inputs to predict air passengers, aircraft movements, air cargo, and financial outputs. The study results suggested that most Italian airports are quite VRS-efficient, and highlighted some reasons to explain the variations in airport efficiency such as airport size, airport management, and the size of work load unit (WLU). Yang (2010a) also evaluated the efficiency and the productivity changes of 12 Asian international airports over the period of 1998 and 2006 using DEA models and MPI. Operating costs and operating revenue were used as the airport input and output variables, respectively. The key findings of the study showed that airports improve their efficiency when they have appropriate scale size and better resource utilisation, and the improvements in technical efficiency may also affect airport efficiency. In the same year, Yang (2010b) added SFA analysis along with DEA models and MPI with the same dataset to re-examine the operational efficiency and the productivity changes of Asian international airports. The study reported that the airports' inefficiency increased over time, and that one output variable used in the SFA analysis could not cover all aspects of the performance estimation implying the data variables selected were not exhaustive.

3.2.4 DEA models with the second-stage analysis

The key determinants causing variations in airport efficiency cannot be clearly understood from looking at the operational and/or financial variables used in the DEA analysis, although DEA studies of airport efficiency evaluations showed the capacity to evaluate airport efficiency (Gillen & Gill, 1997). A clear understanding of the significant factors affecting airport efficiency would provide insight to airport managers and policy makers for improving airport efficiency through benchmarking; it helps airport managers to compare their airports' performance with those of their peers and improve their own operations.

Only a few studies have combined DEA models and the second-stage analysis. Some researchers have used the operational and/or financial variables as the inputs and outputs in DEA models, and then conducted further statistical analysis to identify the significant determinants causing the variations in airport efficiency. For example, Gillen and Lall (1997) provided a very influential paper that applied the DEA and Tobit models to assess and rank the performance of 21 US airports between 1989 and 2003, and also to show the advantages of DEA models for evaluating airport efficiency. They also set up an exemplar for airport efficiency evaluation with the two-stage analysis based on two major aspects: air passenger movements (APM) and air traffic movements (ATM). Similarly, Pels, Nijkamp and Rietveld (2001, 2003) utilised DEA models and followed the approach of Gillen & Lall (1997), separating airport activities into two parts. Their research results were compared to SFA to assess the efficiency of 33 European airports between 1995 and 1997. The conclusions of the study showed that an average airport in Europe operates under Constant Returns to Scale (CRS) when handling air transport movements, but operating under increasing return to scale when handling air passengers. In addition, Abbott and Wu (2002) employed the Total Factor Productivity (TFP) and DEA models to investigate the productivity and efficiency of 12 Australian airports for the period of 1990–2000, and also identified the sources of variations in airport efficiency using the Tobit model. The study reported that airports improved their productivity over the study periods and that the Australian’s largest airport was relatively more efficient than overseas airports. Also, six factors (i.e. the rate of return, capital labour ratio, aircraft standing areas, total asset growth rate for each airport, state dummy for airport ownership, and year dummy) jointly affect airport efficiency.

Barros and Sampaio (2004) used the DEA and Tobit models to assess the efficiency of 14 Portuguese airports between 1990 and 2000. The study revealed that smaller airports are less efficient and that the most efficient airports are located in the main cities. The Tobit model also indicated that four significant factors (i.e. the percentage share held by the regional government, airport location, the population size around the airport, and the ratio of operational costs to sales) can explain the dissimilarities in airport efficiency. Furthermore, the efficiency of 34 Italian airports was studied by Malighetti *et al*. (2007) applying the DEA and Tobit models from 2005 to 2006. The study concluded that larger airports are more efficient than smaller airports. Hub premium (i.e. an airline dominates an airport) and privatisation have positive impacts on airport efficiency, unlike the negative impacts caused by military activities and seasonal effects. Pathomsiri *et al*.

(2006) also employed DEA models to measure the airport productivity of 14 Multiple Airport Systems (MAS) in the US between 2000 and 2002, where the second-stage Censored Tobit regression analysis was performed to analyse the influences of key factors causing the differences in productivity. Four factors (i.e. the utilisation of runway areas, market dominance, the proportion of international passengers, and management style) were determined to cause the variations in airport productivity.

The DEA, MPI, and Tobit models were employed by Li and Liu (2007) to evaluate the efficiency of 41 Chinese airports form 2001 to 2005. They concluded that Chinese airports operated with low technical efficiency levels over the study periods, and six factors (i.e. runway length, passenger terminal area, cargo volume carried per flight, regional GDP per square kilometre, the airport's hub status, and airport location) were considered as the significant factors to explain the variations in airport efficiency. Similarly, Yuen and Zhang (2009) used the DEA, OLS and Tobit models to evaluate a panel of 25 Chinese airports between 1995 and 2006. The findings of the study suggested that five significant factors (i.e. ownership of the listed airports, airport competition, airport localisation programme, the 'open-skies' agreements, and airline mergers) have positive impacts on the efficiency levels of Chinese airports. However, the study included only two inputs and three outputs for Chinese airports, which it could not capture the different operating characteristics and services provided by the Chinese airports.

For comparing airport efficiency worldwide, Perelman and Serebrisky (2010) used the DEA and Tobit models to compare and analyse the technical efficiency of 22 Latin American airports relative to 23 Asia-Pacific airports, 40 European airports, and 63 Canadian and US airports between 2005 and 2006. The research suggested that Latin American airports are less efficient than Asian and North American airports under the CRS model, but Latin America became the second most efficient region under the VRS model behind Asia. Several factors such as institutional variables (private vs. public operation), the socioeconomic environment (GDP), and airport characteristics (hub and share of commercial revenues) were found to be significant determinants for explaining variations in airport efficiency around the world.

Many other studies have used other kinds of second-stage analysis techniques to assess airport efficiency, combining different airport inputs and outputs. For example, Bazargan and Vasigh (2003) adopted DEA models to analyse the efficiency of 45 US airports (i.e. the top 15 large, medium, and small hub airports) between 1996 and 2000. Statistical tests were performed on the resulting DEA indexes to determine whether the size of airport affected airport efficiency. The conclusion was that small hub airports consistently outperform the larger hubs in the US. Barros and Dieke (2008) also used DEA models to measure the efficiency of 31 Italian airports between 2001 and 2003, and employed Simar & Wilson regression analysis to identify the determinants of airport efficiency rather than the Tobit model. The findings of this study revealed that three factors (i.e. the airport's regional hub status, the privately-owned airports, and the WLU parameters) increase airport efficiency. Similarly, DEA model and the second-stage Simar & Wilson methodology were adopted by Malighetti *et al*. (2009) to measure the efficiency of 57 European airports and to identify the efficiency determinants during 2006 focusing on APM and ATM. The results indicated that airport efficiency is positively related to airport's centrality in the European network and the intensity of competition between the airports. Muller, Ulku and Zivanovic (2009) used the Partial Factor Productivity (PFP), DEA, SFA, and Tobit models to analyse the economic and technical performance of 13 UK and German airports from 1998 to 2005 under the scheme of privatisation. The study results indicated that the fully-privatised British airports are more efficient than their German counterparts.

The ability of DEA models to assess airport efficiency, coupled with the ability of second-stage analysis to identify the key determinants that explain the variations in airport efficiency, prompted this study to adopt a method of two-stage analysis: the first-stage analysis used DEA model to examine the operational efficiency of 30 Asia-Pacific airports, and then the second-stage analysis used the OLS and Tobit models to identify the statistically significant factors causing the differences in airport efficiency levels. The DEA, OLS, and Tobit models will be elaborated on in the following sections.

3.3 METHODOLOGY

3.3.1 Data Envelopment Analysis

The DEA model was used to assess the relative efficiency of a group of Decision Making Units (DMUs) by using multiple inputs to produce multiple outputs but without specific *a priori* information relating to a production or cost function (Yang, 2010a). The fundamental concept of a DEA model is that an efficiency frontier is constructed to envelop the observed input and output data, and then the efficiency of each DMU relative to the efficiency frontier is measured (see Figure 3.1).

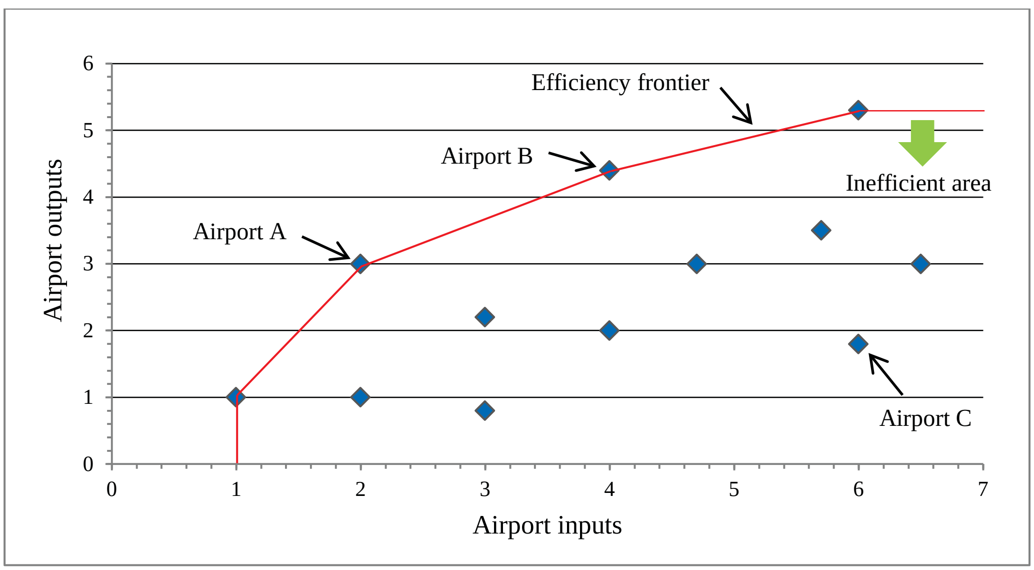

***Figure 3.1*. Efficiency frontier in DEA**

With respect to airport efficiency evaluation, in Figure 3.1, Airport A is considered as efficient as Airport B since both airports lie on the efficiency frontier and their DEA efficiency indexes are equivalent to 1; Airport C, however, is considered as an inefficient airport located underneath the efficiency frontier, and its DEA efficiency index is between 0 and 1.

Following Farrell's (1957) non-parametric production frontier function, Charnes, Cooper and Rhodes (1978) introduced the DEA methodology to evaluate the relative efficiency of a DMU by building a ratio which consists of the maximum weighted outputs to maximum weighted inputs for each DMU subject to a set of conditions (i.e. constraints). Considering a group of airports, where y_{rk} and x_{ik} are the known airport outputs and inputs of the airport k. The DEA efficiency index of an airport is denoted as B_o , which represents the inputs x_{io} $(i = 1, 2, 3, \cdots, n)$ that produce the outputs y_{ro} $(r = 1, 2, 3, \cdots, m)$; u_r and v_i are the weights of aggregation (virtual multipliers), that are non-negative which are chosen to maximise the value of $B_{o.}$ Thus, the fractional programming model is written as shown in Equation (3.1):

$$B_o = \underset{u_r, v_i}{Max} \frac{\sum_{r=1}^{m} u_r y_{ro}}{\sum_{i=1}^{n} v_i x_{io}}$$

Subject to:

$$\frac{\sum_{r=1}^{m} u_r y_{rk}}{\sum_{i=1}^{n} v_i x_{ik}} \leq 1 \quad k = 1, 2, 3, \cdots, L$$

$$u_r, v_i \geq 0, \quad r = 1, 2, 3, \cdots, m, \quad i = 1, 2, 3, \cdots, n \qquad \textbf{(3.1)}$$

where:

$r = 1$ to m

$i = 1$ to n

$k = 1$ to L

y_{rk} = amount of known output r produced by airport k

x_{ik} = amount of known input i utilised by airport k

u_r = weight given to output r

v_i = weight given to input i

The developments of the DEA-CCR and -BCC models are based on the assumptions of CRS and VRS, respectively.[9] The DEA-BCC model is named after Banker, Charnes and Cooper (1984), and it assumes that the border of the efficiency frontier is in the shape of a convex hull. It allows airports operating with lower airport inputs to have an increasing return to scale, and those operating with higher airport inputs to have a decreasing return to scale. The DEA-BCC model is written as shown in Equation (3.2):

$$Max \quad q = \theta + \varepsilon\left[\sum_{i=1}^{n} s_{io}^{-} + \sum_{r=1}^{m} s_{ro}^{+}\right]$$

Subject to:

$$\theta y_{ro} - \sum_{k=1}^{L} \lambda_k y_{rk} \geq 0, \qquad r = 1, 2, 3, \cdots, m$$

$$x_{io} \geq \sum_{k=1}^{L} \lambda_k x_{ik}, \qquad i = 1, 2, 3, \cdots, n$$

$$\sum_{k=1}^{L} \lambda_k = 1$$

$$\lambda_k \geq 0, \qquad k = 1, 2, 3, \cdots, L, \qquad \theta \text{ with unrestricted in sign} \qquad \textbf{(3.2)}$$

where:

q = airport efficiency index

θ = airport efficient unit

s_{io}^{-} and s_{ro}^{+} = airport input and output slacks

λ_k = the dual variable or the scalar vector associated with each airport

[9] Barros and Dieke (2008) stated that Constant Return to Scale (CRS) implies that an increase in a unit's input lead to a proportional increase in its outputs; Variable Return to Scale (VRS) exists with either an increasing return to scale or a decreasing return to scale. An increasing return to scale exists when an increase in a unit's inputs yields a greater than a proportional increase in its output; a decreasing return to scale exists when a decrease in a unit's inputs yields a lower than proportional increase in output.

An airport is considered as a BCC-efficient airport when θ is equivalent to 1 and has zero input and output slacks ($s_{io}^{-} = 0,\ s_{ro}^{+} = 0$). Otherwise, the airport is called a BCC-inefficient airport (Cooper, Seiford & Tone, 2006). The DEA-BCC model is used to measure the Pure Technical Efficiency (PTE) of an airport, and is intended to evaluate how efficient an airport is at managing and using its resources and infrastructure under exogenous conditions; a smaller PTE value means that an airport cannot use its resources and infrastructure to generate air traffic volumes efficiently, and *vice versa*.

3.3.2 OLS and Tobit models

The DEA efficiency indexes obtained from the first-stage DEA analysis are termed the '*raw*' indexes as they do not reflect each sampled airport's specific operating characteristic, or the managerial and operational factors which are under the control of airport management. Importantly, these crucial factors may contribute to variations in airport efficiency (Gillen & Lall, 1997; UK CAA, 2000; Abbott & Wu, 2002). In order to explain their likely impacts on variations in airport efficiency, the OLS and Tobit models have been adopted in this study during the second-stage regression analysis. In specific, the approach here is to run the regression analysis for examining airport operating characteristics and other event variables on the DEA efficiency indexes.

Both the OLS and Tobit models treat the DEA efficiency indexes as the dependent variables. For instance, the Tobit model treats the DEA efficiency indexes as the limited dependent (latent) variables as they fall between 0 and 1. The Tobit analysis is also considered to be another type of regression analysis as 'The Limited Dependent Variable Regression Model' or 'The Censored Normal Regression Model'[10] (e.g. Tobin, 1958; Maddala, 1983; Amemiya, 1984; Gillen & Lall, 1997; Greene, 2008; Gujarati & Porter, 2009; Wooldridge, 2009).

[10] Wooldridge (2009) stated that the censored normal regression model is a special case of the censored regression model where the underlying population model satisfies the classical linear model assumptions.

The OLS model runs as a form of multiple regression analysis where Y_i is the DEA efficiency index of airport i, X_i is the explanatory variable $(X_i = 1, 2, \dots, k)$, β_i is the coefficient estimation $(i = 0, 1, 2, \dots, k)$, and ε_i is the error term. The OLS model is written as shown in Equation (3.3):

$$Y_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki} + \varepsilon_i \qquad \textbf{(3.3)}$$

For the Tobit model, y_i^* is the DEA efficiency index of airport i^{th}. β is the coefficient or the vector of the estimated parameters, X is the matrix of the explanatory variables or underlying latent variables, and ε_i is the error term. The main underlying assumption of Tobit model is $\varepsilon_i \sim \text{iid}\, N\,(0,\ \sigma^2)$ which means that the error term is normal, independent and identically distributed with zero mean and variance σ^2 and it is independent of the explanatory variable X_i. The Tobit model is written as shown in Equation (3.4):

$$y_i^* = \mathrm{X}\beta + \varepsilon_i \qquad i = 1, 2, \dots, n, \qquad \varepsilon_i \sim \text{iid}\, N\,(0,\ \sigma^2) \qquad \textbf{(3.4)}$$

Instead of observing y_i^*, y_i is observed and expressed in Equation (3.5):

$$y_i = \begin{cases} y^* \text{ if } & y_i^* > 0 \\ 0 \text{ if } & y_i^* \leq 0 \end{cases} \qquad \textbf{(3.5)}$$

In addition, the coefficients, $\beta's$, can be estimated with the log-likelihood method. The likelihood function of the Tobit model is written as shown in Equation (3.6) (Amemiya, 1984):

$$L = \prod_0 [1 - \Phi(X\beta/\sigma)] \prod_1 \sigma^{-1} \phi[(y_i - X\beta)/\sigma] \quad \textbf{(3.6)}$$

where ϕ and Φ are the respective probability and cumulative density function of a standard normal variable. However, unlike the OLS model, the estimated coefficients in the Tobit model cannot be interpreted as the marginal effects which indicate the changes in the DEA efficiency indexes with respect to the changes in the corresponding explanatory variables. In other words, the estimated coefficients, $\beta's$, in the Tobit model do not provide the marginal effects. In essence, the marginal effect in the Tobit model measures the expected instantaneous change in the dependent variable as a function of the change in a certain explanatory variable while keeping all other covariates constant. Therefore the marginal effect needs to be calculated for interpreting the effect of the explanatory variables upon the dependent variable in the Tobit model. Equation (3.7) is used to compute the marginal effect of the explanatory variable k in the Tobit model, and it is computed with the sample means of the data (Gillen & Lall, 1997; Greene, 2008):

$$\frac{\partial E[y_i]}{\partial X_k} = \beta_k \quad \textbf{(3.7)}$$

3.4 DATA DESCRIPTION

3.4.1 The dataset

Table 3.2 shows the panel dataset of 30 Asia-Pacific airports for the period of 2002–2008. Annual data was collected with a total of 210 observations. The data was collected from International Civil Aviation Organisation (ICAO), Airport Council International (ACI), Air Transport Research Society (ATRS) - Airport Benchmarking Reports, civil aviation authority (CAAs) of the respective countries, and airports' annual

Table 3.2. ***List of Asia-Pacific airports for the DEA analysis***

Airport code	Airport name	Country, city	Airport status
HKG	Hong Kong International Airport	China, Hong Kong	International hub
PEK	Beijing Capital International Airport	China, Beijing	International hub
CAN	Guangzhou Baiyun International Airport	China, Guangzhou	International hub
MFM	Macau International Airport	China, Macau	Regional hub
SXZ	Shenzhen Bao'an International Airport	China, Shenzhen	Regional hub
XMN	Xiamen Gaoqi International Airport	China, Xiamen	Regional hub
HAK	Haikou Meilan International Airport	China, Haikou	Regional hub
NRT	Narita International Airport	Japan, Tokyo	International hub
KIX	Kansai International Airport	Japan, Osaka	Regional hub
ICN	Incheon International Airport	South Korea, Seoul	International hub
GMP	Gimpo International Airport	South Korea, Seoul	Regional hub
TPE	Taiwan Taoyuan International Airport	Taiwan, Taipei	International hub
KUL	Kuala Lumpur International Airport	Malaysia, Kuala Lumpur	International hub
PEN	Penang International Airport	Malaysia, Penang	Regional hub
BKK	Suvarnabhumi Airport	Thailand, Bangkok	International hub
CNX	Chiang Mai International Airport	Thailand, Chiang Mai	Regional hub
HDY	Hat Yai International Airport	Thailand, Hat Yai	Regional hub
HKT	Puhket International Airport	Thailand, Phuket	Regional hub
SIN	Singapore Changi Airport	Singapore	International hub
MNL	Ninoy Aquino International Airport	Philippines, Manila	International hub
CGK	Soekarno–Hatta International Airport	Indonesia, Jakarta	International hub
SYD	Sydney (Kingsford Smith) Airport	Australia, Sydney	International hub
MEL	Melbourne Airport	Australia, Melbourne	International hub
BNE	Brisbane Airport	Australia, Brisbane	Regional hub
CNS	Cairns Airport	Australia, Cairns	Regional hub
PER	Perth Airport	Australia, Perth	Regional hub
ADL	Adelaide Airport	Australia, Adelaide	Regional hub
AKL	Auckland International Airport	New Zealand, Auckland	International hub
WLG	Wellington International Airport	New Zealand, Wellington	Regional hub
CHC	Christchurch International Airport	New Zealand, Christchurch	Regional hub

Remarks: The classification of an airport's status is based on the airport's strategic role and flight connectivity network. For example, an international hub airport connects to at least 25 international destinations; a region hub or non-hub airport flies to no more than 25 international destinations.

reports and websites. Airport managements have also been contacted to obtain additional information.

3.4.2 Airport input and output variables for the first-stage DEA analysis

A number of different ways have been suggested to select airport input and output variables for the DEA analysis. For example, Barros and Dieke (2008) suggested that the variable selection for airport efficiency evaluation should take data availability, reference in prior literature, and the professional opinion of airport managers into account. Doganis (1992) also claimed that the basic function of airport operations is to deal with air passengers, air cargo, and aircraft movements. For this study, four airport input variables (i.e. number of employees, number of runaways, total runway length, and passenger terminal area) and three airport output variables (i.e. air passenger numbers, air cargo volume, and aircraft movements) were selected for the first-stage DEA analysis.

A more rigid DEA convention was followed to decide the total number of airport observations in association with the total number of airport input and output variables. The minimum number of airports observed should be greater than three times the sum of airport input and output variables to ensure that satisfactory discriminating power is possible (e.g. Banker *et al*., 1989; Parker, 1999; Raab & Lichty, 2002; Cooper, Seiford & Tone, 2006). This study has met this requirement with a sample size of 30 Asia-Pacific airports, and a total of seven airport input and output variables for the first-stage DEA analysis.

The expression of total numbers of airports observed for the DEA analysis can be given as shown in Equation (3.8):

$$n \geq \text{maximum}\{m * s, 3\ (m + s)\} \quad \textbf{(3.8)}$$

where:

n = number of airports observed

m = number of airport input variables

s = number of airport output variables

A summary of the descriptive statistics relating to airport inputs and outputs for 30 Asia-Pacific airports is presented in Table 3.3. It can be seen that there are variations in airport inputs and outputs. Four airport inputs were found to have a large degree of variation in data. The mean employee numbers showed a decline between 2003 and 2007 and an increase in 2008, since advanced airport technology improved airport operations and delivered better services to customers; furthermore, extra staff was recruited after 2007 to support the expansions of most airports and to meet increasing airport traffic demand. Other airport inputs (i.e. number of runways, total runway length, and passenger terminal area) show the increases made to accommodate airport traffic growth over the years. For instance, the mean airport infrastructure in 2002 included 199,513 m^2 of passenger terminal area, 1.7 runways, and 5,376 m of runway length; the mean airport infrastructure in 2008 increased to 297,974 m^2 of passenger terminal area, 1.8 runways, and 5,876 m of runway length. It must be emphasised that most airports have multiple runways, but the number of runways per airport was rather stable over the years, which was partly due to the majority of sampled airports being small, and the constructions or expansions of runways often requires larger investments and long-term planning.

For airport output statistics, the figures of three airport outputs (i.e. air passenger numbers, air cargo volume, and aircraft movements) were found to vary during the study periods. For instance, the mean annual air passenger numbers handled by an airport increased from 13.0 million in 2002 and reached to 19.8 million in 2008, and also showed growth during the study periods. The same observations hold for annual air

Table 3.3. ***Descriptive statistics of airport input and output variables (2002−2008)***

Airport input and output variables	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Number of employees							
Mean	947	1,065	1,034	1,064	884	882	928
Median	428	423	404	408	383	364	364
Maximum	6,669	8,140	8,872	7,984	4,217	3,796	3,998
Minimum	68	68	70	70	83	77	77
Standard deviation	1,332	1,643	1,689	1,594	1,034	953	1,039
Number of runways							
Mean	1.7	1.7	1.7	1.7	1.7	1.8	1.8
Median	2	2	2	2	2	2	2
Maximum	3	3	3	3	3	3	3
Minimum	1	1	1	1	1	1	1
Standard deviation	0.6	0.6	0.6	0.6	0.6	0.6	0.7
Total runway length-m ('000)							
Mean	5.4	5.5	5.6	5.6	5.6	5.8	5.9
Median	5.5	5.8	5.8	5.8	5.8	5.8	5.8
Maximum	8.9	8.9	9.8	9.8	10.8	11.5	11.5
Minimum	1.9	1.9	1.9	1.9	1.9	1.9	1.9
Standard deviation	2.0	2.1	2.2	2.2	2.2	2.4	2.5
Passenger terminal area-m^2 ('000)							
Mean	200	193	199	248	256	279	298
Median	128	113	113	148	146	135	138
Maximum	634	638	634	825	825	1382	138
Minimum	15	15	15	15	6	6	6
Standard deviation	188	189	195	225	245	313	314
Air passengers numbers ('000,000)							
Mean	13.0	13.1	15.5	16.5	18.0	19.3	19.8
Median	10.8	12.5	14.8	15.6	16.6	17.2	17.4
Maximum	33.9	34.9	38.0	41.0	48.7	53.6	55.9
Minimum	0.4	0.7	1.2	1.2	1.3	1.4	1.3
Standard deviation	10.1	9.6	11.3	12.5	13.7	14.6	14.9
Air cargo volume-tonnes ('000)							
Mean	520.7	540.2	604.5	628.7	654.1	671.2	651.1
Median	246.0	247.6	234.1	225.6	226.7	218.3	215.1
Maximum	2,504.6	2,668	3,119	3,433.4	3,611.1	3,774.2	3,660.9
Minimum	3.6	2.8	2.8	2.6	2.3	1.6	1.2
Standard deviation	669.6	710.2	811.9	845.8	833.1	915.9	884.5
Aircraft movements ('000)							
Mean	112	115	129	136	148	155	161
Median	116	124	126	128	149	149	152
Maximum	242	236	305	342	386	407	438
Minimum	8	9	18	18	15	17	17
Standard deviation	66	67	81	90	98	102	104
Number of airports observed	30	30	30	30	30	30	30

Sources: ICAO, ACI, ATRS, civil aviation authorities, and airports' annual reports and websites.

cargo volume and aircraft movements; both figures indicated an increase over the years, although annual air cargo volume experienced a drop in 2008. The mean annual aircraft movements were approximately 111,695 in 2002 and 160,882 in 2008, which is equivalent to 40% growth during the study periods. Moreover, annual air cargo volume achieved a 28.9% increase between 2002 and 2007, but showed a decline of ~3% decline in 2008.

3.4.3 Key determinants for the second-stage OLS and Tobit regression analysis

Three tasks were performed in this study to develop the key determinants in explaining the variations in airport efficiency. First, the airport input and output variables used in the first-stage DEA analysis will not be reused as the explanatory variables in the second-stage OLS and Tobit regression analysis, avoiding the problem of double-counting and possibly obtaining misleading or biased results (Lin, 2008). Second, prior studies relating to airport efficiency were examined to identify the potential explanatory variables for the second-stage OLS and Tobit regression analysis (see Table 3.4). Lastly, an attempt was made to look at other principles applying the OLS and Tobit models that may assist in developing other relevant explanatory variables for the second-stage regression analysis (e.g. Oum & Yu, 1994; Zheng, Liu & Bigsten, 1998; Fethi, Jackson & Weyman-Jones, 2000; Boame, 2004; Chiou & Chen, 2006).

Table 3.4. ***Explanatory variables used by the airport studies with the OLS and Tobit regression analysis***

Authors and date	**Dependent variable(s)**	**Explanatory variables**
Gillen & Lall (1997)	DEA efficiency index	Number of airline hubs; total number of gates; terminal area; baggage belts per gate; proportion of gates in common use; proportion of gates in exclusive use; compensatory financing; year dummy; airport dummy (i.e. Atlanta, San-Francisco, Minneapolis & St. Paul dummy; Seattle-Tacoma, and Phoenix); proportion of international passengers
Abbott & Wu (2002)	DEA efficiency index and productivity change index	Rate of return; capital /labour ratio; aircraft standing area; total asset growth rate for each airport; state dummy (i.e. airport ownership); year dummy
Barros & Sampaio (2004)	DEA efficiency index	Time trend; market share of airports; percentage of share held by the local government; airport location dummy; agglomeration (i.e. population living in the vicinity of the airport); ratio of operational costs to sale
Pathomsiri (2006)	DEA efficiency index	The percentage of international passengers; non-delayed flights/land area; non-delayed flights/runway area; cargo/runway area; delay/air passengers; year dummy
Pathomsiri *et al*. (2006)	DEA efficiency index	Airport management dummy; average number of passengers per flight; percentage of international passengers; market share of annual aircraft movements; market share of total annual passengers; total annual passengers per runway area; annual aircraft movements per land area; annual aircraft movements per runway area; year dummy
Li & Liu (2007)	DEA efficiency index	Runway length; terminal area; cargo volume carried per flight; passenger numbers carried per flight; GDP per square kilometre; airport hub dummy; airport location dummy (i.e. city)
Barros & Dieke (2008)	DEA efficiency index	Year trend dummy; hub dummy; Work load units (WLUs); private management dummy; north dummy (i.e. location of airport)
Malighetti *et al*. (2007)	DEA efficiency index	Herfindahl-Hirschman Index (HHI) for available seat kilometres; military dummy; private airport dummy (i.e. airport ownership); season dummy
Muller, Ulku & Zivanoic (2009)	DEA efficiency index	Number of gates; number of check-in-counters; number of runways; country (UK) dummy: being private dummy; being partially private dummy; year dummy

Continued on next page

Authors and date	**Dependent variable(s)**	**Explanatory variables**
Ulku (2009)	DEA efficiency index	Work load units (WLUs) for airport size; private share; regulation dummy; staff costs; Passenger/ATM (aircraft size); percentage of international passengers
Yuen & Zhang (2009)	DEA efficiency index	Airport localisation dummy; log (distance); international hub; regional hub; tourist city; runway length index; terminal area index; passenger index; cargo index; air movement index; city population; GDP per-capita; the ‘open-skies’ dummy; airline mergers dummy; Guangzhou new airport dummy; Shanghai Pudong airport dummy
Perelman & Serebrisky (2010)	DEA efficiency index	Private airport dummy; regulation authority dummy; GDP per capita; tourism expenditures per capita; population dummy; hub dummy; aeronautical revenue; Asia dummy; Europe dummy; Canada and US dummy; year dummy

Remarks: Summarised from the prior literature and tabled by authors and date.

Taking the extant literature and data availability into account, twelve major groups of explanatory variables were developed for the second-stage OLS and Tobit regression analysis as shown in Table 3.5. The motives for incorporating them will be discussed in the following paragraphs. Specifically, it appears that YEAR dummy, GDP per capita, management/ownership dummy (MGT dummy), the airport's hub status (Hub dummy), and the percentage of international passengers (INTL_PAX) are the most commonly used explanatory variables to explain variations in airport efficiency, and therefore, they are treated as the 'benchmarking model' during the second-stage OLS and Tobit regression analysis along with other selected airport operating characteristics and factors.

Table 3.5. ***List of explanatory variables identified for the OLS and Tobit models***

	Explanatory variables	**Descriptions**
1	YEAR dummy	Each study period
2	GDP per capita	GDP per capita of the country or city in which an airport is located
3	MGT dummy	Airport management/ownership
4	HUB dummy	The airport's hub status
5	INTL_PAX	The percentage of international passengers handled by an airport
6	ALLIANCE dummy	Airline alliance membership of dominant airline(s) of an airport
7	POPULATION dummy	The airport's hinterland population
8	OPS_HR	Airport's daily operating hours
9	DIRECT_INTL	Number of the airport's direct outbound international destinations/cities
10	DIRECT_DOM	Number of the airport's direct outbound domestic destinations/cities
11	OPS_AIRLINE	Number of airlines that provide scheduled flight services to an airport alone
12	CODESHARE	Number of airlines that provide scheduled flight services with allied or partner airlines to an airport (e.g. codeshare flights)

A dummy variable for each year across the entire analysis period was introduced. The YEAR dummy is intended to account for any changes or to capture the anomalies happening during a particular year. Importantly, those anomalies are not captured by any other explanatory variables during the OLS and Tobit regression analysis.

Economic growth has been one of the key determinants affecting air transport demand, and there is a mutual causal relationship between GDP and air travel (e.g. Cline *et al*., 1998; Graham, 1998a and b; Graham, 1999; Profillids, 2000; Graham, 2006; Boeing, 2008; Ishutkina & Hansman, 2009). Therefore the variable of GDP per capita may have a significant effect for explaining variations in airport efficiency. A high GDP per capita may imply more airport demand from a city or country as the result of more business travelling and more people using the faster and more expensive model of air transportation for tourism and for visiting friends and relatives (VRF) purposes (Schafer & Victor, 2000). Additionally, GDP has a strong positive relationship with the air cargo industry (e.g. Kasarda & Green, 2005; Williams, 2006; Yao & Yang, 2008; Hsu *et al*., 2009).

It can be argued that airport management/ownership can improve an airport's efficiency. Airport ownership can be classified into two distinct groups within the sampled Asia-Pacific airports: (i) the government-controlled or owned airports, and (ii) the private/public corporation-controlled or owned airports (Hooper, 2002; Oum, Adler & Yu, 2006; Oum, Yan & Yu, 2008). The dummy variable of airport management/ownership (MGT dummy) was introduced to examine the effect of airport ownership upon efficiency. The MGT dummy takes the value of 1 when an airport is government-controlled or owned, and 0 otherwise.

To capture the level and the importance of the flight connectivity network and the strategic location of an airport, the dummy variable of an airport's hub status (HUB dummy) was introduced to explain the variations in airport efficiency. It is evident that the operations of hub-and-spoke networks have been the common practices for major airlines since the deregulation and the liberalisation of the air transport industry. As a consequence, the airline deregulation helped to establish airline hub airports worldwide. Such operations bring benefits to airlines in terms of frequent flight movements, fewer aircraft being required and higher load factors. Therefore the HUB dummy is considered to have a significant impact on an airport's efficiency. An airport's status can be classified as an international hub airport, a regional hub airport or a non-hub airport.[11] The HUB dummy takes the value of 1 when an airport is an international hub airport, and 0 otherwise.

The handling of international passenger traffic is believed to require more airport services and facilities than domestic passenger traffic, but airports always collect more revenues from international passenger traffic via the airport. From this, the variable of international passengers handled by an airport (INTL_PAX) is expected to generate negative impacts on its efficiency. The effect of international passenger traffic upon an airport's efficiency, however, depends on how many airport facilities or resources need to be invested to attract international passengers travelling through that airport if airport revenues are taken into account. Due to the problem of data availability, airport revenues will not be considered in this study.

To capture whether an airline is associated with a strategic global airline alliance, the ALLIANCE dummy was introduced to explain the variations in airport efficiency, where the ALLIANCE dummy takes the value of 1 when the dominant airline(s) of an airport becomes a member of one of the major strategic global airline alliances,[12] and 0 otherwise. Apart from these three strategic global airline alliances, many airlines worldwide may also form their own partnerships in different formats (e.g. Qantas Airways (Star Alliance) and Emirates Airline have agreed to establish a global partnership from April 2013, and Air New Zealand (Star Alliance) and Cathay Pacific Airways (Oneworld) have implemented a codeshare agreement to operate the route

[11] Refer to Table 3.2 which gives the hub status of the sampled Asia-Pacific airports.

[12] Three major strategic global airline alliances consist of oneworld, Star Alliance, and SkyTeam.

Hong Kong–London route jointly in November 2012).[13] In general, the formation of strategic alliances or allied operations between airlines can have significant effects upon an airport's efficiency, as the airport may experience a larger amount of connecting traffic (i.e. transfer or transit passengers). This is mainly because the strategic global airline alliances are considered to bring benefits to air passengers such as convenience, ease of transfer, ticketing and coordination of flight schedules, and extensive flight connectivity networks to different regions worldwide. Moreover, airlines involve with higher levels of cooperation generally obtain larger market shares and route network shares compared with airlines on the same routes which have not entered into any form of alliances (e.g. Chan, 2000; Wang, Evans & Turner, 2004; Weber, 2005; Iatrou & Alamdari, 2005; Cento, 2009). Therefore the number of strategic global alliances between airlines is expected to grow in the future, and airlines which are left out of this system may find them unnecessary, and thus become the niche operators (Oum & Park, 1997).

The size of the hinterland population of an airport has been considered as the exclusive driving force of the air travel demand of that airport (Strand, 1999). Logically, an airport's demand increases when the airport serves bigger population. However, the actual size of an airport's hinterland population cannot be ideally defined since improvements in aircraft technology, the construction of global strategic airline alliances, and the creation of hub-and-spoke networks (Graham, 1999; Graham & Guyer, 2000). The POPULATION dummy was introduced to represent the size of an airport's hinterland population, whereby POPULATION dummy takes the value of 1

[13] The partnership between Qantas Airways and Emirates Airline, aims to deliver the best in their respective flight networks and frequencies, lounges, loyalty programmes, and customer experience. Also, Qantas Airways will move its hub at Singapore Changi Airport to Dubai International Airport, which may reduce the amount of transit traffic to Europe via Singapore Changi Airport transported by Qantas Airways. This could possibly affect the airport's traffic volume and efficiency. In addition, the codeshare agreement between Air New Zealand and Cathay Pacific Airways is believed to produce benefits to both airlines, as they will thus face less competition on the London route. However, it is extremely difficult to investigate the actual impact of all airline alliances or partnerships on all the sampled Asia-Pacific airports (i.e. alliances other than the three major strategic global alliances) because it is difficult to obtain data on how each alliance affects an airport's efficiency.

when an airport's hinterland population size is believed to be greater than 4 million, and 0 otherwise.[14]

The variable of airport's daily operating hours, OPS_HR, may reasonably be expected to be an important factor in determining an airport's efficiency (Humphreys & Francis, 2000).[15] For example, longer operating hours at an airport allow it to handle more air passenger traffic and a greater air cargo volume as well as improving its efficiency level. In fact, this is not necessarily true, since an airport's efficiency evaluation needs to take the level of inputs and outputs for that airport into account. For instance, passenger airlines do not prefer to operate flights after mid-night when potential air passenger traffic is lower, unlike the freighters, which always operate during the night slots.

An airport's network is normally represented by its flight network or the number of direct and indirect destinations connecting with that airport. If more destinations or cities are served by an airport, the airport will have a greater ability to transport or handle more air passenger traffic and air cargo volume, thus leading to higher efficiency accordingly. However, it is difficult to examine an airport's indirect flight connectivity network,[16] so therefore, direct outbound destinations connecting with an airport are considered sufficient to capture an airport's flight connectivity network; direct domestic networks (DIRECT_DOM) and direct international networks (DIRECT_INTL)

[14] The criteria of 4 million people for an airport's hinterland population was selected with reference to the population size of Singapore, since its annual population size was less than 4 million over the study periods. In addition, Singapore (Changi) International Airport (SIN) acts as one of the major international gateway hub airports in the Asia-Pacific region and, more importantly, its air passenger traffic has frequently ranked inside the world's top 30 busiest passenger airports between 2002 and 2008.

[15] The daily operating hours of an airport take into account the curfew hours implemented by airport management and the local government.

[16] Air travellers may have choice of stops (e.g. one, two or more stops) to reach to their destinations.

connected by an airport were therefore collected to show its direct flight connectivity network.[17]

Airline operations are believed to exert a significant influence upon an airport's efficiency. If more airlines provide scheduled or non-scheduled flight services to and from an airport, this may possibly bring more air passenger numbers, air cargo volume, and aircraft movements to that airport, as well as defining its hub status in the region.[18] Focusing on air passenger traffic, two major types of airlines in general provide scheduled flight services: (i) airlines that provide scheduled flight services alone (OPS_AIRLINE), and (ii) airlines that operate codeshare flights with allied or partner airlines (CODESHARE). Hence, the information relating to the variables of OPS_AIRLINE and CODESHARE were collected for analysing their impact on airport efficiency.

3.5 ESTIMATION OF RESULTS

3.5.1 Results of the DEA-Output-VRS model

The DEA Output-Oriented[19] and Variable Return to Scale framework (The DEA-Output-VRS model) was selected for the first-stage DEA analysis because of the differences in the scale of operations and capacity among the sampled Asia-Pacific

[17] With the problem of data limitation, only data from the month of December of each study year with respect to the number of direct outbound domestic destinations and international destinations connecting to each sampled Asia-Pacific airport were collected. In a sense, this still provides a good representation of the selected airports' flight connectivity networks since they take advantage of the peak travelling period of December, when airlines transport more air passenger traffic, rather than shrinking their flight connectivity networks.

[18] It is common practices for airlines to transport air cargo using the cargo compartments or the belly spaces of passenger planes.

[19] Wober (2007) indicated that the output-oriented model required a given level of inputs to achieve the maximum output levels. In this study, the DEA Output-Oriented model means that airports focus on maximising three categories of air traffic outputs (i.e. air passenger numbers, air cargo volume, and aircraft movements), holding all of the airport inputs constant.

airports and the selected input variables involved different periods for changes and investments. For example, airport staff had a short-term nature – airport managers can easily change staff numbers by cutting temporary staff from the work force, depending on the airport's traffic demand. The building of passenger terminal may involve a relatively short- to medium-term timeframe (2−5 years), but the expansion of existing runway length can involve medium-term planning (5 years) and the building of an additional runway can involve long-term planning (more than 10 years). Therefore the DEA output-oriented and VRS model is a sensible method for assessing airport efficiency in this study. Table 3.6 shows three groups of airports with reference to changes in airport efficiency, the DEA efficiency indexes for each airport over the years and the percentage of efficient airports during each study year.

It should be noted that the DEA analysis in this study is a methodology which simply describes the relative efficiency of an airport within a group. More importantly, the DEA efficiency index is an indication of an airport's efficiency relative to the other sampled airports, but has no absolute values and does not offer any relevant explanations as to why an airport may become relatively efficient or inefficient. Possible explanations for the alterations of an airport's relative operational efficiency will be provided where appropriate in the following sections.

The results of the DEA-Output-VRS model in Table 3.6 show that at least 40% of the sampled Asia-Pacific airports are considered as efficient between 2002 and 2008. In the total sample, seven airports were found to be the most efficient over the entire study periods having consistently full DEA efficiency indexes, namely Hong Kong (HKG), Auckland (AKL), Melbourne (MEL), Beijing (PEK), Penang (PEN), Taipei (TPE), and Wellington (WEL). They are also considered the best performers relative to other airports in the group. Five international hub airports, namely HKG, AKL, MEL, PEK, and TPE were the best performing airports among the Asia-Pacific airports during the study periods. This is consistent with the concept that the international hub or gateway airports are able to attract and handle more air transport demand than the regional or non-hub airports, leading to higher efficiency. Also, their strategic roles and extensive flight connectivity networks reflect their ability to attract more international and

Table 3.6. ***DEA efficiency indexes of Asia-Pacific airports (2002−2008)***

	Airport code	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Best Performers [a]	HKG	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
	AKL	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
	MEL	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
	PEK	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
	PEN	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
	TPE	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
	WEL	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
Moderate performers (improvement) [b]	CAN	0.699	0.639	0.672	0.763	0.730	**1.000**	**1.000**
	CNX	0.637	0.622	0.752	**1.000**	**1.000**	**1.000**	**1.000**
	HDY	0.999	0.999	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
	NRT	**1.000**	**1.000**	**1.000**	0.983	0.960	**1.000**	**1.000**
	SYD	0.978	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
	SZX	0.953	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
Moderate performers (deterioration) [c]	ADL	**1.000**	**1.000**	**1.000**	0.595	0.526	0.521	0.572
	BKK	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.919
	BNE	0.947	**1.000**	**1.000**	**1.000**	0.985	0.989	0.960
	CGK	0.503	0.895	0.918	0.897	0.859	**1.000**	0.976
	HAK	**1.000**	0.827	0.952	**1.000**	0.818	0.606	0.653
	MFM	0.959	0.606	0.814	**1.000**	**1.000**	**1.000**	0.847
	MNL	0.679	0.682	0.810	0.759	0.903	**1.000**	0.682
	KIX	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.766	0.814
Worst performers [d]	CHC	0.683	0.704	0.674	0.897	0.745	0.721	0.722
	CNS	0.254	0.292	0.252	0.544	0.460	0.676	0.436
	GMP	0.948	0.907	0.679	0.730	0.690	0.654	0.677
	HKT	0.774	0.535	0.679	0.484	0.748	0.900	0.863
	ICN	0.821	0.817	0.833	0.754	0.910	0.859	0.791
	KUL	0.660	0.734	0.677	0.591	0.502	0.677	0.707
	PER	0.491	0.893	0.497	0.659	0.667	0.673	0.690
	SIN	0.855	0.859	0.815	0.804	0.764	0.823	0.788
	XMN	0.437	0.434	0.482	0.549	0.579	0.784	0.630
	Efficient airports (%)	40	47	50	50	47	57	43

Remarks: Bold typeface indicates the most efficient airports relative to the other sampled airports in the Asia-Pacific region (i.e. DEA efficiency index = 1.000). An airport is considered as relatively inefficient if the DEA efficiency index is smaller than 1.000. Superscript [a] indicates an airport achieved consistently full efficiency levels between 2002 and 2008. Superscript [b] indicates an airport showed an improvement in efficiency levels between 2002 and 2008. Superscript [c] indicates an airport showed a deterioration in efficiency levels between 2002 and 2008. Superscript [d] indicates an airport never achieved full efficiency levels between 2002 and 2008.

domestic passenger traffic (i.e. origin–destination (O&D) traffic and connecting traffic). To gain a deeper insight, the full efficiency of HKG, PEK, and TPE for all seven years is likely to be linked to fact that their respective airport traffic volumes were consistently ranked inside the world's top 30 busiest passenger airports for the period of 2002 and 2008. PEN and WEL, on the other hand, act as the regional hubs for their respective provincial areas.

The remaining 23 sampled airports were considered relatively inefficient compared with the best performing airports in the group. Amongst them, nine airports never achieved full efficiency levels during the study periods, consisting of Christchurch (CHC), Cairns (CNS), Gimpo (GMP), Phuket (HKT), Incheon (ICN), Kuala Lumpur (KUL), Perth (PER), Singapore (SIN), and Xiamen (XMN). Interestingly, three major international hub and gateway airports (i.e. ICN, KUL, and SIN) were considered to be the worst performers. These might be largely related to the consequences of under-utilisation or overinvestment in airport resources or high capacity airports handling lower amounts of airport traffic.[20] Further investigations revealed that ICN and KUL maintained a relatively lower efficiency level during the study periods. This poor airport efficiency across the years did not result from recent expansions but from ongoing overcapacity. Likewise, part of the explanation of SIN's inefficiency is the result of its passenger terminal expansion in 2007, while its air passenger numbers only increased by less than 3% between 2007 and 2008, leaving the airport with significant excess capacity.

GMP's inefficiency emerged after the opening of ICN in 2000, which adversely affected international passenger traffic. More importantly, the efficiencies of CNS, PER, and XMN were found to be consistently lower compared with the other sampled airports. XMN showed a small amount of growth in efficiency in 2007 but at a more modest level

[20] Arguably, airport terminal expansion could have a positive long-term impact on airport profitability since the development of the terminal will allow an airport: (i) to achieve growth through additional flexibility and capacity, thereby enabling airlines to grow their business; (ii) to achieve a step change in airport retail business capacity; and/or (iii) to increase non-aeronautical revenues. Airport profitability is one of the important aspects used to determine an airport's efficiency level. However, the actual impact of airport terminal expansion on each sampled Asia-Pacific airport's profitability is extremely difficult to measure and no such data were available at the time of the research. Thus, airport profitability has not been included in this research.

compared to PER. CNS was the worst performing airport in the group during the study periods. CHC experienced its highest efficiency level in 2005, but it is difficult to pinpoint the reasons for its inefficiency over latter years.

Another group of 14 airports was considered to be the moderate performers since they became efficient in at least one of the seven years during the study periods. These airports either showed the improvements (six airports) or the deteriorations (eight airports) in their efficiency levels across the analysis periods and there was no regular trend with respect to their respective efficiency levels. For the improving airports, in particular, Guangzhou (CAN) deserves to be explored why its efficiency improved and the airport became efficient after 2007. Its expansion expanded the airport's flight connectivity network, covering more than 200 routes, which translated into an increase in airport traffic. Chiang Mai (CNX) showed improved efficiency after 2004 and attained full efficiency afterwards as a result of the positive growth in airport traffic during that period and the downsizing of passenger terminal areas in 2006. Sydney (SYD) was ranked as one of the world's top 30 busiest passenger airports in 2003, and its growth after 2003 could be attributable to its strategic role served as the main international gateway hub airport to and from Australasia and Oceania. Similarly, Shenzhen (SZX) showed a remarkable improvement in efficiency becoming an efficient airport since 2003 and experiencing more than 34% growth for each of three airport outputs between 2003 and 2008, largely due to the rapid economic growth of the PRD region in Mainland China.

Passenger terminal expansion was the main contributing factor to the deteriorations in efficiency of Adelaide (ADL), Haikou (HAK), and Manila (MNL). In addition, the decline in CGK's efficiency may be related to the Bali bombings that occurred in 2002 and 2005; these disruptive events had significant negative impacts on international passengers visiting Indonesia.[21] Moreover, Kansai (KIX) became inefficient after 2006

[21] The first Bali bombing occurred on October 12, 2002, which killed 38 Indonesians and 164 foreigners from over 22 countries. The second Bali bombing occurred on October 01, 2005, killing 20 people and injuring 129 people. These incidents had a significant adverse effect upon the tourism industry of Indonesia, especially international travellers to Bali.

as an additional runway came into operation in 2007,[22] but its air traffic volumes did not respond with a significant increase accordingly. Macau (MFM) also showed an improvement in efficiency before 2007, experiencing full efficiency between 2005 and 2007, but the negative airport traffic growth caused it to be inefficient in 2008.

Apart from the best performing airports, six airports were considered to be satisfactorily efficient airports (i.e. having efficiency indexes well above 0.900 but smaller than 1), including Bangkok (BKK), Brisbane (BNE), Hat Yai (HDY), Narita (NRT), Sydney (SYD), and Shenzhen (SZX). For BKK, the sudden decline in its efficiency in 2008 was primarily the consequence of Thailand's political unrest, which triggered negative airport traffic growth. BNE was able to maintain a rather stable efficiency level during the study periods; it is in a prime location for the holiday makers to travel to the principal Australian tourist attraction – the Gold Coast – but negative air cargo growth caused the airport's inefficiency between 2006 and 2008. HDY could have maintained its relatively higher efficiency levels over the study years, since it acts as the main gateway for air travellers to visit southern Thailand and for Muslims in the region on their annual pilgrimage to Mecca. NRT became inefficient between 2005 and 2006 as annual air passenger numbers and annual aircraft movements increased by less than 3%, and also annual air cargo volume experienced negative growth in 2005 and 2006. The possible reasons for SYD and SZX's full efficiency levels have been discussed above, but both airports were relatively inefficient in 2002.

3.5.2 Average DEA efficiency index

The average performance of the sampled Asia-Pacific airports during one particular year compared to other years is very important, as this indicates which year is the best performing year with respect to overall airport efficiency. This is in line with the study of Sengupta (1995), which stated that industrial competitiveness or efficiency can be evaluated through the analysis of average efficiencies.

[22] KIX operated the second runway on August 02, 2007.

Figure 3.2 shows the average DEA efficiency indexes and the number of efficient airports for the sampled Asia-Pacific airports. Over the study periods, variations in the average DEA efficiency indexes were found among the sampled airports. They show an upward trend from 2002 to 2005, then a drop in 2006, then another increase in 2007 and lastly a drop in 2008. The lowest and highest average DEA efficiency indexes are in 2002 (0.843) and 2007 (0.888), respectively. This indicates that the majority of Asia-Pacific airports did not achieve their maximum output levels throughout the study periods. It also corresponds to the fact that the smallest and largest number of efficient airports appeared during 2002 and 2008. Furthermore, the smallest average DEA efficiency index (in 2002) can be interpreted as meaning that, on average, the Asia-Pacific airports were only 84.3% efficient in that year, or that, on average, the airports could almost increase by an additional 15.7% of outputs to attain their maximum outputs using the same amount of inputs.

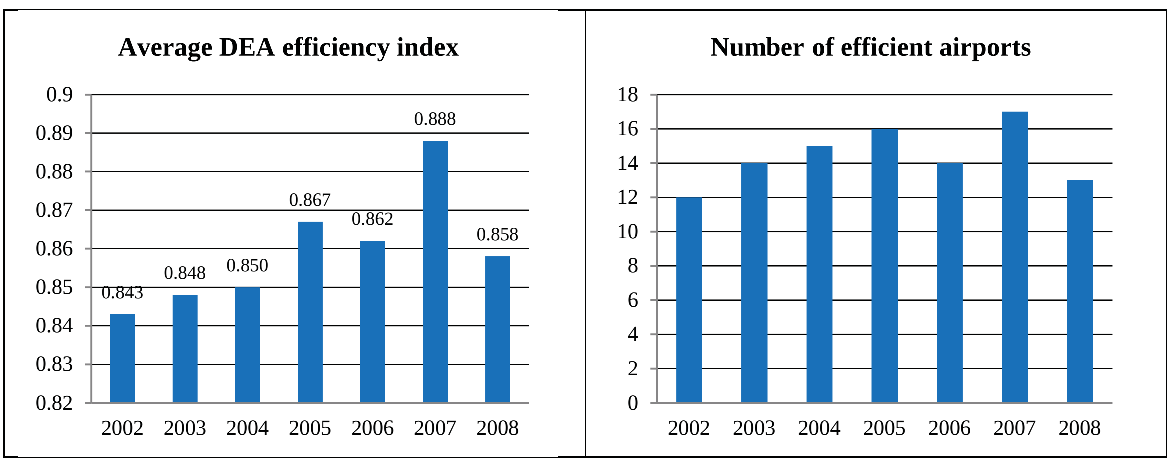

***Figure 3.2.* Average DEA efficiency index and numbers of efficient airports (2002−2008)**

Only 12 and 14 efficient airports were found in 2002 and 2003, respectively, which could largely be attributable to the after impact of September 11 terrorist attacks in 2001 and the SARS outbreak in late 2002 and mid-2003. These unfavourable incidents led to the relatively poor performance of Asia-Pacific airports, which handled fewer air passenger traffic and aircraft movements in 2002 and 2003, respectively.[23] However, air cargo traffic was not as seriously affected as air passenger traffic during the SARS outbreak. The average airport efficiency seemed to rebound during 2004 and 2005, when the higher average DEA efficiency indexes and more efficient airports were reported, or it could be said that the Asia-Pacific airports enjoyed a more favourable operating environment in these two years and became more efficient and competitive than in previous years.

The declines in average airport efficiency that appeared in 2006 and 2008 could possibly due to aviation fuel price surges alongside the global economic downturn. These unfavourable economic factors had negative impacts for the worldwide air transport industry and, as a consequence, led to the slump in air passenger travel worldwide. In contrast, the best performing year was witnessed in 2007, when the airport industry in the Asia-Pacific region seemed to benefit from a more favourable economic atmosphere for their operations.

3.5.3 Results of the OLS and Tobit models

The correlations of the explanatory variables are shown in Table 3.7. These suggest an absence of the multicollinearity problem among the explanatory variables in both the OLS and Tobit models, with the highest correlation (0.815) being seen between OPS_AIRLINE and CODESHARE. The estimated results for the OLS and Tobit models

[23] The September 11 terrorist attacks occurred in 2001 and triggered the significant decline in air passenger travel worldwide. In addition, the SARS outbreak happened between November 2002 and July 2003, which prompted many countries worldwide to issue travel warnings to travellers regarding the most affected countries, including Hong Kong and Mainland China. These incidents adversely affected air passenger travel around the world, particularly, in the Asia-Pacific region.

are provided in Tables 3.8 and 3.9.[24] Robust standard errors were calculated and *t*-statistics were generated accordingly to take care of heteroscedasticity. The marginal effects were also calculated for the Tobit models. The notation relating to the dependent variable (i.e. the DEA efficiency indexes obtained from the first-stage DEA analysis) and the explanatory variables for the second-stage OLS and Tobit regression analysis are also given at the bottom of the table.

Four explanatory variables were found to be significant factors for explaining variations in airport efficiency in either the OLS model or the Tobit model, or in both. They included the HUB dummy, OPS_HR, the POPULATION dummy, and the ALLIANCE dummy. Only the HUB dummy was reported to be statistically significant in both the OLS and Tobit models. This suggests that an airport that serves as an international hub airport is more efficient than those that serve as a regional hub airports or non-hub airport. The marginal effects for the Tobit models suggest that for an airport that acts as an international hub airport, its efficiency level will be increased by 0.028–0.046 units.

The OPS_HR and POPULATION dummy variables are not statistically significant in the OLS models. However, they became statistically significant in the Tobit models. The expected coefficient sign of OPS_HR should be positive, as longer daily operating hours at an airport lead to higher efficiency. However, the negative coefficients for OPS_HR variables were reported in both models which implied that shorter operating hours at an airport might negatively influence its operations and trigger lower airport efficiency. The marginal effects for the Tobit models suggest that for every hour reduced from an airport's daily operating hours, an airport's efficiency would drop around 0.005 units, with less airport traffic being handled.

[24] Smaller values of R^2 were seen in Tables 3.8 and 3.9, mainly because of the second-stage OLS and Tobit regression analysis did not employ the same variables used in the first-stage DEA analysis. However, testing the approach suggested by Yuen and Zhang (2009), the values of R^2 for the OLS and Tobit models could be improved by creating indexes for the first-stage airport input and output variables, and then including them as explanatory variables during the second-stage regression analysis. The indexes aim to control the potential shocks that may occur (e.g. the yearly airport efficiency indexes can be significantly affected by demand shocks). The rationale is similar to that of including year dummy variables as discussed in Section 3.4.3. More importantly, similar results were obtained regarding the significant factors for explaining the variations in airport efficiency as presented in this study.

Table 3.7. ***Correlations of explanatory variables for the OLS and Tobit models***

	GDP per capita	MGT dummy	HUB dummy	INTL_ PAX	OPS_ HR	POPULATION dummy	ALLIANCE dummy	DIRECT_ INTL	DIRECT_ DOM	OPS_ AIRLINE	CODE-SHARE
GDP per capita	1.000										
MGT dummy	-0.661	1.000									
HUB dummy	0.056	0.089	1.000								
INTL_PAX	0.254	-0.039	0.557	1.000							
OPS_HR	-0.184	0.1194	0.225	0.274	1.000						
POPULATION dummy	-0.271	0.471	0.605	0.299	0.115	1.000					
ALLIANCE dummy	0.537	-0.386	-0.050	0.018	-0.392	-0.341	1.000				
DIRECT_INTL	0.126	0.092	0.772	0.785	0.229	0.577	0.126	1.000			
DIRECT_DOM	-0.231	0.035	0.115	-0.502	0.206	-0.259	-0.273	-0.149	1.000		
OPS_AIRLINE	0.020	0.196	0.764	0.606	0.259	0.633	0.076	0.917	0.091	1.000	
CODESHARE	0.277	-0.098	0.784	0.646	0.133	0.481	0.195	0.857	0.001	0.815	1.000

Remarks: A high correlation exists between the variables of DIRECT_INTL and OPS_AIRLINE, respectively. In order to avoid the multicollinearity problem in this study, the variable of DIRECT_INTL would not be included during the second-stage OLS and Tobit regression analysis.

Table 3.8. ***Estimation results for the OLS models***

Dependent variable = DEA efficiency indexes					
Explanatory variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
GDP per capita	0.032	0.027	0.029	0.009	0.005
	(1.34)	(1.11)	(1.16)	(0.35)	(0.18)
MGT dummy	0.033	0.035	0.046	0.035	0.045
	(0.58)	(0.63)	(0.76)	(0.61)	(0.76)
HUB dummy	0.139**	0.142**	0.170**	0.135*	0.159
	(2.01)	(2.07)	(2.02)	(1.93)	(1.89)
INTL_PAX	-0.001	-0.001	-0.001	-0.001	-0.001
	(-1.14)	(-0.89)	(-1.11)	(-0.85)	(-0.67)
OPS_HR	-	-0.009	-	-	-0.006
		(-0.85)			(-0.52)
POPULATION dummy	-	-	-0.055	-	-0.040
			(-0.65)		(-0.47)
ALLIANCE dummy	-	-	-	0.104**	0.096*
				(2.31)	(2.08)
R^2	0.04	0.05	0.05	0.07	0.07
Partial-R^2	-	0.01	0.01	0.03	0.03
Observation	210	210	210	210	210

Remarks: *, **, and *** indicate that the explanatory variable is significant at the 0.10, 0.05, and 0.01 significance level, respectively. *t*-statistics are given in parentheses. Panel regression analysis was calculated based on the random effect after performing the Hausman test. Partial-R^2 indicates model improvement after an additional explanatory variable was added into the benchmark model as shown in Column (1).

Notations:

Explanatory variables	**Descriptions**
GDP per capita	GDP per capita of the country or city in which an airport is located (in logarithm)
MGT dummy	1 if an airport is government-controlled or owned; 0 otherwise
HUB dummy	1 if an airport is the international hub airport; 0 otherwise
INTL_PAX	Percentage of international passengers handled by an airport
OPS_HR	Airport's daily operating hours
POPULATION dummy	1 if an airport's hinterland population is more than 4 million people; 0 otherwise
ALLIANCE dummy	1 if the dominant airline of an airport becomes a member of a major strategic global airline alliance; 0 otherwise

Table 3.9. ***Estimation results for the Tobit models***

Dependent variable = DEA efficiency indexes					
Explanatory variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
GDP per capita	0.010	-0.001	0.001	0.005	0.001
	[0.003]	[-0.000]	[0.002]	[0.001]	[0.000]
	(0.87)	(-0.11)	(0.58)	(0.43)	(0.04)
MGT dummy	0.006	0.003	0.032	0.005	0.0.043
	[0.002]	[0.001]	[0.009]	[0.001]	[0.012]
	(0.23)	(0.13)	(1.07)	(0.19)	(1.53)
HUB dummy	0.104***	0.106***	0.142***	0.103***	0.166***
	[0.029]	[0.029]	[0.039]	[0.028]	[0.046]
	(3.88)	(3.94)	(4.63)	(3.80)	(4.83)
INTL_PAX	-0.000	0.000	-0.000	-0.000	0.0000
	[-0.000]	[0.000]	[-0.000]	[-0.000]	[0.000]
	(-0.29)	(0.83)	(-0.17)	(-0.13)	(1.02)
OPS_HR	-	-0.013***	-	-	-0.017***
		[-0.004]			[-0.005]
		(-3.07)			(-3.56)
POPULATION dummy	-	-	-0.071**	-	-0.105**
			[-0.020]		[-0.029]
			(-2.25)		(-3.10)
ALLIANCE dummy	-	-	-	0.017	-0.037
				[0.005]	[-0.010]
				(0.56)	(-1.26)
R^2	0.09	0.12	0.10	0.09	0.16
Partial-R^2	-	0.03	0.01	0.00	0.07
Log-likelihood	70.183	74.375	72.134	70.316	78.425
Observation	210	210	210	210	210

R*emarks*: *, **, and *** indicate that the explanatory variable is significant at the 0.10, 0.05, and 0.01 significance level, respectively. *t*-statistics are given in parentheses. The marginal effects of the explanatory variables are printed in square brackets. Partial-R^2 indicates model improvement after an additional explanatory variable was added into the benchmark model as shown in Column (1).

Notations:

Explanatory variables	**Descriptions**
GDP per capita	GDP per capita of the country or city in which an airport is located (in logarithm)
MGT dummy	1 if an airport is government-controlled or owned; 0 otherwise
HUB dummy	1 if an airport is the international hub airport; 0 otherwise
INTL_PAX	Percentage of international passengers handled by an airport
OPS_HR	Airport's daily operating hours
POPULATION dummy	1 if an airport's hinterland population is more than 4 million people; 0 otherwise
ALLIANCE dummy	1 if the dominant airline of an airport becomes a member of a major strategic global airline alliance; 0 otherwise

The expected sign of coefficient estimation for the POPULATION dummy should be positive, as a larger hinterland population may generate more airport demand, thus leading to higher efficiency. Surprisingly, the POPULATION dummy has a negative impact on airport efficiency in both the OLS and Tobit models. This suggests that an airport that serves a larger hinterland population is less efficient than airports that serve a smaller hinterland population, or else a larger hinterland population may possibly negatively affect an airport's efficiency. The marginal effects for the Tobit models suggest that if an airport serves a larger hinterland population, its efficiency would drop between 0.020 and 0.029 units.

The significant ALLIANCE dummy variable was reported in the OLS model, which suggests that if an airport's dominant airline enters a strategic global airline alliance, this might positively influence its home-based airport's efficiency. The marginal effects for the Tobit models suggest that if the dominant airline of an airport enters a strategic global airline alliance, the airport's efficiency will increase by 0.005 units as the allied airlines could share airport facilities to handle more connecting traffic.

The remaining variables are not statistically significant in either the OLS or Tobit models. The GDP per capita variable in both the OLS and Tobit models was reported as having a positive coefficient but was statistically insignificant. However, this still suggests that both models illustrate a positive relationship between the GDP per capita of a country or city with an airport's traffic demand. Furthermore, GDP per capita always involves trend characteristics and its expected effect in explaining variations in airport efficiency could have been captured by the YEAR dummy variables. The marginal effects of the Tobit models suggest that for every one unit of increase in GDP per capita, airport efficiency improve by a maximum of 0.003 units, *ceteris paribus*. For the MGT dummy variable, the coefficients for the Tobit models suggest that government-controlled or owned airports operate with the higher efficiency levels than privately-controlled or owned airports, and the marginal effects indicate that they would be more efficient than their counterparts by 0.001–0.012 units.

The variable of INTL_PAX was found to be insignificant in both the OLS and Tobit models to account for variations in airport efficiency.[25] In the econometrical sense, this could be mainly because their expected effects have already been captured by other explanatory variables in the models, or the study periods of the selected airport dataset are not long enough to fully support the likely impacts of this variable on airport efficiency. In most cases, both the OLS and Tobit models showed the insignificant negative coefficients for the INTL_PAX variable. The marginal effects for the Tobit models suggest that for every percentage increase in international passengers handled by an airport, its efficiency would be only minimally reduced.

3.6 DISCUSSION

The first aim of this study was to investigate the relative operational efficiency of 30 Asia-Pacific airports using the DEA-Output-VRS model, and to identify how efficient HKG compared to other Asia-Pacific airports. There was evidence that Hong Kong (HKG) was one of the most efficient airports between 2002 and 2008, along with Auckland (AKL), Melbourne (MEL), Beijing (PEK), Penang (PEN), Taipei (TPE), and Wellington (WLG) airports. This finding confirms a number of studies − for example, Zhang (2003), Williams (2006), Lam, Low and Tang (2009), and Yang (2010a and b) − all of whom claimed that that HKG was one of the most efficient and successful airports in the Asia-Pacific region by handling and transporting a significant amount of airport traffic.

The second aim of this study was to investigate which factors affect airport efficiency using the OLS and Tobit regression analysis. Arguably, variations in airport efficiency can be attributable to a number of specific factors, such as the airport's specific operating characteristics, and managerial and operational factors, as suggested by Gillen and Lall (1997), UK CAA (2000), and Abbott and Wu (2002). This means that in this

[25] The variables of DIRECT_DOM, OPS_AIRLINE, and CODESHARE were also considered in both the OLS and Tobit models. However, they were found to be statistically insignificant in explaining the variations in airport efficiency, and also produced inconsistent estimation results.

case, the reasons for the variations in airport efficiency among the sampled Asia-Pacific airports can be explained by those determinants during the study periods. Twelve groups of explanatory variables were investigated: the YEAR dummy, GDP per capita, airport's management/ownership, the airport's hub status, the percentage of international passengers handled by an airport, airline alliance membership of the dominant airline(s) of an airport, the airport's hinterland population, the airport's daily operating hours, the number of the airport's direct outbound international and domestic destinations/cities, the number of airlines that provide scheduled flight service at an airport alone, and the number of airlines that provide scheduled flight services with allied or partner airlines to an airport (codeshare flights).

From the OLS and Tobit regression analysis in this study, the Tobit model was found to be the more appropriate method for identifying and investigating which factors explain the variations in airport efficiency, since the Tobit model is considered as the more robust model for verifying the results of the OLS model (i.e. the naïve model) (Gillen & Lall, 1997; Yuen & Zhang, 2009). Overall, the findings of this study suggest that four factors (i.e. the airport's hub status, the airport's daily operating hours, the airport's hinterland population, and airline alliance membership of the dominant airline(s) of an airport) significantly affect airport efficiency.

Of the four significant factors, the airport's hub status suggests that an airport that serves as an international hub airport will be more efficient than a regional hub airport or non-hub airport. This finding supports the existing literature (e.g. Gillen & Lall, 1997; Lin & Hong, 2006; Li & Liu, 2007; Fung *et al*., 2008; Yuen & Zhang, 2009; Perelma & Serebrisky, 2010), which claimed that the international hub airports possess size and location advantages for transporting more airport traffic.

In addition, an airport's daily operating hours were either related or closely related to airport efficiency. The airport's daily operating hours were reported as having a negative coefficient, which suggests that if airport management and the government reduced an airport's operating hours (e.g. curfew hours being implemented to restrict aircraft operations beyond the specified hours), this will trigger lower airport efficiency. As such, this finding supports the perspective argued by Humphreys and Francis (2000), and demonstrates that the duration of airport operating hours is a factor that affects airport operation and efficiency. However, this situation may not apply to Sydney (Kingford Smith) Airport and Narita International Airport, where their operations and the resultant efficiency are not significantly affected by the implementation of a curfew policy. Operating hours could thus be a factor to be considered when planning a new airport.

The finding that an airport's hinterland population has a negative coefficient sign suggests that larger airport infrastructure or capacity need to be constructed to accommodate a larger hinterland population and the forecasted growth of airport traffic demand in the Asia-Pacific region. However, air transport demand and airport operations are inevitably affected by unwanted adverse incidents or difficult operating conditions that lead to lower airport efficiency (e.g. O'Connor, 1995; Park, 2003; Grais, Ellis & Glass, 2003; McKercher & Hui, 2004; Pine & McKercher, 2004; Siu & Wong, 2004; Kozak, Crotts & Law, 2007). Also, it should be acknowledged that it is extremely difficult to define the exact size of airport's hinterland size due to improvements in aircraft technology that allow longer distance to be flown, the formation of strategic global alliances between airlines, and the establishment of hub-and-spoke networks by many airlines (Graham, 1999; Graham & Guyer, 2000).

The finding related to airline alliance membership of the dominant airline(s) of an airport provided evidence to support the argument of Gillen and Lall (1997), who claimed that common use of airport facilities can improve efficiency by allocating passenger terminal facilities for airlines of a particular alliance so they have exclusive use of the passenger terminals. This gives airlines an incentive to use the designated passenger terminals more efficiently. Also, the current situation shows that an increasing number of large or legacy airlines have joined or intend to enter three major strategic global airline alliances (i.e. oneworld, Star Alliance, and SkyTeam). The key issue is that allied activities between airlines are seen to affect airport operations in different ways such as a specific passenger terminal (e.g. Narita International Airport's Terminal

One) being designated for a group of airlines associated with a particular alliance (in Narita's case, Star Alliance) (Cento, 2009).

Apart from these four factors, the finding related to the percentage of international passengers handled by an airport appears to be consistent with the findings of Pathomsiri *et al*. (2006), who claimed that the handling of international passenger traffic has a negative impact on an airport's efficiency. Both the OLS and Tobit models reported an insignificant negative coefficient estimation for this factor, which could be explained by how airport managers strive to improve their airports' infrastructure and capacity for handling more international passenger numbers, as these are one of the main airport revenue streams.

It is worthwhile to note that the finding of airport management/ownership does not appear to be consistent with the body of literature relating to the effect of airport management/ownership upon airport efficiency (e.g. Zhang, Liu & Bigsten, 1998; Martin & Roman, 2001; Hooper, 2002; Pels, Nijkamp & Rietveld, 2003; Findlay & Goldstein, 2004; Oum, Adler & Yu, 2006; Barros & Dieke, 2007; Malighetti *et al*., 2007; Oum, Yan & Yu, 2008; Yang, Tok & Su, 2008; Muller, Ulku & Zivanoic, 2009). This could be explained by the fact that the majority of international hub airports in the Asia-Pacific region (e.g. HKG and SIN) are still under government ownership and control, since the governments in the region consider an airport to be the strategic asset and/or an engine to contribute economic development of the country and city (Doganis, 1992). Indeed, most government-controlled or owned airports tend to operate on a more commercial basis, similar to privately-controlled airports, rather than being guided by non-economic political objectives while facing the growth in air transport demand and other emerging competitors in the region (Hooper, 2002). Furthermore, many Asia-Pacific airports have been privatised and listed in the stock exchange (Oum, Adler & Yu, 2006; Yang, Tok & Su, 2008). Thus, this study again showed that it may be difficult to comprehend the likely effect of airport management/ownership upon airport efficiency due to the mixture of government-controlled/owned airports and privately-run airports around the Asia-Pacific region.

There are at least two potential limitations in this study. First, as the selection of twelve major groups of possible factors to explain the variations in airport efficiency were a self-selecting procedure, the unique operating characteristics of each sampled airports in this study may not have been presented. For example, some airports have a strong competitive position in transporting air cargo traffic. Second, it should be acknowledged that the second-stage OLS and Tobit regression analysis mainly focuses on investigating the information related to the air passenger traffic of Asia-Pacific airports, without considering other relevant information such as air cargo information (Pathomsiri, 2006; Li & Liu, 2007; Yuen & Zhang, 2009).[26] This may also limit the generalisation of the results to identify the significant factors that are likely to affect the efficiency levels of Asia-Pacific airports which operate in the highly dynamic landscape of airport industry in the region. As such, it may be difficult to obtain a clear understanding of to what extent other unidentified factors may affect airport efficiency in the Asia-Pacific region.

In conclusion, the findings of this study suggest that seven airports (i.e. Hong Kong (HKG), Auckland (AKL), Melbourne (MEL), Beijing (PEK), Penang (PEN), Taipei (TPE), and Wellington (WLG) airports) are considered to be the efficient airports which operate at the efficiency frontier, and the remaining airports were relatively inefficient (which includes nine airports that never achieved full efficiency, and 14 airports that were able to achieve full efficiency in at least one year during the period of analysis). Moreover, the average DEA efficiency indexes of Asia-Pacific airports suggest a varying trend throughout the study periods, and that most airports operate below their optimal output levels.

Four factors were identified as being significant in accounting for the identified variations in airport efficiency among the Asia-Pacific airports: (i) the airports that act as international hub airports will be more efficient than regional hub airports or non-hub airports, (ii) shorter daily operating hours trigger lower airport efficiency, (iii) when an airport caters to a larger hinterland population, it will become less efficient than the airports that serve a smaller population, and (iv) if the dominant airline of an airport

[26] The reason for not including information of air cargo traffic relating to the sampled airports in the research is because this information could not be obtained or was difficult to obtain.

enters a strategic global airline alliance, this may improve its home-based airport’s efficiency.

CHAPTER 4 : NETWORK ANALYSIS OF ASIA-PACIFIC AIRPORTS AND HONG KONG AS CHINA'S PRIMARY PASSENGER GATEWAY

4.1 INTRODUCTION

The deregulation of the airline industry in the US and Europe, and the growth of hub-and-spoke operations in many airlines worldwide has structurally changed the nature and levels of competition among airlines and airports (Bowen, 2000; Shon, Chang & Lin, 2001; Wei & Hansen, 2006). The widespread utilisation of hub-and-spoke networks by airlines has also made an airport's competitiveness and performance relative to other interregional/internetwork airports become an increasingly challenging task (Shaw, 1993; Burghowt *et al*., 2009; Malighetti *et al*., 2009). In particular, the level of competition between the major Asian international airports has intensified as they have striven to capture an increasing amount of international passenger traffic. This has prompted enormous airport developments and expansions across the region recently (e.g. O'Connor, 1995; Mok, 1998; Oum & Yu, 2000; Park, 2003; Williams, 2006; Winston & Ru, 2008). Several new international gateway hub airports have already been opened and started operations, including HKIA (1998), Shanghai Pudong International Airport (1999), Seoul Incheon International Airport (2001), Guangzhou Baiyun International Airport (2004), and Bangkok Suvarnabhumi International Airport (2006).

An important question is how the performance of international hub airports can be measured and compared. Often, lists of airports are ranked by location-based measures or airport traffic statistics (e.g. air passengers numbers, air cargo volume, and aircraft movements) (ACI, 2010). Although these three major airport output variables or performance indicators are valuable in understanding an airport's performance, they do not provide any relevant information with respect to the competitive position of an airport's flight connectivity network. In order to understand an airport's competitiveness relative to other airports within the same airport network, an airport's flight connectivity network needs to be considered.

Airport performance and competitiveness evaluations in the Asia-Pacific region have been less studied compared with in the US and Europe. For example, Park (2003) used 'five core factors', which consist of spatial factors, facility factors, demand factors, service factors, and managerial factors to evaluate the competitive strengths of eight major Asian airports in terms of air passenger traffic and air cargo volume. Zhang *et al*. (2004) compared air cargo traffic of three major Chinese international airports and HKIA. Moreover, Matsumoto (2004, 2007) used basic gravity models, which tried to explain air passenger traffic and air cargo flows between major airports worldwide. Moreover, several studies have used network-related measures to measure and compare the performance of Asia-Pacific airports such as connectivity and centrality. Two studies (Li & Cai, 2004; Bagler, 2008) used the network approach to examine airport networks in Mainland China and India, respectively. In addition, Lee (2009) analysed the major cities' networkability worldwide from an international air passenger flow perspective between 1992 and 2004. Furthermore, the methodology of the NetScan Connectivity Units (CNU) model has been utilised to analyse the competitive position of major Asia-Pacific airports and their respective flight connectivity networks between 2001 and 2007 (Burghouwt *et al*., 2009; de Wit *et al*., 2009). To enhance the existing knowledge with regard to an airport's performance and hub competitiveness relative to other neighbouring competitors operating in the Asia-Pacific region, this study aims to investigate HKIA's flight connectivity network, especially its competitive position to connect to different regions worldwide relative to other Asia-Pacific airports and its role as China's primary passenger gateway.

The format of this chapter is structured as follows. Section 4.2 presents the literature relating to the different methodologies used to measure and compare an airport's network connectivity, and to compare airport network measurement models as well as exploring their suitability to measure the flight connectivity networks of Asia-Pacific airports. Section 4.3 outlines the methodology of CNU model used to measure and compare an airport's direct, indirect, and hub connectivity. Section 4.4 describes the data periods and the information used for the analysis of Asian international airports' networks and HKIA's role as China's primary passenger gateway. Section 4.5 presents and discusses the results of the CNU model for measuring and comparing direct, indirect, and hub connectivity of Asia-Pacific airports. Section 4.6 reports on and discusses the research results of HKIA's role as China's primary passenger gateway. Section 4.7 discusses and summarises the key findings of this chapter.

4.2 LITERATURE REVIEW OF AIRPORT HUB/NETWORK MEASURES

4.2.1 Models used in the literature

In the framework of airport network analysis or airport hub/network connectivity measures, airports represent nodes and route connection(s) between airports (Paleari, Redondi & Malighetti, 2010). In graph theory, connectivity can be defined as the degree to which nodes in a network are connected to each other (Burghouwt & Redondi, 2009). An airport's connectivity measure describes either how easily an airport can reach the rest of the network starting from a specific airport, or the number of opportunities for interconnections offered by an airport (Redondi, Malghetti & Paleari, 2010). In addition, the concept of hub connectivity is particularly important for measuring the competitive position of hub airports in a certain market (Burghouwt & Veldhuis, 2006). Often, hub connectivity refers to the number and quality of indirect flights available to air travellers via an airline hub. Hub connectivity levels depend on three conditions: (i) the number of markets or destinations link the hub airports with direct flights, (ii) flight frequencies, and (iii) arrival and departure times of the flights scheduled at the hub airports (Boostma, 1997). Furthermore, the indirect connectivity of an airport is associated with the concept of hub connectivity (Malighetti, Paleari & Redondi, 2008).

With respect to the attractiveness of an airport's indirect connectivity, Burghouwt (2007) suggested that this is determined by number of flight frequencies available at airports and the length of connecting or waiting times. It also depends on travel time, routing factor,[27] airfares, loyalty to airlines, preferences for the specific airports or airlines, comfort, and an airport's amenities (e.g. Veldhuis, 1997; Burghouwt & de Wit, 2005; Veldhuis, 2006; Burghouwt & Redondi, 2009; de Wit *et al*., 2009; Paleari, Redondi & Malighetti, 2010). On the other hand, air passengers flying with direct flights often have little choice over the airport(s) if only one or two airlines fly directly on that particular route, but the situation is somewhat different for indirect flight connections or transfer services available as the alternatives. However, even when direct flights are available to air passengers, indirect flight connections can often still provide worthwhile alternatives in terms of airfares and flight schedules, allowing airports and airlines to capture more air passenger traffic (Dennis, 1999).

There is no standard measure of an airport's flight connectivity network in the literature of the air transport industry. Table 4.1 shows two distinct groups of airport hub/network connectivity models from spatial coordination and temporal coordination, respectively. From the perspective of spatial coordination, three different models (i.e. the Hub Potential model, the Gross Vertex Connectivity model, and the Short Path Length (SPL) model) were developed to evaluate an airport's hub/network connectivity spatially. For example, Dennis (1999) utilised a less detailed and more straightforward approach to measure the 'Hub Potential' of US and European airports, by just counting number of incoming and outgoing flight movements. The main drawback of this model was that it takes no account of waiting time or flying distances required by air travellers to reach to their destinations. In addition, the Gross Vertex Connectivity model was used to examine the hub connectivity of 29 US domestic airports (Ivy, 1993; Ivy, Fik & Malecki, 1995). Moreover, the SPL models were used to compute the minimum travel steps travelling from one airport to another within US, Europe, Germany, and India (e.g. Freeman, 1977; Shaw, 1993; Shaw & Ivy, 1994; Bagler, 2008; Cronrath, Arndt & Zock, 2008; Malighetti *et al*., 2009). SPL models consider two important factors such as

[27] Burghouwt and Redondi (2009) indicated that the routing factor is the ratio between actual flight distances (km/time) and the theoretical distance of a direct flight.

Table 4.1. ***Comparisons of airport hub/network connectivity models and their suitability for measuring Asia-Pacific airports' networks***

Models, authors, and date	**Theoretical assumptions**	**Data requirement**	**Suitability**
		Spatial coordination	
Hub Potential Dennis (1999)	It investigates flight frequencies flying between hub airports (i.e. incoming and outgoing flights).	Number of flights (i.e. incoming and outgoing flights); flight frequency	To measure hub potential and forecast transfer traffic. Less applicable to measuring the Asia-Pacific airports because the model does not consider temporal coordination and routing factor.
Gross Vertex Connectivity Ivy (1993); Ivy, Fik & Malecki (1995)	It sums up all possible flight paths between airports with three or fewer flight segments, weighted by a scalar value.	Flight schedules (i.e. direct and indirect flights); all non-stop flight information on all carriers	To deal with domestic hubs in nature. Less applicable to measuring the Asia-Pacific airports because the model does not consider temporal coordination and routing factor.
Shortest Path Length (SPL) Freeman (1977); Shaw (1993); Shaw & Ivy (1994); Bagler (2008); Cronrath, Ardnt & Zock (2008); Malighetti *et al*., (2009)	It assumes the shortest path is the travel path involving the minimum number of steps or stops travelling from an airport to another airport.	flight schedules (i.e. departure and arrival time); flight frequency; operating time	To show the shortest path or minimum steps for air passengers travelling between airports, considering the concepts of 'betweenness' and 'centrality'. Less applicable to measuring the Asia-Pacific airports because the model does not consider temporal coordination and routing factor.
		Temporal coordination	
Doganis & Dennis Connectivity Dennis & Doganis (1989); Dennis (1994a and b)	It counts the number of flight connections. Indirect flight connections meet the conditions of minimum and maximum connecting time and routing factor.	Minimum connection time; total flights; scheduled departures	To compare the hubbing performance of major airports and identify the market served through airline schedule analysis. Somewhat applicable to measure the Asia-Pacific airports with temporal coordination taken into consideration.
Bootsma Connectivity Bootsma (1997)	It considers minimum and maximum connecting time and classify them as 'excellent', 'good' or 'poor'	Airline schedules; flight time; minimum connection time	To show the development of decision support tools for analysis and design of flight schedule structures for hub airports. Somewhat applicable to measuring the Asia-Pacific airports with the emphasis on flight schedule development.

Continued on next page

Models, authors, and date	Theoretical assumptions	Data requirement	Suitability
WNX Weighted Number of Connections (weighted connectivity) Burghouwt & de Wit (2005); Burghouwt (2007)	It counts the number of indirect flight connections weighted by their quality in terms of transfer and detour time.	minimum connection time; actual in-flight time; Great-Circle distance	To assess the indirect connectivity of hub airports and identify their hub positions (i.e. all-round hubs and hinterland hubs, etc). To show the wave-system structure positively affecting the total indirect connectivity of a hub airport. Somewhat applicable to measuring the Asia-Pacific airports because the model considers temporal coordination and routing factor.
CNU Veldhuis (1997); IATA (2000); Veldhuis & Kroes (2002); Burghouwt & Veldhuis (2006); Burghouwt *et al*. (2009); de Wit *et al*. (2009); Kim & Park (2011)	It counts the number of connecting opportunities (direct and indirect flights), and weights these connections in terms of transfer and detour time relative to a theoretical direct flight, since the quality of direct and indirect flight connections are different.	Flight schedules (i.e. arrival and departure times); minimum connection time; Great-Circle distance; flight time	To benchmark the competitive position of hub airports using direct, indirect, and hub connectivity. Highly applicable to measuring the Asia-Pacific airports because the model considers temporal coordination and routing factor.
WCN Weighted Number of Connections (Danesi Connectivity) Danesi (2006)	It counts the number of direct and indirect flight connections weighted by their quality in terms of transfer and detour time.	Flight schedules (i.e. arrival and departure times); transfer time; maximum acceptable connecting time between flights; minimum connection time; flight time; Great-Circle distance	Not particular applicable to analysing airport hubs. Less applicable to measuring the Asia-Pacific airports because the model is more useful for hub schedule analysis.
Number of Connection Patterns Budde, de Wit & Burghowt (2008)	It assesses the number of statistically significant patterns of incoming and outgoing flights.	Flight frequency per week; connection time	Not particularly applicable to analysing hub performance of Asia-Pacific airports because the model tends to focus on airline flight schedules.

Continued on next page

Models, authors, and date	Theoretical assumptions	Data requirement	Suitability
Quickest Path Length Centrality and Accessibility Paleari, Redondi & Malighetti (2010)	It assumes the quickest path which involves the minimum travel time between each pair of airports.	Flight time; waiting time at the intermediate airports; flight frequency; number of routes within the network	Similar to the SPL model. Highly applicable to measuring the Asia-Pacific airports because the model considers temporal coordination and routing factor, as well as having the ability to analyse airport network connectivity in a larger scale.

Remarks: Adapted from Burghouwt & Redondi (2009), Redondi & Burghouwt (2010), and the author's own research.

the ‘betweenness’ and ‘centrality’ of an airport. Also, the shortest path lengths between airports in SPL models accounts for the average minimum travel steps needed to get to each of the other airports. However, the main drawback of this model was its failure to take into account the temporal coordination of airline flight schedules and routing factor for measuring an airport’s hub/network connectivity, and also requires larger computational effort.

Arguably, the spatial coordination measures are not suitable for measuring an airport’s hub/network connectivity, because of the adoption of hub-and-spoke networks by many airlines worldwide, which have led to spatial reorganisations of the flight networks coordinating with the reorganisation of flight schedules (Burghouwt, Hakfoort & Ritsema, 2003). To address this important issue, many newly-developed models have incorporated temporal coordination to measure an airport’s hub/network connectivity. For example, the Doganis & Dennis Connectivity model used the connectivity ratio to measure airports’ hub connectivity in the US and Europe, which considered indirect flight connection times and routing factor (Dennis & Doganis, 1989; Dennis, 1994a and b). In addition, the Bootsma Connectivity model was developed by Bootsma (1997) to investigate airline flight schedule development for the European hinterland hubs using KLM as the case study. Moreover, two studies (Burghouwt & de Wit, 2005; Burghouwt, 2007) employed the Weighted Number of Connections model or the Weighted Connectivity model to investigate temporal concentrations and configuration of the air transport network in Europe after deregulation. Both studies suggested that wave system structures have a positive impact on the total indirect connectivity of hub airports, and that airline hubs with wave system or bank structures generally performed better because of the increased indirect connectivity given the number of direct flights.

The CNU model was first developed by Veldhuis (1997) to analyse Amsterdam/Schiphol Airport, focusing on the quality and frequency of connecting flights. The CNU variable is considered as the function of flight frequency, travel time, transfer time, and flying distances between the origins and the destinations. The CNU model was also used by IATA (2000) to measure and compare airports’ network connectivity worldwide. Other studies (e.g. Veldhuis & Kroes, 2002; Burghouwt &

Veldhuis, 2006; Burghouwt *et al*., 2009; de Wit *et al*., 2009) also adopted the CNU methodology to measure the competitive position of airport networks in Western Europe, the transatlantic market, and the Asia-Pacific region. In addition, to measure an airport's network connectivity from the air passenger traffic perspective, the CNU model has been modified to measure the air cargo network connectivity of Seoul Incheon International Airport (Kim & Park, 2011). Moreover, the WCN Weighted Number of Connections model or Danesi Connectivity was developed to measure airline hub timetable co-ordination and the connectivity of European airlines (Danesi, 2006). The results indicated that the model is able to generate more accurate estimates than the connectivity ratio produced by Dennis and Doganis (1989), but it has limited utility, being only applicable to hub schedule analysis and for airline managers. Additionally, the Number of Connection Patterns model was used to measure the significant patterns of the incoming and outgoing flights of an airport, using the temporal connectivity of the Lufthansa's schedule at Frankfurt Airport as an example (Budde, de Wit & Burghouwt, 2008). Nevertheless, none of these temporal coordination models have a focus on investigating the quickest path for air passengers travelling from the origin to the destination. It is logical to think that every passenger wants to reach their destinations in the quickest time. To combine the minimum travel steps methodology − the SPL model (Malghetti *et al*., 2008), the Quickest Path Length Centrality and Accessibility (QPL) model was developed to compute the quickest travel times between any pair of airports in the Chinese, European and US airport networks, and their respective connectivity levels (Paleari, Redondi & Malighetti, 2010). The results suggested that the QPL model can be applied to airport hub/network connectivity measures at a larger scale (i.e. global) compared with six other temporal coordination measures discussed above.

4.2.2 Comparisons of airport hub/network connectivity models and their suitability for measuring Asia-Pacific airports' networks

For descriptive and comparison purposes, Table 4.1 illustrates the theoretical assumptions of the airport hub/network connectivity models, their data requirements, and their suitability for measuring airport hub/network connectivity in the Asia-Pacific region. Major dissimilarities among airport hub/network connectivity models result mainly from spatial coordination, temporal coordination, routing factor, connection quality, and the global/local perspective being considered during the analysis. It should be noted that not all measures are suitable for this study to measure and compare the flight connectivity network of Asia-Pacific airports, and possibly require different levels of computational effort. The choice of hub/network connectivity measure is nevertheless dependent on data requirement and the scope of complexity of the analysis (Burghouwt & Redondi, 2009). Thus, amongst the identified models, the CNU model was selected for this study to measure and compare the airport hub/network connectivity of major Asian international airports concerning data requirement and its suitability. In addition, prior studies also suggested that the CNU model has the ability to measure and compare airports' flight connectivity networks by considering the number and quality of flight connections between any pair of airports.

4.3 METHODOLOGY OF NETSCAN CONNECTIVITY UNITS

An airport's hub/network connectivity can be considered as the number of flight connections between each pair of airports, irrespective of whether they are direct or indirect flight connections. However, the quality of a direct flight connection is not equal to that of an indirect flight connection for air passengers travelling from the origin to the destination. Theoretically, the CNU model quantifies the quality of an indirect flight connection and scales it to the quality of a theoretical direct flight connection. The model recognises the hub/network connectivity of an airport involving direct connectivity, indirect connectivity, and hub connectivity (see Figure 4.1).

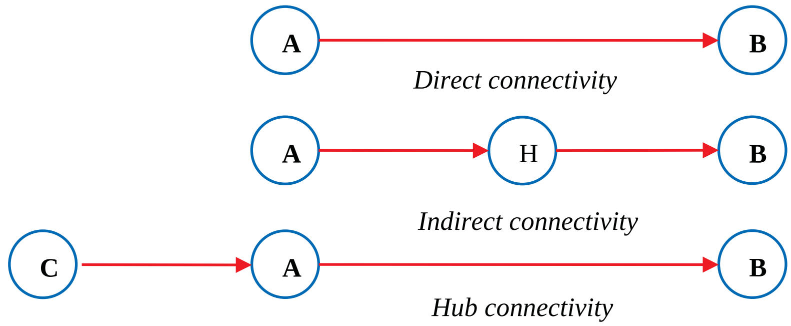

***Figure 4.1*. Types of airport hub/network connectivity**

Direct connectivity means that air passengers can take direct or non-stop flights available at Airport A to Airport B; indirect connectivity means that air passengers need to travel through an intermediate Airport H or make a stopover at Airport H to Airport B; hub connectivity means that air passengers take connections with a transfer at Airport A between Airport C and Airport B.[28]

With respect to flight connection quality, the CNU model assigns a connection quality index to every flight connection between airports, ranging between 0 and 1. The logic is that a direct or non-stop flight for air passengers travelling from the origin to the destination will be assigned a value of 1; a smaller connection quality index will be assigned to an indirect flight for which air passengers need to fly between airports because extra travel time is required for transfer time and detour time during the journey. If the additional travel time required for an indirect flight connection exceeds a certain limit, the connection quality index of that flight will be equivalent to 0 (Veldhuis, 1997; Burghouwt *et al*., 2009; de Wit *et al*., 2009).

To compute the connection quality index for a theoretical direct flight, the CNU model takes account of total flight time, total flying distances between origin and destination airports, aircraft flight speeds, and time required for take-off and landing. Lastly, the total number of connections or connectivity units between airports can be derived,

[28] To measure and compare an airport's indirect and hub connectivity, this study only considered one-stop connection at intermediate airport for air passengers travelling from the origin to the destination.

which is the final product of the connection quality index of each flight and the frequency of flight operation per time unit (day, week or year). Put simply, the CNU variable is the function of travel time (i.e. total flight time, plus transfer time or waiting time at intermediate airport(s) if required), total flying distances between airports, and flight frequency. This methodology can be applied to measure each type of flight connection (direct, indirect, and hub connectivity) between airports. The formulae are given in Equation (4.1):[29]

1. $NST = \frac{40 + 0.068 * gcd}{60}$

2. $MAXT = (3 - 0.075 * NST) * NST$

3. $PTT = FLT + (3 - 0.075 * NST) * TRT$

4. $QUAL = 1 - \left(\frac{PTT - NST}{MXT - NST}\right)$

5. $CNU = QUAL * DOP$ **(4.1)**

where:

NST = Non-stop travel time (in hours)

gcd = Great-Circle distance (in kilometres)

$MAXT$ = Maximum perceived travel time (in hours)

PTT = Perceived travel time (in hours)

FLT = Total flight time (in hours)

[29] According to de Wit *et al*. (2009), Formula 1 assumes that flight speed is 1/0.068 = 14.7 km per minute and 20 minutes are allowed for takeoff and landing, respectively. Formula 2 is empirically derived from trip data, and from passenger surveys on travel patterns and traffic behaviour within Europe. The rationale is that MAXT increases with the increase in NST, but with a decreasing incremental ratio, and therefore the estimated model was specified as a quadratic function. Formula 3 consists of flying time and transfer time, but an additional time penalty for transfer time has been included in this formula to reflect the inconvenience caused. Formula 4 computes a connection quality index between any pair of airports, ranging between 0 and 1. Formula 5 provides a total connection quality index between airport pairs that considers the frequency of flight operations. It must be emphasised that the findings about each airport's connectivity are sensitive to the choice of parameter value in Equation 4.1.

TRT = Transfer time (in hours)

$QUAL$ = Connection quality index of the flight

CNU = Total number of connections

DOP = Day of flight operations

4.4 DATA DESCRIPTION

Table 4.2 lists a panel of the 13 Asia-Pacific airports included for measuring and comparing their flight connectivity networks. This study based on Official Airline Guides (OAG), which publishes the monthly route schedules of major airlines including scheduled flight data on the direct and indirect flight connections between airports worldwide. The study periods are the second week of December during 2002, 2006, and 2010.

Table 4.2. ***List of 13 Asia-Pacific airports for flight connectivity network measurement***

Airport code	Airport name	Country, city
HKG	Hong Kong International Airport	China, Hong Kong
PEK	Beijing Capital International Airport	China, Beijing
PVG	Shanghai Pudong International Airport	China, Shanghai
CAN	Guangzhou Baiyun International Airport	China, Guangzhou
SXZ	Shenzhen Bao'an International Airport	China, Shenzhen
XMN	Xiamen Gaoqi International Airport	China, Xiamen
MFM	Macau International Airport	China, Macau
NRT	Narita International Airport	Japan, Tokyo
ICN	Incheon International Airport	South Korea, Seoul
TPE	Taiwan Taoyuan International Airport	Taiwan, Taipei
KUL	Kuala Lumpur International Airport	Malaysia, Kuala Lumpur
BKK	Suvarnabhumi Airport	Thailand, Bangkok
SIN	Singapore Changi Airport	Singapore

In order to obtain a fair comparison of the flight connectivity networks among the sampled Asia-Pacific airports, the Minimum Connection Time (MCT) allowed for air passengers to transit or transfer between flights at airports was set to 45 minutes or more. In addition, Table 4.3 shows the one-stop connecting traffic (i.e. indirect and hub connectivity) and transfer time allowed for air passengers to transfer or transit at intermediate airports.[30] Moreover, both online and offline connections were considered in this study,[31] since many major airlines have not yet entered into strategic global airline alliances during the study periods such as Emirates, Air China, China Eastern Airlines, China Southern Airlines, and China Airlines. Lastly, codeshare flights between airlines were only counted once during the measurement.

Table 4.3. ***One-stop connection and transfer time allowed for indirect and hub connectivity***

Types of connectivity	**One-stop connecting traffic or hub traffic**	**Transfer time**
Indirect traffic	Via an intermediate airport	2 hours
Connecting or hub traffic	From originating international destination via an intermediate airport to final international destination	2 hours
	From originating domestic destination via an intermediate airport to final international destination	2 hours
	From originating domestic destination via an intermediate airport to final domestic destination	2 hours
	From originating international destination via an intermediate airport to final domestic destination	3 hours

For the analysis of HKIA's role as China's primary passenger gateway, the number of international visitors departing for Mainland China via Hong Kong by air transport between 2006Q1 and 2011Q3 was collected from Hong Kong Tourism Board (HKTB).

[30] In general, two hours of transfer time is sufficient for air passengers to make a transfer or transit at an intermediate airport to the destination. However, extra time is required for air passengers to clear the Customs and the Immigration Department during the journey, and therefore, a three hour limitation has been allowed for a specific type of hub connectivity (i.e. from originating international destination via an intermediate airport to final domestic destination).

[31] Online connection refers to one that transfers between two flights that need to take place between flights from the same airline or partner airlines within the same strategic global airline alliance, whereas an offline connection refers to one that transfers between two flights that can take place between any airlines.

This represents the share of China's total inbound international passenger traffic by air transport from different regions being captured by Hong Kong. In addition, the same period of quarterly data relating to China's total inbound international visitors by air transport was also collected from China National Tourism Administration (CNTA).[32]

4.5 RESULTS OF THE CNU MODEL

4.5.1 Airport's direct connectivity

4.5.1.1 Growth in airport's direct connectivity

Figure 4.2 and Table 4.4 show the growth (or change) in the direct connectivity of Asia-Pacific airports during 2002, 2006, and 2010. Most airports improved their direct connectivity at different scales during the study periods. For example, all Chinese airports had at least a 134.7% growth in their direct connectivity, and while other Asia-Pacific airports in the group just achieved moderate growth rates, except for BKK, NRT, and MFM, which experienced declines in 2010. More specifically, PEK had the leading position of having the highest direct connectivity among the Asia-Pacific airports throughout the study periods (i.e. 2,361 CNU in 2002, 3,852 CNU in 2006, and 5,541 CNU in 2010). In 2010, the second largest airport was CAN (3,525 CNU), followed by PVG (2,903 CNU), BKK (2,773 CNU), SIN (2,766 CNU), and HKG (2,611 CNU) (see Table 4.5). MFM's direct connectivity never reached the milestone of 1,000 CNU throughout the years.

[32] CNTA only publishes the quarterly data relating to China's total inbound international visitors by air transport since 2009.

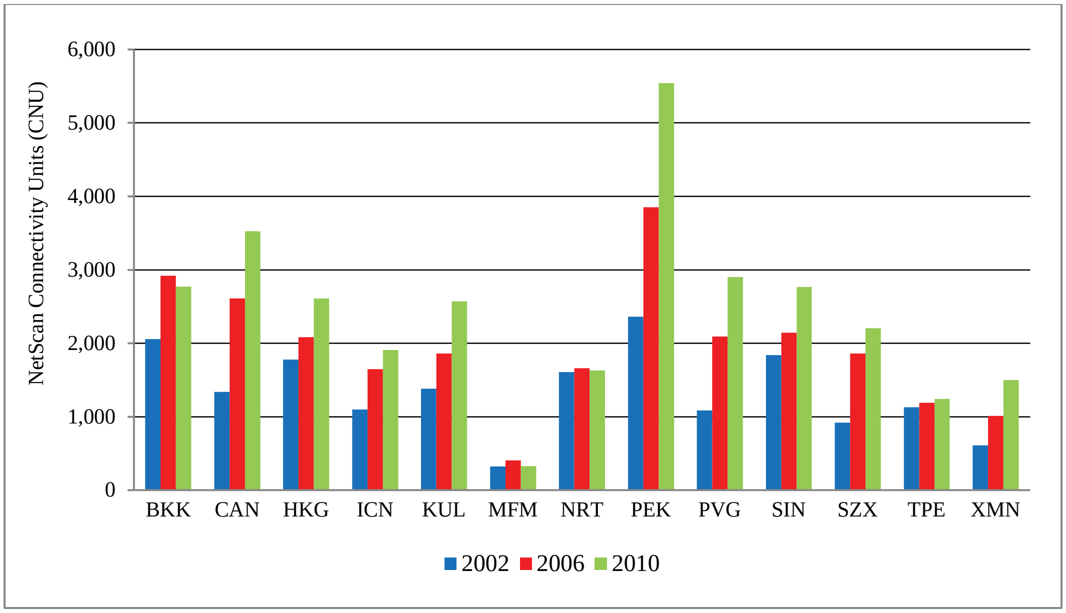

***Figure 4.2*. Direct connectivity of Asia-Pacific airports (2002–2010)**

4.5.1.2 Airport's direct international and domestic connectivity

An airport's direct connectivity can also be classified into direct international and domestic connectivity as illustrated by Figure 4.3. SIN and HKG had the highest direct international connectivity among the Asia-Pacific airports over the years, whereas the Chinese airports and MFM had the lowest direct international connectivity. Moreover, it is important to note that the direct domestic connectivity of PEK, CAN, SZX, and XMN contributed more than an average of 77.4% to their respective direct connectivity networks throughout the study periods (see Table 4.5), indicating that the Chinese airports had smaller direct international flight connectivity networks compared to other major Asian international hub airports, or established extensive direct domestic networks. Neither HKG, SIN, TPE nor MFM offered domestic flight networks.

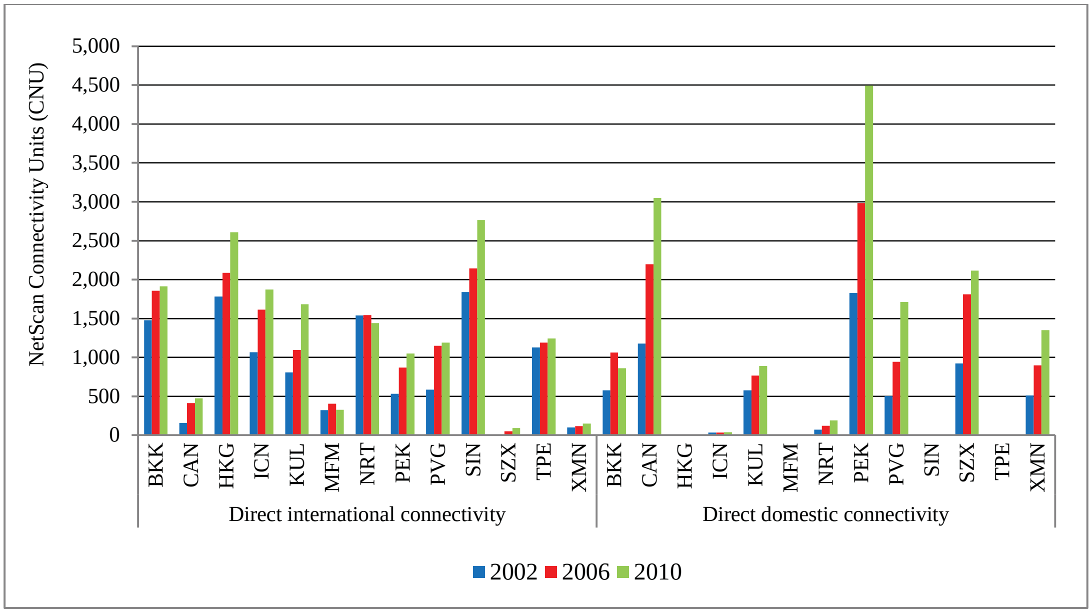

Figure 4.3. **Direct connectivity (international and domestic) of Asia-Pacific airports (2002−2010)**

Table 4.6 shows the percentage growth in the direct international and domestic connectivity of Asia-Pacific airports between 2002 and 2010. Four Chinese airports (PVG, CAN, PEK, and SZX) have shown a remarkable level of expansion in their direct international and domestic flight connectivity networks during the study periods, equalling to at least 97% and 129.5%, respectively for direct international and domestic networks. For example, PVG and CAN have successfully established themselves as the major domestic hubs and the international gateway hub airports in Mainland China, and their newly-built airport infrastructure has enabled them to transport an increasing amount of domestic and international passenger traffic as well as handling the more frequent flights operated by major local and foreign airlines. PEK remained its prominent position of serving China's political centre – Beijing – using its extensive direct domestic and international flight connectivity networks. In addition, SZX took advantage of rapid economic growth in the PRD region which led to the swift expansion in its direct international and domestic flight networks. Moreover, XMN continued to grow its direct domestic networks by around 164.6%, but just achieved modest growth in its direct international flight networks.

Other Asia-Pacific airports demonstrated varying growth rates for their respective direct international and domestic connectivity. With respect to the direct international connectivity, KUL showed approximately a 108.9% growth rate between 2002 and 2010, followed by ICN (75.8%), SIN (50.3%), HKG (46.6%), BKK (29.3%), TPE (10.3%), and MFM (0.9%) (see Table 4.6). Also, HKG, SIN, and TPE continued to expand their international flight connectivity networks during the study periods. Nevertheless, KUL and BKK increased their direct domestic connectivity by 54.1% and 48.5% resulting from increasing domestic air travel demand. BKK's smaller positive growth in direct international connectivity (3%) and its declining direct domestic connectivity (-19.1%) between 2006 and 2010 could largely be due to the unfavourable outcome of Thailand's political unrest, which caused fewer direct international and domestic flights into Bangkok. For ICN, the growth in the direct international connectivity was larger than the direct domestic connectivity across the years, and its direct domestic connectivity for the period of 2006 and 2010 was much lower than that of the previous period. NRT experienced a decline (-6.3%) in its direct international connectivity over the study periods because more international airlines shifted their international flight services to Tokyo Haneda International Airport (HND), but more domestic flights started to operate from NRT, although HND was still the main domestic hub to transport domestic passenger traffic within Japan. MFM showed a significant negative growth (-19.3%) in its direct international flight networks between 2006 and 2010, causing it to have the smallest growth among the Asia-Pacific airports over the years.

Table 4.4. ***Percentage growth in direct, indirect, and hub connectivity of Asia-Pacific airports (2002−2010)***

Airport code	**Direct connectivity**			**Indirect connectivity**			**Hub connectivity**		
	2002−2006	**2006−2010**	**2002−2010**	**2002−2006**	**2006−2010**	**2002−2010**	**2002−2006**	**2006−2010**	**2002−2010**
BKK	41.9	-5.1	34.7	-45.9	17.8	-36.3	137.5	-7.0	120.9
CAN	94.9	35.0	163.1	223.0	-24.1	145.3	183.6	65.6	369.7
HKG	17.1	25.2	46.6	-47.3	9.9	-42.1	30.7	21.3	58.6
ICN	50.0	15.8	73.8	-26.8	-32.6	-50.6	46.9	68.4	147.5
KUL	34.5	38.3	86.0	-70.2	75.1	-47.8	32.3	86.4	146.7
MFM	25.0	-19.3	0.9	-100.0	0	-100.0	72.3	48.7	156.2
NRT	3.3	-1.7	1.6	-69.6	-22.7	-76.5	23.4	-3.4	19.2
PEK	63.2	43.8	134.7	-46.3	-20.9	-57.5	124.2	65.6	271.2
PVG	92.2	38.8	166.8	-79.4	-45.9	-88.8	209.6	77.0	448.1
SIN	16.6	29.0	50.3	-54.4	-2.6	-55.6	39.8	43.1	100.0
SZX	102.0	18.5	139.4	-100.0	0	3.4	244.0	23.9	326.2
TPE	5.5	4.5	10.3	-36.4	-19.4	-48.8	-3.4	6.3	2.6
XMN	65.3	48.1	144.7	-11.1	-15.6	-25.0	215.0	55.3	389.3

Remarks: All figures above are given in percentages (%).

Table 4.5. ***Direct connectivity (total, international, and domestic) of Asia-Pacific airports (2002−2010)***

Airport code	2002			2006			2010		
	Total	**Intl (%)**	**Dom (%)**	**Total**	**Intl (%)**	**Dom (%)**	**Total**	**Intl (%)**	**Dom (%)**
BKK	2,058	71.9	28.1	2,921	63.6	36.4	2,773	69.0	31.0
CAN	1,340	11.9	88.1	2,611	15.9	84.1	3,525	13.4	86.6
HKG	1,781	100	0	2,085	100	0	2,611	100	0
ICN	1,099	96.9	3.1	1,649	97.8	2.2	1,910	98.0	2.0
KUL	1,383	58.3	41.7	1,860	58.8	41.2	2,573	65.4	34.6
MFM	324	100	0	405	100	0	327	100	0
NRT	1,608	95.6	4.4	1,661	92.8	7.2	1,633	88.2	11.8
PEK	2,361	22.6	77.4	3,852	22.6	77.4	5,541	18.9	81.1
PVG	1,088	53.8	46.2	2,091	54.9	45.1	2,903	41.0	59.0
SIN	1,840	100	0	2,145	100	0	2,766	100	0
SZX	922	0	100.0	1,862	2.8	97.2	2,207	4.1	95.9
TPE	1,129	100	0	1,191	100	0	1,245	100	0
XMN	613	16.6	83.4	1,013	11.5	88.5	1,500	9.9	90.1

Remarks: Total denotes an airport's total number of flight connectivity. Intl (%) denotes the percentage of an airport's direct international connectivity. Dom (%) denotes the percentage of an airport's direct domestic connectivity.

Table 4.6. ***Percentage growth in direct connectivity (international and domestic) of Asia-Pacific airports (2002−2010)***

Airport code	Direct international connectivity			Direct domestic connectivity		
	2002–2006	2006–2010	2002–2010	2002–2006	2006–2010	2002–2010
BKK	25.6	3.0	29.3	83.6	-19.1	48.5
CAN	159.4	14.2	196.3	86.1	38.9	158.6
HKG	17.1	25.2	46.6	0	0	0
ICN	51.5	16.1	75.8	5.9	5.6	11.8
KUL	35.7	53.9	108.9	32.8	16.1	54.1
MFM	25.0	-19.3	0.9	0	0	0
NRT	0.3	-6.5	-6.3	70.0	61.3	174.3
PEK	63.0	20.8	97.0	63.2	50.6	145.7
PVG	96.4	3.7	103.6	87.3	81.7	240.4
SIN	16.6	29.0	50.3	0	0	0
SZX	100.0	75.0	100.0	96.3	16.9	129.5
TPE	5.5	4.5	10.3	0	0	0
XMN	13.7	27.6	45.1	75.5	50.7	164.6

Remarks: All figures above are given in percentages (%).

4.5.1.3 Airport's direct connectivity to regions

The competitiveness of an airport's direct connectivity to connect to a specific region or air transport market cannot be illustrated by the growth (or change) in its direct connectivity (international and/or domestic direct connectivity). Table 4.7 shows the classification of regions connected to the Asia-Pacific airports, including domestic destinations, Africa, Other Asia, Central Asia, North Asia, Southeast Asia, West Asia, Europe, Australasia and Oceania, the Middle East, North America, and South America. Figure 4.4 shows the levels of direct connectivity of Asia-Pacific airports connecting to a specific region between 2002 and 2010. The competitive ranking of each airport's direct connectivity to regions relative to other Asia-Pacific airports is shown in Table 4.8.

As discussed in Section 4.5.1.2, all Chinese airports were designed and oriented to connect to domestic destinations, and most of these airports expanded their direct international connectivity to different regions worldwide during the study periods. For

Table 4.7. ***The classification of regions connected to Asia-Pacific airports***

Regions	**Countries**
Africa	South Africa, Ethiopia, Algeria, Chad, Egypt, Kenya, Libya, Madagascar, Mozambique, Nigeria, Sudan, Zimbabwe, Libya, Angola, Ivory Coast, Ghana, Burundi, Mali, Morocco, Benin, Tanzania, Cameroon, Mayotte, Uganda, Republic of Congo, Botswana, Djibouti, Malawi, Zambia, Tunisia
Other Asia	Mainland China, Hong Kong (China), Macau (China), India, Taiwan, Sri Lanka, Iran, Bangladesh, Mongolia, Nepal, Pakistan, Bhutan
Central Asia	Kazakhstan, Kyrgyzstan, Turkmenistan, Uzbekistan
North Asia	Japan, North Korea, South Korea
Southeast Asia	Singapore, Malaysia, Thailand, Philippines, Vietnam, Indonesia, Brunei Darussalam, Burma, Cambodia, Lao People's Democratic Republic, Myanmar, Palau
West Asia	Maldives, Mauritius, Seychelles
Europe	The United Kingdom, Germany, France, the Netherlands, Russia, Belgium, Italy, Denmark, Finland, Greece, Hungary, Norway, Romania, Spain, Sweden, Switzerland, Turkey, Ukraine, Czech Republic, Austria, Scotland, Ireland, Cyprus, Portugal, Latvia, Estonia, Poland, Croatia
Australasia and Oceania	Australia, Christmas Island (Australia), New Zealand, Fiji, Papua New Guinea, New Caledonia, Solomon Islands, Nauru
Middle East	Bahrain, United Arab Emirates, Qatar, Saudi Arabia, Israel, Jordan, Kuwait, Lebanon, Oman, Yemen, Libya, Syria
North America	United States of America, Canada, Guam, Jamaica, Mexico
South America	Brazil, Argentina, Peru, Costa Rica

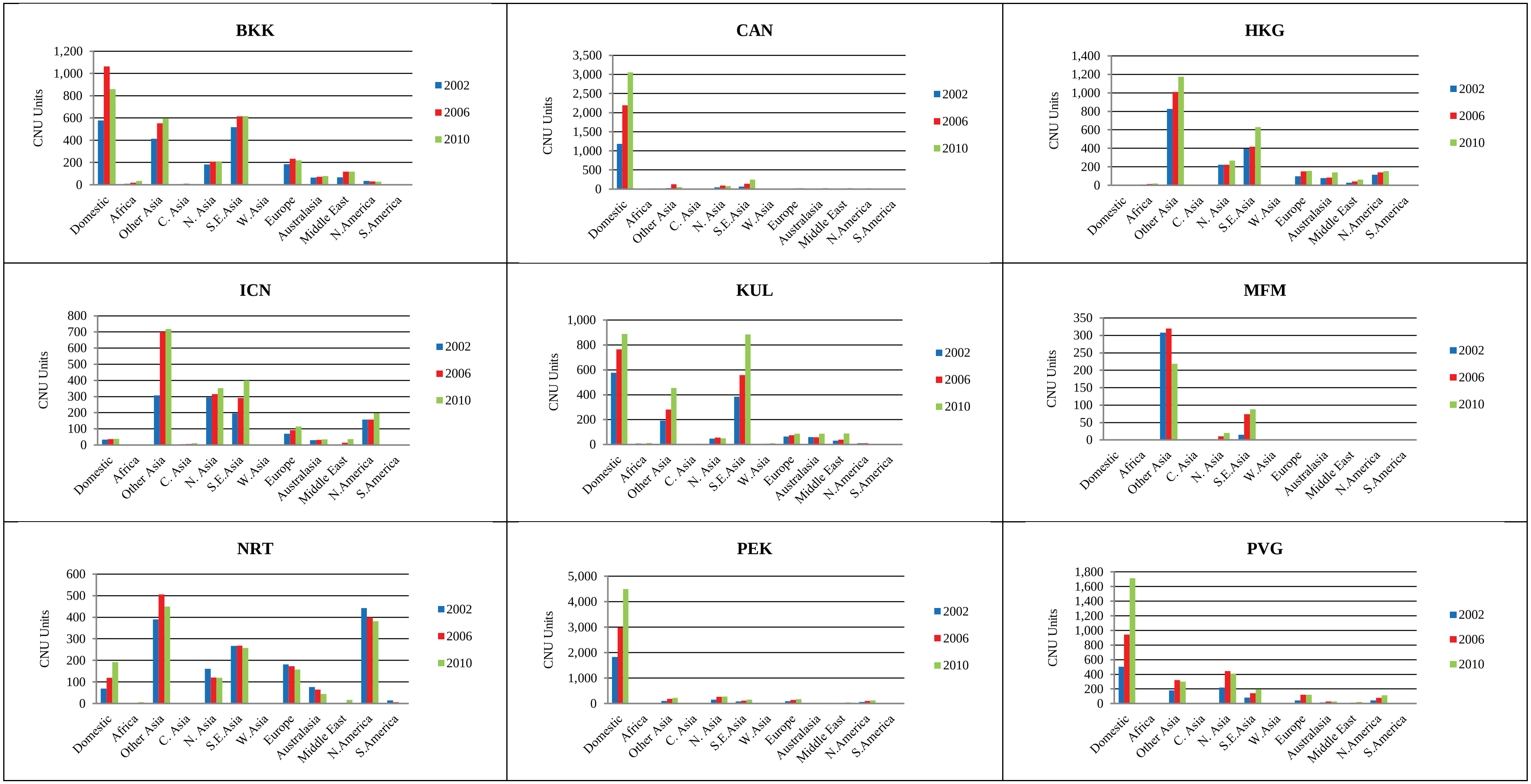

Figure 4.4. **Direct connectivity of Asia-Pacific airports to regions (2002−2010)**

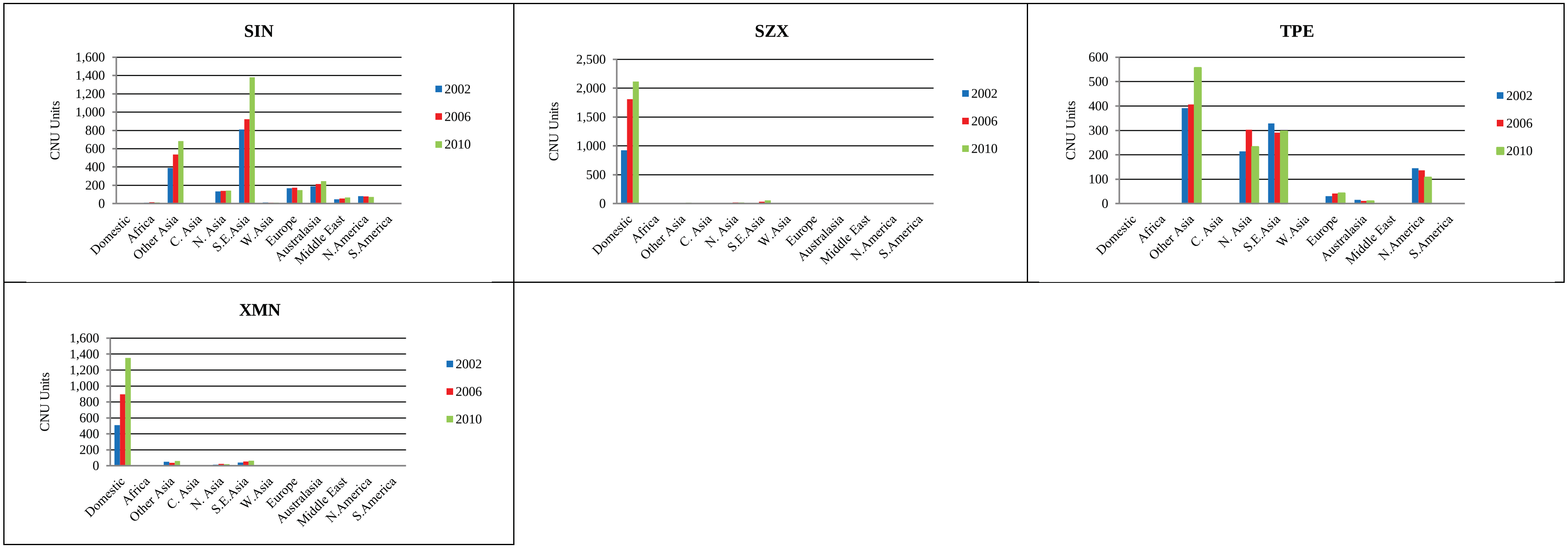

Figure 4.4. (Continued)

Table 4.8. ***The competitive ranking of the airports' direct connectivity to regions (2002−2010)***

Regions	BKK	CAN	HKG	ICN	KUL	MFM	NRT	PEK	PVG	SIN	SZX	TPE	XMN
Domestic-02	4	**2**	10	9	5	10	8	**1**	7	10	**3**	10	6
Domestic-06	4	**2**	10	9	7	10	8	**1**	5	10	**3**	10	6
Domestic-10	7	**2**	10	9	6	10	8	**1**	4	10	**3**	10	5
Africa-02	**1**	4	**1**	**3**	**2**	4	**3**	**3**	4	**1**	4	4	4
Africa-06	**1**	4	**3**	7	6	9	8	5	9	**2**	9	9	9
Africa-10	**1**	4	**2**	8	6	9	7	**3**	9	5	9	9	9
Other Asia-02	**2**	10	**1**	5	6	5	4	8	7	**3**	11	**3**	9
Other Asia-06	**3**	11	**1**	**2**	9	8	5	10	7	4	13	6	12
Other Asia-10	4	12	**1**	**2**	6	10	7	9	8	**3**	13	5	11
C.Asia-02	3	5	5	**1**	**1**	5	5	**2**	5	5	5	5	5
C. Asia-06	**1**	5	5	3	4	5	4	**2**	5	5	5	5	5
C.Asia-10	3	5	5	**1**	3	5	4	**2**	5	5	5	5	5
N. Asia-02	5	10	**2**	**1**	9	12	6	7	**3**	8	13	4	11
N. Asia-06	6	9	5	**2**	10	13	8	4	**1**	7	12	**3**	11
N. Asia-10	6	9	4	**2**	10	12	8	**3**	**1**	7	11	5	11
S.E.Asia-02	**2**	10	**3**	7	4	12	6	9	8	**1**	13	5	11
S.E.Asia-06	**2**	8	4	5	**3**	10	6	9	7	**1**	12	5	11
S.E.Asia-10	4	8	**3**	5	**2**	11	7	10	9	**1**	13	6	12
W.Asia-02	4	4	3	4	**2**	4	3	4	4	**1**	4	4	4
W.Asia-06	4	4	3	4	**2**	4	3	4	4	**1**	4	4	4
W.Asia-10	3	4	3	6	**2**	6	4	6	5	**1**	6	6	6
Europe-02	**1**	10	4	6	7	11	**2**	5	8	**3**	11	9	11
Europe-06	**1**	9	**3**	6	7	10	**2**	4	5	**2**	10	8	10
Europe-10	**1**	9	4	7	8	11	**3**	**2**	6	5	11	10	11
Australasia-02	4	9	**2**	6	5	10	**3**	9	8	**1**	10	7	10
Australasia-06	**3**	10	**2**	6	5	11	4	8	7	**1**	11	9	11
Australasia-10	4	8	**2**	6	**3**	11	5	9	7	**1**	11	10	11
M.East-02	**1**	8	4	7	**3**	8	8	5	8	**2**	8	6	8
M.East-06	**1**	8	**3**	6	4	10	10	5	7	**2**	10	9	10
M.East-10	**1**	7	4	6	**2**	10	9	5	8	**3**	10	10	10
N.America-02	8	10	4	**2**	9	11	**1**	6	7	5	11	**3**	11
N.America-06	7	8	**3**	**2**	9	10	**1**	5	6	6	10	4	10
N.America-10	8	9	**3**	**2**	10	11	**1**	4	5	7	11	6	11
S.America-02	3	3	3	3	2	3	**1**	3	3	3	3	3	3
S.America-06	4	4	4	4	2	4	**1**	3	4	4	4	4	4
S.America-10	4	4	4	2	3	4	2	3	**1**	4	4	4	4

Remarks: Bold typeface and shaded numbers mean that an airport has a stronger competitive position for offering more direct connectivity to a specific region relative to other Asia-Pacific airports (i.e. 1 is the highest ranking). Equal rankings are assigned to the airports with the same direct connectivity during the same year.

example, PEK expanded its direct connectivity to every region or air transport market over the years, and also established the largest level of direct connectivity to domestic destinations, Africa, Central Asia, Europe, Australasia and Oceania, the Middle East, and North America. CAN also increased its direct connectivity to Africa, Southeast Asia, Europe, and the Middle East during the study periods. Its expansion in direct connectivity (78%) to Southeast Asia in 2010 gave it the largest direct connectivity to the region among all Chinese airports, but its direct connectivity to Other Asia (54 CNU), North Asia (79 CNU), and North America (4 CUN) reduced during the same year. For instance, 54 weekly direct flights connected to Other Asia in 2010, which equalled to more than 128% international flights being unscheduled by local or foreign airlines.

Compared with PEK and CAN, PVG had a lower domestic connectivity, mainly because of the split-up between Shanghai Hongqiao International Airport (SHA) and PVG for handling domestic and international passenger traffic, but PVG still offered a stronger direct flight connectivity network to domestic cities over the years.[33] For instance, it had the stronger competitive position connecting air passengers to North Asia (409 CNU), Other Asia (299 CNU), Australasia and Oceania (30 CNU), and South America (4 CNU) in 2010. It is worthwhile to mention that PVG established the largest direct connectivity to South America among the Asia-Pacific airports in 2010, and also its direct connectivity to North America almost increased by 162% throughout the study periods. In addition, SZX and XMN only established smaller direct international flight connectivity networks to the regions in Asia, including Other Asia, North Asia, and Southeast Asia.

Amongst the sampled Asia-Pacific airports, HKG had the dominant position for offering direct connectivity to Other Asia, offering 1,009 and 1,174 weekly flights in 2006 and 2010, respectively (see Table 4.8). Most flights were scheduled to connect to major cities in Mainland China and Taiwan. Moreover, it maintained moderate growth

[33] Shanghai Hongqiao International Airport (SHA) mainly handles domestic passenger traffic and Shanghai Pudong International Airport (PVG) mainly handles international passenger traffic to and from Mainland China.

to connect to other regions over the years, including Africa, North Asia, Southeast Asia, Europe, Australasia and Oceania, the Middle East, and North America. TPE's direct flight connectivity network was more oriented to Asia-specific destinations (i.e. Other Asia, North Asia, and Southeast Asia) and North America. In particular, it benefited from the signing of cross-strait (direct air link) agreement that allows direct flights to be operated between Mainland China and Taiwan after April 2008, leading to its stable growth in direct connectivity to Mainland China. Its negative growth in direct connectivity to Southeast Asia (-30%) and North America (-27%) between 2006 and 2010 was caused by many airlines scaling back flight operations to these regions. For MFM, it only provided direct flight services to Other Asia, North Asia, and Southeast Asia, but its direct connectivity to North Asia and Southeast Asia also grew in view of increasing numbers of holiday makers and gambling tourists visiting Macau.

As for two major North Asian airports, neither ICN nor NRT established greater direct connectivity to their respective domestic destinations, operating just 38 and 192 weekly flights in 2010, respectively.[34] ICN continued to expand its direct connectivity to all regions worldwide over the study periods; Southeast Asia was the fastest growing region. It also established the highest direct connectivity to Central Asia (12 CNU) in 2010 and was ranked as the second strongest airport to connect to Other Asia and North America during 2006 and 2010 (see Table 4.8). Overall, ICN maintained a strong competitive position connecting air passengers to Southeast Asia, North Asia, Europe, the Middle East, North America, and South America. With respect to NRT, direct connectivity to most regions declined during the study periods, with the exception of Africa and the Middle East. The signing of the 'open-skies' agreement between Japan and the US has allowed NRT to successfully maintain and strengthen its strong competitive position in the trans-Pacific market connecting to North America, offering more than 382 weekly direct flights during each of the study periods. Also, it offered strong direct connectivity to Other Asia, Southeast Asia, Europe, and South America.

[34] Lieshout and Matsumoto (2012) indicated the designation of Incheon International Airport (ICN) and Narita International Airport (NRT) to handle international passenger traffic to and from South Korea and Japan, respectively; domestic passenger traffic in both countries is mainly handled by Gimpo International Airport (GMP) and Tokyo Haneda International Airport (HND), respectively.

Concerning three Association of Southeast Asia Nations (ASEAN) airports in Southeast Asia, SIN's direct flight connectivity network expanded throughout the study periods, and it was the most competitive airport, providing the highest direct connectivity to three regions over the years, namely Southeast Asia (1,381 CNU), West Asia (11 CNU), and Australasia and Oceania (245 CNU) (see Table 4.8). It also offered a relatively stronger direct connectivity to Other Asia and the Middle East, but its direct connectivity to Europe and North America decreased by almost 10% and 16% for 2006 and 2010. In addition, BKK and KUL were more oriented to domestic connectivity, with greater direct domestic connectivity. In most cases, BKK showed modest growth rates in direct connectivity to connect to all regions, apart from Europe and North America, throughout the study periods. It offered the highest direct connectivity to Africa (35 weekly flights), Europe (219 weekly flights), the Middle East (118 weekly flights) in 2010 among the Asia-Pacific airports. Similarly, KUL shrank its direct connectivity to North Asia and North America, whereas its direct connectivity expanded to other regions during the study periods. For example, it established a comparatively strong direct flight connectivity network to several regions in 2010, including Southeast Asia (884 CNU), Australasia and Oceania (86 CNU), the Middle East (88 CNU), and West Asia (10 CNU).

In short, PEK, CAN, SZX, XMN, BKK, and KUL were more oriented to domestic cities. The airports with the highest direct connectivity to the regions were:

- Africa (BKK, HKG, and PEK)
- Other Asia (HKG, ICN, SIN, and BKK)
- Central Asia (ICN, PEK, and BKK)
- North Asia (PVG, ICN, PEK, and HKG)
- Southeast Asia (SIN, KUL, HKG, and BKK)
- West Asia (SIN and KUL)
- Europe (BKK, NRT, PEK, and SIN)
- Australasia and Oceania (SIN, HKG, BKK, and KUL)
- the Middle East (BKK, SIN, and KUL)

- North America (NRT, ICN, HKG, and TPE)
- South America (PVG and NRT)

HKG established a very strong competitive position for directly connecting to six regions, including Africa, Other Asia (which includes Mainland China), North Asia, Southeast Asia, Australasia and Oceania, and North America between 2002 and 2010.

4.5.2 Airport's indirect connectivity

Given the direct relationship between an airport's direct and indirect connectivity as shown in Section 4.3, an airport's indirect connectivity is largely dependent on its direct flight connectivity network and its position within the network (Malighetti *et al*., 2008). Often, it is acknowledged that the growth in the direct connectivity of an airport will lead to a decline in the indirect connectivity of that airport. In addition, airlines prefer to operate more frequent direct flights between airports or cities rather than providing indirect flight connections to air passengers or channelling them via multiple intermediate airports, since flight frequency and connectivity network together with travel times are always considered by air passengers as the key factors to choose an airline and/or airport during their journey.[35] Figure 4.5 shows that declining indirect connectivity appeared in general among the Asia-Pacific airports over the years, although BKK, HKG, and KUL had the reverse trend in 2010. This situation further confirmed by Table 4.4 which indicates that negative growth rates of indirect connectivity were seen in most Asia-Pacific airports, and all of the airports have shown positive growth rates in their direct connectivity over the years. In particular, NRT

[35] Operating costs for direct flight operations were not considered in this study. However, from an economic and business point of view, without losing the global reach, airlines often look for cooperation from alliance members or codeshare partners to help on unprofitable routes instead of operating direct flights by themselves, and in return such airline activities may increase an airport's indirect connectivity but reduce its direct connectivity accordingly. However, in some instances, airlines will provide direct flights or operate Origin–Destination (O–D) routings where the yield of such routings exceeds the combined segments yield through intermediate hubbing. On the other hand, air travellers may prefer and take advantage of an airport's frequent flight connections and extensive connectivity networks during their trips for a wide range of personal reasons such as shopping and visiting friends and family. For example, many Chinese travellers are still using Hong Kong as the transit point to their destinations.

(1,008 CNU) led indirect connectivity among the Asia-Pacific airports during 2002, but experienced a significant drop for the period of 2002 and 2006. HKG still offered a stronger indirect flight connectivity network to connect air passengers to different regions over the years, especially to Europe. In addition, BKK, SIN, and TPE also established strong indirect flight connectivity networks to connect air passengers to other regions worldwide.

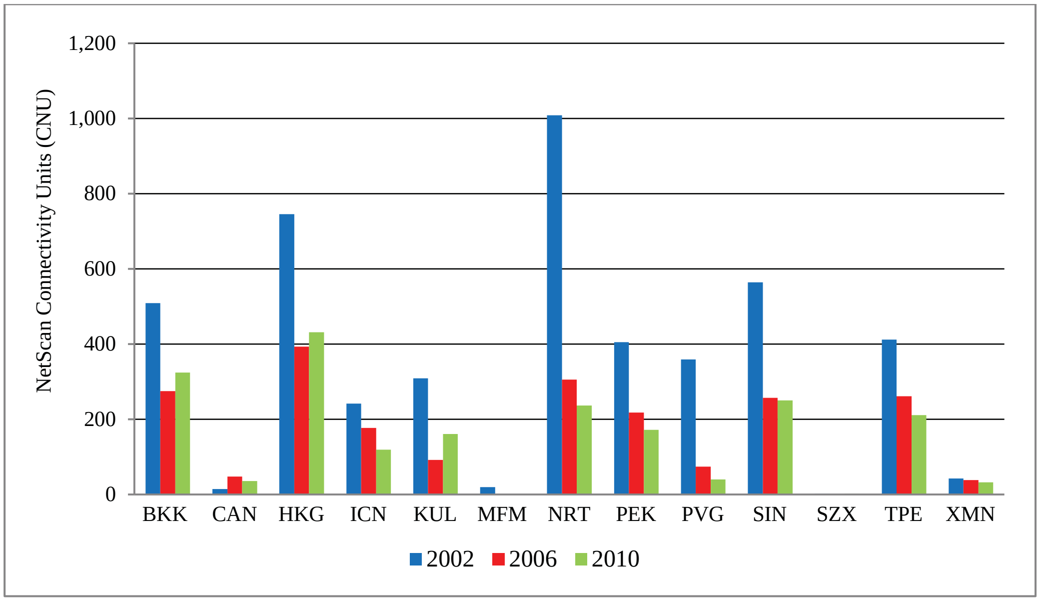

***Figure 4.5*. Indirect connectivity of Asia-Pacific airports (2002–2010)**

4.5.3 Airport's hub connectivity

4.5.3.1 Growth in airport's hub connectivity

As seen from the previous sections, neither direct nor indirect connectivity measures could provide any insight into an airport's hub competitiveness of flight connectivity and types of hub traffic via (with a transfer at) an airport to the destinations. Recall that an airport's hub connectivity refers to the number and the quality of indirect flight connections available to air passengers via intermediate airport(s) to the destinations (see Section 4.3). The growth (or change) in hub connectivity of Asia-Pacific airports between 2002 and 2010 are shown in Table 4.4 and Figure 4.6. Amongst the Asia-Pacific airports, PEK had the leading position for offering hub connectivity over the years, followed by BKK, SIN, HKG, NRT, PVG, CAN, KUL, and ICN. Some other airports were less hub-connected, namely TPE, SZX, XMN, and MFM.

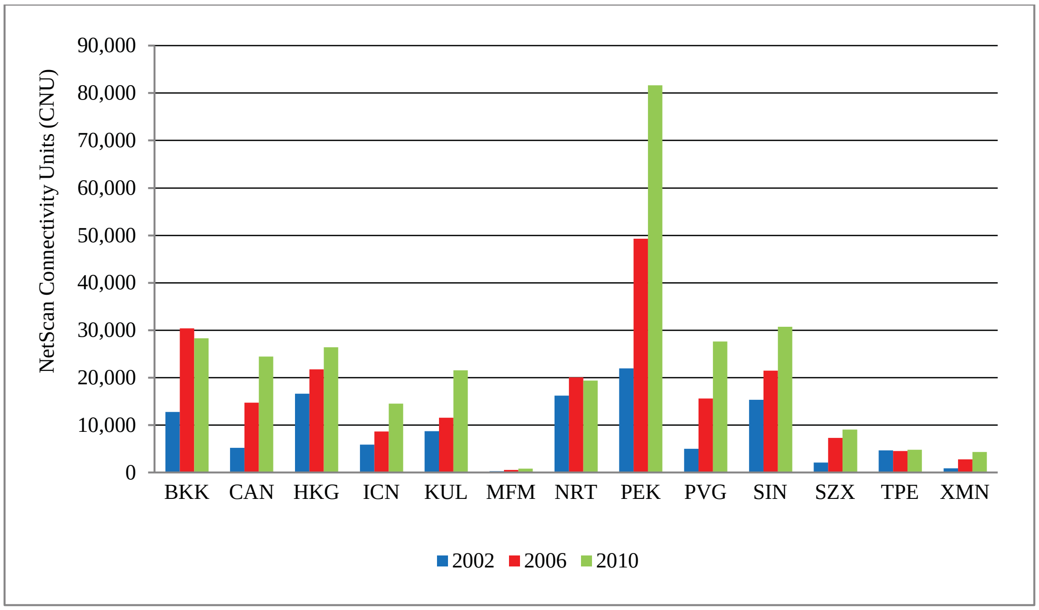

***Figure 4.6*. Hub connectivity of Asia-Pacific airports (2002–2010)**

Concerning the percentage growth of hub connectivity, all Asia-Pacific airports expanded their hub connectivity to different magnitudes during the study periods. For example, the Chinese airports had the largest growth rates in hub connectivity: PVG, 448.1%; XMN, 389.3%; CAN, 369.7%; SZX, 326.2%; PEK, 271.2%. This suggested that the Chinese airports have quickly developed themselves into the domestic or international hubs to handle the increasing domestic and international passenger traffic within Mainland China and from overseas countries. Moreover, other five Asian international airports showed significant levels of expansions in hub connectivity: MFM, 156.2%; ICN, 147.5%; KUL, 146.7%; BKK, 120.9%; SIN, 100%. Also, the third-tier airports presented modest growth rates: HKG, 58.6%; NRT, 19.2%; TPE, 2.6%. During 2006 and 2010, most Asian airports continued their growth but the magnitudes were smaller than in the previous period, except for KUL, ICN, SIN, and

TPE. Only BKK (-7.0%) and NRT (-3.4%) experienced declining hub connectivity during this period.

4.5.3.2 Airport's hub connectivity to regions

An airport's direct connectivity network has implications for its hub connectivity. Often, the larger direct connectivity of an airport will lead to higher hub connectivity for that airport. Owing to the differences in the airports' hub connectivity, geographical differences appear in hub connectivity among the Asia-Pacific airports, and variations in the type of hub traffic passing through those airports to the destinations. In order to measure and compare hub connectivity among the Asia-Pacific airports geographically, the ideal measure should again follow the regional classification for direct connectivity measurement as shown in Table 4.7. Figure 4.7 depicts the airports' hub connectivity to connect to a specific region between 2002 and 2010, and the competitive ranking of each airport's hub connectivity to regions relative to other Asia-Pacific airports is shown in Table 4.9.

Considering airports' geographical differences, all Chinese airports specialised in domestic hub connectivity and demonstrated the highest growth rates (at least 283.8%) between 2002 and 2010. More specifically, PEK offered the stronger hub connectivity to Africa, Europe, and Central Asia over the years, and also its hub connectivity to the Middle East increased by around 153% during the period of 2006 and 2010. PVG led the hub connectivity to North Asia among the Asia-Pacific airports in 2010, and expanded its hub connectivity to all regions worldwide throughout the study periods (see Table 4.9). Moreover, CAN increased its hub connectivity to all regions in 2010 and especially offered stronger hub connectivity to Southeast Asia.

HKG led the hub connectivity to Africa and Other Asia (which includes Mainland China) among the Asia-Pacific airports over the years, and also maintained relatively stronger hub connectivity to Southeast Asia, North Asia, Australasia and Oceania, and

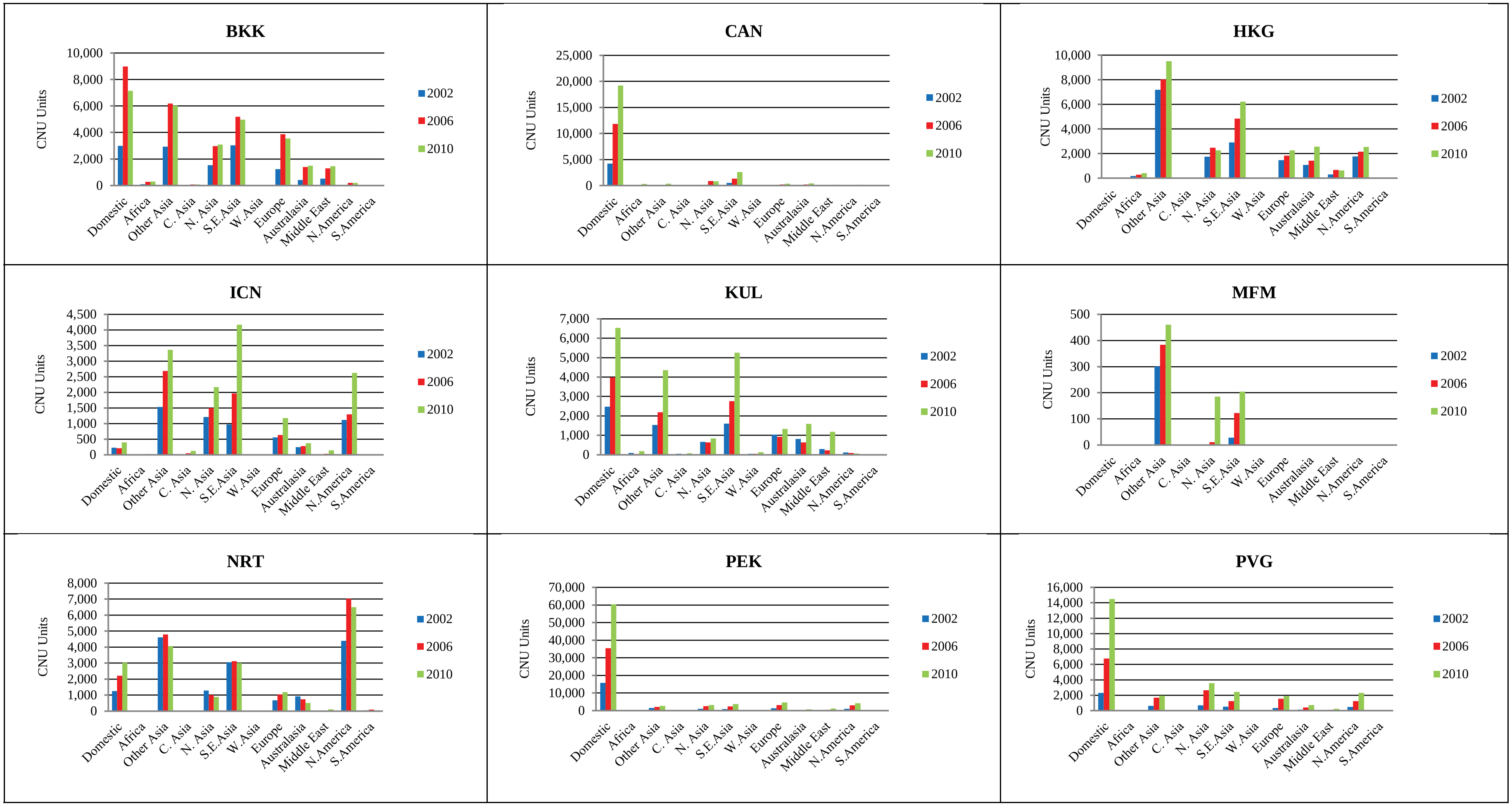

Figure 4.7. **Hub connectivity of Asia-Pacific airports to regions (2002−2010)**

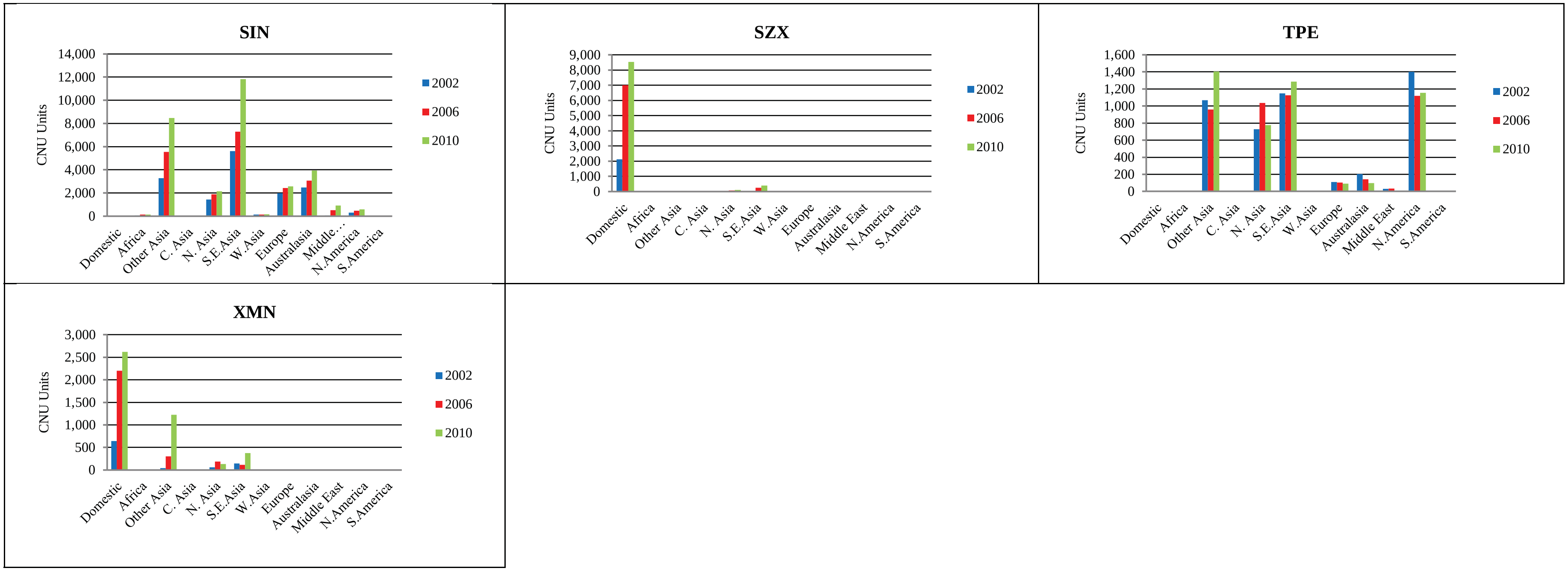

Figure 4.7. (Continued)

Table 4.9. ***The competitive ranking of the airports' hub connectivity to regions (2002−2010)***

Regions	**BKK**	**CAN**	**HKG**	**ICN**	**KUL**	**MFM**	**NRT**	**PEK**	**PVG**	**SIN**	**SZX**	**TPE**	**XMN**
Domestic -02	**3**	**2**	10	9	4	10	7	**1**	5	10	6	10	8
Domestic-06	**3**	**2**	10	9	6	10	7	**1**	5	10	4	10	8
Domestic-10	5	**2**	10	9	6	10	8	**1**	**3**	10	4	10	7
Africa-02	**2**	8	**1**	6	**3**	8	7	5	8	4	8	8	8
Africa-06	**1**	4	**2**	8	6	9	7	5	9	**3**	9	9	9
Africa-10	**3**	4	**1**	8	5	9	7	**2**	9	6	9	9	9
Other Asia-02	4	12	**1**	6	7	10	**2**	5	9	**3**	13	8	11
Other Asia-06	**2**	12	**1**	5	7	10	4	6	8	**3**	13	9	11
Other Asia-10	**3**	12	**1**	6	4	11	5	7	8	**2**	13	9	10
C.Asia-02	3	6	6	4	**2**	6	5	**1**	6	6	6	6	6
C.Asia-06	**2**	6	6	3	4	6	5	**1**	6	6	6	6	6
C.Asia-10	4	6	6	**2**	3	6	5	**1**	6	6	6	6	6
N.Asia-02	**2**	10	**1**	5	9	12	4	6	8	**3**	13	7	11
N.Asia-06	**1**	9	4	6	10	13	8	**3**	**2**	5	12	7	11
N.Asia-10	**3**	9	4	5	8	11	7	**2**	**1**	6	13	10	12
S.E.Asia-02	**3**	9	4	7	5	12	**2**	8	10	**1**	13	6	11
S.E.Asia-06	**2**	8	**3**	7	5	12	4	6	9	**1**	11	10	13
S.E.Asia-10	4	**2**	**2**	5	**3**	13	7	6	9	**1**	11	10	12
W.Asia-02	5	5	3	5	**2**	5	4	5	5	**1**	5	5	5
W.Asia-06	5	5	3	5	**2**	5	4	5	5	**1**	5	5	5
W.Asia-10	4	3	7	8	**2**	8	6	8	5	**1**	8	8	8
Europe-02	4	10	**2**	7	5	11	6	**3**	8	**1**	12	9	13
Europe-06	**1**	9	4	8	7	11	6	**2**	5	**3**	11	10	11
Europe-10	**2**	9	4	8	6	11	7	**1**	5	4	11	10	11
Australasia-02	5	9	**2**	6	4	11	**3**	8	10	**1**	11	7	11
Australasia-06	**3**	8	**2**	7	5	11	4	10	6	**1**	11	9	11
Australasia-10	4	8	**2**	9	**3**	11	7	5	6	**1**	11	10	11
M.East-02	**1**	8	**2**	7	**3**	8	8	5	8	4	8	6	8
M.East-06	**1**	7	**2**	9	5	10	10	4	6	**3**	10	8	10
M.East-10	**1**	7	5	8	**2**	10	9	6	6	4	10	10	10
N.America-02	10	9	**2**	4	8	11	**1**	5	6	7	13	**3**	11
N.America-06	8	10	**3**	4	9	11	**1**	**2**	5	7	11	6	11
N.America-10	8	9	4	**3**	10	11	**1**	**2**	5	7	11	6	11
S.America-02	2	2	2	2	2	2	**1**	2	2	2	2	2	2
S.America-06	3	3	3	3	3	3	**1**	3	3	3	3	3	3
S.America-10	5	5	5	5	3	5	2	4	**1**	5	5	5	5

Remarks: Bold typeface and shaded numbers mean that an airport has a stronger competitive position for offering more hub connectivity to a specific region relative to other Asia-Pacific airports (i.e. 1 is the highest ranking). Equal rankings are assigned to the airports with the same hub connectivity during the same year.

North America (see Table 4.9). However, declining hub connectivity to the Middle East, North Asia, and West Asia appeared in 2010. With respect to North Asian airports, NRT continued to act as the most important hub airport connecting to North America, but decreased its hub connectivity to North Asia and Australasia and Oceania over the years. ICN's hub connectivity grew for all regions during the study periods, especially to Other Asia, Central Asia, Southeast Asia, and North America.

With respect to the ASEAN airports, SIN had the highest hub connectivity to Southeast Asia, West Asia, and Australasia and Oceania during the study periods (see Table 4.9), and its hub connectivity to all regions have grown since 2006. In addition, BKK had the strongest hub competitive position for offering the highest hub connectivity to the Middle East during each of the study years (see Table 4.9), but decreased its hub connectivity to Southeast Asia, Europe, North America, and domestic connectivity. Generally, BKK built a stronger hub connectivity network to Africa, Other Asia, Southeast Asia, and Europe over the years. KUL grew its domestic hub connectivity at a greater pace (163.7%) and established a relatively stronger hub connectivity network to Other Asia, Southeast Asia, the Middle East, and Australasia and Oceania during the study periods. Specifically, it reversed its declining hub connectivity to several regions in 2010, including Africa, Central Asia, North Asia, Europe, Australasia and Oceania, the Middle East, and North America. TPE was the least hub-connected airport among the major Asian international gateway hub airports in 2010 showing the declining hub connectivity to North Asia, Europe, Australasia and Oceania, and the Middle East, but still maintained strong hub connections to North America over the years. MFM was the worst hub-connected airport among the Asia-Pacific airports mainly because of its smaller direct international flight connectivity network.

In short, PEK, CAN, BKK, and PVG established larger domestic hub connectivity networks connecting domestic passengers within the countries. The airports with the highest hub connectivity to the regions were:

- Africa (HKG, BKK, and PEK)

- Other Asia (HKG, SIN, and BKK)
- Central Asia (PEK and ICN)
- North Asia (PVG, PEK, and BKK)
- Southeast Asia (SIN, HKG, BKK, and KUL)
- West Asia (SIN and KUL)
- Europe (PEK, BKK, and SIN)
- Australasia and Oceania (SIN, HKG, BKK, and KUL)
- the Middle East (BKK, KUL, and HKG)
- North America (NRT, PEK, HKG, and ICN)
- South America (NRT and PVG)

HKG established the stronger position for offering hub connectivity to six regions, including Africa, Other Asia (which includes Mainland China), Southeast Asia, Australasia and Oceania, the Middle East, and North America between 2002 and 2010.

4.5.3.3 Hub traffic of Asia-Pacific airports

The hub connectivity measure in the previous section tried to provide an insight of how competitive airports are at acting as the aviation hubs connecting air passengers within the country and to a specific region, but a clear understanding of the types of hub traffic travelling through an airport might indicate the role and/or the orientation of that airport. Four major types of hub traffic travelling through the Asia-Pacific airports can be identified as shown in Figure 4.8:[36] (i) from the originating international destination via an intermediate airport to the final international destination (International-to-International), (ii) from the originating international destination via an intermediate

[36] (i) 'International-to-International' represents international passenger traffic from one's own country (a foreign country relative to the airport) to a third country via an intermediate airport in other country, e.g. from Singapore to San Francisco via Hong Kong. (ii) 'International-to-Domestic' represents international passenger traffic from one's own country to a second country via the domestic airport in the second country, e.g. from Singapore to Gold Coast via Sydney. (iii) 'Domestic-to-International' represents domestic passenger traffic from one's own country via an intermediate airport in the same country to a second country, e.g. Shenzhen to New York via Beijing. (iv) 'Domestic-to-Domestic' represents domestic passenger traffic via an intermediate airport in the same country to another domestic destination within the border, e.g. Shenzhen to Beijing via Guangzhou.

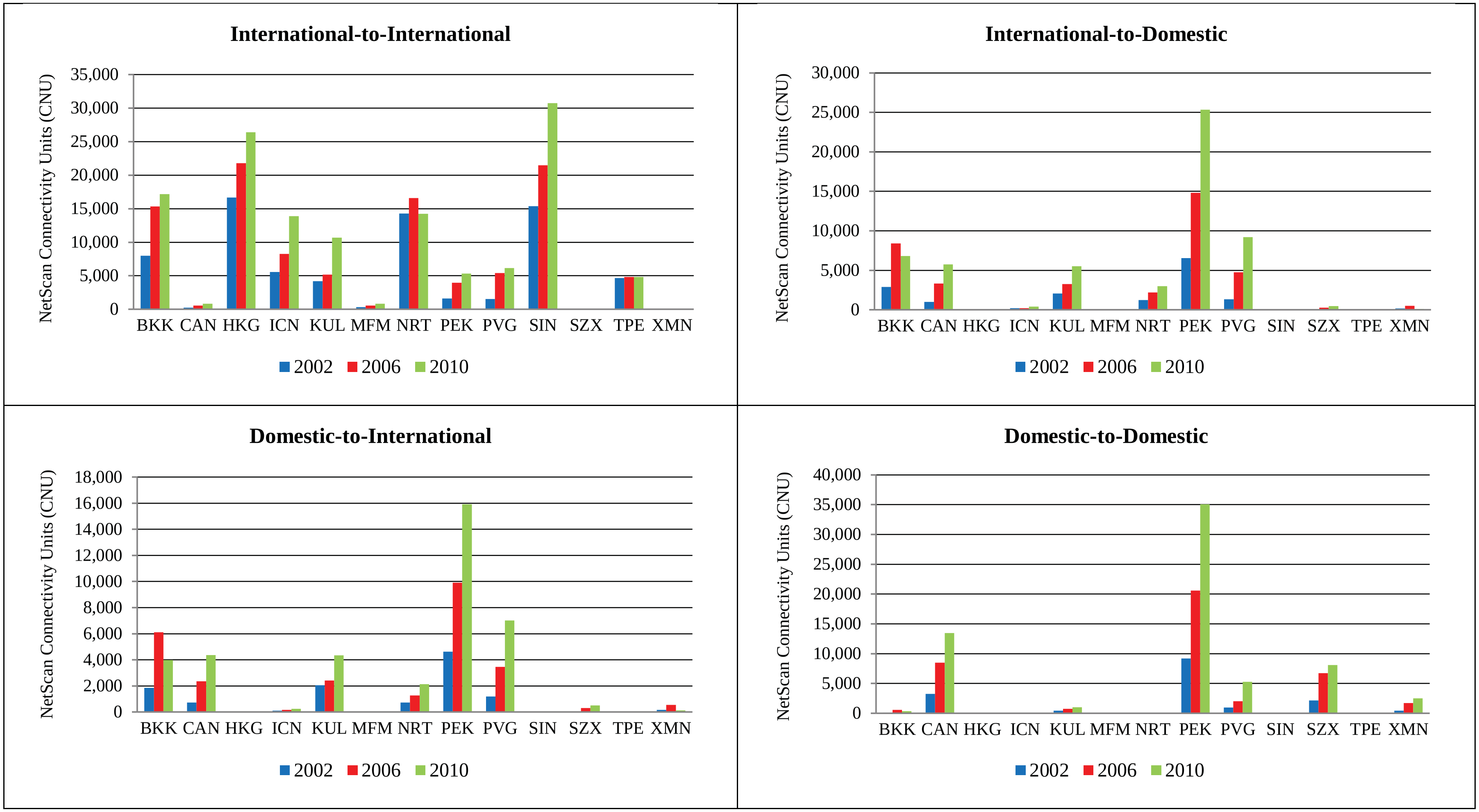

Figure 4.8. **Types of hub traffic handled by Asia-Pacific airports (2002−2010)**

airport to the final domestic destination (International-to-Domestic), (iii) from the originating domestic destination via an intermediate airport to the final international destination (Domestic-to-International), and (iv) from the originating domestic destination via an intermediate airport to the final domestic destination (Domestic-to-Domestic).

The hub connectivity networks of SIN and HKG allowed them to handle the highest volumes of 'International-to-International' hub traffic, indicating their prominent positions of international gateway hub airports in the Asia-Pacific region to transport international passengers across the borders, followed by BKK, NRT, ICN, KUL, PVG, and TPE. This finding was consistent with the fact that these major Asian international gateway hub airports with stronger direct international connectivity networks to connect air passengers to different regions worldwide (see Table 4.6 and Figure 4.3).

One should note that an airport's direct domestic connectivity has a direct relationship with the other three kinds of hub traffic it handles that involve domestic destinations, such as 'International-to-Domestic', 'Domestic-to-International', and 'Domestic-to-Domestic'. Often, the larger direct domestic connectivity network of an airport is, the more likely the airport is to increase the amount of that airport's hub traffic connecting transfer and/or transit passengers to either domestic or international destinations, and *vice versa*. Given PEK's largest domestic flight connectivity network, it had the leading position in handling hub traffic among the Asia-Pacific airports, for 'International-to-Domestic', 'Domestic-to-International', and 'Domestic-to-Domestic' hub connectivity (connecting domestic or international passengers travel within Mainland China or to and from overseas cities), followed by PVG, BKK, KUL, and CAN. Also, all Chinese airports had relatively stronger flight connectivity networks to transport and handle 'Domestic-to-Domestic' hub traffic within Mainland China, which is evident from the rapid expansions in their direct domestic connectivity over the study years (see Table 4.4 and Figure 4.3).

4.6 HKIA AS CHINA'S PRIMARY PASSENGER GATEWAY

The previous sections on airport connectivity network measures have shown that HKG has established a strong direct and hub connectivity network to seven regions around the world, including Africa, Other Asia, North Asia, Southeast Asia, Australasia and Oceania, the Middle East, and North America. Given that China's more liberalised air transport policy and its WTO membership now allow more market access to the Chinese air transport market by foreign airlines, coupled with China's booming international passenger traffic, these provide opportunities for Chinese carriers and foreign airlines to add flight frequencies and expand their Chinese networks. To capture China's increasing international travel demand, many major international airports in the Asia-Pacific region and elsewhere have already established direct or indirect flight connections to five major international airports in Mainland China[37] (e.g. Chin, 1997; Cheong, 2000; Sit, 2001; Seabrooke *et al*., 2003; Zhang, 2003; Zhang & Li, 2003; Hui, Hui & Zhang, 2004; Sit, 2004; Sung, 2002; Sung, 2004).

Under this circumstance, it is reasonable to think that other airports' flight connectivity networks to the identified Chinese airports will adversely affect Hong Kong's long-established position as the main transit point for interchanging and connecting international passengers to Mainland China. Figure 4.9 shows HKG had the leading position for offering the largest direct and hub connectivity to Mainland China among the Asia-Pacific airports and other major international airports elsewhere between 2002 and 2010.

[37] The five major Chinese international airports referred to in this study are PEK, PVG, CAN, SZX, and XMN.

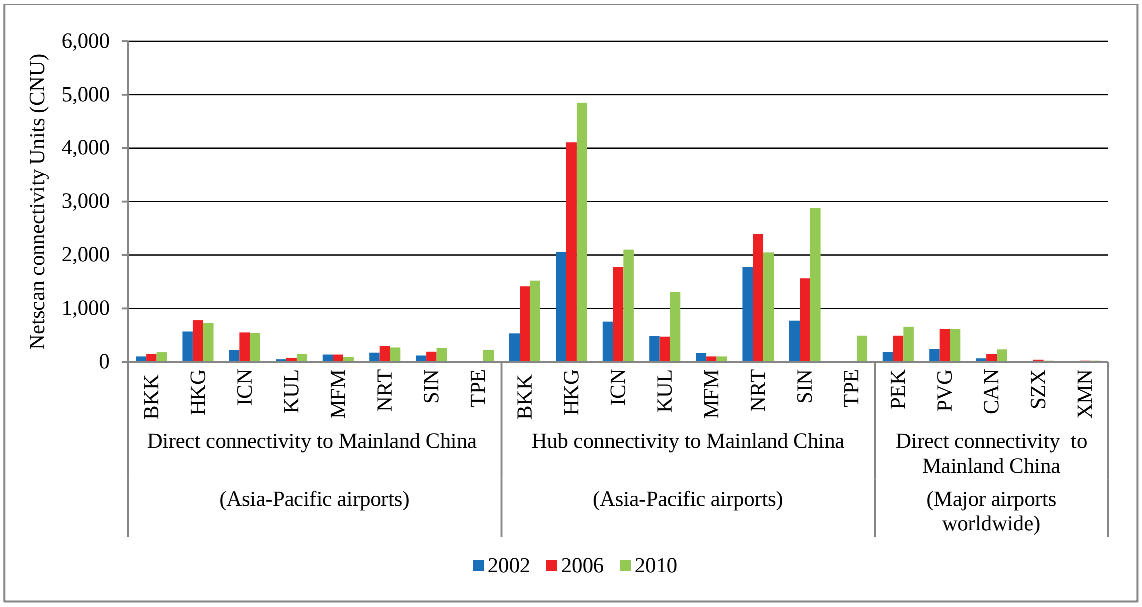

Figure 4.9. **Direct and hub connectivity to Mainland China (2002−2010)**

Given HKG's stronger direct and hub connectivity to Mainland China, this information still could not pinpoint HKG's role as China's primary passenger gateway relative to other major international airports in the Asia-Pacific region and elsewhere, without knowing the actual portion of China's total inbound international visitors by air transport travelling through HKG to Mainland China, in other words, the market share captured by HKG. In investigating HKG's role as China's primary passenger gateway, it is logical that if a larger amount of international visitors travel through HKG to Mainland China, fewer international visitors opt to make stopover(s) via other intermediate airports on their way to Mainland China, or to fly directly to Chinese cities from their origins, and *vice versa*.[38]

Figure 4.10 shows international visitors departure for Mainland China via Hong Kong by air transport between 2006Q1 and 2011Q3. Inspection of the geographic data shows that international visitors originating from the air transport markets of Australasia and Oceania, South and Central America, Macau, North America, and Europe were the largest groups travelling through HKG to visit Mainland China, which contributed at

[38] In general, three different types of air transport channels can be chosen by international visitors to travel to Mainland China: (i) making a stopover via HKIA, (ii) making stopover(s) via other intermediate airport(s) which have flight connections to Chinese cities, or (iii) flying directly to Chinese cities from their origins.

least an average of 6.8% to China's total inbound international visitor numbers by air transport during the study periods. In particular, Australasia and Oceania were the largest contributors (an average of 10.9%) of traveller through HKG to Mainland China throughout the study periods, ahead South and Central America with 9.3%.

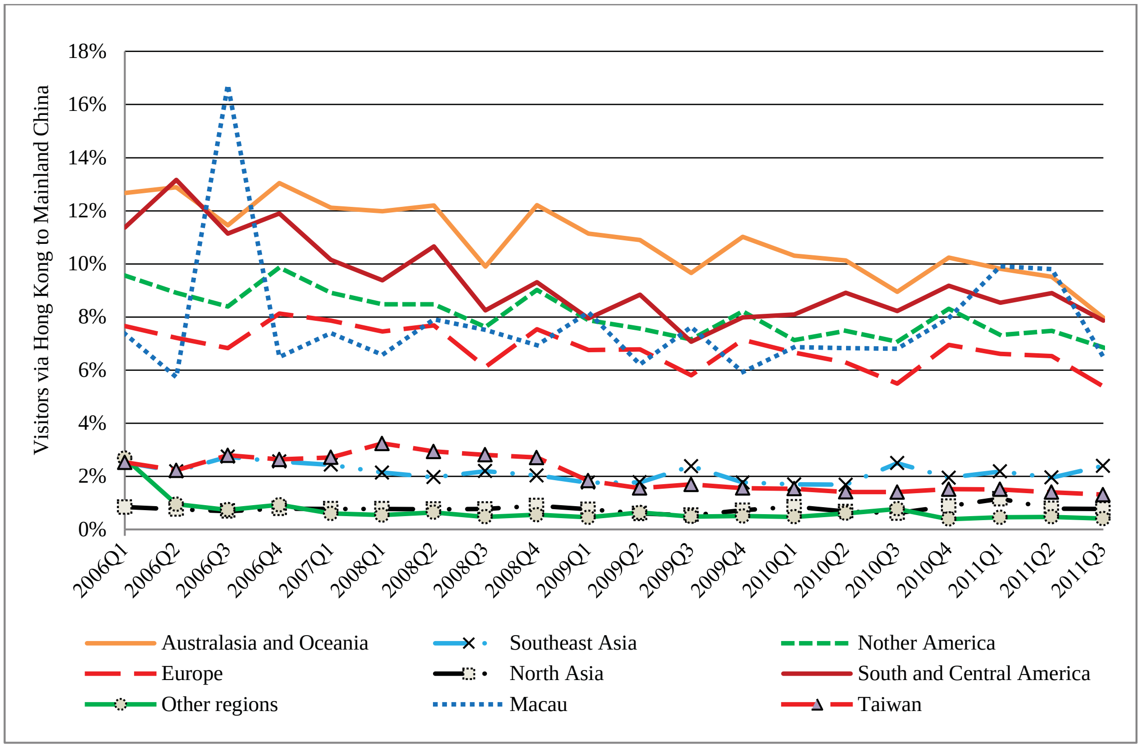

***Figure 4.10*. International visitors departure for Mainland China via Hong Kong by air transport (2006Q1−2011Q3)**

However, HKG experienced declining international visitors from the air transport markets of Australasia and Oceania, South and Central America, North America, and Europe during the study periods. For example, Australasia and Oceania's international visitor numbers travelling through HKG slipped from an average of 9.7% between 2006Q1 and 2010Q2 to 9.3% during 2011Q3. Similarly, South and Central America showed steady declines until 2009Q3, followed by a rebound and a dip during 2011Q3. Furthermore, North America and Europe presented the similar patterns of falling international visitors passing through HKG to Mainland China, but HKG still handled an average of 8.1% and 6.8% of China's total inbound international passenger traffic from these two markets, respectively. In addition, a stable trend was associated with

Macau throughout the study periods, despite a significant spike (16.5%) during 2006Q3. It is clear that HKG captured a significant portion of China's total inbound international passenger traffic by air transport from these key air transport markets, or it successfully attracted them away from other international airports in the Asia-Pacific region and elsewhere to visit Mainland China. Thus, HKG maintained its prominent role as China's primary passenger gateway serving these particular air transport markets.

In contrast, only a smaller but regular amount of international visitors chose to travel through HKG to Mainland China from markets like, Taiwan, Southeast Asia, North Asia, and other regions, equivalent to less than an average of 2.1% throughout the study periods. This situation implies that the majority of China's inbound international visitors by air transport from these markets via other intermediate airports travelled to Chinese cities or flew directly to Mainland China from their originating airports, instead of opting to travel through HKG for their journey. From the market share perspective, HKG cannot be recognised as China's primary passenger gateway for these specific markets concerning the actual share of China's total inbound international visitors by air transport it handled. However, HKG has still maintained its position for serving these air transport markets without losing a significant market share to other competing airports around the Asia-Pacific region and elsewhere.

4.7 DISCUSSION

The deregulation of the air transport industry and the hub-and-spoke networks of airline operations have caused many changes to the airline and airport industry around the world (Bowen, 2000; Shon, Chang & Lin, 2001; Wei & Hansen, 2006). In particular, the growth in air travel demand in the Asia-Pacific region has led to intensified competition among the major international airlines and the key international gateway hub airports (O'Connor, 1995; Park, 2003; Williams, 2006). Therefore the first aim of this study was to investigate the network performance or hub competitiveness of the flight connectivity of Asia-Pacific airports using the CNU model. The CNU model was used to measure and compare the direct, indirect, and hub connectivity of 13 Asia-Pacific airports between 2002 and 2010.

The findings of this study indicate that the rapid growth of flight connectivity networks of major Asia-Pacific airports has resulted in increased competition to capture increasing volumes of international passenger traffic in the region. Indeed, this finding is consistent with the studies of Oum and Yum (2000), Robinson (2006), and Williams (2006), all of whom claimed that the threats from nearby international airports are likely to undermine HKG's prominent role as the major international passenger hub airport in the Asia-Pacific region. Furthermore, it is argued that HKG's leading air cargo hub status is also facing challenge from the rapid international network expansion of major international cargo hub airports around the Asia-Pacific region (Zhang 2003; Zhang *et al*., 2004). Thus, this study showed that it may be straightforward to understand the immediate impact of the new international flight connectivity networks of major Asian international gateway hub airports on HKG's role as the main air transport hub for air passenger and air cargo traffic in the Asia-Pacific region, since all the Asian governments and airport authorities intend to develop their aviation hubs into key air transport hubs in the region (Park, 2003).

The findings presented in this study also provide evidence to suggest that there is potential for HKG to lose its key role as the primary passenger gateway to Mainland China − although it has established the highest flight connectivity network to Chinese cities. This is mainly the result of substantial international flight network expansions by three major Chinese international gateway hub airports (i.e. Beijing, Shanghai Pudong, and Guangzhou airports), and more frequent direct flights connecting to Mainland China from other major international gateway hub airports in the Asia-Pacific region and elsewhere (Robinson, 2006; Williams, 2006; Winston & Rus, 2008).

It is argued that HKG's role as China's primary passenger gateway may not last. This argument is in line with Zhang *et al*. (2004, p.95), who claimed that "neither the [Hong Kong's] gateway role nor the hub role should be taken for granted, and it will be risky to think that the hub role may be maintained forever and ... high growth rates will persist for a long time". Therefore the second aim of this study was to investigate whether HKG can still maintain its role as China's primary passenger gateway to handle China's inbound international visitors by air transport using the market share analysis. The findings provide evidence to suggest that HKG's role as China's primary passenger gateway is being challenged by the major international airports in the Asia-Pacific region and elsewhere in different ways, despite its strongest direct and hub connectivity to Chinese cities (e.g. Robinson, 2006; Williams, 2006; Wang & Jin, 2007; HKAA, 2011). Thus, this study suggests that HKG has been affected by competing airports regarding connecting passenger traffic to Mainland China. As a consequence, this could lead to HKG's slower growth relative to other international airports such as Singapore (Changi) International Airport.

At least two key potential limitations apply to this study. First, the findings from the market share analysis could not allow a completed conclusion to be drawn regarding HKG's role as China's primary passenger gateway, although, to a certain extent, the share of China's total inbound international visitors handled by HKG may suggest this role (Robinson, 2006). Nevertheless, this finding suggests a difficulty in understanding how significant other international airports in the Asia-Pacific region and elsewhere are in affecting the volume of China's inbound international passenger traffic via HKG. Second, in the econometric sense, the existing information about China's inbound international visitors travelling through HKG could not support further statistical analysis to investigate the extent that other international airports handle connecting passenger traffic to Mainland China or lure them away from HKG – those airports also have flight connections to Mainland China – especially the major international gateway hub airports in the Asia-Pacific region (Wooldridge, 2009). It is worthwhile to note that access to the data of connecting passenger traffic to Mainland China via major international airports in the Asia-Pacific region and elsewhere was not available at the time of the analysis of this matter.

In conclusion, all Asia-Pacific airports have shown growth in direct and hub connectivity during the study periods, but experienced declines in indirect connectivity.

The fastest network expansion can be found at the Chinese airports, especially three Chinese international gateway hub airports: Beijing, Shanghai Pudong, and Guangzhou airports. Their growth rates for direct, indirect, and hub connectivity are at a much higher rate than other Asia-Pacific airports. On the other hand, only Bangkok airport experienced deteriorating network performance. HKG established the strongest connectivity to Other Asia (which includes Mainland China) and had a competitive position for connecting air passengers to several regions around the globe such as Africa, North Asia, Southeast Asia, Australasia and Oceania, the Middle East, and North America. More importantly, HKG is still considered as the main transit airport for China's inbound international visitors, including those from Australasia and Oceania, South and Central America, Macau, North America, and Europe.

CHAPTER 5 : FORECASTING OF HONG KONG AIRPORT'S PASSENGER THROUGHPUT

5.1 INTRODUCTION

In the 15 years since the opening of the new HKIA at Chek Lap Kok, its airport traffic volumes (i.e. air passenger numbers and air cargo volume) has grown steadily, except in the aftermath of the September 11 terrorist attacks in US and during the SARS outbreak (e.g. Grais, Ellis & Glass, 2003; McKercher & Hui, 2004; Pine & Mckercher, 2004; Siu & Wong, 2004; Kozak, Crotts & Law, 2007). HKIA has also experienced a tremendous challenge in the face of competition from nearby major international airports located in the PRD region, in Mainland China, and in the neighbouring Asian nations. In terms of future air passenger demand at HKIA, it has been predicted (e.g. Hobson & Ko, 1994; Seabrooke *et al*., 2003; Zhang, 2003; Robinson, 2006; Williams 2006; Ishutkina & Hansman, 2009) that a decline in air passenger and cargo throughput will occur and its dominant role as the international hub and gateway to Mainland China will result in fierce competition. Furthermore, Zhang *et al*. (2004, p.95) stated that "neither the [Hong Kong's] gateway role nor the hub role should be taken for granted, and it will be risky to think that the hub role may be maintained forever and .... high growth rates will persist for a long time".

HKIA is one of the international gateway hub airports in the Asia-Pacific region handling significant amounts of connecting traffic (i.e. transfer and transit traffic) through the airport to different regions worldwide, and this traffic will have a significant impact on the analysis and forecasting of airport passenger demand. An accurate and reliable method of airport passenger demand forecasting is required to assist the short- and long-term planning and decision-making from different entities such as the planning of airport infrastructure and capacity from the government of Hong Kong and the airport authority, as well as flight network planning from home-based airlines.

Tourist demand and the international air cargo hub status of HKIA has already been the subject of many prior studies (e.g. Rimmer, 1992; Schwieterman, 1993; Waters, 1997; Cho, 2003; Hiemstra & Wong, 2003; Song, Wong & Chon 2003; Zhang, 2003; Zhang, Jenkins & Qu, 2003; Hui, Hui & Zhang, 2004; Zhang *et al*., 2004; Williams, 2006; Zhang, Jenkins & Qu, 2006; Wang & Cheng, 2010; Cheng, 2011). Surprisingly, few studies have forecasted airport passenger demand for Hong Kong. These significant shortfalls in prior research with respect to HKIA are the main objective of this study: forecasting and predicting whether its future passenger throughput will continue to grow or decline. Furthermore, it aims to enhance the existing knowledge with respect to the development and application of suitable forecasting models to this specific type of international gateway hub airport.

The current study is believed to be the first empirical study to employ the Box–Jenkins Autoregressive Integrated Moving Average (ARIMA) methodology to build and estimate the Seasonal ARIMA (SARIMA) model and ARIMAX model with explanatory variables for forecasting HKIA's passenger throughput, and also to project its future growth trend for the period of 2011–2015. The forecasting results offer an insight with respect to the growth (or decline) in HKIA's future passenger traffic, and more importantly, this projection highlights the challenges for policy makers, the airport authority, and airline management to meet the changing demand of air passenger traffic for Hong Kong.

The format of this chapter is structured as follows. Section 5.2 presents the literature review related to the Box–Jenkins ARIMA models employed to forecast air travel demand in the air transportation industry and the tourism industry. Section 5.3 outlines the popular methods of airport traffic demand forecast, the strengths and weaknesses of the time series forecasting methods, and the Box–Jenkins ARIMA model and intervention model. Section 5.4 describes the data period and the variables of interest used as well as detailing the ARIMA modelling approach. Section 5.5 presents the empirical results of the SARIMA and ARIMAX models for forecasting future passenger traffic for HKIA. Section 5.6 discusses and summarises the key findings of this chapter.

5.2 LITERATURE REVIEW OF THE BOX–JENKINS ARIMA METHODOLOGY

It should be noted that although other forecasting models are available for air travel demand and airport demand forecast, this review only presents the Box–Jenkins ARIMA models as they have been widely used in forecasting air travel demand for the air transportation industry and the tourism industry.

Numerous studies have used the Box–Jenkins ARIMA models to forecast an airport's traffic demand. Table 5.1 shows a summary of the Box–Jenkins ARIMA models used for forecasting air travel demand and tourist numbers. For example, Uddin, McCullough and Crawford (1985) adopted the ARIMA and regression models to predict airline passenger traffic at Robert Mueller Municipal Airport, and the forecasting results of both models showed reasonable predictability when compared with the forecasts of aviation authorities. Cheung (1991) also employed the ARIMA models and vector autoregressive moving average methods to forecast number of incoming aircraft and passenger arrivals to HKIA between January 1975 and December 1990, and found that the univariate ARIMA models are more accurate than the multivariate models based on one-step ahead and 12-step ahead forecasts. In addition, both the short- and long-term air travel demand forecasts for Honolulu International Airport were investigated by Kawad and Prevedouros (1995), who found that the long-term air travel forecasts should resort to a combination of trend extrapolation with the ARIMA model and educated estimates based on contemporary macroeconomic literature. Prevedouros (1997) used the ARIMA model and explanatory variables with time series regression models to forecast tourist arrivals at Honolulu International Airport from five different destinations, and also predicted five-year ahead arrival volumes. The significance of this study was that the ARIMA forecasting of explanatory variables for the regression analysis is proven to be a reliable method for airport demand forecast. Abed and Bafail (2001) examined the forecasting performance of exponential smoothing, regression models (linear and non-linear), and ARIMA models for forecasting number

Table 5.1. ***Air travel demand forecast using the Box–Jenkins ARIMA models***

Authors and date	Methodology	Airports or countries studied	Items to be forecasted	Significance and forecasting performance
		Airport industry		
Uddin, McCullough & Crawford (1985)	ARIMA model, regression model	Robert Muller Municipal Airport	Air passenger traffic	Both models indicated reasonable predictability.
Cheung (1991)	ARIMA model, vector autoregressive moving average methods	Hong Kong International Airport	Number of incoming aircraft and passenger arrivals	Univariate ARIMA models were more accurate than multivariate ARIMA models.
Pitfield (1993)	ARIMA model, intervention analysis	UK	Monthly domestic route traffic	ARIMA model is superior in replicating traffic data and generating forecasts with intervention analysis.
Kawad & Prevedouros (1995)	ARIMA models	Honolulu International Airport	Air travel demand	Long-term forecasts for airports resort to a combination of trend extrapolation with ARIMA and educated estimates based on contemporary economic literature.
Prevedouros (1997)	ARIMA model, explanatory variables with time series regression model	Honolulu International Airport	Tourist arrivals from five destinations	ARIMA forecasting of explanatory variables for regression analysis was a reliable method for airport demand forecasting.
Aded & Bafail (2001)	Exponential smoothing, regression models, ARIMA model	Jeddah International Airport	Arrival/departure passengers and aircraft movements	The non-linear regression model was the most accurate model for airport demand forecasting.
Chen & Chen (2003)	Multivariate ARIMA model and intervention analysis	Taiwan	Air transportation demand for Taiwan	Both models suggested that the significant impact of the lifting of the Taiwan–China ban on air transport demand between Taipei–Hong Kong route.
Andreoni & Postorino (2006)	Univariate and multivariate ARIMAX models	Reggio Calabria Airport	Air passenger throughput	Both models provided satisfactory forecasting results, but the multivariate model provided more explanatory powers.

Continued on next page

Authors and date	Methodology	Airports or countries studied	Items to be forecasted	Significance and forecasting performance
Jia *et al*. (2007)	ARIMA model	Beijing Capital International Airport	Airport passenger throughput	ARIMA model provided an accurate forecast of airport passenger volumes.
Payne & Taylor (2007)	ARIMA model, Autoregressive-seasonal-trend model	Central Illinois Regional Airport	Airport passenger volumes	Both models provided accurate forecasts, but the autoregressive seasonal trend model outperformed ARIMA model counts for trend and seasonality.
Lee (2009)	ARIMA model, intervention method	Kaohsiung International Airport	Airport traffic demand	Both models provided reliable short-term forecasts.
Abdelghany & Guzhva (2010)	ARIMAX model	Philadelphia International Airport	Airport passenger demand	The model could accurately predict an airport's short-term demand.
Samagaio & Wolters (2010)	SARIMA model, Holt-Winters method	Lisbon Airport	Airport passenger numbers	The forecasting results fitted with other studies and the seasonal ARIMA model might be only accurate in the short-term.
Tourism industry				
Chu (1998)	SARIMA model, sine wave nonlinear regression model	Singapore	International tourist numbers	The models generated the accurate forecast results with small Mean Absolute Percentage Error (MAPE) figures.
Lim & McAleer (2002)	Various ARIMA, SARIMA model	Hong Kong, Malaysia, and Singapore	Tourist arrivals	No single model has been found to have consistently superior forecasting performance.
Cho (2003)	Exponential smoothing, univariate ARIMA model, Artificial Neural Networks (ANN)	Hong Kong	Visitor arrivals	Exponential smoothing and univariate ARIMA model could produce accurate forecasts, but was outperformed by ANN model.
Song, Witt & Lai (2003)	Autoregressive distributed lag model, ARIMA model, other techniques	Thailand	Tourist demand from Australia, Japan, Korea, Malaysia, Singapore, UK, and the US	ARIMA models produced reasonable predictions.

Continued on next page

Authors and date	**Methodology**	**Airports or countries studied**	**Items to be forecasted**	**Significance and forecasting performance**
Akal (2004)	ARMAX model	Turkey	Tourism revenues	The ARMAX model could accurately forecast international tourism revenues for Turkey dependent on earlier arrivals at one, two, and four lagged periods.
Vu & Tuner (2006)	Basic structured model, SARIMA model	Thailand	Guest domestic and international arrivals into nine regions in Thailand	The ARIMA model could accurately forecast the regional tourism demand not only in Thailand, but also for other countries.
Chu (2008)	Fractionally ARIMA model combining economic and political shocks	Singapore	Monthly international tourist arrivals	The forecast models yielded small MAPEs.
Chu (2009)	Three ARMA-based methods	Nine major tourist destinations	Tourist arrivals	The models were reported to be quite accurate and in some cases the MAPEs were lower than 2%.
Lim, McAleer & Min (2009)	ARIMAX models	Taiwan and New Zealand	Japanese tourist arrivals to Taiwan and New Zealand	The ARIMAX model supported the economy theory which states that the demand of international travel is positively related to the income of the origin country.
Chang & Liao (2010)	SARIMA models	Taiwan	Monthly Taiwanese tourists to Hong Kong, Japan, and the US	The fitted models obtained lower MAPEs.
Nanthakumar & Ibrahim (2010)	SARIMA models	Malaysia	International tourism demand	The models provided reliable forecasts of tourism demand.

Remarks: All studies adopted the Box–Jenkins ARIMA based models.

of the arrival and departure passengers and aircraft movements for Jeddah International Airport between 1975 and 1996, and then projected airport traffic for six years ahead. The key findings of the study indicated that a non-linear regression cubic model is the most suitable model for airport demand forecast. Jia *et al*. (2007) outlined the ARIMA model for forecasting air passenger throughput at Beijing Capital International Airport (China) based on the monthly airline passenger data from between January 2004 and June 2004. The empirical results showed that the ARIMA model provides an accurate forecast of airline passenger numbers and airport passenger throughput. Payne and Taylor (2007) also illustrated the procedures for building and estimating the ARIMA and autoregressive-seasonal-trend models for forecasting air passenger traffic at Central Illinois Regional Airport. This study was different from other forecasting airport studies because it demonstrated the autoregressive seasonal trend model outperformed the ARIMA model with its consideration of trend and seasonality. Similarly, the seasonality has been considered by Samagaio and Wolters (2010), who applied the SARIMA model and the Holt-Winters method for examining the official forecasts of Lisbon Airport's passenger numbers between 2008 and 2020; the conclusion was that the forecasting results of the SARIMA model appear to be acceptable in the short run.

The ARIMAX approach has also been widely applied to forecast airport traffic demand. Often, the ARIMAX model is actually derived from the ARIMA methodology combined with the intervention model. Pitfield (1993) examined the efficiency of ARIMA models and regression models in simulating the UK's monthly domestic route traffic, and the conclusion was that the ARIMA models are far superior in terms of its efficiency in replicating the data and generating traffic forecasts with the intervention analysis. Chen and Chen (2003) also combined the multivariate ARIMA model and intervention analysis to predict Taiwan's air transportation demand under the impact of aviation policy change. The results showed that air traffic demand between Taipei and Hong Kong has been heavily affected by the intervention (i.e. the lifting of Taiwan–Mainland China travel ban). Similarly, the univariate and multivariate ARIMAX models used by Andreoni and Postorino (2006) to forecast air transport demand at Reggio Calabria Airport in Southern Italy between 1990 and 2006, investigating the impact of recent modifications in air transport supply. The findings of this study showed that both ARIMA models provided satisfactory forecasting results, but the multivariate

ARIMA model provided more explanatory power, as it incorporated explanatory variables for forecasting airport passenger throughput. Recently, Lee (2009) estimated air traffic volumes at Kaohsiung International Airport (Taiwan) using monthly data from 2004–2008 and forecasted traffic for five month ahead by employing the ARIMA and intervention models, in which the interventions (shocks) including direct flights between Mainland China and Taiwan, holiday periods, and fuel costs. However, it was concluded that forecasting models can only provide an accurate short-term forecast. Lastly, Abdelghany and Guzhva (2010) used Philadelphia International Airport to illustrate short-term airport demand forecast by employing the ARIMAX models incorporating various external factors such as seasonality, fuel prices, airline strategies, incidents, financial conditions, and airport activity levels, and also applied and validated the modelling to the 100 largest US airports. The empirical results showed that an airport's short-term demand can be predicted with acceptable accuracy, even with a simple time series forecasting model.

In the context of the tourism industry, tourist demand is considered to have a direct relationship with the air transportation industry, and the Box–Jenkins ARIMA methodology becomes one of the most popular methods for forecasting tourist numbers owing to "its ability to handle any series, its theoretical foundation and its operational success" (Vanhove, 2005, p.151). Alongside with the univariate ARIMA models, the SARIMA models have also become a popular technique to forecast tourist demand for a country and/or region during last decade since seasonality is a major factor influencing the tourism industry worldwide and exists in most of the tourist arrival time series (Song & Li, 2008). For example, Chu (1998) employed combined non-seasonal and seasonal ARIMA models and a sine wave nonlinear regression forecasting model to predict international tourism arrivals for Singapore from January 1977 to December 1987. The forecasting results were compared with prior studies and revealed that the proposed models have the smallest Mean Absolute Percentage Error (MAPEs). Vu and Turner (2006) also used the basic structured model (BSM) and the SARIMA model to forecast domestic and international guest arrivals into nine city-based regions in Thailand using accommodation data from 1996 to 2002, with an *ex ante* forecasting period of 2003 and 2004. The findings indicated that the regional guest arrival data are useful for accurately forecasting the regional tourism demand not only in Thailand but also for other countries. In addition, Chang and Liao (2010) also applied the SARIMA models for forecasting the monthly tourist departures from Taiwan to Hong Kong, Japan, and the US. Low MAPEs were obtained for the forecasting models demonstrating the adequacy of fitted models. Furthermore, Nanthakumar and Ibrahim (2010) adopted the SARIMA model to estimate international tourism demand and generated a one-period ahead forecast for Malaysia, and the results concluded that the fitted SARIMA model was able to provide a reliable tourism demand forecast.

Various ARIMA and SARIMA models were adopted by Lim and McAleer (2002) to estimate the tourist arrivals to Hong Kong, Malaysia, and Singapore for the period of 1975–1989, but their findings were in conflict and suggested that no single model has consistently superior forecasting performance, but the ARIMA models are quite accurate for Hong Kong and Malaysia (but not Singapore). Cho (2003) also modelled visitor arrivals to Hong Kong from six countries (i.e. the US, UK, Singapore, Japan, Taiwan, and Korea) between 1974 and 2000 using exponential smoothing, univariate ARIMA, and Artificial Neural Networks (ANN). The research results suggested that exponential smoothing and the ARIMA model are sufficiently adequate in predicting tourist arrivals but they are outperformed by the ANN model. Furthermore, the forecasting performances of the autoregressive distributed lag model (ADLM), the ARIMA model, and other forecasting techniques were compared by Song, Witt and Li (2003), for estimating Thailand’s tourist demand from Australia, Japan, Korea, Malaysia, Singapore, UK, and the US. The empirical results suggested that the ARIMA models always produce the most modest predictions. Similarly, Chu (2009) compared the forecasting performances of three ARMA-based methods with various forecasts for predicting tourist arrivals across nine major tourist destinations in the Asia-Pacific region. The forecasting performances of the ARMA-based models were reported to be quite accurate and in some cases the magnitudes of the MAPEs were lower than 2%.

Apart from the Box–Jenkins SARIMA models, the ARIMAX models have become very common for tourism demand forecast, because of its ability to include related causative factors into the ARIMA models. Chu (2008) used the fractionally ARIMA model combining economic and political shocks to predict the monthly international tourist arrivals in Singapore, and the forecasting models yielded small MAPEs. Similarly, Lim, McAleer and Min (2009) adopted the ARIMAX model to forecast tourist arrivals from Japan to Taiwan and New Zealand. The findings suggested that the ARIMAX model can support the economic theory that international travel demand is positively related to the income level of the origin country. Furthermore, the ARMAX model has been used by Akal (2004) to forecast Turkey's tourism revenues. The forecast was an important stimulus for the Turkish government to improve and strengthen the tourism sector, and became a major contributing factor for later economic development.

5.3 METHODOLOGY

5.3.1 Popular methods of airport traffic demand forecast

A variety of methods have been used by airport authorities, aviation agencies, airlines, the industry associations, and the academic research community for forecasting and analysing the air passenger demand of an airport, including econometric methods, time series forecasting methods, market share analysis, industry survey, expert judgment, and scenario analysis (e.g. ICAO, 1985; FAA, 2001; TRB, 2002; Scarano, 2007; Spitz & Golaszewski, 2007; Janic, 2008). These methods can be grouped into the quantitative and qualitative approaches. The quantitative time series forecasting techniques can be further classified into univariate and multivariate approaches (Cho, 2003). The univariate approach is to extrapolate the historical patterns of time series and try to predict their trend in the future, but ignoring other causative factors. The multivariate approach uses multivariate regression techniques for identifying the functional relationships between various variables of interest.

5.3.2 Strengths and weaknesses of the time series forecasting methods

The main advantages related to the time series forecasting methods are their simplicity in forecasting, the lower amount of data required for forecasts, and fewer costs in data collection and model estimation (e.g. Sarames, 1973; Wells & Young, 2004; Spitz & Golaszewski, 2007; Song & Li, 2008). Likewise, the univariate approach requires minimal data that comprise only a time series of the variable of interest being forecasted. The time series forecasting models, however, can vary in complexity (Shaw, 1979). Additionally, the time series forecasting methods can be fairly accurate in the short-term forecasts such as monthly, weekly, and hourly variation of air passenger traffic at airports, but are less accurate for the long-term forecasts (Spitz & Golaszewski, 2007; Karlaftis, 2010). The latter aspect is the main disadvantage of the time series forecasting methods. Furthermore, Wang and Yu (2007, p.4) suggested that "the main advantage of time series [forecasting] method remains its power to explain periodic effects, including seasonal and weekly phenomena, as well as the general trend that follow economic development are also explainable by this model".

In addition to that, the time series forecasting methods do not attempt to explain any reasons for the changes occur or identify the causes of growth. More importantly, their forecasting performance can often be undermined by their ability to link the future growth of the variable of interest with the expected development of causative factors (Abed, Bafail & Jasimuddin, 2001; Karlaftis, 2010). These disadvantages can be partly solved by the multivariate approach which incorporates explanatory variables into the forecasting models (e.g. Cho, 2003; Spitz & Golaszewski, 2007; Janic, 2008; Karlaftis, 2010).

5.3.3 The Box–Jenkins ARIMA model and the intervention model

i. The Box–Jenkins ARIMA model

This section outlines the practical dimensions of the implementation of Box–Jenkins ARIMA methodology.[39] The acronym ARIMA is used to indicate the autoregressive, integrated, and moving average combined method. As its name suggestsd, the Box–Jenkins ARIMA models are theoretically built from the observed time series data on three individual underlying process components: Autoregressive (AR), Moving Average (MA), and Integrated (I). In practice, the Box–Jenkins methodology uses autoregressive integrated moving average process to suggest the most appropriate form of a forecasting model for the time series data.

To combine a pth-order autoregressive process and a qth-order moving average process, a mixed autoregressive moving average model: ARMA ($p, \ q$) is written as shown in Equation (5.1):

$$Y_t = \alpha + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_p \varepsilon_{t-q}$$

(5.1)

It is important to note that the ARMA models can only manage and forecast the stationary time series. Otherwise, inconsistent estimates are obtained.[40] Therefore a non-stationary time series needs to be transformed to become stationary by applying

[39] Few studies (e.g. Box & Jenkins, 1976; Nihan & Holmesland, 1980; Pankratz, 1983; Box, Jenkins & Reinsel, 2008; Gujarati & Porter, 2009) have illustrated the implementation of the Box–Jenkins ARIMA methodology for time series forecasting.

[40] Lim and McAleer (2003) stated that a time series is stationary when its mean and variance do not change over time, or it invariably refers to 'weakly stationary'. If a time series is non-stationary, it is difficult to estimate the mean with any degree of precision because the variance of the process increases (with a limit) as the number of observations increases. Hence, the estimated mean will be unreliable and inconsistent, and also tends to provide extremely large forecasted errors.

differencing before forecasting.[41] Under this circumstance, the necessary level of differencing (I (d)) is added to the ARMA model, making it the autoregressive integrated moving average model or ARIMA (p, d, q) model, expressed in the compact notation shown in Equation (5.2):

$$\Phi(\mathrm{B})\nabla^{d} Y_{t} = \theta(\mathrm{B})\varepsilon_{t} \tag{5.2}$$

Combining the non-seasonal stationary ARIMA (p, d, q) model and the seasonal stationary ARIMA $(\mathrm{P}, \mathrm{D}, \mathrm{Q})$s model, where s denotes the seasonal pattern presented in the time series (i.e. monthly, quarterly, or twice yearly). Thus, the Seasonal ARIMA model can be either written as the SARIMA $(p, d, q)\times(\mathrm{P}, \mathrm{D}, \mathrm{Q})$s model or in the compact notation shown in Equation (5.3):

$$\Phi(\mathrm{B})\omega(\mathrm{B})\nabla^{d}\nabla_{\mathrm{s}}{}^{\mathrm{D}} Y_{t} = \alpha + \theta(\mathrm{B})\Theta(\mathrm{B})\varepsilon_{t} \tag{5.3}$$

where:

$\Phi(\mathrm{B})$ denotes the polynomial non-seasonal AR process of order p

$\omega(\mathrm{B})$ denotes the polynomial seasonal AR process of order P

$\theta(\mathrm{B})$ denotes the polynomial non-seasonal MA process of order q

$\Theta(\mathrm{B})$ denotes the polynomial seasonal MA process of order Q

$\nabla^{d}\nabla_{\mathrm{s}}{}^{\mathrm{D}}$ denotes the level of differencing for non-seasonal and seasonal processes

Y_{t} denotes the dependent variable to be forecasted

ε_{t} denotes the error time in the model

α denotes the constant in the model

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[41] Williams (2007) indicated that differencing creates a transformed series which consists of the differences between lagged observations in the original time series.

ii. Intervention model

The intervention model is an approach to incorporate the impacts of interventions or exogenous shocks into the forecasting model, which may distort the accuracy and performance of the forecasting model, such as governmental policy change and natural disasters. To examine the effects of exogenous shocks, deterministic dummies are incorporated into the forecasting model to develop an intervention model. Often, the SARIMA models are combined with the intervention analysis to include interventions or exogenous shocks into the forecasting models; importantly, their impacts can be considered as either permanent or temporary effects.

I can be an indicator variable, which can have the permanent effect or step function, S_t:

$$S_t = \begin{cases} 1, & if\ t \geq T(at\ and\ after\ the\ intervention) \\ 0, & if\ t < T(before\ the\ intervention) \end{cases}$$

Or I can be an indicator variable, which can have the temporary effect or impulse function, P_t:

$$P_t = \begin{cases} 1, & if\ t = T(at\ the\ intervention) \\ 0, & if\ t \neq T(not\ at\ the\ intervention) \end{cases}$$

If we insert the interventions or shocks into the SARIMA $(p, d, q)\times(\mathrm{P}, \mathrm{D}, \mathrm{Q})$s model in Equation (5.3), the compact notation of intervention model can be written as shown in Equation (5.4):

$$\Phi(\mathrm{B})\omega(\mathrm{B})\nabla^{d}\nabla_{s}{}^{\mathrm{D}}Y_t = \alpha + Ⓗ(\mathrm{B})\Theta(\mathrm{B})\varepsilon_t + x_t \qquad \textbf{(5.4)}$$

where:

$\Phi(\mathrm{B})$ denotes the polynomial non-seasonal AR process of order p

$\omega(\mathrm{B})$ denotes the polynomial seasonal AR process of order P

Ⓗ(B) denotes the polynomial non-seasonal MA process of order q

$\Theta(\mathrm{B})$ denotes the polynomial seasonal MA process of order Q

$\nabla^{d}\nabla_{s}{}^{\mathrm{D}}$ denotes the level of differencing for non-seasonal and seasonal processes

Y_t denotes the dependent variable to be forecasted

ε_t denotes the error time in the model

α denotes the constant in the model

x_t denotes the response function (i.e. step function or impulse function), or sum of the response functions, to one or more interventions

5.3.3.1 Four steps of the Box–Jenkins ARIMA modelling procedure

An important question emerges as to how many orders of AR (p) and MA (q) should be included in the non-seasonal ARIMA model, and how many orders of AR (P) and MA (Q) for the SARIMA model. Four main steps were suggested to perform the ARIMA models: identification, estimation, diagnostic checking, and forecasting (Box & Jenkins, 1976; Box, Jenkins & Reinsel, 2008; Gujarati & Porter, 2009).

i. Identification

The analysis begins with identification, which aims to understand the pattern of the time series data or the initial ARIMA model by plotting the time series to be analysed and forecasted. The plotting may suggest a linear trend and a seasonal pattern (i.e. repeating every 12 months) as well as indicating whether the mean of the time series is stationary or not. If the mean of the time series is not relatively constant over time, a natural logarithmic transformation is required to stabilise the variance. Moreover, the Autocorrelation Function (ACF), the Partial Autocorrelation Function (PACF), and the resulting correlograms provide additional insights into the stationarity of the time series.

The ACF (r_k) represents the autocorrelation with k time periods between the time series or observations, i.e. Y_t and Y_{t-k}, where Y_t is the Y value at time t, $\bar{Y}$ is the sample mean of Y, k is the number of periods between the observations in the time series (Payne & Taylor, 2007). The formula of ACF is written as shown in Equation (5.5):

$$r_k = \frac{\sum_{t=1}^{n-k}(Y_t - \bar{Y})(Y_{t+k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2} \qquad k = 0, 1, \ldots \tag{5.5}$$

In similar fashion, the PACF (ϕ_{kk}) measures the correlations between the time series or observations after controlling for the correlations at the immediate lags or taking the effect of intervening observations into account (Payne & Taylor, 2007; Gujarati & Porter, 2009). The PACF removes the effect of shorter lag autocorrelations from the correlation estimate at longer lags. The value of PACF at the given lag will vary between –1 and +1, with the values near ±1 indicating a stronger correlation. For instance, the PACF between Y_t and Y_{t+3} considers the periods of Y_{t+1} and Y_{t+2} in the time series. The formula is written as shown in Equation (5.6):

$$\phi_{kk} = \frac{r_k - \sum_{j=1}^{k-1} \phi_{k-1,j} . r_{k-1}}{1 - \sum_{j=1}^{k-1} \phi_{k-1,j} . r_j} \qquad k = 2, 3, \ldots \tag{5.6}$$

where $\phi_{kj} = \phi_{k-1,j} - \phi_{kk}\phi_{k-1,k-j}$ and $k = 3, 4, \ldots; j = 1, 2, \ldots; k-1$

For the identification of the orders of AR (p), MA (q), and the level of differencing (d) for the non-seasonal ARIMA models, there is a rule of thumb which indicates that the maximum autocorrelation and partial autocorrelation used to specify an ARIMA model is approximately $n/4$, where n represents the number of observations in the time series (Box & Jenkins, 1976; Payne & Taylor, 2007). Moreover, the correlograms of ACF and PACF provide a visual idea of the orders of AR (p) and MA (q), and the level(s) of differencing (d) required to make the time series being stationary, as well as whether any seasonality in the time series exists. In addition, over-fitting should also be avoided during the identification stage, and the appropriate ARIMA structures should be selected using the principle of parsimony.[42] Thus, if an ARIMA model has a large number of AR and MA lags which may give poor performance, it may be optimal to return to the initial identification stage and consider a more parsimonious model.

One statistical approach is commonly adopted to test the stationary or unit root of the time series by applying the Augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1976). Wooldridge (2009, p.847) also indicated that the "unit root of time series means that a highly persistent time series process where the current value equals last period's value plus a weakly dependent disturbance". In performing the ADF test, there are three possible cases including no constant or trend, constant only, and constant plus a deterministic trend term. Therefore the following regression equations are involved.

$$\Delta Y_t = \gamma Y_{t-1} + \sum_{t=1}^{k} \beta_t \Delta Y_{t-1} + \varepsilon_t \qquad \text{(No constant or trend)}$$

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \sum_{t=1}^{k} \beta_t \Delta Y_{t-1} + \varepsilon_t \qquad \text{(Constant only)}$$

$$\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \sum_{t=1}^{k} \beta_t \Delta Y_{t-1} + \varepsilon_t \qquad \text{(Constant plus a deterministic trend term)}$$

[42] The principle of parsimony adopted in this study is that the simplest explanation that can explain the time series data is preferred.

In practice, the ADF test starts with the selection of the appropriate lag length for testing.[43] It begins with the model which includes no constant or trend, and continues to find a more specific model using t-statistics. In this test, the null hypothesis of the unit root in the time series ($\gamma = 0$) and the test statistics are compared with the corresponding critical values in the Dickey–Fuller test (1976). If the null hypothesis fails to reject, then γ is equal to zero, suggesting that the unit root might be present and the time series is not stationary, and therefore, appropriate levels of differencing required for stabilising the fluctuation of the time series. More importantly, at the end of the identification step, it would be possible to know the pattern of the time series (i.e. the orders of AR (p), AR (P), MA (q), and MA (Q)), the level(s) of differencing (d) and (D) required for establishing a tentative non-seasonal and seasonal ARIMA model with the stationary time series.

ii. Estimation

After identifying the appropriate orders for AR, MA, and the required level(s) of differencing for the non-seasonal and seasonal components in the tentative ARIMA model, the estimation of coefficient of parameters can then be performed with either the iterative Ordinary Least Squares (OLS) method or the Maximum Likelihood (ML) method. Several tentative ARIMA models are considered to be accurate for modelling the time series: the Akaike Information Criterion (ACI) (1974) and the Schwarz Information Criterion (BIC) (1978) have the tests that can be used to assist the selection of appropriate ARIMA models.[44]

In terms of the evaluation of forecasting accuracy between tentative forecasting models, Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) are the popular statistical tests to be calculated for measuring forecasting accuracy. The calculation of MAPE values can be performed as shown in Equation (5.7):

[43] If too many lags are included, the power of the test will be reduced accordingly. Under the General-to-Specific (GS) approach for the ADF test, 12 or 13 lags will be normally picked for testing the monthly data, 2 or 3 lags for testing the annual data, and 4 or 5 lags for testing the quarterly data.

[44] Small values of the AIC and the SIC test results help in determining the best-fit ARIMA model compared with the values of tentative forecasting models.

$$\text{MAPE} = \frac{1}{n}\sum_{t=T+1}^{T+n}\left|\frac{\hat{y}_t - y_t}{y_t}\right|\times 100 \tag{5.7}$$

where $\hat{y}_t$ $(t = 1, 2, \ldots, n)$ is the forecasted value, and y_t $(t = 1, 2, \ldots, n)$ is the actual value. The lower MAPE value of a forecasting model, the better its forecasting performance will be (Chen, Chang & Chang, 2009; Chu, 2009). Table 5.2 shows the values of MAPE to evaluate the forecasting accuracy of a forecasting model (Lewis, 1982).

Table 5.2. ***MAPE values for the forecasting model evaluation***

MAPE (%)	**Level of accuracy for evaluation**
MAPE ≤ 10%	Highly accurate forecasting
10% < MAPE ≤ 20%	Good forecasting
20% < MAPE ≤ 50%	Reasonable forecasting
MAPE > 50%	Inaccurate forecasting

In addition, the calculation of RMSE can be performed as shown in Equation (5.8):

$$\text{RMSE} = \sqrt{\sum_{\text{t=T+1}}^{\text{T+n}}(\hat{y}_t - y_t)^2}\ /n \tag{5.8}$$

where $\hat{y}_t$ $(t = 1, 2, \ldots, n)$ is the forecasted value, and y_t $(t = 1, 2, \ldots, n)$ is the actual value. A lower RMSE value for a forecasting model suggests that the model has a smaller sample standard deviation for the forecast errors in the forecasting model and has better forecasting performance.

iii. Diagnostic checking

For the diagnostic checking, the adequacy of the selected ARIMA model is checked by considering the properties of residual autocorrelation presented in the forecasting model or whether the residuals are the 'white noise' characteristics.[45] In addition, the randomness of the residual autocorrelation from the chosen ARIMA models can also be checked by the ACF and PACF residual correlograms. The criterion is that both the ACF and PACF residuals should be within $\pm 2/\sqrt{n}$ of zero and within the 95% of significance level. In this case, further investigations of new ARIMA models are not required.

In addition, the Ljung–Box *Q*-statistics can also be used to test the null hypothesis of no autocorrelation up to lag k (Ljung & Box, 1978). For interpreting the estimated results of Ljung–Box *Q*-statistics, if the *p*-value associated with the *Q*-statistics is larger than α at lag k (i.e. *p*-value $<\alpha$), we fail to reject the null hypothesis of no autocorrelations up to lag k, the chosen ARIMA model is considered inadequate for forecasting, and then a new or modified ARIMA model should be established until a satisfactory model can be determined. The formula for the Ljung–Box *Q*-statistics is given in Equation (5.9):

$$Q_m = n\,(n+2)\sum_{k=1}^{m}\frac{r_k^2}{T-k} \tag{5.9}$$

where:

r_k = the residual autocorrelation at lag k

T = the number of observations in the time series

m = the number of time lags included in the test

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[45] '*White noise*' characteristics implies that the residuals in the forecasting model are normal, independent, and identically distributed with zero mean and variance σ^2, $\varepsilon_t \sim \text{iid } N\,(0, \sigma^2)$.

iv. Forecasting

The forecasting process can be performed using static or dynamic forecast. The static forecast is very straightforward. It is sometimes called as the *one-step ahead* forecast into the future using actual numbers rather than forecasted values for lagged dependent variables. The dynamic forecast is considered as the *n-step ahead* forecast in which the previously forecasted values for the lagged dependent variables are used in forming forecasts of current values. After the forecasting process, the out-of-sample or *ex-post* forecasts are used for evaluating the forecasting accuracy of forecasting models by comparing respective actual values with forecasted values in the times series. The out-of-sample periods are the periods after the end of the sample period for modelling the forecasting model, and the latest periods are set aside for checking forecasting accuracy. Often, the forecasting model is considered to be accurate if it has a good out-of-sample predictive power when a smaller forecasted error exists between actual and forecasted values.

5.4 DATA DESCRIPTION AND THE BOX–JENKINS ARIMA MODELLING APPROACHES

The monthly data for the air passenger traffic of HKIA between January 1993 and August 2011 were obtained from the airport authority and Civil Aviation Authority of Hong Kong. Future passenger traffic for HKIA was modelled and forecasted using the Box–Jenkins ARIMA methodology (i.e. the SARIMA and ARIMAX models) and its future airport passenger throughput ahead to December 2015 was predicted.

The SARIMA model was used to model HKIA's monthly air passenger traffic between January 1993 and November 2010, which contained 215 observations. The remaining data from December 2010 to August 2011 were used for evaluating the *ex-post* forecasting performance of the forecasting model. Furthermore, concerning the impact of different countries or regions upon air travel demand for Hong Kong, the total air passenger traffic travelling to HKIA was split and grouped into 11 principal origins, namely Mainland China, Other Asia, the Middle East, Europe, Africa, Southeast Asia, Taiwan, Japan, Australasia and Oceania, the United Kingdom, and North America. Each of the identified origins was forecasted by the SARIMA model. These forecasting results are important to policy-making and future market segment analysis in Hong Kong's tourism industry.

An accurate and reliable airport-specific demand forecast is necessarily guided by its endogenous and exogenous forces for a local or non-local forecast (Strand, 1999). In addition, air passenger throughput of an airport will be largely affected by its ability and strategic role for transporting air passengers to and from the countries or regions, as well as the economic and operating environment in which the airport deals with. Therefore the ARIMAX model (i.e. the multivariate ARIMA model) was computed to take into account the identified endogenous or exogenous variables and shock effects in the cause-effect time series regression model (e.g. Akal, 2004; Andreoni & Postorino, 2006; Williams, 2007; Lim, McAleer & Min, 2009; Abdelghany & Guzhva, 2010; Postorino, 2010). The ARIMAX model only forecasted HKIA's monthly passenger throughput between January 2001 and November 2010, which contained 102 observations, mainly because of the limitation of available data with respect to the variables of interest which are deemed to have a significant impact on the forecasting of HKIA's future passenger throughput. Information relating to the explanatory variables over the forecasting periods was mainly collected from the airport authority, Hong Kong Tourism Board (HKTB), Hong Kong Census and Statistics Department (HKCSD), and the International Monetary Fund. Data from December 2010 to August 2011 was used for out-of-sample validation purposes.

5.5 ESTIMATION RESULTS

5.5.1 SARIMA models for HKIA and its 11 principal origins

As stated in Section 5.4, future passenger traffic for HKIA as a whole and for its 11 principal origins were modelled and forecasted by the SARIMA models during the first part of forecast. After the graphical analysis, all of the time series were found to exhibit different trends along with the possibility of seasonal patterns. The logarithm transformation has been chosen to stabilise all of the time series. Figure 5.1 displays the time plot of ln (monthly air passenger traffic) for HKIA and for its 11 principal origins between January 1993 and August 2011. The seasonality plots of all of the time series are also shown in Figure 5.2.

Five principal origins (i.e. Mainland China, Taiwan, Southeast Asia, Japan, and Other Asia) occupied the vast majority of HKIA's passenger throughput during the study periods, equalling an average of 77.5% of its monthly passenger traffic. This suggested that Hong Kong serves as one of the primary passenger gateway hub airports to Mainland China and is the airline crossroad of Asia-Pacific countries. Moreover, air passenger traffic for HKIA and from its eight principal origins (i.e. Mainland China, Other Asia, the Middle East, Europe, Southeast Asia, Australasia and Oceania, North America, and Africa) clearly showed upward trends over the study periods, but the trends for Japan and Taiwan were quite stable. However, the SARS outbreak caused an abrupt decline in air passenger numbers travelling through HKIA between late 2002 and mid-2003 (i.e. November 2002−July 2003) for all of the time series. In addition, the seasonality plots presented that the highest concentrations of air passengers traffic travelling to HKIA from different origins occur every July, August, and December which are the peak travelling periods during the summer holidays and Christmas, whereas the lowest amount of air passenger traffic appeared during the months of May and June.

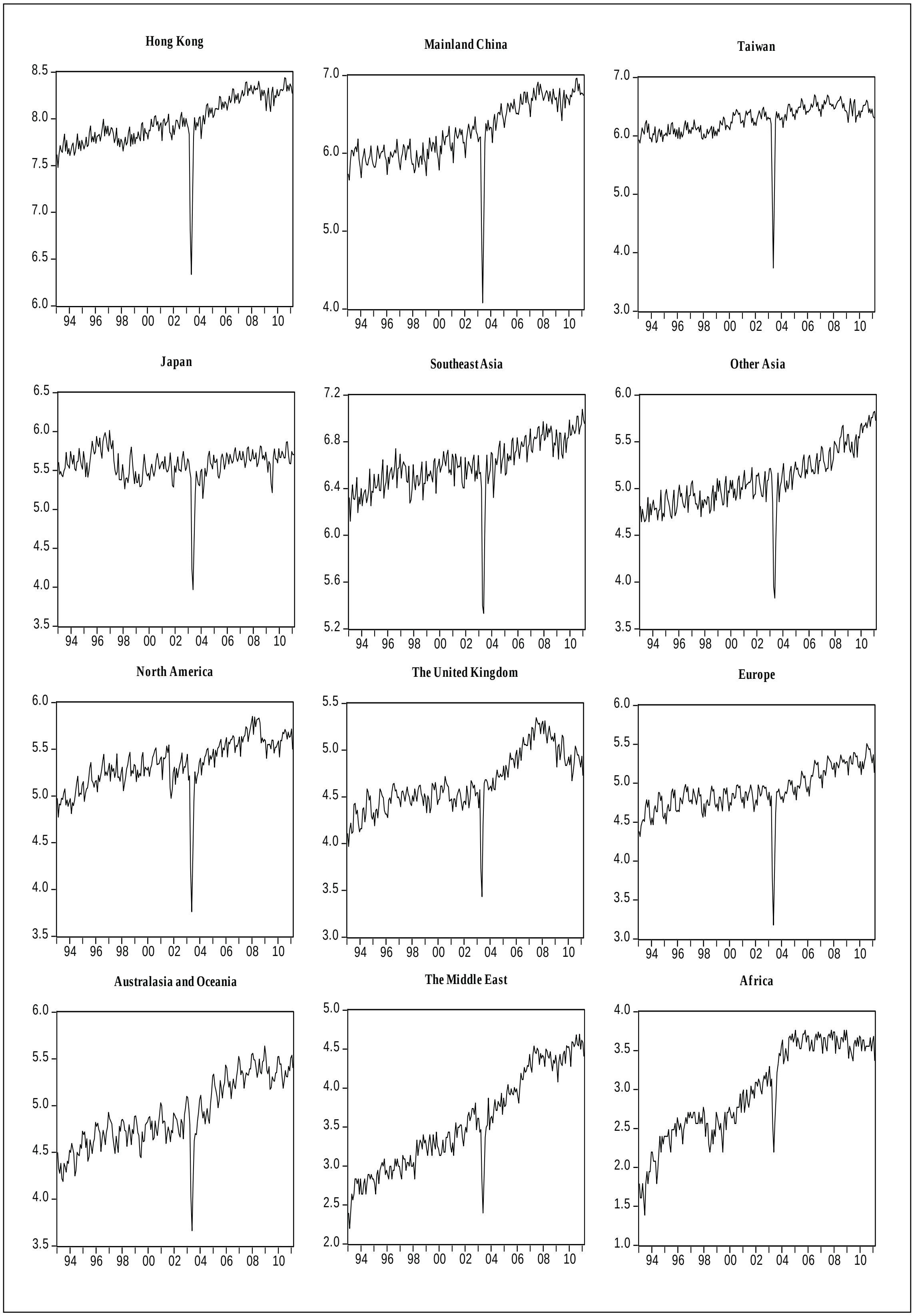

***Figure 5.1*. The time plots of ln (monthly air passenger traffic) for HKIA and its 11 principal origins (January 1993−August 2011)**

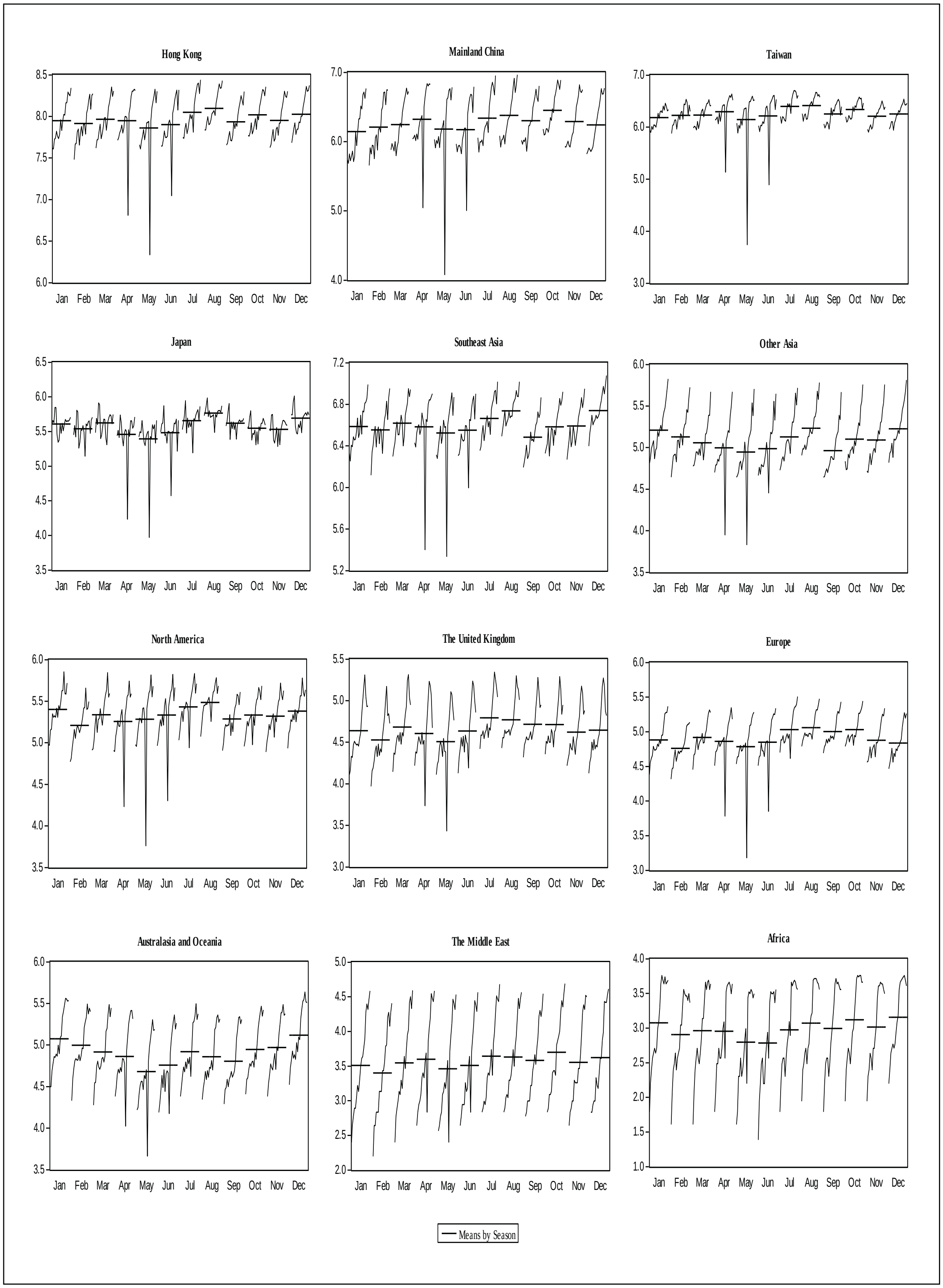

Figure 5.2. **Seasonality plots of ln (monthly air passenger traffic) for HKIA and its 11 principal origins (January 1993−August 2011)**

Before performing the estimations of ln (monthly air passenger traffic) time series for HKIA and for its 11 principal origins, all of the time series need to be stationary (absence of a unit root). The ADF tests were used to check whether the time series of origins were stationary including 'no constant or trend', 'constant only', or 'constant plus a deterministic trend term'.[46] Table 5.3 presents the ADF test results of ln (monthly air passenger traffic), which indicate that only Japan is stationary, since the null hypothesis of a unit root in the time series is rejected at the 0.05 significance level (p-value < 0.05). In addition, the time series of HKIA, Taiwan, and North America have a trend stationary, as the null hypothesis of unit roots can be rejected at the 0.05 significance level. However, after applying first-order differencing, the remaining time series are also stationary and followed an integration of order 1, I(1). Further tests were not performed.

Table 5.3. ***ADF tests for HKIA and its 11 principal origins (January 1993−November 2010)***

Origins	**Constant only**		**Constant & Trend**	
	ln (APT)	Δln (APT)	ln (APT)	Δln (APT)
HKIA	0.486	0.000	0.042**	0.000
Mainland China	0.741	0.000	0.093*	0.000
Taiwan	0.113	0.000	0.004***	0.000
Japan	0.015**	0.000	0.065*	0.000
Southeast Asia	0.372	0.000	0.053*	0.000
Other Asia	0.952	0.000	0.408	0.000
North America	0.212	0.000	0.038**	0.000
The United Kingdom	0.558	0.000	0.616	0.000
Europe	0.614	0.000	0.152	0.000
Australasia and Oceania	0.685	0.000	0.468	0.000
The Middle East	0.881	0.000	0.081*	0.000
Africa	0.460	0.001	0.618	0.002

Remarks: ln (APT) denotes ln (monthly air passenger traffic). The values stated above are p-values. *, **, and *** indicate that the explanatory variable is significant at the 0.10, 0.05, and 0.01 significance level, respectively.

[46] The ADF test results for '*no constant or trend*' were not reported since they provided similar test results to '*constant only*' In addition, if the time series is stationary without the deterministic trend term, this means that the time series is stationary with a constant at that level; if the time series is stationary with '*constant plus a deterministic trend term*', this means that the time series is trend stationary at that level.

With the stationary time series, both the ACF and PACF correlograms were used to identify the orders of the autoregressive components, AR (p) and AR (P), and the moving average components, MA (q) and MA (Q), for the time series for HKIA and for its 11 principal origins.[47] After extensive trial-and-error specification, and also using the lowest AIC and SIC test results, the best-fit models with the best forecasting performance for forecasting future passenger traffic for HKIA and for its 11 principal origins were identified. To confirm the adequacy of the selected SARIMA models, the ACF and PACF diagnostic correlograms as well as the Ljung–Box Q-statistics verified that the residual series have the 'white noise' characteristics and no significant autocorrelation was present in the residual series, and therefore, the SARIMA models were adequately estimated.

After identifying the best-fit SARIMA models for HKIA and for its 11 principal origins, the best-fit models were estimated based on the OLS estimation procedure. The regression results are given in Table 5.4, providing that all of the AR and MA terms are statistically significant at least ≥ 0.05 significance level, and the estimated parameters of AR and MA terms are less than one, supporting the required 'stationarity' and 'invertibility' conditions.[48] For instance, the best-fit SARIMA $(1,0,1)\times(1,0,1)_{12}$ model for HKIA has the overall predictable power with an adjusted-R^2 of 0.86 and lower values of MAPE and RMSE, which also indicates that the forecasting model is highly accurate for forecasting HKIA's passenger traffic (see Table 5.4). With respect to the estimated results of HKIA's 11 principal origins, the most appropriate SARIMA models are $(1,1,2)\times(1,0,1)_{12}$ for Mainland China, SARIMA $(1,0,1)\times(0,0,1)_{12}$ for Taiwan, SARIMA $(1,0,1)\times(1,0,1)_{12}$ for Japan, SARIMA $(1,1,2)\times(1,0,1)_{12}$ for Southeast Asia, SARIMA $(1,1,2)\times(1,0,1)_{12}$ for Other Asia, SARIMA $(1,0,1)\times(1,0,1)_{12}$ for North America, SARIMA $(2,1,1)\times(1,0,0)_{12}$ for the United Kingdom, SARIMA $(1,1,2)\times(1,0,1)_{12}$ for Europe, SARIMA $(1,1,2)\times(1,0,1)_{12}$ for Australasia and Oceania, SARIMA$(1,1,1)\times(1,0,0)_{12}$ for the Middle East, and SARIMA $(1,1,2)\times(1,0,0)_{12}$ for

[47] Refers to Appendix A, which shows the ACF and PACF correlograms for the time series for HKIA and for its 11 principal origins.

[48] Payne and Taylor (2007) stated that '*stationarity*' applies to the autoregressive terms and ensures that the forecasting model will generate forecasts whose variance does not increase without a limit. '*Invertibility*' applies to the moving average term and ensures that the weights placed on past observations decline as one moves further into the past.

Table 5.4. ***SARIMA models of the monthly passenger traffic for HKIA and its 11 principal origins (January 1993−November 2010)***

	Hong Kong	**Mainland China**	**Taiwan**	**Japan**	**Southeast Asia**	**Other Asia**	**North America**	**The United Kingdom**	**Europe**	**Australasia and Oceania**	**The Middle East**	**Africa**
Explanatory variables	**Coefficients**	**Coefficients**	**Coefficients**	**Coefficients**	**Coefficients**	**Coefficients**	**Coefficients**	**Coefficients**	**Coefficients**	**Coefficients**	**Coefficients**	**Coefficients**
Constant	4.839***	0.449	5.894***	5.598***	-0.198*	-0.305***	-18.704	0.004	-0.191	0.187	0.007	0.009
	(3.19)	(1.14)	(156.13)	(36.51)	(-2.23)	(-2.46)	(-0.28)	(0.42)	(-0.57)	(0.54)	(1.04)	(0.28)
Trend	0.010**	-0.001	0.003***	-	0.001***	0.001***	0.019	-0.000	0.000	-0.000	0.000	-0.000
	(2.55)	(-1.79)	(7.55)		(3.41)	(3.99)	(0.47)	(-0.24)	(0.86)	(-0.57)	(0.47)	(-0.19)
AR(1)	0.588***	0.441***	0.468***	0.722***	0.525***	0.569***	0.728***	0.746***	0.613***	0.557***	0.766***	-0.707***
	(3.98)	(2.88)	(3.00)	(8.51)	(4.66)	(3.74)	(6.24)	(5.33)	(5.63)	(2.85)	(7.67)	(-5.40)
AR(2)	-	-	-	-	-	-	-	-0.292**	-	-	-	-
								(-2.53)				
SAR(12)	0.959***	0.965***	-	0.960***	0.957***	0.958***	0.991***	0.525***	0.976***	03973***	0.513***	0.465***
	(72.36)	(52.66)		(80.09)	(105.33)	(113.95)	(153.84)	(4.14)	(74.29)	(122.95)	(5.04)	(6.95)
MA(1)	0.550***	-0.483***	0.426*	0.393***	-0.586***	-0.664***	0.535***	-0.828***	-0.455***	-0.547***	-0.987***	0.551***
	(4.69)	(-3.21)	(1.71)	(4.33)	(-4.60)	(-3.95)	(4.18)	(-10.88)	(-2.79)	(-3.50)	(-208.74)	(3.33)
MA(2)	-	-0.514***	-	-	-0.408***	-0.332*		-	-0.540***	-0.293**	-	-0.289**
		(-3.50)			(-3.18)	(-1.96)			(-2.97)	(-2.37)		(-2.54)
SMA(12)	-0.970***	-0.965***	0.233**	-0.943***	-0.966***	-0.946***	-0.935***	-	-0.923***	-0.949***	-	-
	(-8180.90)	(-73.49)	(2.21)	(-71.77)	(-40.49)	(-43.03)	(-46.44)		(-27.14)	(-31.48)		
Adj-R^2	0.86	0.43	0.65	0.76	0.58	0.62	0.87	0.37	0.58	0.62	0.35	0.37
AIC	-1.764	-0.938	-0.629	-1.530	-1.698	-1.838	-1.872	-1.606	-1.738	-2.095	-1.385	-1.445
SIC	-1.665	-0.823	-0.550	-1.447	-1.582	-1.723	-1.774	-1.507	-1.623	-1.980	-1.303	-1.346
MAPE (%)	1.04	1.70	2.01	2.29	1.40	1.67	2.00	3.96	2.07	3.69	3.93	4.51
RMSE	0.17	0.22	0.24	0.21	0.15	0.14	0.19	0.24	0.17	0.23	0.20	0.28

Remarks: *, **, and *** indicate that the explanatory variable is significant at the 0.10, 0.05, and 0.01 significance level, respectively. *t*-statistics are printed in parentheses.

Africa. Their respective MAPE errors ranged from 1.40% to 4.51%, which suggested that these fitted SARIMA models could generate highly accurate forecasts

As noted above, the main aim of this study is to perform future passenger traffic forecasts for HKIA ahead to 2015. Figure 5.3 shows HKIA's future passenger demand is projected to maintain stable growth from 2011 to 2015. Concerning air passenger traffic for HKIA's 11 principal origins, Japan is projected to remain stable. Southeast Asia, Other Asia, North America, the United Kingdom, Europe, Australasia and Oceania, and the Middle East are likely to see growth. To be more specific, HKIA will experience the largest growth in air travel demand from Southeast Asia, Other Asia, and Europe. To a larger extent, these origins will support HKIA's future passenger growth demand, as well as maintaining and strengthening its role as one of the main international gateway hub airports in the Asia-Pacific region. However, negative growth in air passenger traffic is predicted for Mainland China, Taiwan, and Africa. Their declines will be largely related to fewer Chinese nationals travelling to Hong Kong in the future and because the liberalisation of China's air transport industry allows many local and foreign airlines to establish more frequent direct flight services to connect to the major Chinese international airports and overseas cities. In particular, Beijing, Shanghai Pudong, Guangzhou, Shenzhen, and Xiamen airports have started to capture significant amounts of connecting traffic travelling through HKIA and have attracted more outbound international passengers flying directly from China to foreign countries (e.g. Robinson & Bamford, 1978; Hui, Hui & Zhang, 2004; Ngo, 2005; Wang & Jin, 2007; Winston & Rus, 2008; Chow & Fung, 2009). In addition, HKIA is also regarded as one of the key transit points for Taiwanese travellers to make a stopover when visiting Mainland China, but the signing of the cross-strait (direct air link) agreement between Mainland China and Taiwan is expected to cause a decline in air passenger traffic from Taiwan travelling through HKIA to Mainland China in the future.

In evaluating the forecasting performance, all of the fitted SARIMA models were able to forecast future passenger traffic for HKIA and for its 11 principal origins with the remarkably high accuracy levels. However, larger residuals were found in the origins of Africa, Japan, the United Kingdom, and North America. It must be highlighted that

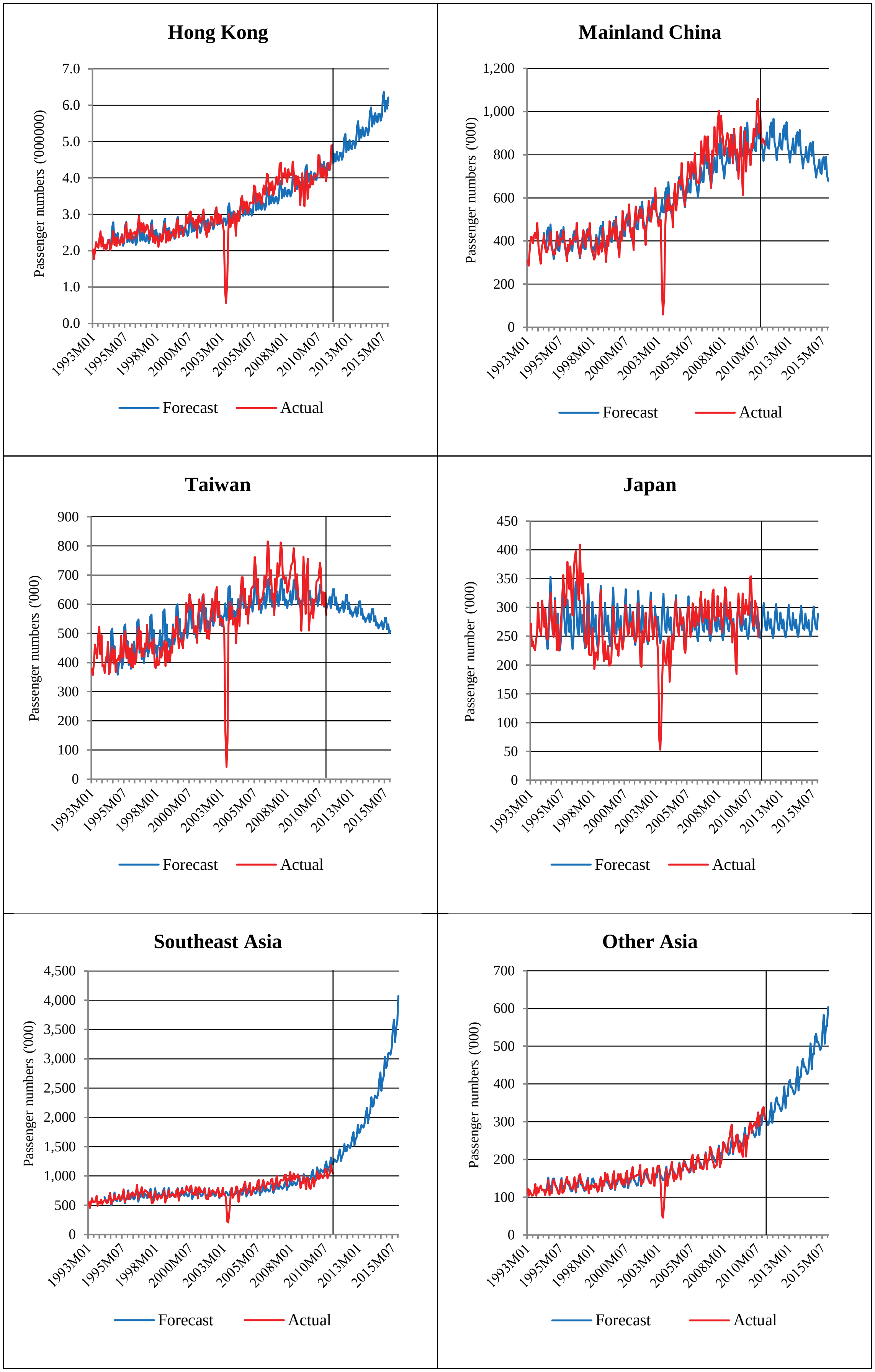

***Figure 5.3.* SARIMA models for the monthly air passenger traffic projection of HKIA and its 11 principal origins (January 1993−December 2015)**

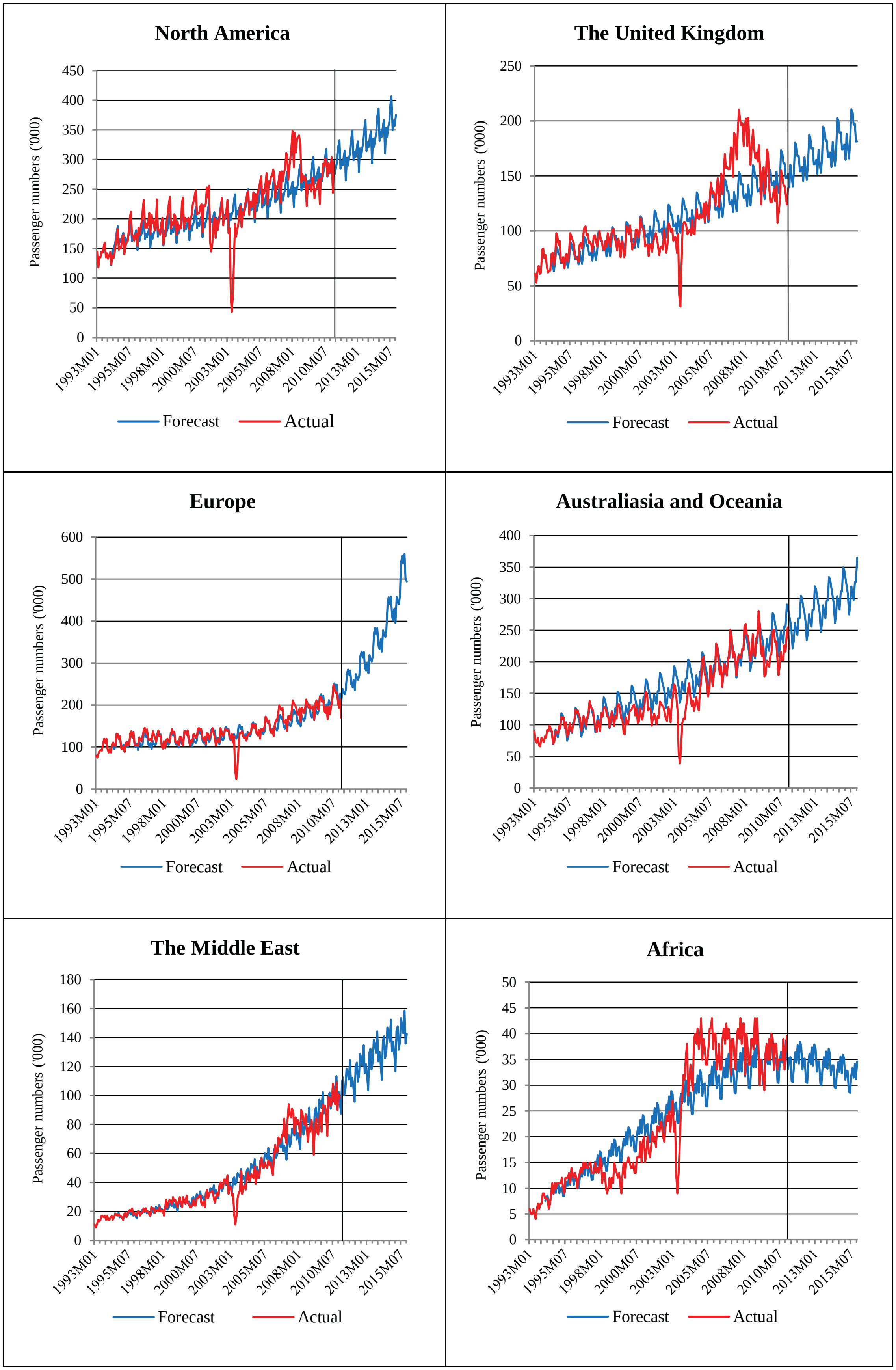

Figure 5.3 (continued)

none of the fitted SARIMA models could successfully capture the negative effect of the SARS outbreak (i.e. the outlier) showing a larger degree of residuals during this particular period (see Figure 5.3).

5.5.2 The ARIMAX model for HKIA

5.5.2.1 Performance of the SARIMA model

The ARIMAX model was employed to model HKIA's monthly passenger traffic for the period of January 2001 and November 2010, which takes into account the effects of exogenous factors and the airport's operating characteristics. Given the nature of the ARIMAX model (i.e. the multivariate ARIMA model), the SARIMA model need to be initially computed prior to the modelling of the ARIMAX model for forecasting airport passenger throughput for Hong Kong.[49]

To forecast the ln (monthly air passenger traffic) time series using the SARIMA model, the ADF test was performed to test the stationarity of the time series for HKIA, the results indicated that the null hypothesis of a unit root being present in the time series can be rejected above the 0.05 significance level (p-value < 0.05), indicative of the time series being stationary with constant and trend effect at an $\mathrm{I}(0)$ process. A further differencing process was not required. In addition, both the ACF and PACF correlograms also indicated that the time series has some seasonal, autoregressive and moving average processes, justifying the use of the SARIMA model for forecasting HKIA's monthly passenger traffic. After extensive trial-and-error specification, the best-fit SARIMA model – the one that has the smallest AIC and SIC test values – for forecasting HKIA's monthly passenger traffic is the SARIMA $(1,0,1)\times(1,0,1)_{12}$ model. Furthermore, both the ACF and PACF diagnostic correlograms verified that the residual series are the 'white noise' characteristics, and the Ljung–Box Q-statistics confirmed

[49] Section 5.3.3 and Section 5.3.3.1 illustrated the four steps used to compute the SARIMA model for this study based on the Box–Jenkins ARIMA methodology.

the randomness of residuals in the fitted SARIMA model.[50] Table 5.6 shows that all of the AR and MA terms are statistically significant at the 0.01 significance level, and their values suggested the requirements of 'stationarity' and 'invertibility' are met, but the trend is not significant. Overall, the best-fit SARIMA model for HKIA has predictive power with an adjusted-R^2 of 0.85 and it is highly accurate with the smaller MAPE (063%) and RMSE (0.03). HKIA's future monthly passenger traffic demand is also projected to steadily grow to 2015 with a smaller growth rate (see Figure 5.7).

Using the selected best-fit SARIMA $(1,0,1)\times(1,0,1)_{12}$ model, the ARIMAX model continues to incorporate the identified explanatory variables for modelling and forecasting future passenger traffic for HKIA. It should be noted that at this stage all relevant exogenous and/or endogenous factors are carefully considered in view of their likely impacts on the forecasting of HKIA's future passenger throughput. More importantly, the selection of explanatory variables for the ARIMAX model is largely influenced by a rule to construct a more parsimonious and multivariate forecasting model which can accurately forecast HKIA's future passenger traffic (Lorek & Willinger, 1996). Looking at prior studies and HKIA's unique operating characteristics, several explanatory variables were identified for the ARIMAX modelling, which are discussed in the following sections.

5.5.2.2 Explanatory variables for the ARIMAX model

i. Originating and connecting traffic

HKIA is one of the world's largest airports and is classified as an intercontinental gateway airport,[51] transporting very large amounts of international passengers across the borders (i.e. originating and connecting traffic) as well as serving most destinations worldwide. In terms of airport hinterland size, HKIA can also be considered as a

[50] Refer to Appendix B, which shows the ACF and PACF correlograms for the time series for HKIA (SARIMA model).

[51] Matthiessen (2004) claimed that HKIA can be classified as an international gateway airport based on the airport classification.

‘fortress hub’ airport which serves catchments far greater in extent than the metropolitan region within which it is located (Graham, 1999).

Two types of air passenger traffic travel through HKIA: (i) originating or local traffic which is the traffic either starting or ending a trip at the airport as the origin and the destination, and (ii) connecting traffic (i.e. transfer or transit traffic), which is the traffic travelling from an airport to another airport transferring at the intermediate airport (de Neufville, 1995; Wei & Hansen, 2006). Moreover, transfer passengers arrive and depart an airport on different flights, whereas transit passengers arrive an airport and subsequently depart in a flight having the same flight number (e.g. ICAO, 1985; de Neufville, 1995; McKercher & Tang, 2004; Janic, 2008). HKIA has successfully established its prominent role as an international gateway hub airport to the PRD region and to other major cities in Mainland China, and the main air transport hub to Asian countries or the ‘superhub’ to Asia, providing frequent flights and extensive flight connectivity networks by transferring significant amounts of international passengers through Hong Kong from a large number of places to many other places worldwide (e.g. O’Connor 1995; Oum & Yu, 2000; Zhang *et al*., 2004; Mason, 2007; Oum, Zhang & Fu, 2009). Therefore separate analyses of originating and connecting traffic travelling through HKIA need to be performed for obtaining more reliable estimates of its future passenger throughput in the ARIMAX model.

ii. Visitors by air transport

HKIA is a travel gateway to a large number of destinations and regions worldwide with frequent and extensive flight services being available, particularly for five major destination types of tourists travelling through Hong Kong, namely Single Destination, Gateway Destination, Egress Destination, Hub Destination, and Touring Destination.[52] More importantly, Hong Kong is a major tourist destination in Asia and considered a ‘shopping paradise’ by most tourists. More than 80% of tourists visited Hong Kong by air transport in the past (Weisel, 1997; Choi, Chan & Wu, 1999; Doong, Wang & Law, 2008). In addition, the reports of HKTB reported that an average of 12.6% of Chinese citizens used air transport to visit Hong Kong annually between 2001 and 2010, and

[52] Refer to Table 2.1, which shows these five major types of tourists travelling through Hong Kong.

also the total number of visitors to Hong Kong by air transport has grown more than 3.72 times over the years (see Figure 5.4). This suggests that number of visitors by air transport to Hong Kong has an important impact on the forecasting of HKIA's future passenger throughput, and thus, this variable is incorporated into the ARIMAX model.

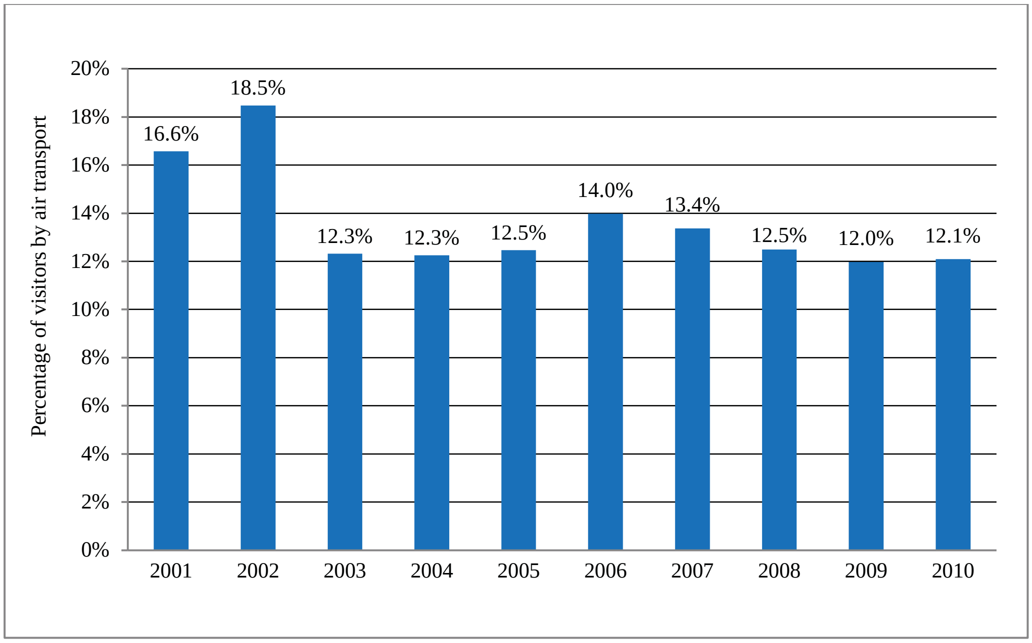

Figure 5.4. **Chinese citizens visiting Hong Kong by air transport**

Interventions and shocks

Another important issue for forecasting accurate passenger demand for an airport is the actual and likely impacts of interventions or shocks during the estimations. As explained in Section 5.3.3, this issue can be solved by employing an intervention analysis that incorporates the appropriate independent variable time series (e.g. the deterministic dummy variables) into the forecasting model in accordance with the nature of permanent or temporary effects of an event. Similarly, the forecasting of HKIA's passenger throughput was deemed to be disrupted by the impacts of exogenous shocks and government policies (i.e. aviation regulations and tourism policies) in the past and the future. One should notice that it would be impossible to discuss all of the interventions or shocks affecting HKIA's passenger throughput forecast, and thus several key events have been identified, as well as their likely effects, as illustrated in Figure 5.5.

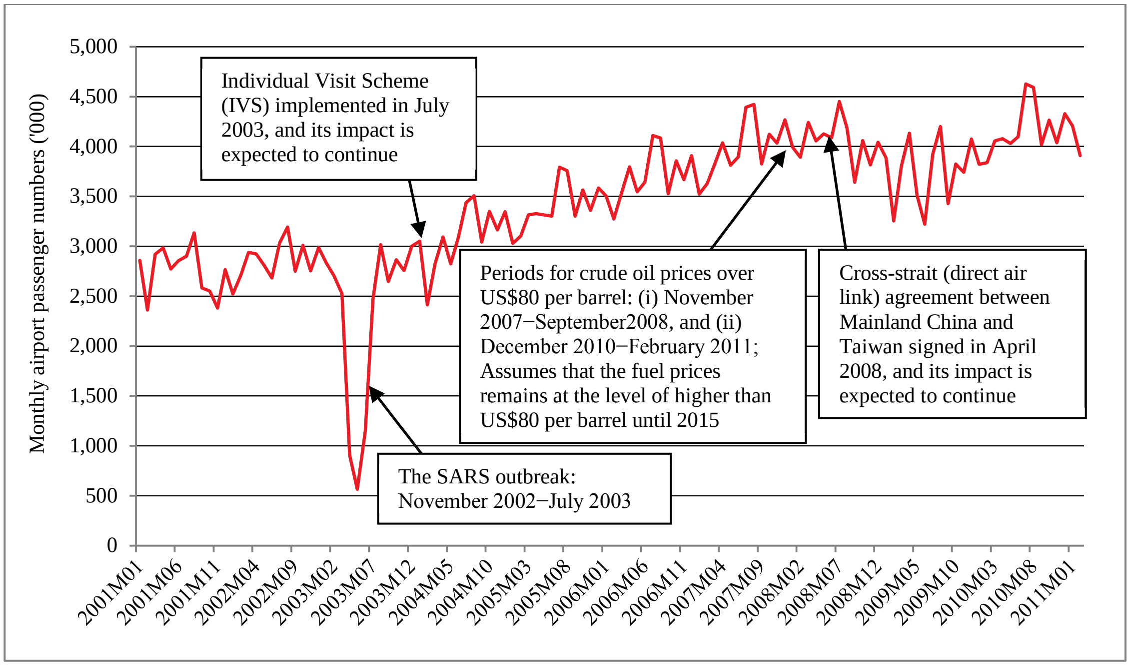

***Figure 5.5*. The likely effects of interventions upon HKIA's monthly air passenger traffic (January 2001−December 2015)**

iii. The SARS outbreak

The SARS outbreak had a negative impact on HKIA's passenger demand during the periods from November 2002 to July 2003, leading the declines in air passenger traffic travelling through HKIA (e.g. Grais, Ellis & Glass, 2003; Lam, Zhong & Tan, 2003; Pine & Mckercher, 2004; Siu & Wong, 2004; Robinson, 2006). Although this kind of disruptive event cannot be predicted in advance, it can still distort the forecasting accuracy of the ARIMAX model if its impact is not considered properly. The variable of $SARS_t$ was incorporated into the ARIMAX model to show its likely effect upon month t of HKIA's passenger throughput:

$$SARS_t = \begin{cases} 1, & if \;\; t = November\ 2002 - July\ 2003\ (at\ the\ intervention) \\ 0, & if \;\; t \neq November\ 2002 - July\ 2003\ (not\ at\ the\ intervention) \end{cases}$$

iv. Cross-strait agreement between Mainland China and Taiwan

Direct air transport links were prohibited between Mainland China and Taiwan as the result of political tensions since 1949. In the past, the cross-strait air traffic (i.e. air passengers and air cargo) was normally routed through a third nation or an intermediary as the transit point prior to entering the border on either side. HKIA, however, became the most convenient place for air passengers transiting and air cargo trans-shipment due to its strategic location and geographic proximity to both Mainland China and Taiwan. Importantly, the earlier rigid air travel restrictions across the Taiwan strait assisted growth in the airline industry and airport operations of Hong Kong, where Taiwan was the second largest source market for Hong Kong after Mainland China (Oum & Yu, 2000). The cross-strait agreement or '*sang tong*' between Mainland China and Taiwan was signed and the direct air travel was lifted in April 2008, and the agreement was expected to have an adverse effect upon total number of Taiwanese travellers passing through Hong Kong to Mainland China. In particular, three Chinese airports (i.e. Fuzhou, Xiamen, and Shanghai Pudong airports) were expected to become the new top three passenger transit airports when considering Mainland China and Taiwan air links commercially (e.g. Hobson & Ko, 1994; Waters, 1997; Mok & Dewald, 1999; Oum & Yu, 2000; Shon, Chang & Lin, 2001; Clark, 2002; Lin & Chen, 2003; Seabrooke *et al*., 2003; Zhang, 2003; Hui *et al*., 2004; Zhang *et al*., 2004; Robinson, 2006; Guo *et al*., 2006; Chang, Hsu & Lin, 2011; Lau *et al*., 2012). Therefore the variable of $Cross\ Strait\ agreement_t$ was incorporated into the ARIMAX model, which represents the effect of signing the cross-strait agreement between Mainland China and Taiwan in month t affecting the number of Taiwanese travellers passing through HKIA to Mainland China:

$$Cross\ Strait\ agreement_t = \begin{cases} 1, & if\ \ t \geq April\ 2008\ (at\ and\ after\ the\ intervention) \\ 0, & if\ \ t < April\ 2008\ (before\ the\ intervention) \end{cases}$$

v. Fuel prices

Fuel prices always affect air travel demand while airlines seek to offset operating costs by imposing fuel surcharges; also, air travellers appear to be very sensitive to fare increases (Straszheim, 1978; Abrahams, 1983). For instance, HKIA experienced abrupt declines in air passenger traffic during periods when crude oil prices reached the level of US$80 per barrel or more: (i) November 2007−September 2008, and (ii) December 2010−July 2011.[53] For the estimation, the crude oil prices was assumed to maintain at the level of more than US$80 per barrel for the period of March 2011 and December 2015, and it will continue to affect air travel demand for HKIA.[54] Therefore the variable of $Fuel\,prices_t$ was incorporated in the ARIMAX model, which corresponds to the monthly change of crude oil prices in month t affecting the number of air passengers travelling through HKIA:

$$Fuel\,prices_t = \begin{cases} 1, & if\;\; t \geq US\$80\; per\; barrel\; (at\; and\; after\; the\; intervention) \\ 0, & if\;\; t \neq US\$80\; per\; barrel\; (not\; at\; the\; the\; intervention) \end{cases}$$

vi. Individual Visit Scheme

China's openness to the outside world encouraged more cross-border travel for Chinese citizens, but the ability of Chinese residents travel internationally depends largely on two essentials such as adequate personal income and official permission from the Chinese government. In addition, China's rapid economic development has led to the tremendous growth in its outbound and inbound tourism (e.g. Yu & Lew, 1997; Lew, 2002; Zhang, Jenkins & Qu, 2003; Zhang & Lew, 2003; Arlt, 2006; Ryan & Gu, 2009).

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[53] Data relating to the monthly crude oil prices was obtained from the US Energy Information Administration and Illinois Oil & GAS Association.

[54] The variable of fuel prices and the dummy variable of fuel prices were investigated during the ARIMAX modelling. Due to the lack of future monthly crude oil prices, the Box–Jenkins SARIMA methodology was adopted to forecast their future prices for the period of August 2011 to December 2015. However, the forecasting results indicated explosive future crude oil prices (i.e. reaching about $190 per barrel in 2015), which is not consistent with those of government and industry forecasts. For example, the US Energy Information Administration predicted that crude oil prices will reach around $95 per barrel in 2015. In addition, the unforeseeable global economic situation and its likely impacts on future crude oil prices cannot be accurately predicted in advance, and therefore, the use of dummy variable of fuel prices is appropriate for the ARIMAX modelling.

Mainland China is expected to become the world's biggest source of outbound tourism, sending 115 million of its nationals abroad annually by 2020 (Wong, Bauer & Wong, 2008).

Tourism has a close relationship with the airline industry, and the growth of China's outbound tourism market is believed to have a significant impact on the air transportation industry and airport operations of Hong Kong. In order to boost the Hong Kong's tourism industry, the policy of Individual Visit Scheme (IVS) between Mainland China and Hong Kong was introduced in July 2003. This seeks to simplify travel applications for Chinese citizens visiting Hong Kong. Among the approved 49 Chinese IVS cities, Chinese residents from Guangdong, Shenzhen, Shanghai, and Beijing were the main sources of visitors travelling to Hong Kong for shopping and sightseeing (e.g. Zhang, Jenkins & Qu, 2003; Martin, 2007; Choi *et al.*, 2008; Yeung & Shen, 2008; Cheng, 2011). To consider the possible effect of IVS upon HKIA's future passenger throughput in month *t*, the variable of IVS_t was incorporated into the ARIMAX model:

$$IVS_t = \begin{cases} 1, & if\ \ t \geq July\ 2003\ (at\ and\ after\ the\ intervention) \\ 0, & if\ \ t < July\ 2003\ (before\ the\ intervention) \end{cases}$$

5.5.2.3 Forecasting of connecting traffic and visitors by air transport for HKIA

The ARIMAX procedure for forecasting HKIA's future passenger throughput is to incorporate the selected best-fit SARIMA $(1,0,1)\times(1,0,1)_{12}$ model (see Section 5.4 and Section 5.5.1), three major types of air passenger traffic travelling through HKIA (i.e. originating traffic, connecting traffic, and visitors by air transport) and the identified effects of interventions or shocks over the forecasting periods (i.e. the SARS outbreak, the cross-strait agreement between Mainland China and Taiwan, fuel prices, and Individual Visitor Scheme (IVS)) into the time series forecasting regression model. It should be noted that the forecasting accuracy of ARIMAX model for forecasting HKIA's future passenger traffic is largely dependent on the accuracy of the forecasted values of the explanatory variables incorporated into the forecasting model. The unknown forecasted values of the explanatory variables and the likely impacts of interventions or shocks need to be carefully estimated (ICAO, 1985). If the underlying assumptions of explanatory variables are changed, even modestly, a completely different forecast may result (de Neufville, 1991). In order to forecast future values of those of identified explanatory variables accurately in the ARIMAX model, the approach is to use available forecasts and/or estimates from external sources, or to apply the ARIMA methodology for forecasting the explanatory variables which could not be obtained or were difficult to collect.

With respect to originating traffic, GDP per capita is considered as the market size and the level of economic development of a country or city, and also it is often used as a proxy due to its direct correlation with air travel demand (e.g. Cline *et al*., 1998; Graham, 2006; Boeing, 2008; Yao & Yang, 2008; Ishutkina & Hansman, 2009; Suryani, Chou & Chen, 2010). The available forecast of Hong Kong's GDP per capita for the period of April 2011 to December 2015 was obtained from the IMF.[55] In addition, the future values of connecting traffic travelling through HKIA and visitors by air transport travelling to Hong Kong are not known or are extremely difficult to obtain due to the lack of published data, and thus, these two variables were forecasted by employing the Box–Jenkins ARIMA methodology as outlined in Section 5.3.3. The best-fit forecasting model for ln (Connecting traffic) is the SARIMA $(1,0,1)\times(1,0,1)_{12}$ model and that for ln (Visitors by air transport) is the SARIMA $(2,0,1)\times(1,0,1)_{12}$ model[56] (see Table 5.5). Both forecasting models were highly accurate, with lower MAPEs and RMSEs, respectively.

[55] For validation purposes, both IMF and HKCSD offered the same figures for Hong Kong's GDP per capita between 2001 and 2010. Therefore the IMF's forecasts for Hong Kong's GDP per capita form a reliable external data source in the ARIMAX modelling.

[56] The ADF results indicated that the times series of ln (Connecting traffic) and ln (Visitors by air transport) are stationary with constant only at the 0.05 significance level. In addition, Appendix C shows the ACF and PACF correlograms for the time series of ln (Connecting traffic) and ln (Visitors by air transport).

Table 5.5. ***SARIMA models of connecting traffic for HKIA and visitors by air transport to Hong Kong (January 2001−November 2010)***

Dependent variables	ln (Connecting traffic)	ln (Visitors by air transport)
Explanatory variables	**Coefficients**	**Coefficients**
Constant	14.293***	15.540***
	(184.36)	(16.22)
AR(1)	0.587***	0.858***
	(3.68)	(5.13)
AR(2)	-	-0.307**
		(-2.02)
SAR(12)	0.784***	0.948***
	(9.78)	(20.51)
MA(1)	0.501***	0.669**
	(3.28)	(7.98)
SMA(12)	-0.938***	-0.955***
	(-39.37)	(-45.22)
Adj-R^2	0.81	0.86
AIC	-1.013	-1.041
SIC	-0.887	-0.890
MAPE (%)	0.88	0.98
RMSE	0.24	0.28

Remarks: *, **, and *** indicate that the explanatory variable is significant at the 0.10, 0.05, and 0.01 significance level, respectively. *t*-statistics are printed in parentheses.

The amount of connecting traffic travelling through HKIA is projected to grow at a smaller scale for the period of March 2011 to December 2015 (see Figure 5.6). However, this situation also highlights the challenges faced by the airport authority and the government of Hong Kong to maintain HKIA as the main air transport hub in the Asia-Pacific region and the primary passenger gateway to Mainland China while facing three different levels of competition, including sub-national competition from international airports in Southern China (the PRD region), national competition from three major Chinese international gateway hub airports, and regional competition from other major international gateway hub airports around the Asia-Pacific region.

For sub-national competition, HKIA has been associated with a cluster of five airports in the PRD region in Mainland China collectively, identified as the A5 group, namely Hong Kong, Guangzhou, Shenzhen, Zhuhai, and Macau airports. These airports operate within a 200-kilometre radius and this multiple airport region has one of the highest airport densities in the world. This makes HKIA very sensitive to increased competition

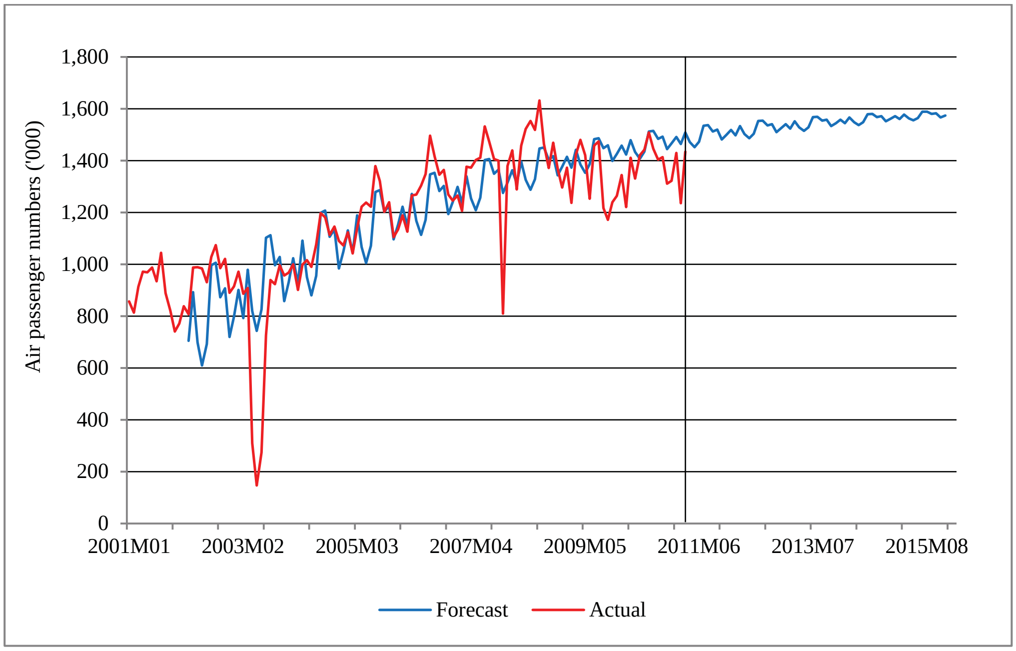

Figure 5.6. **Projection of connecting traffic travelling through HKIA (January 2001−December 2015)**

within Southern China. For national competition, three major Chinese international hub airports (i.e. Beijing, Shanghai Pudong, and Guangzhou airports) started to share and take away a large share of connecting traffic visiting Chinese cities through their increasingly more extensive Chinese airport networks and more frequent flights, rather than travelling through HKIA (e.g. Robinson & Bamford, 1978; Yam & Tang, 1996; Mok, 1998; Starkie, 2002; Zhang, 2003; Hui, Hui & Zhang, 2004; Zhang *et al*., 2004; Ngo, 2005; Wang *et al*., 2006; Williams, 2006; Wang & Jin, 2007; Winston & Rus, 2008; Yeung & Shen, 2008; Chow & Fung, 2009). For regional competition, HKIA faces the competition from the major international gateway hub airports in the Asia-Pacific region (i.e. Bangkok, Singapore, Kuala Lumpur, Tokyo, Seoul, and Taipei). It is obvious that the high population density, strong economic growth, improving political stability, and widespread adoption of the 'open-skies' policies in the Asia-Pacific region have boosted the regional air transport demand. Such growing air transport demand has resulted in fierce competition between these major Asian international gateway hub airports (e.g. Hobson & Ko, 1994; O'Connor, 1995; Chin, 1997; Li, 1998; Mok, 1998; Bowen, 2000; Chan, 2000; Chang, Cheng & Wang, 2003; Park, 2003; Rimmer, 2003; Matsumoto, 2004, 2005, 2007; Williams, 2006; Winston & Rus, 2008). Importantly, the regional competition from the major Asian international gateway hub airports could have two significant negative impacts on HKIA's passenger traffic: (i) gateway traffic to the PRD region and other major cities in Mainland China, and (ii) hub traffic for Asian destinations.

On the other hand, the number of future visitors by air transport travelling to Hong Kong is projected to grow steadily towards 2015 (see Figure 5.7). In this context, it can be said that the future growth in visitors by air transport travelling to Hong Kong will exert a significant impact on HKIA's future passenger throughput, and also Hong Kong will continue to maintain its current position as one of the major tourist destinations in Asia for shopping and sightseeing.

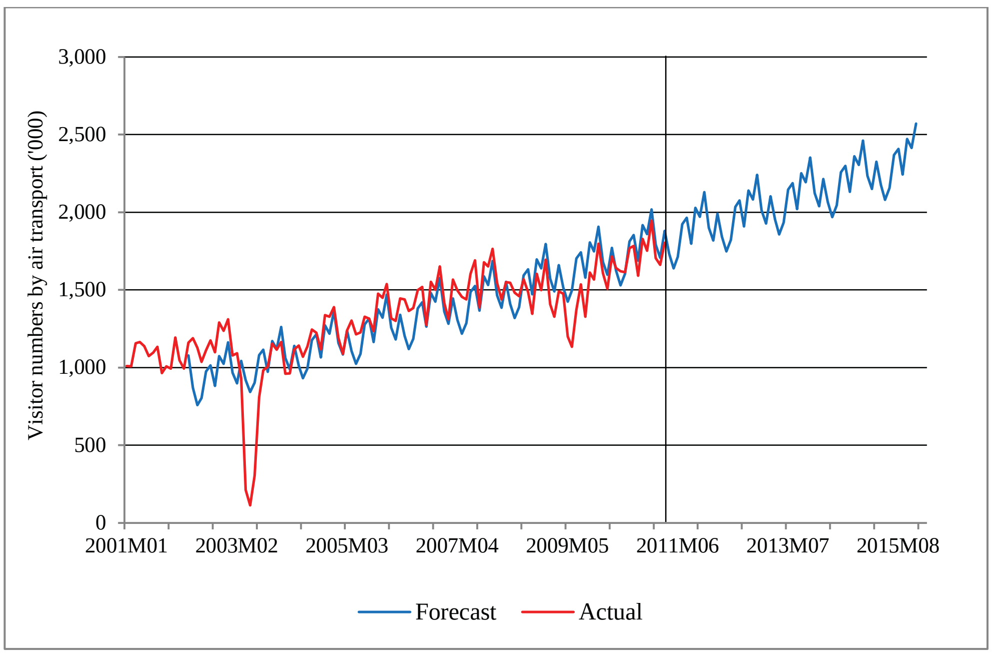

***Figure 5.7*. Projection of visitors by air transport travelling to Hong Kong (January 2001−December 2015)**

5.5.2.4 Estimated results of the ARIMAX model for HKIA

To forecast HKIA's future passenger throughput using the ARIMAX model, the General-to-Specific (GS) approach was adopted to determine the lags of ln (GDP per capita), ln (Connecting traffic), and ln (Visitors by air transport) by eliminating the lagged variables which were statistically insignificant during the time series regression analysis (Henry, 1995; Song, Wong & Chon, 2003; Balli & Elsamadisy, 2010). Table 5.6 shows the regression outputs of the best-fit ARIMAX model which had a good fit with an adjusted-R^2 of 0.99 and reported a highly accurate forecast with the remarkable values of MAPE (0.13%) and RMSE (0.12); the forecasting model also had the 'white noise' characteristics of the residual series confirmed by both the ACF and PACF residual correlograms and the Ljung–Box *Q*-statistics.[57] These results suggested that the fitted ARIMAX model is acceptable for forecasting HKIA's future passenger throughput.

Most explanatory variables in the ARIMAX model were reported to be statistically significant at above the 0.10 significance level, except the variables of $\ln(\text{GDP per capita})_{t-1}$, $\ln(\text{GDP per capita})_{t-2}$, and IVS. It should be mentioned that the likely impacts of Hong Kong's GDP per capita on number of originating traffic travelling through HKIA should take into account the present and previous four month's Hong Kong GDP per capita data. Furthermore, HKIA's monthly passenger traffic forecast was significantly affected by the present period of connecting traffic travelling through HKIA and number of visitors by air transport travelling to Hong Kong. Moreover, the SARS outbreak, the cross-strait agreement between Mainland China and Taiwan, and fuel prices exerted significant impacts on HKIA's monthly passenger traffic forecast, as expected. However, IVS became statistically insignificant in forecasting HKIA's future monthly passenger traffic as the majority of Chinese citizens visiting Hong Kong still use land transportation for crossing the border from the city of Shenzhen to Hong Kong.

[57] Refer to Appendix B, which shows the ACF and PACF correlograms for the time series for HKIA (ARIMAX model).

Table 5.6. ***SARIMA and ARIMAX models of the monthly passenger traffic for HKIA (January 2001−November 2010)***

Dependent variable = ln(air passenger traffic)		
	SARIMA model	**ARIMAX model**
Explanatory variables	**Coefficients**	**Coefficients**
Constant	15.693***	6.095***
	(17.30)	(7.59)
Trend	-0.001	0.002***
	(-0.29)	(3.12)
AR(1)	0.574***	0.482***
	(7.09)	(3.79)
SAR(12)	0.858***	0.788***
	(9.37)	(14.78)
MA(1)	0.650***	-0.997***
	(5.38)	(-29.38)
SMA(12)	-0.944***	-0.931***
	(-34.15)	(-45.86)
ln (GDP per capita)	-	0.350*
		(2.02)
ln (GDP per capita)$_{t-1}$	-	-0.198
		(-0.75)
ln (GDP per capita)$_{t-2}$	-	-0.326
		(-1.49)
ln (GDP per capita)$_{t-3}$	-	-0.371**
		(-2.43)
ln (GDP per capita)$_{t-4}$	-	0.404***
		(3.12)
ln (Connecting traffic)	-	0.237***
		(5.42)
ln (Visitors by air transport)	-	0.489***
		(13.40)
SARS	-	-0.027*
		(-1.87)
Cross-strait agreement	-	-0.028***
		(-3.15)
Fuel prices	-	0.050***
		(6.06)
IVS	-	-0.013
		(-0.78)
Adj-R^2	0.85	0.99
AIC	-1.490	-4.432
SIC	-1.339	-3.995
MAPE (%)	0.63	0.13
RMSE	0.03	0.12

Remarks: *, **, and *** indicate that the explanatory variable is significant at the 0.10, 0.05, and 0.01 significance level, respectively. *t*-statistics are printed in parentheses. The lag of each explanatory variable is decided when it becomes statistically significant using *t*-statistics. AR and MA terms included in the ARIMAX model are to capture autoregressive and moving average relationships in the time series.

To express the best-fit ARIMAX model for forecasting HKIA's future passenger throughput into the compact notation as below, ln (monthly air passenger traffic) (or ln (APT)) for HKIA at month t depends on ln (GDP per capita) from month t to month t-4, ln (Connecting traffic) (or ln (C)) in the same month t, ln (Visitors by air transport) (or ln (V)) in the same month t, and other identified interventions or shocks during the forecasting periods:

$$
\begin{aligned}
(1-\Phi_1 B^1)(1-\omega_{12}B^{12})\ \ln(\mathrm{APT})_t \quad &= \left(1-\theta_1 B^1\right)(1-\Theta_{12}B^{12})\cdot \varepsilon_t \\
&+ \beta_1 \ln\ (\text{GDP per capita})_t \\
&+ \beta_2\ \ln\ (\text{GDP per capita})_{t-1} \\
&+ \beta_3\ \ln\ (\text{GDP per capita})_{t-2} \\
&+ \beta_4\ \ln\ (\text{GDP per capita})_{t-3} \\
&+ \beta_5\ \ln\ (\text{GDP capita})_{t-4} \\
&+ \alpha_1\ \ln \mathrm{C}_t + \partial_1\ \ln \mathrm{V}_t \\
&+ \text{SARS} + \text{Cross-strait agreement} + \text{Fuel prices} \\
&+ \text{Individual Visit Scheme} + \text{Constant} + \text{Trend}
\end{aligned}
$$

Figure 5.8 shows the forecasted monthly passenger traffic for HKIA from the SARIMA and ARIMAX models for the period of January 2001 to December 2015. It is found that the ARIMAX model with additional explanatory variables has more predictive power than the SARIMA model, as the forecasted values more closely resemble actual values. Similarly, the ARIMAX model projects a steady growth in future passenger throughput for HKIA ahead to 2015.

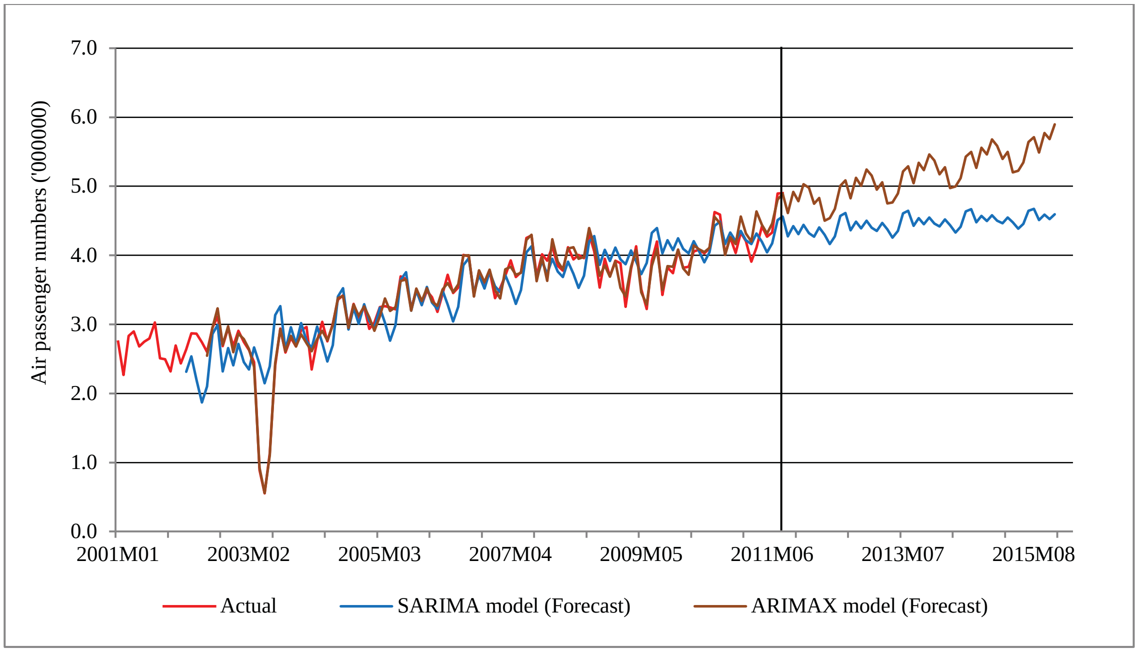

Figure 5.8. **SARIMA and ARIMAX models for the monthly passenger traffic projection for HKIA (January 2001−December 2015)**

5.5.3 Evaluation of forecasts

It is important to reiterate that the main aim of this study is to model the SARIMA and ARIMAX models for forecasting future passenger growth trends for HKIA ahead to 2015. However, it is also important to check the forecasting accuracy of three selected Box–Jenkins ARIMA-based models using out-of-sample data between December 2010 and August 2011. Table 5.7 shows the forecasting performances of three best-fit ARIMA-based models by comparing the actual and forecasted values of HKIA's monthly passenger throughput.[58]

Overall, the forecasting performances of three best-fit ARIMA-based models for forecasting HKIA's future passenger throughput were highly accurate and the forecasted errors ranged from 0% to 11.3%. An important finding was that the

[58] Wooldridge (2009) illustrated the procedure for transforming the forecasted values of ln (monthly air passenger traffic) to the forecasted absolute values. The residuals presented in the time series have been taken into account during the transformation process.

Table 5.7. ***Forecasting performances of three ARIMA-based models***

		SARIMA model [a]		SARIMA model [b]		ARIMAX model [b]	
Periods	**Actual**	**Forecast**	**Forecasted error**	**Forecast**	**Forecasted error**	**Forecast**	**Forecasted error**
Dec 2010	4,328	4,438	-2.5%	4,354	-0.6%	4,562	-5.1%
Jan 2011	4,206	4,235	-0.7%	4,221	-0.3%	4,315	-2.5%
Feb 2011	3,909	4,192	-6.8%	4,163	-6.1%	4,202	-7.0%
Mar 2011	4,114	4,396	-6.4%	4,318	-4.7%	4,637	-11.3%
Apr 2011	4,419	4,389	0.7%	4,194	5.4%	4,439	-0.5%
May 2011	4,268	4,209	1.4%	4,043	5.6%	4,315	-1.1%
Jun 2011	4,329	4,318	0.2%	4,170	3.8%	4,458	-2.9%
Jul 2011	4,895	4,777	2.5%	4,509	8.6%	4,807	1.8%
Aug 2011	4,898	4,898	0%	4,560	7.4%	4,890	0.2%

Remarks: The forecasted absolute air passenger traffic values have been transformed from the forecasted values of ln (monthly air passenger traffic). All of the actual and forecasted values are stated in thousands ('000). Superscript [a] indicates the forecasting sample period is between January 1993 and November 2011. Superscript [b] indicates the forecasting sample period is between January 2001 and November 2011.

forecasted errors of three fitted ARIMA-based models fluctuated during the *ex-post* forecasting periods. Surprisingly, the longer forecasting sample periods of SARIMA model presented the smallest overall forecasted errors among three ARIMA models with different forecasting sample periods, implying that the SARIMA model with a longer forecasting sample period has better out-of-sample predictive power; the forecasted errors of the SARIMA model with a longer forecasting sample period are smaller compared with those of the SARIMA and ARIMAX models with a shorter sample forecasting period. Moreover, the forecasted errors presented in the SARIMA model[b] (i.e. the shorter forecasting ample periods) after a four-month horizon were larger than those of the ARIMAX model. This finding supports Nanda (1988), who claimed that the multivariate model is always preferred as being a good univariate model. Again, obtaining the best-fit Box–Jenkins ARIMA forecasting models with the highest possible forecasting accuracy is not the main objective of this study; the aim is to project the future growth trend of passenger throughput for HKIA.

5.6 SCENARIO ANALYSIS

The previous ARIMAX model forecasted that HKIA's monthly passenger traffic would grow in the future; however, it is expected that the forecasting results may be sensitive to changes in some of the underlying assumptions (e.g. the changes in Hong Kong's future GDP per capita and/or fuel prices). Although it is impossible to forecast HKIA's future passenger throughput with 100%t certainty, it is still possible to understand the sensitivity of the forecasts to changes in many of the assumptions: Scenario analysis provides researchers with the ability to explicitly test the sensitivity of their forecasting models and results to changes in the underlying assumptions and associated practices (Schwartz, 1996; Craig, Gadgil & Koomey, 2002).

Uncertainty surrounding the global financial crisis and the resulting recession has important implications for the forecasting results of this study and the parameters of Hong Kong's future GDP per capita and fuel prices, and thus this study's ability to evaluate their impacts on HKIA's future passenger throughput. Consequently, this study used scenario analysis to model HKIA's future passenger throughput using three different scenarios to 2015:

- Scenario 1: Original (Baseline) forecast using the parameters shown in Table 5.6;
- Scenario 2: The parameters shown in Table 5.6 and the forecasted Hong Kong's future GDP per capital per annum will decrease by 5% between September 2011 and December 2015;
- Scenario 3: The parameters shown in Table 5.6 and the future fuel prices will remain below US$80 per barrel for the period of September 2011 to December 2015;

The projected results from the three scenarios suggest that HKIA's future monthly passenger traffic is expected to maintain similar growth trends to 2015 (see Figure 5.9). The projections also show that fuel prices (below US$80 per barrel) could exert a larger impact on HKIA's future passenger throughput compared with Hong Kong's declining future GDP per capita. In other words, fuel prices (below US$80 per barrel) are likely to become a more significant factor for undermining HKIA's future growth, as its projected growth trend is smaller than or does not seem to be as optimistic as that of Hong Kong's declining future GDP per capita.

In comparison with the original (baseline) forecast and the other two scenarios, Hong Kong's declining future GDP per capita was not found to have a relatively strong impact on HKIA's future passenger throughput as the effect of fuel prices (below US$80 per barrel). Scenario 2 and Scenario 3 in this study have presented similar growth trends up to 2015 and both key factors could exert different levels of unwanted impact on HKIA's future performance. For example, the original forecast projected HKIA's monthly passenger numbers to reach 5.90 million in December 2015, and the projections for Hong Kong's declining future GDP per capital and fuel prices (below US$80 per barrel) are 5.87 million and 5.68 million, respectively. In addition, the projections of Scenario 2 and Scenario 3 could imply that HKIA's future growth will not rely only on the projected growth of local passengers travelling through the airport, but also pinpoint HKIA's role as one of the key international Asian gateway hub airports transporting air travellers across the region.

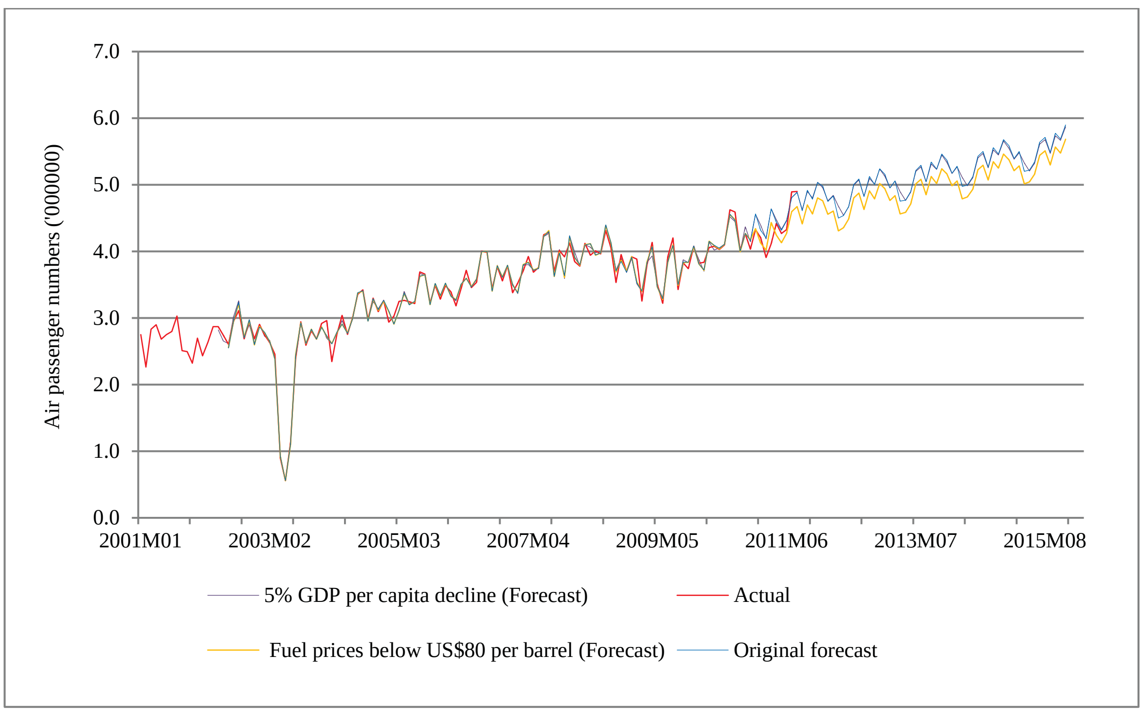

***Figure 5.9*: ARIMAX models for HKIA's monthly passenger traffic projected with the forecasted decline in Hong Kong's GDP per capita and fuel prices (January 2001–December 2015)**

5.7 DISCUSSION

The main aim of this study was to investigate the future passenger throughput of HKIA using the Box–Jenkins SARIMA and ARIMAX models. The findings suggest that HKIA's future passenger throughput will grow at a smaller rate until 2015. Even more importantly, the findings show no major difference regarding the potential of HKIA to maintain its role as the main air transport hub in the Asia-Pacific region in the near future, although it is facing increased competition from the smaller international airports in Southern China (the PRD region), the international gateway hub airports in Mainland China, and around the Asia-Pacific region (e.g. Seabrooke *et al*., 2003; Zhang, 2003; Robinson, 2006; Ishutkina & Hansman, 2009). In line with the argument of Zhang (2004, p.95), who claimed that "it will be risky to think that [HKIA's] hub role may be maintained forever and …. high growth rates will persist for a long time", it could be therefore be assumed that HKIA may struggle to maintain its continued growth into the future as it faces intense competition over international passenger traffic, especially connecting traffic to Mainland China and elsewhere.

Two key issues are believed to affect HKIA's future passenger throughput. First, the amount of connecting traffic via HKIA will significantly affect its role as one of the key transit hub airports in the Asia-Pacific region. The findings suggest that the connecting traffic via HKIA is expected to grow at a smaller scale. This finding confirms the argument of Williams (2006, p.57), who claimed that "the market competition is promised for East Asia, with Hong Kong, Singapore, Seoul, and Guangzhou airport, such air transport activities might create significant impacts on HKIA's future". Also, increased competition from the Asian international gateway hub airports may have two significant negative impacts on HKIA's passenger throughput in two ways: (i) gateway traffic into the PRD region and Mainland China, and (ii) hub traffic for Asian destinations. Nevertheless, this finding also provides support to show the current situation of HKIA: the signing of the cross-strait agreement between Mainland China and Taiwan has caused a fall in Taiwanese travellers transiting Hong Kong to Chinese cities (Chang, Hsu & Lin, 2011; Lau *et al*., 2012). Taiwanese travellers flying between Hong Kong and Taiwan have always been ranked as the first or second most important market for HKIA (Guo *et al*., 2006).

Second, visitors by air transport travelling to Hong Kong − irrespective of whether they are origin–destination (O&D) traffic or connecting traffic via HKIA to the destinations − are expected to exert a significant impact on HKIA's passenger throughput. In particular, increasing numbers of Chinese nationals are using HKIA in their overseas trips (HKTB, 2010). This finding suggests that despite more direct flight connectivity being available at the major Chinese international airports, many Chinese travellers are still using HKIA as the gateway or the transit point to their international destinations, taking advantage of its frequent flight connections and extensive connectivity network (e.g. Yu & Lew, 1997; Mak, 2003; Zhang, Jenkins & Qu, 2003; Zhang, Jenkins & Qu, 2006).

It is argued that in this study the ARIMAX model with explanatory variables is a more appropriate methodology than the SARIMA model for forecasting HKIA's future passenger throughput. For example, the higher Adj-R^2 value indicates a better predictive power of the ARIMAX model by incorporating the identified key factors that are deemed to affect HKIA's future passenger throughput. This finding is supported by, for example, Cho (2003), Spitz and Golaszewski (2007), Janic (2008), and Karlaftis (2010), all of whom claimed that the limitation of univariate time series forecasting methods (i.e. the SARIMA model) can be partly solved by the multivariate approach that incorporates the explanatory variables into the forecasting model. However, the selection of explanatory variables was a self-selecting procedure, and this may limit the accuracy of the forecasting results to predict HKIA's future passenger throughput.

There are potentially two limitations to this study. First, although the Box–Jenkins SARIMA model and the ARIMAX model with explanatory variables have reported highly accurate forecasting results to forecast future passenger throughput for HKIA and for its 11 principal origins, the most important limitation was that their forecasts only offered a short-term forecast due to the inherited limitations of the time series forecasting methods. Second, the forecasting of air passenger traffic for HKIA and for its 11 principal origins are not influenced only by the ARIMA pattern plus three specific types of air passenger traffic passing through HKIA (i.e. originating traffic, connecting traffic – transfer and transit passengers via HKIA, and visitors by air transport travelling to Hong Kong) and the other identified explanatory variables that have been incorporated into the ARIMAX modelling. The likely impacts of other changing external demand-driving forces (e.g. employment, local population, hinterland population, and airport competition, etc) and internal demand-driving forces (e.g. airline capacity, airfares, and the airport's flight connectivity network, etc) have not been considered during the forecasting of air passenger traffic for HKIA and for its 11 principal origins (Janic, 2008).

In conclusion, two forecasts were performed for forecasting HKIA's future passenger throughput with different forecasting sample periods considering data availability for analysis. First, the SARIMA models were modelled to forecast air passenger traffic for HKIA and for its 11 principal origins using the monthly time series data between January 1993 and November 2010. Second, the ARIMAX model with explanatory variables was modelled to forecast HKIA's future passenger throughput based on the forecasting sample periods of January 2001 to November 2010. Both the SARIMA and ARIMAX models provided accurate and reliable forecast results with MAPE errors of less than 10% on average and smaller RMSE values, and also showed acceptable forecasted errors when the forecasted and actual values were compared. Overall, HKIA's future passenger throughput is projected to maintain a growth trend ahead to 2015 according to both the SARIMA and ARIMAX models. Furthermore, the market segmentation analysis suggested that three principal origins of HKIA will bring less air passenger traffic to Hong Kong in the near future, including Mainland China, Taiwan, and Africa. On the other hand, air passenger traffic from several principal origins is projected to grow, with different magnitudes; for example, Other Asia, Europe, and Southeast Asia are likely to show the largest growth. Also, scenario analysis (i.e. the forecasts for the scenarios where Hong Kong's future GDP per capita decreases by 5% per annum and fuel prices below US$80 per barrel) was conducted in this study to assess their potential impact on HKIA's future passenger throughput; the results from both scenarios present similar results indicating that HKIA's future passenger throughput will continue to grow but the projected growth will continue at different levels.

CHAPTER 6 : CONCLUSION

"Hong Kong is not merely a piece of transport infrastructure that serves the local travelling public. It is an international aviation hub that generates enormous economic value for Hong Kong."

(HKIA Master Plan, 2030)

6.1 INTRODUCTION

Since its opening in 1998, Hong Kong International Airport (HKIA) has successfully established itself as one of the main international gateway hubs in the Asia-Pacific region and the primary gateway to Mainland China. There is concern about the potential loss of HKIA's leadership as the key international passenger hub in the Asia-Pacific region as it faces increased competition from rival international airports in the region. HKIA's recent slower growth in air passenger numbers compared to other major Asian international gateway hub airports has brought serious concerns to the government of Hong Kong and the airport authority about its long-term growth. In particular, the rapid international network expansion of three main Chinese international gateway hub airports and the smaller international airports in Southern China (the PRD region) have become threats to the role of HKIA as China's primary passenger gateway.

The continued long-term growth of HKIA is the key to facilitate the future development of Hong Kong's economy and its tourism industry, and thus understanding HKIA's performance and its role as the main air transport hub in the Asia-Pacific region requires further investigation. Although literature review revealed that Hong Kong's airport industry is a well-researched topic from different perspectives, there is little research on some important issues related to HKIA such as airport efficiency, the airport's network and connectivity, and future airport passenger throughput. To address this issue and to comprehend HKIA's ability to maintain its role as the main air transport hub in the

Asia-Pacific region and the primary passenger gateway to Mainland China, this thesis aimed to investigate these three specific areas of HKIA empirically.

Three key research questions were addressed in this thesis: (i) to assess HKIA's operational efficiency compared to other Asia-Pacific airports, and determine the significant drivers of the variations in airport efficiency, (ii) to investigate the competitiveness of HKIA's flight network connectivity and hub status compared to other Asia-Pacific airports and its ability to maintain its role as China's primary passenger gateway, and (iii) to forecast HKIA's future passenger throughput.

This chapter is structured as follows. Section 6.2 summarises the key findings of each of the empirical studies, and describes how the individual studies contributes toward a collective understanding of HKIA's role as the main air transport hub in the Asia-Pacific region and China's primary passenger gateway. Section 6.3 discusses the implications of this research. Section 6.4 outlines the contributions of this thesis. Section 6.5 and Section 6.6 discuss the limitations of the research and suggestions for further research. The concluding remarks of this thesis are presented in Section 6.7.

6.2 KEY FINDINGS OF THE THESIS

To analyse these research questions, three separate but related empirical studies were developed to address the role of HKIA as the main air transport hub in the Asia-Pacific region and the primary passenger gateway to Mainland China. Each of the empirical studies employed different empirical models, datasets, and estimation methods to answer the research questions.

6.2.1 Operational efficiency of HKIA

Given increased airport competition around the Asia-Pacific region, airport efficiency has become one of the critical issues for airport management to address. An assessment of HKIA's operational efficiency allows us to understand its performance relative to other Asia-Pacific airports. Further identification of the significant factors that caused the variations in airport efficiency also becomes important to airport efficiency improvements. The following research question was developed to investigate these issues.

Research Question 1: How efficient are HKIA's operations compared to those of other Asia-Pacific airports and what factors explain the variations in airport efficiency?

Data Envelopment Analysis (DEA) was used to assess the relative operational efficiency of a panel of 30 Asia-Pacific airports between 2002 and 2008, followed by the Ordinary Least Squares (OLS) and Tobit models to determine the key determinants for explaining the variations in airport efficiency. The first-stage DEA Output Oriented and Variable Return to Scale framework (The DEA-Output-VRS model) revealed that seven airports (i.e. Hong Kong, Auckland, Melbourne, Beijing, Penang, Taipei, and Wellington airports) are considered to be the most efficient airports among the 30 Asia-Pacific airports analysed. A further nine airports never achieved their full efficiency potential. An important observation was that HKIA is one of the most efficient airports in the Asia-Pacific region in terms of its operational efficiency and performance throughout the period of analysis. During the second-stage analysis, the OLS and Tobit regression analysis were applied to determine the key determinants that might explain the variations in airport efficiency using the first-stage DEA efficiency indexes. Four factors were found to be significant for explaining the identified variations in airport efficiency, including the airport's hub status, the airport's daily operating hours, the airport's hinterland population size, and the dominant airline(s) of an airport entering the strategic global airline alliance.

6.2.2 Network analysis of HKIA and its role as China's primary passenger gateway

The rapid development and network expansions of the major international airports around the Asia-Pacific region have resulted in fierce regional airport competition. This has also created a major threat to HKIA. The analysis of HKIA's flight connectivity network provides evidence that indicates HKIA's competitive position and hub status in connecting air travellers to different regions worldwide and its role as China's primary passenger gateway compared to other Asia-Pacific airports. The following research question was developed to investigate these issues.

Research Question 2: How does HKIA's flight connectivity and its role as China's primary passenger gateway compare to other Asia-Pacific airports, and has this changed over times?

The NetScan Connectivity Units (CNU) model was employed to measure and compare direct, indirect, and hub connectivity among the 13 major Asia-Pacific airports between 2002 and 2010, to obtain a justification of HKIA's competitive position and hub status relative to its peers in respect of flight connectivity network to regions. The CNU model suggested that all airports in the Asia-Pacific region have grown their respective direct and hub connectivity networks at different magnitudes over the years, but indirect connectivity networks decreased at accelerating rates accordingly. The Chinese airports (i.e. Beijing, Shanghai Pudong, Guangzhou, Shenzhen, and Xiamen airports) increased their respective direct and hub connectivity at a greater pace compared to other Asia-Pacific airports. The growth in direct and hub connectivity among the other sampled airports varied considerably. Furthermore, Hong Kong and Singapore airports have established the largest direct international flight networks and hub traffic among the sampled Asia-Pacific airports, becoming the two main international air transport hubs in the Asia-Pacific region. In particular, HKIA established the strongest connectivity to Other Asia (which includes the strongest direct and hub connectivity to Mainland China), and also has a strong competitive position to connect air travellers to regions such as Africa, North Asia, Southeast Asia, Australasia and Oceania, the Middle East, and North America.

It is difficult to investigate HKIA's role as the primary passenger gateway to Mainland China, although it had the strongest connectivity (i.e. direct and hub connectivity) to Mainland China among the Asia-Pacific airports during the analysis periods. The share of international visitors departing for Mainland China via HKIA could provide a meaningful indication with respect to its role as China's primary passenger gateway airport whilst looking at whether other international airports in the Asia-Pacific region and elsewhere – have flight connections to Mainland China. Therefore China's total inbound international visitors by air transport were analysed in respect of different markets or the group of countries in a region. The market share analysis concluded that HKIA was the main transit point or connecting airport to handle a significant portion of China's total inbound international travellers from Australasia and Oceania, South and Central America, Macau, North America, and Europe between 2006Q1 and 2011Q3. In addition, HKIA maintained its ability to transport a smaller but regular amount of China's total inbound international visitors by air transport from Taiwan, Southeast Asia, North Asia, and Other Asia.

6.2.3 Forecasting of HKIA's future passenger throughput

In the face of increased regional airport competition, there is a risk that HKIA will lose its role as the key international passenger hub in the Asia-Pacific region. An accurate and reliable forecasting of HKIA's future passenger throughput may suggest what its future role is, and also to assist the short- and long-term planning of airport infrastructure and capacity from the government of Hong Kong and the airport authority. Thus, the following research question was developed to forecast the future passenger throughput for HKIA.

Research Question 3: Will HKIA's future passenger throughput continue to grow?

The Box–Jenkins Seasonal ARIMA (SARIMA) and ARIMAX models were used to model and forecast air passenger traffic for HKIA and for its 11 principal origins ahead to 2015. It must be highlighted that the SARIMA and ARIMAX models used different forecasting period lengths, as the amount of available time series data of the variables of interest was limited: (i) January 1993−November 2010 for the SARIMA model for HKIA and its 11 principal origins, and (ii) January 2011−November 2011 for the ARIMAX model for HKIA only. Unlike the SARIMA model, the ARIMAX model (i.e. the multivariate model) combines the Box–Jenkins SARIMA model with the selected explanatory variables that are deemed to have the impacts on the forecasting of HKIA's future passenger throughput in the time series regression model. The explanatory variables incorporated in the ARIMAX model included Hong Kong's GDP per capita, connecting traffic passing through HKIA, visitors by air transport travelling to Hong Kong, the SARS outbreak, the cross-strait (direct air link) agreement between Mainland China and Taiwan, fuel prices, and the Individual Visit Scheme (IVS).

In terms of forecasting accuracy, the best-fit SARIMA and ARIMAX models were highly accurate with lower MAPE and RMSE values. The *ex-post* forecasts presented the acceptable forecasting errors ranging from 0% to 11.3%. Overall, the longer forecasting periods of SARIMA model presented the smallest forecasting errors. In addition, the ARIMAX model with explanatory variables, with a shorter forecasting period, was more accurate than the SARIMA model with the same forecasting periods for forecasting HKIA's future passenger throughput. Most importantly, both the SARIMA and ARIMAX models presented similar projections indicating that HKIA's future passenger throughput will continue to grow ahead to 2015.

6.3 GENERAL DISSCUSSION

6.3.1 Evidence that HKIA's future growth is under threat

One of the key findings of this thesis appear to be that there is a consensus among the three empirical studies indicating HKIA is likely to maintain its role as the main air transport hub in the Asia-Pacific region and the primary gateway to Mainland China. However, it is likely to face rapid international network expansions and increased competition from the major international gateway hub airports in Mainland China and around the Asia-Pacific region.

There are several Asian international hub airports (e.g. Beijing, Shanghai Pudong, Guangzhou, and Singapore airports) that could become serious challengers to HKIA's future role as the key aviation hub for transporting connecting passenger traffic across the regions. Evidence presented in Chapter 4 suggests that many Asia-Pacific airports have significantly increased and expanded their flight connectivity networks to capture increasing air travel demand in the region. Also, it was found in Chapter 5 that the amount of connecting passenger traffic passing through HKIA is expected to grow at a smaller scale in the coming future. However, this situation is largely dependent upon the future growth of the international flight connectivity networks of the major Asian international hub airports in the region; the levels of network expansion of the major Asian international hub airports will have a direct negative impact on HKIA's connecting passenger traffic, especially international passengers travelling to Mainland China (Robinson, 2006; Williams, 2006). Indeed, these findings suggest an immediate threat that may slow down HKIA's future growth is coming from the smaller international airports in Southern China (the PRD region). Furthermore, HKIA's long-term success depends on the development processes of other international gateway hub airports in Mainland China and around the Asia-Pacific region. For example, Guangzhou Baiyun International Airport will have five runways in operation by 2030 to accommodate the expected future growth of domestic and international passenger traffic (HKAA, 2011). However, future airport coordination among the A5 group (i.e. Hong Kong, Guangzhou, Shenzhen, Xiamen, and Macau airports) is likely to improve their airport operational efficiency and customer services, and thus reduce competitions between airports in the PRD region as well as in the downstream airline markets (Oum & Yu, 2000). Arguably, HKIA and its neighbouring airports may benefit in a similar manner as co-coordination of air traffic movements by the Port Authority of New York and New Jersey (Mok, 1998).

Another important issue appears to be that the actions of the government of Hong Kong and the airport authority to deal with the current issues − the lack of airport capacity to meet future airport traffic demand and increased airport competition – are critical to maintain HKIA's role as an aviation hub in the region and to sustain Hong Kong's future competitiveness and economic growth. Although this thesis does not explore any specific actions undertaken by the government of Hong Kong and the airport authority to maintain and enhance HKIA's role in the future, HKIA's Master Plan 2030 is a good sign to show how government policy makers are mapping out a future development strategy for HKIA. It outlines the airport facility expansions and capacity enhancement required to meet the long-term air traffic demand of HKIA, and the final choice is to build a third runway, additional passenger terminal areas, aircraft parking spaces, and apron areas.

6.3.2 Implications for the Hong Kong government and the airport authority

The finding in Chapter 3 that the significant effect of an airport's hinterland population upon an airport's efficiency is critical for Hong Kong's airport authority. This factor may affect HKIA's efficiency and future air passenger demand. This finding supports the arguments of Graham (1999) and Graham and Guyer (2000), who claimed that the size of an airport's hinterland can be greatly changed by improvement in aircraft technology, the construction of strategic global airline alliances, and the creation of Hub-and-Spoke networks by airlines. In this case, Hong Kong's airport authority may want to examine the importance of the airport's hinterland in HKIA's future air passenger volumes, by investigating to what extent HKIA relies on the hinterland (e.g. the increase in Mainland China's population) in the neighbouring areas as the single product to support its future growth and success. For instance, it would be interesting for the airport authority to investigate how much of HKIA's future growth between 2012 and 2030 can be accounted for by changes within the airport's hinterland.

According to HKIA's Master Plan 2030, HKIA is in a hurry to operate with a three-runway system to meet the long-term needs of Hong Kong up to and possibly beyond

2030 (HKAA, 2011). The findings of this thesis provide evidence to support the prior literature (Zhang, 2003; Robinson, 2006; Williams, 2006), all of which claimed that the improved efficiency of the major Asian international airports to handle airport traffic (i.e. air passenger numbers, air cargo volume, and aircraft movements), the rapid expansion of international flight connectivity networks among the Asia-Pacific airports, and the smaller growth rate of future air passenger traffic and/or connecting traffic via HKIA would undermine its overall competitiveness. Also, it is acknowledged that future analysis of these issues would be required to yield robust results, the findings may ultimately be useful for the government of Hong Kong and the airport authority to determine what actions need to be undertaken to enhance HKIA's role as the main air transport hub in the Asia-Pacific region and China's primary passenger gateway.

The research results of Chapter 5 reported in this thesis regarding air passenger traffic for HKIA's 11 principal origins also have important implications. Accurate tourism forecasting of tourist arrivals from different regions or areas is one of the greatest challenges faced by the policy makers in Hong Kong government and the tourism industry (Song, Wong & Chon, 2003). Failure to anticipate increases in tourism demand or tourist arrivals may lead to considerable shortfalls in the supply of tourism infrastructure, because of the lead times involved in building and providing this infrastructure (Cho, 2003).

6.3.3 Application to other major international airports

This thesis analysed HKIA's operation and future growth by investigating three different aspects such as airport efficiency, the airport's network and connectivity, and future airport passenger throughput. In practice, it will be very useful if one could extend the study framework in this thesis to investigate other international hub airports in the global context. Indeed, the methodology for the analysis and forecasting of air passenger demand at large hub airports has previously well developed in the field of the air transport industry (Janice, 2008). It is argued that the time-series regression technique (i.e. the ARIMAX model with the selected explanatory variables) developed in this thesis to analyse and forecast HKIA's future passenger throughput could inform the design of econometric models applied to the forecasting of air passenger change at other international hub airports.

6.4 CONTRIBUTIONS OF THE THESIS

The analysis of HKIA's role as the main air transport hub in the Asia-Pacific region and the primary passenger gateway to Mainland China provides an original contribution to the literature. Moreover, this thesis made several contributions to the existing literature for understanding HKIA's performance and future development – through the empirical analysis of three important aspects of HKIA such as airport efficiency, the airport's network and connectivity, and future airport passenger throughput. Furthermore, the results complied in this thesis suggest a number of contributions with respect to each of the empirical studies.

The analysis of HKIA's operational efficiency has extended the existing literature (i.e. Lam, Low & Tang, 2009; Yang 2010) to assess the operational efficiency of the major Asia-Pacific airports. Relatively few studies have paid attention to the development of econometric analysis for identifying the significant determinants that explain the variations in airport efficiency, especially the airports in the Asia-Pacific region. The identification of significant determinants in airport efficiency differentials provides managerial insight to airport management to improve an airport's operational efficiency if those factors are not beyond their control.

For the analysis of HKIA's network performance, this empirical study contributed to the existing knowledge, for example, Burghouwt *et al*. (2009) and de Wit *et al*. (2009), with the measurement of the growth (or change) in the flight connectivity networks of major Asia-Pacific airports, and also to pinpoint the respective hub competitiveness to different regions among HKIA's peers. Furthermore, this empirical study was the first analysis which combined the research results of measuring the flight connectivity networks of Asia-Pacific airports with the market share analysis in investigating

HKIA's role as China's primary passenger gateway. With this analysis framework, it is possible to present a fairer result with respect to HKIA's role.

For the forecasting of HKIA's future passenger throughput, this empirical study was the first study to employ the Box–Jenkins ARIMA methodology (the SARIMA model and the ARIMAX model with explanatory variables) for forecasting future air passenger numbers. The forecasting results of both Box–Jenkins ARIMA-based models projected the future passenger traffic growth for HKIA, and also highlighted the challenges for policy makers to accommodate increasing volume of future passenger traffic travelling through HKIA from different principal origins worldwide. Furthermore, the ARIMAX model can be developed to allow for the forecasting of tourism demand for Hong Kong (i.e. groups of countries, individual countries, regions or local areas) if Hong Kong Tourism Board wants to understand the future tourism infrastructure required to accommodate the forecasted tourism demand, irrespective of the increase or fall in tourist arrivals.

6.5 LIMITATIONS OF RESEARCH

There are a number of potential limitations to the findings reported in this thesis. The general limitation was that identical data periods or analysis periods for the three empirical studies could not be successfully gathered. This is one of the main impediments to drawing a generalised conclusion for the thesis. In addition to different data periods, the research results obtained from each of the empirical studies in the thesis also suggest further specific limitations.

In Chapter 3, the key limitation is that the second-stage OLS and Tobit regression analysis only focused on investigating the airport passenger traffic data to identify the key determinants that lead to the variations in airport operational efficiency. The problem was that other potentially important information that could explain the variations in operational efficiency among the sampled Asia-Pacific airports was not included or have been omitted in the research, mainly because of their unavailability at the time of the research or the data was extremely difficult to gather, for example, air cargo traffic information (Pathomsiri, 2006; Li & Liu, 2007; Yuen & Zheng 2009). Indeed, the simple inclusion of airport passenger traffic information for the airport efficiency evaluation did not present the unique operating characteristics of each sampled airport or illustrate the dynamic landscape of the airport industry across the Asia-Pacific region.

In Chapter 4, it is acknowledged that HKIA is facing intense competition from the major international gateway hub airports in the Asia-Pacific region and elsewhere, especially regarding its leading position to handle connecting passenger traffic to Mainland China. However, the research results from the market share analysis could not provide evidence to support a conclusion regarding HKIA's role as China's primary passenger gateway, although, to a certain extent, the share of China's total inbound international visitors handled by HKIA may suggest this role. However, in the econometric sense, the existing information about China's inbound international visitors travelling through HKIA could not support further statistical analysis or yield the robustness regarding how significantly other key international hub airports elsewhere affect HKIA's transit hub role by luring away connecting passenger traffic to Mainland China – those hub airports also have flight connections to Mainland China, especially the major Asian international gateway hub airports (Wooldrige, 2009). It is worthwhile to note that the access to the data of connecting passenger traffic to Mainland China via other key international airports in the Asia-Pacific region and elsewhere was not available at the time of the analysis.

Looking at the findings in Chapter 5, it has been noted that the accuracy of the forecasting results of the Box–Jenkins SARIMA and ARIMAX models is only limited to the short-term forecasting due to the inherited limitations of the time series forecasting methods. Another limitation was that the forecasting of air passenger traffic for HKIA and for its 11 principal origins is not influenced only by the ARIMA pattern plus three particular types of air passenger traffic passing through Hong Kong (i.e. originating traffic, connecting traffic – transfer and transit traffic via HKIA, and visitors by air transport to Hong Kong) and the other identified explanatory variables incorporated into the ARIMAX forecasting model. Consequently, it is possible that the forecasting models used in this thesis may suffer the problem of the omission of potentially important variables or the inadequate use of the determinants in the air passenger demand forecasting model. Specifically, the likely impacts of changing external demand-driving forces (e.g. employment, local population, hinterland population, and airport competition, etc) and internal demand-driving forces (e.g. airline capacity, airfares, and an airport's flight connectivity network, etc) have not been considered and incorporated during the forecasting of air passenger traffic for HKIA and for its 11 principal origins (Janic. 2008).

6.6 SUGGESTIONS FOR FUTURE RESEARCH

There are several potential areas for future research. First, the identification of significant determinants to explain the variations in airport efficiency during the second-stage OLS and Tobit regression analysis could be extended to include the information relating to air cargo transport and flight movements of airports – both airport activities are major airport outputs or key airport performance indicators. Also, their inclusion is important so that future research on this matter can have a better consideration of the diverse operating characteristics of Asia-Pacific airports in respect of their capacity to handle air cargo traffic and aircraft movements. Thus, inclusion of these factors could provide a generalised conclusion of what the significant factors are that explain the variations in airport efficiency from the second-stage OLS and Tobit regression analysis. In addition, for theoretical development, the first-stage DEA model could possibly be used to make an analysis for comparing the categorical input and output measures such as the operating conditions of airports (i.e. hub or non-hub airports, airport revenue from handling air passenger numbers, air cargo volume, and aircraft movements), which would also provide a fairer and meaningful comparison of airport efficiency.

Second, future research undertaken to investigate the role of HKIA as China's primary passenger gateway should incorporate the information regarding the number of China's inbound international visitors and/or connecting passenger traffic to Mainland China via other major international airports in the Asia-Pacific region and elsewhere. In the econometric sense, such important information provides a clear understanding of

HKIA’s competitive position to transport and handle China’s inbound international passengers relative to other competing international airports in the Asia-Pacific region and elsewhere, particularly the major Asian international gateway hub airports.

Lastly, a thorough analysis and forecasting of air passenger traffic for HKIA and for its 11 principal origins should be conducted in a way that is similar to the forecasts for HKIA using the Box–Jenkins ARIMAX modelling presented here. This should incorporate other relevant external and internal demand driving forces that may have the impacts on its air passenger demand. In particular, it is essential to forecast the growth (or change) in visitor arrival patterns for each of HKIA’s 11 principal regions, which would allow Hong Kong’s tourism industry and airport authority to manage them with efficient planning. Additionally, the analysis and forecasting of HKIA’s future passenger throughput could be further performed for the segments of origin–destination (O&D) traffic and connecting traffic (i.e. transit and transfer traffic) via HKIA to its major air transport markets. The knowledge about connecting passenger traffic volumes travelling through HKIA would add further insight into its role as the key transit hub in the Asia-Pacific region to transport international passengers across the regions.

6.7 CONCLUDING REMARKS

HKIA has become one of the main air transport hubs in the Asia-Pacific region and the primary passenger gateway to Mainland China, even though it has continued to face increased competition from other major international gateway hub airports in Mainland China and around the Asia-Pacific region as well as some unfavourable operating conditions. However, increased regional airport competition has raised concerns that HKIA could lose its role as the main air transport hub in Asia-Pacific region and China’s primary passenger gateway. The three separate but related empirical studies developed in this thesis investigated the performance and future development of HKIA, including airport efficiency evaluation, airport network and connectivity analysis, and future airport passenger throughput forecasting.

The findings of the research concluded that HKIA has maintained its role as the main air transport hub in the Asia-Pacific region and China's primary passenger gateway with the support of efficient operations and competitive international flight connectivity networks. The forecasts estimated that its future passenger throughput will continue to grow. Unfortunately, the research in this thesis only focused on investigating three specific aspects of HKIA; if possible, future research on HKIA's future growth could be conducted by extending the empirical models and datasets adopted in the thesis or by employing new estimation methods to investigate other important areas of HKIA rather than three main focuses in this thesis.

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APPENDIX A

ACF and PACF correlograms for HKIA and 11 principal origins (January 1993–November 2010)

Hog Kong

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>ACF</th><th>PACF</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>0.020</td><td>0.020</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>-0.002</td><td>-0.002</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>3</td><td>-0.091</td><td>-0.091</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>4</td><td>0.018</td><td>0.022</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>0.033</td><td>0.033</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>6</td><td>0.012</td><td>0.002</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>0.018</td><td>0.022</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>-0.032</td><td>-0.028</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>9</td><td>0.055</td><td>0.057</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>10</td><td>0.079</td><td>0.080</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>11</td><td>0.001</td><td>-0.009</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>12</td><td>-0.023</td><td>-0.014</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>0.003</td><td>0.018</td></tr>
</table>

Mainland China

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>ACF</th><th>PACF</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>0.061</td><td>0.061</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>0.042</td><td>0.038</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>3</td><td>-0.051</td><td>-0.057</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>4</td><td>0.067</td><td>0.072</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>-0.005</td><td>-0.010</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>6</td><td>0.055</td><td>0.048</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>-0.034</td><td>-0.033</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>-0.021</td><td>-0.027</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>9</td><td>0.075</td><td>0.089</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>10</td><td>-0.012</td><td>-0.032</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>11</td><td>0.026</td><td>0.027</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>12</td><td>-0.020</td><td>-0.014</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>0.033</td><td>0.024</td></tr>
</table>

Taiwan

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>ACF</th><th>PACF</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>0.061</td><td>0.061</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>0.042</td><td>0.038</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>3</td><td>-0.051</td><td>-0.057</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>4</td><td>0.067</td><td>0.072</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>-0.005</td><td>-0.010</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>6</td><td>0.055</td><td>0.048</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>-0.034</td><td>-0.033</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>-0.021</td><td>-0.027</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>9</td><td>0.075</td><td>0.089</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>10</td><td>-0.012</td><td>-0.032</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>11</td><td>0.026</td><td>0.027</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>12</td><td>-0.020</td><td>-0.014</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>0.033</td><td>0.024</td></tr>
</table>

Japan

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>ACF</th><th>PACF</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>-0.013</td><td>-0.013</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>-0.031</td><td>-0.031</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>3</td><td>-0.011</td><td>-0.012</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>4</td><td>0.002</td><td>0.001</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>0.034</td><td>0.033</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>6</td><td>0.046</td><td>0.047</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>0.024</td><td>0.028</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>0.002</td><td>0.006</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>9</td><td>0.060</td><td>0.063</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>10</td><td>0.148</td><td>0.151</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>11</td><td>-0.011</td><td>-0.004</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>12</td><td>-0.105</td><td>-0.101</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>0.065</td><td>0.063</td></tr>
</table>

Southeast Asia

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>ACF</th><th>PACF</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>0.004</td><td>0.004</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>0.013</td><td>0.013</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>3</td><td>0.011</td><td>0.011</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>4</td><td>-0.008</td><td>-0.008</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>5</td><td>0.075</td><td>0.075</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>6</td><td>0.071</td><td>0.071</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>-0.014</td><td>-0.016</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>0.003</td><td>-0.001</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>9</td><td>0.003</td><td>0.003</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>10</td><td>0.165</td><td>0.163</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>11</td><td>0.021</td><td>0.010</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>12</td><td>-0.035</td><td>-0.044</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>-0.004</td><td>-0.006</td></tr>
</table>

Other Asia

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>ACF</th><th>PACF</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>0.027</td><td>0.027</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>0.043</td><td>0.042</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>3</td><td>-0.118</td><td>-0.121</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>4</td><td>-0.004</td><td>0.001</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>0.052</td><td>0.063</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>6</td><td>-0.011</td><td>-0.030</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>0.013</td><td>0.008</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>0.007</td><td>0.023</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>9</td><td>-0.044</td><td>-0.052</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>10</td><td>0.109</td><td>0.113</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>11</td><td>0.053</td><td>0.058</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>12</td><td>0.013</td><td>-0.017</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>13</td><td>-0.029</td><td>-0.008</td></tr>
</table>

North America

Autocorrelation	Partial Correlation		ACF	PACF
.|. |	.|. |	1	0.044	0.044
.|. |	.|. |	2	0.017	0.015
*|. |	*|. |	3	-0.144	-0.146
.|. |	.|. |	4	-0.022	-0.010
.|. |	.|. |	5	0.030	0.038
.|. |	.|. |	6	-0.003	-0.027
.|. |	.|. |	7	0.031	0.027
.|. |	.|. |	8	-0.004	0.004
.|. |	.|. |	9	0.029	0.025
.|. |	.|. |	10	0.033	0.038
.|. |	.|. |	11	-0.029	-0.033
.|. |	.|. |	12	0.049	0.057
.|. |	.|. |	13	-0.063	-0.056

The United Kingdom

Autocorrelation	Partial Correlation		ACF	PACF
.|. |	.|. |	1	0.046	0.046
*|. |	*|. |	2	-0.123	-0.125
.|* |	.|* |	3	0.168	0.183
.|. |	.|. |	4	-0.011	-0.051
.|. |	.|. |	5	-0.052	-0.002
.|. |	.|. |	6	0.029	-0.005
.|. |	.|. |	7	-0.015	-0.015
.|. |	.|. |	8	0.008	0.025
.|. |	.|. |	9	-0.006	-0.021
.|. |	.|. |	10	-0.045	-0.033
.|. |	.|. |	11	0.029	0.027
*|. |	*|. |	12	-0.172	-0.194
*|. |	*|. |	13	-0.154	-0.110

Europe

Autocorrelation	Partial Correlation		ACF	PACF
.|. |	.|. |	1	0.048	0.048
.|. |	.|. |	2	0.001	-0.002
*|. |	*|. |	3	-0.116	-0.117
.|. |	.|. |	4	0.028	0.040
.|. |	.|. |	5	-0.054	-0.058
.|. |	.|. |	6	0.072	0.066
.|. |	.|. |	7	-0.061	-0.062
.|. |	.|. |	8	0.054	0.049
.|. |	.|. |	9	0.021	0.035
.|. |	.|. |	10	0.044	0.020
.|. |	.|. |	11	-0.001	0.019
.|. |	.|. |	12	-0.003	-0.014
*|. |	.|. |	13	-0.069	-0.050

Australasia and Oceania

Autocorrelation	Partial Correlation		ACF	PACF
.|. |	.|. |	1	0.011	0.011
.|. |	.|. |	2	0.023	0.023
.|. |	.|. |	3	-0.045	-0.046
*|. |	*|. |	4	-0.082	-0.082
.|. |	.|. |	5	0.045	0.049
*|. |	*|. |	6	-0.068	-0.068
.|. |	.|. |	7	0.061	0.054
.|. |	.|. |	8	-0.034	-0.035
.|. |	.|. |	9	0.031	0.032
.|. |	.|. |	10	0.040	0.032
.|. |	.|. |	11	0.023	0.034
.|. |	*|. |	12	-0.064	-0.081
.|. |	.|. |	13	-0.030	-0.009

The Middle East

Autocorrelation	Partial Correlation		ACF	PACF
.|. |	.|. |	1	0.055	0.055
.|. |	.|. |	2	-0.016	-0.019
.|. |	.|. |	3	0.043	0.045
*|. |	*|. |	4	-0.095	-0.101
.|. |	.|. |	5	-0.041	-0.028
.|. |	.|. |	6	-0.014	-0.017
.|. |	.|. |	7	0.052	0.062
.|. |	.|. |	8	-0.012	-0.026
.|* |	.|* |	9	0.104	0.106
*|. |	*|. |	10	-0.093	-0.120
*|. |	.|. |	11	-0.088	-0.059
*|. |	*|. |	12	-0.110	-0.124
*|. |	*|. |	13	-0.128	-0.088

Africa

Autocorrelation	Partial Correlation		ACF	PACF
.|. |	.|. |	1	0.017	0.017
.|. |	.|. |	2	-0.036	-0.037
.|. |	.|. |	3	-0.022	-0.020
*|. |	*|. |	4	-0.080	-0.080
*|. |	*|. |	5	-0.152	-0.152
.|. |	.|. |	6	-0.049	-0.055
.|. |	.|. |	7	-0.040	-0.058
.|. |	.|. |	8	0.064	0.047
.|. |	.|. |	9	0.041	0.010
.|. |	.|. |	10	0.067	0.040
.|. |	.|. |	11	-0.023	-0.042
**|. |	**|. |	12	-0.208	-0.220
*|. |	.|. |	13	-0.069	-0.063

APPENDIX A: (Continued)

APPENDIX B

ACF and PACF correlograms for HKIA (January 2001–November 2010)

HKIA (SARIMA model)					HKIA (ARIMAX model)				
Autocorrelation	Partial Correlation		ACF	PACF	Autocorrelation	Partial Correlation		ACF	PACF
.|. |	.|. |	1	0.039	0.039	.|. |	.|. |	1	-0.003	-0.003
.|. |	.|. |	2	-0.015	-0.017	.|. |	.|. |	2	-0.011	-0.011
*|. |	*|. |	3	-0.150	-0.149	.|* |	.|* |	3	0.102	0.102
.|. |	.|. |	4	0.016	0.028	.|. |	.|. |	4	-0.028	-0.028
.|. |	.|. |	5	-0.036	-0.043	.|. |	.|. |	5	0.003	0.006
.|. |	.|. |	6	0.019	0.000	.|. |	.|. |	6	0.002	-0.009
.|. |	.|. |	7	-0.035	-0.031	.|. |	.|. |	7	0.019	0.025
*|. |	*|. |	8	-0.069	-0.080	*|. |	*|. |	8	-0.166	-0.170
.|. |	.|. |	9	0.026	0.037	*|. |	*|. |	9	-0.165	-0.169
.|* |	.|* |	10	0.177	0.165	*|. |	*|. |	10	-0.109	-0.129
*|. |	*|. |	11	-0.146	-0.191	*|. |	*|. |	11	-0.089	-0.071
*|. |	*|. |	12	-0.159	-0.141	**|. |	**|. |	12	-0.213	-0.220
.|. |	.|. |	13	-0.053	0.007	.|* |	.|. |	13	0.076	0.073

APPENDIX C

ACF and PACF correlograms for connecting traffic for HKIA and visitors by air transport to Hong Kong (January 2001–November 2010)

Connecting traffic for HKIA					Visitors by air transport to Hong Kong				
Autocorrelation	Partial Correlation		ACF	PACF	Autocorrelation	Partial Correlation		ACF	PACF
.|. |	.|. |	1	0.029	0.029	.|. |	.|. |	1	0.029	0.029
.|. |	.|. |	2	0.018	0.018	.|. |	.|. |	2	-0.052	-0.053
*|. |	*|. |	3	-0.106	-0.107	.|. |	.|. |	3	-0.026	-0.023
.|. |	.|. |	4	0.002	0.008	.|* |	.|* |	4	0.130	0.129
.|. |	.|. |	5	-0.032	-0.029	.|. |	.|. |	5	-0.036	-0.047
*|. |	*|. |	6	-0.119	-0.130	.|. |	.|. |	6	0.017	0.033
.|. |	.|. |	7	-0.005	0.005	.|. |	.|. |	7	-0.021	-0.021
.|. |	.|. |	8	-0.060	-0.064	.|. |	.|. |	8	-0.012	-0.027
.|. |	.|. |	9	0.056	0.033	.|. |	.|. |	9	-0.033	-0.022
.|* |	.|* |	10	0.122	0.126	.|. |	.|. |	10	0.065	0.057
*|. |	*|. |	11	-0.090	-0.126	*|. |	*|. |	11	-0.097	-0.101
*|. |	*|. |	12	-0.114	-0.121	*|. |	*|. |	12	-0.098	-0.085
*|. |	.|. |	13	-0.075	-0.042	*|. |	*|. |	13	-0.111	-0.108