PERFORMANCE MEASUREMENT OF 6 MAIN PUBLIC AIRPORTS OF THAILAND. THE IMPACT OF PRE- AND POST-COVID-19 PANDEMIC CRISIS.

BY

MR. NATTAWAT BENJAPARN

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF ECONOMICS
(INTERNATIONAL PROGRAM)
FACULTY OF ECONOMICS
THAMMASAT UNIVERSITY
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THESIS

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ENTITLED

PERFORMANCE MEASUREMENT OF 6 MAIN PUBLIC AIRPORTS OF THAILAND. THE IMPACT OF PRE- AND POST-COVID-19 PANDEMIC CRISIS.

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Thesis Title	PERFORMANCE MEASUREMENT OF 6 MAIN PUBLIC AIRPORTS OF THAILAND. THE IMPACT OF PRE- AND POST-COVID-19 PANDEMIC CRISIS.
Author	Mr. Nattawat Benjaparn
Degree	Master of Economics (International Program)
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ABSTRACT

Tourism is the main factor to drive the GDP of Thailand since 1995. The revenue from the tourism sector is more than 15 percent of GDP every year since 2015. The components to support the sustainable development of Tourism are infrastructure, hotel industry, favorable government policy, and trade fairs. This thesis focuses only on infrastructure as the airport sector by measuring the full performances of the 6 main public airports in Thailand. These airports include Suvarnabhumi Airport (BKK) in Samut Prakan, Don Mueang International Airport (DMK) in Bangkok, Phuket International Airport (HKT) in Phuket, Chiang Mai International Airport (CNX) in Chiang Mai, Hat-Yai International Airport (HDY) in Songkhla, and Mae Fah Luang-Chiang Rai International Airport (CEI) in Chiang Rai. These airports have handled more than 80 percent of all passengers in Thailand's airports every year since 2008. All airports are operated by the Airports of Thailand Public Company Limited, one of the biggest Thai Companies.

The thesis contains 2 major analysis parts. The first part analyses the full performance measurement of the airports between 2007 to 2020 by employing the data envelopment analysis (DEA), Malmquist total factor productivity index (MPI), and Simar and Wilson Bootstrapping regression. The DEA model is employed to measure the technical efficiency scores of the airports. The MPI model measures productivity growths of the airports by decomposing into the technical efficiency change (TEC) and technical change (TC). The Simar-Wilson model employs to test which micro and macro factors will affect the airports' efficiency scores. The findings of this part report the airport hubs can perform better than non-airport hubs. Both percent of international passenger and low-cost carriers (LCCs) movements increased the airports' efficiency scores. The macro shocks of the global financial crisis between 2008 to 2009 and the COVID-19 pandemic in 2020 declined the performances of the airports. The airports had the trends of technical efficiency and total factor productivity progress since 2007, but these values had dropped more than 40 percent in 2020.

The second part forecasts the recovery period of the airports after the COVID-19 occurred in 2020 for the next 10 years by predicting the efficiency scores and productivity changes of the airports between 2021 to 2030. The findings of this part report that every airport except BKK and HDY will spend at least 6 years to perform the same as in 2019. In the post-Covid-19 period, taking the advantage of new technologies will be the main factor to drive productivity growth. In contrast, the airports tend to regress in the working system in labor.

Lastly, the findings in thesis can suggest various policies to the airports for transforming the traditional airports into smart airports within a few years after the pandemic. The policies include setting the new working systems such as Agile, Lean, and Talent density and adopting new technologies such as the internet of things (IOT), big data, and artificial intelligence (AI) to improve TEC and TC, respectively. These suggestions will help the airports in reducing the time for transformation.

Keywords: Air Transportation, Performance Measurement, Linear Programming, Data Envelopment Analysis (DEA), Malmquist Total Factor Productivity Index (MPI), Simar and Wilson Bootstrapping Regression, Air Transportation, Aviation Industry.

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"Rules for Happiness: something to do, someone to love, and something to hope for."

Immanuel Kant (1724 - 1804)

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Nattawat Benjaparn

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CHAPTER 1
INTRODUCTION

1.1 Statement of Problem

International Civil Aviation Organization (ICAO) World Civil Aviation Report in 2016 forecasted that the world air traffic passenger movements between 2015 to 2035 will be compound annual growth rate (CAGR) at 4.3% per year and 4.1% between 2015 to 2045. While in South-East Asia between 2015 to 2035, air traffic domestic movements will grow at 5.3% per year and 5.4% per year for air traffic international movements (CAAT, 2019). This supports that the aviation sector is kept going up with the expansion of the tourism sector. In Thailand, the gross domestic product (GDP) from the tourism sector was 17.95%, 17.79%, and 17.64% in 2017, 2018, and 2019, respectively (Statista, n.d.). CAAT reported in 2018 (CAAT, 2018) that the statistics of air passenger traffic movements in Thailand had grown up from 58 million passengers in 2009 to 162 million passengers in 2018. The compound annual growth rate in 10 years was 10.8%. It was 10% growth per year for international movements and 11.6% growth per year for domestic passenger movements. This evidence shows that the aviation industry is very important for the growth of the tourism sector in Thailand.

However, the rapid growth of the aviation sector is a big factor that allows this sector to emit the highest Greenhouse gas more than every sector. The report of the American Meteorological Society in 2018 showed that in 2018, Greenhouse gas, Carbon dioxide (CO_2), Methane, and Nitrous oxide were the most emitted in our history. This made the weather of the world was hotter by 43% from 1990. The aviation sector emitted the highest Greenhouse gas between 1990 to 2018. Within this period, the Greenhouse gas was emitted from this sector more than 114 percent. Between 2013 to 2018, the aviation sector emitted CO_2 more than 26 percent. In 2050, this sector could be the only sector that emitted the CO_2 as 25% of all sectors in the world (Voice News, 2019). In 2019, the UN launched the program called "Carbon Offsetting and Reduction

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Scheme for International Aviation (CORSIA)" to manage the CO_2 emissions problem from the aviation sector. This program began in 2020 (Carbon Brief, 2019) in the same as the COVID-19 pandemic period. We have been waiting for a long time to see that this program will help to mitigate the emission problem or not.

In 2020, the world had faced the beginning period of the COVID-19 pandemic. It made all sectors encountered severe problems. For the aviation industry, ICAO reported an overall reduction of 2,690 million passengers around the world comparing with 2019. They were declined by more than 60%. The overall airports lost their passengers approximately 64.2% and airlines for 66.3%. The global economy faced a decline in GDP of 4.3% (ICAO, 2021). That was worse than the period of the global financial crisis in 2008-2009. For Thailand, the GDP had declined by 6.6 percent (IMF, 2021). After the COVID-19 pandemic, many analysts believe that the world will face a new way of living called the "New Normal" (Allianz, 2020; The Japan Times, 2020). The COVID-19 pandemic accelerates the growth of adopting new technologies to firms and people. For example, the working from home policy was used during the lockdown period. Many people use the online platform for working, shopping, learning, and relaxing. As these results, the stock prices of technology companies grow rapidly in this period (Hoon Smart, 2020).

The post-COVID-19 pandemic will be the world that companies hire fewer workers. Some low-skilled jobs will be replaced by machines and technologies. Many companies had adapted their organizations because they faced technology disruptions before the COVID-19 pandemic in 2020. Most of them laid off their unskilled employees and adopted new technologies instead. They hired high-skilled workers who can be best with technologies to make the good performances of the firms. The example was many Startup companies. They hired a few high-potential workers and used a lot of new technologies to improve their productivity and the flow of operational efficiencies. This made most of them grew rapidly in the short term. The streaming company as Netflix shows their policy to hire only a group of very high-skilled employees called "Talent Density" (Hasting and Meyer, 2020; McCord, 2018). Many

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rapid growth companies in this century use new management systems called “Lean” and “Agile” (The Standard, 2020).

The new environments will challenge the old fashion working system. Some companies who can adapt their organizations to new technologies efficiently can survive and otherwise cannot. The aviation industry is facing the same problem as other sectors. Some airports transformed their old airports into new airports by adopting new technologies to improve their performances. The new airport of this era is called “Smart Airport”. This kind of airport will adopt new technologies such as biometric facial recognition, artificial intelligence (AI), the internet of things (IOT), and 5G to reduce the time when passengers take at check-in counters. The face recognition technology will replace the old versions to confirm identity as a passport or citizen card. The future trend of aviation movements will use a lot of big data to improve their operations and make productivity improvements. These will help Smart Airports handle more passengers, aircraft movements, and tourists efficiently within the limiting area of the airports (Post Today, 2019; Smart SME, 2018; MGR Online, 2020).

Thailand is a tourism hub for international tourists. The total number of tourists in Thailand is more than 190 million in 2019 (Thailand’s Ministry of Tourism and Sports, 2020). Don Mueang International Airport (DMK) was the biggest hub of low-cost carriers (LCCs) passengers all around the world in 2015 and 2018. The aviation commercial industry is very important for the expansion of the tourism sector in Thailand. Currently, Thailand has 4 big airport hubs such as DMK, Suvarnabhumi Airport (BKK), Chiang Mai International Airport (CNX), and Phuket International Airport (HKT). BKK is the one of biggest airports in Asia.

The best performances of airports can help Thailand’s tourism sector to expand and accommodate the higher number of tourists who come into Thailand through the air transportation channel. The research in developed countries had studied the performance measurement of the airports in the Asia-Pacific region, Europe, North America, and South America. The results of productivity and efficiency measurement of the airports could help the stakeholders in the tourism and aviation sectors to design the policies to stimulate the growth of their businesses.

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This thesis is the first research project that measures the full performances of the 6 main public airports in Thailand. This thesis employs the data envelopment analysis (DEA) model to measure the operational efficiencies of the 6 main public airports in Thailand for 14 years and considers the external factors that affect the level of efficiencies such as political conflict, financial crisis, and the pandemic of the COVID-19. This study also employs Malmquist's total factor productivity index (MPI) model to estimate the technology adoption rates of the individual airports. The MPI model can help to test the level of productivity changes for each airport in the study periods. Lastly, the thesis uses a basic time-series method to forecast the trends of efficiency and productivity in terms of technology adoptions and technical efficiency changes of the individual airports in the next 10 years after the pandemic passed.

1.2 Motivation of the Study

A few research papers had studied about performance measurement of Thailand's airports. Pandey (2016) studied the service quality of BKK and DMK. Kratudnak and Tippayawong (2018) studied the service quality of CNX and DMK. In addition, Sopadang and Suwanwong (2016) employed the DEA model to test whether CNX with the other 19 ASEAN airports existed efficiently in very short periods. Sopadang and Suwanwong (2016) studied the airport connectivity of DMK and tested whether DMK had enough capability to be the biggest LCCs airport in the world. However, nobody studied the productivity growth of airports in Thailand. There existed only one research measuring the efficiency levels of 6 airports in Thailand for a period (Rapee and Peng, 2014). However, no research paper seriously studied the full performance measurement of the 6 Thailand's main public airports with the long period of data and considered the external factors that affected the operational efficiencies of the airports. This thesis will be the first research project in Thailand that considers the impact of the COVID-19 pandemic in 2020 with the newest data on the performance in both terms of efficiency and productivity changing of the aviation industry. Lastly, this thesis is the first work that considers the future performances of the 6 main public

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airports of Thailand by applying the time-series method to forecast the number of passenger and aircraft movements of the individual airports for the next 10 years after the COVID-19 pandemic in 2020. Moreover, this is the first study that employs forecasting data to estimate the future performances of airports in Thailand.

To fill research gaps in the literature, this thesis measures the efficiency and productivity of the 6 main public airports of Thailand that cover the longest period of data. This study covers the data between the year BKK opened in 2007 until the recent year in 2020. They represent the full panel 14 years data of all the 6 main public airports in Thailand operated by the Airport of Thailand Public Company Limited (AOT).

This thesis employs the DEA model proposed by Charnes et al. (1978) to measure the technical efficiency levels of the airports and the MPI model proposed by Fare et al. (1994) to measure the productivity growth of the airports in the study periods. This study also employs the Simar and Wilson Bootstrapping Regression model (Simar and Wilson, 2007) to test whether external factors affect the airports' efficiency scores. Lastly, this study uses a time-series method to forecast the recovery trends of the passenger and aircraft movements for the 6 main public airports of Thailand after the unexpected shock from the COVID-19 pandemic in 2020.

1.3 Objectives

This study comprises 5 major objectives as follows:

1) Identifying whether the 6 main public airports of Thailand had good performances in terms of technical efficiency between 2007 to 2020 by employing the data envelopment analysis (DEA) model and showing which external factors in Thailand context contributed to the efficiency levels of the airports.
2) Identifying whether the 6 airports had the productivity progress or regress between 2007 to 2020 by employing Malmquist's total factor productivity index (MPI) model.

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3) Discussing the impact of the COVID-19 pandemic of the year 2020 on the performances of the 6 main public airports in Thailand.
4) Forecasting the future performances of the airports in the post-COVID-19 period between 2021 to 2030 by employing the autoregressive (AR) model.
5) Suggesting future policies to transform the traditional airports into Smart Airports.

1.4 Contribution of the Study

This thesis divides the analysis part into 2 subparts: 1) Measuring the technical efficiency scores and productivity growth of the 6 main public airports in Thailand between 2007 to 2020 and discussing the impact of the COVID-19 pandemic in 2020. 2) Forecasting the recovery trends in terms of the operational efficiencies and productivity growth of the airports in the post-COVID-19 period between 2021 to 2030.

This study measures the past performances of the 6 main public airports and forecasts the future performances. The results of this thesis will help the authorities and stakeholders in the field of air transportation and the tourism sector to design the appropriate policies to promote sustainable development in this industry. They can employ the models in this thesis with their future and forecasting data to estimate their performances and capabilities to be the guidelines for improving their operating systems to get more productivity.

This thesis can be useful to policymakers and authorities to set the strategies for developing the environmental and new working systems of airports to accommodate the higher number of tourists in the future. These can guide the stakeholders in the air transportation field for adopting new working systems and new technologies to transform the old version airports into smart airports.

1.5 Organization of the Study

This thesis composes of 9 chapters. The next chapter discusses the overview of the 6 main public airports in Thailand. Chapter 3 discusses all theories that are applied to the methodologies in this study. Chapter 4 provides literature reviews of the previous studies. Chapter 5 discusses the methodologies employing in this thesis. Chapter 6 explains all secondary data and forecasting data by the AR model and the Excel Linear Forecast function. Chapter 7 reports all results. Discussion, limitations, and suggestions are presented in chapter 8. Lastly, chapter 9 is the conclusion.

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CHAPTER 2
AN OVERVIEW OF THE 6 MAIN PUBLIC AIRPORTS IN THAILAND

Thailand has 39 public airports in the entire country. The 6 main public airports are operating by Airports of Thailand Public Company Limited (AOT). The 2 international airports are in Bangkok and the other 4 international airports have located at regional sites such as Chiang Mai, Phuket, Songkhla, and Chiang Rai. AOT is one of the biggest companies in Thailand and the biggest airport organization in the world.

The 29 regional airports are operating by Thailand's Department of Airports (DOA). Only one airport belongs to Royal Thai Navy called "U-Tapao Pattaya International Airport (UTP)". The last 3 airports are under the Bangkok Airways Public Company Limited. They are Sukhothai Airport (THS), Samui Airport (USM), and Trat Airport (TDX). Table 2.1 shows the list of all 39 public airports in Thailand.

Table 2.1

List of public airports in Thailand

Airport name	Province served	IATA airport code	Operator
Buriram Airport	Buriram	BFV	DOA
Suvarnabhumi Airport	Samut Prakan	BKK	AOT
Mae Fah Luang-Chiang Rai International Airport	Chiang Rai	CEI	AOT
Chumphon Airport	Chumphon	CJM	DOA
Chiang Mai International Airport	Chiang Mai	CNX	AOT

Table 2.1

List of public airports in Thailand (Cont.)

Airport name	Province served	IATA airport code	Operator
Don Mueang International Airport	Bangkok	DMK	AOT
Hat-Yai International Airport	Songkhla	HDY	AOT
Mae Hong Son Airport	Mae Hong Son	HGN	DOA
Hua Hin Airport	Prachuap Khiri Khan	HHQ	DOA
Phuket International Airport	Phuket	HKT	AOT
Krabi International Airport	Krabi	KBV	DOA
Khon Kaen Airport	Khon Kaen	KKC	DOA
Nakhon Phanom Airport	Nakhon Phanom	KOP	DOA
Loei Airport	Loei	LOE	DOA
Lampang Airport	Lampang	LPT	DOA
Mae Sot Airport	Tak	MAQ	DOA
Betong Airport	Yala	N.A.	DOA
Nakhon Ratchasima Airport	Nakhon Ratchasima	NAK	DOA
Narathiwat Airport	Narathiwat	NAW	DOA

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Table 2.1

List of public airports in Thailand (Cont.)

Airport name	Province served	IATA airport code	Operator
Nan Nakhon Airport	Nan	NNT	DOA
Nakhon Si Thammarat Airport	Nakhon Si Thammarat	NST	DOA
Pattani Airport	Pattani	PAN	DOA
Phisanulok Airport	Phitsanulok	PHS	DOA
Phetchabun Airport	Phetchabun	PHY	DOA
Phrae Airport	Phrae	PRH	DOA
Surin Airport	Surin	PXR	DOA
Pai Airport	Mae Hong Son	PYY	DOA
Roi Et Airport	Roi Et	ROI	DOA
Sakon Nakhon Airport	Sakon Nakhon	SNO	DOA
Trat Airport	Trat	TDX	Bangkok Airways
Sukhothai Airport	Sukhothai	THS	Bangkok Airways
Tak Airport	Tak	TKT	DOA
Trang Airport	Trang	TST	DOA
Ubon Ratchathani Airport	Ubon Ratchathani	UBP	DOA
Ranong Airport	Ranong	UNN	DOA
Surat Thani International Airport	Surat Thani	URT	DOA

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Table 2.1

List of public airports in Thailand (Cont.)

Airport name	Province served	IATA airport code	Operator
Samui International Airport	Songkhla	USM	Bangkok Airways
Udon Thani International Airport	Udon Thani	UTH	DOA
U-Tapao International Airport	Rayong	UTP	Royal Thai Navy

Note. From AOT's Corporate Presentation (2020) and List of airports in Thailand (n.d.).

This thesis focuses on the 6 main public airports in Thailand operating by AOT. These 6 airports handled the number of passenger movements more than 86% of all airports in Thailand in 2019. The total number of passengers of all airports was 165 million passengers in 2019, but only 6 airports of AOT handled 143.02 million passengers (AOT's Corporate Presentation, 2019; CAAT, 2019). Table 2.2 shows the comparing the total number of aircraft movements between the 6 main public airports and all public airports in Thailand. Figure 2.1 uses the information in Table 2.2 to plot the graphs. Table 2.3 shows the comparing the total number of passenger movements between the 6 main public airports and all public airports in Thailand. Figure 2.2 also uses the information in Table 2.3 to plot the graphs. Both Table 2.2 and Table 2.3 show that the 6 main public airports handled the total number of passenger and aircraft movements more than 80 percent of all airports every year since 2008.

This chapter discusses the background of AOT, the future development plan of the 6 airports, and the severe problem of the COVID-19 pandemic on these airports. This thesis measures the full performances of the 6 main public airports in Thailand in both terms of technical efficiency and productivity growth for 14 years and

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forecasts the future performances of these airports for the next 10 years. This information will be useful for the policymakers to set their strategies and stimulate the sustainable development growth of the tourism sector in Thailand after the crisis in 2020.

Table 2.2

Comparing the total passenger movements that the 6 main public airports of AOT handled with all public airports in Thailand between 2008 to 2020

Year	Number of passengers of AOT (million)	Number of passengers of Thailand (million)	Ratio
2008	54.41	57	95.46%
2009	53.94	58	93.00%
2010	58.24	63	92.44%
2011	66.37	74	89.69%
2012	76.13	83	91.72%
2013	88.29	97	91.02%
2014	90.53	104	87.05%
2015	109.82	127	86.47%
2016	121.71	141	86.32%
2017	133.12	152	87.58%
2018	140.47	162	86.71%
2019	143.02	165	86.68%
2020	46.64	58	80.41%

Note. From CAAT’s air transportation statistics between 2017 to 2020 and AOT’s air traffic reports between 2015 to 2020.

Table 2.3

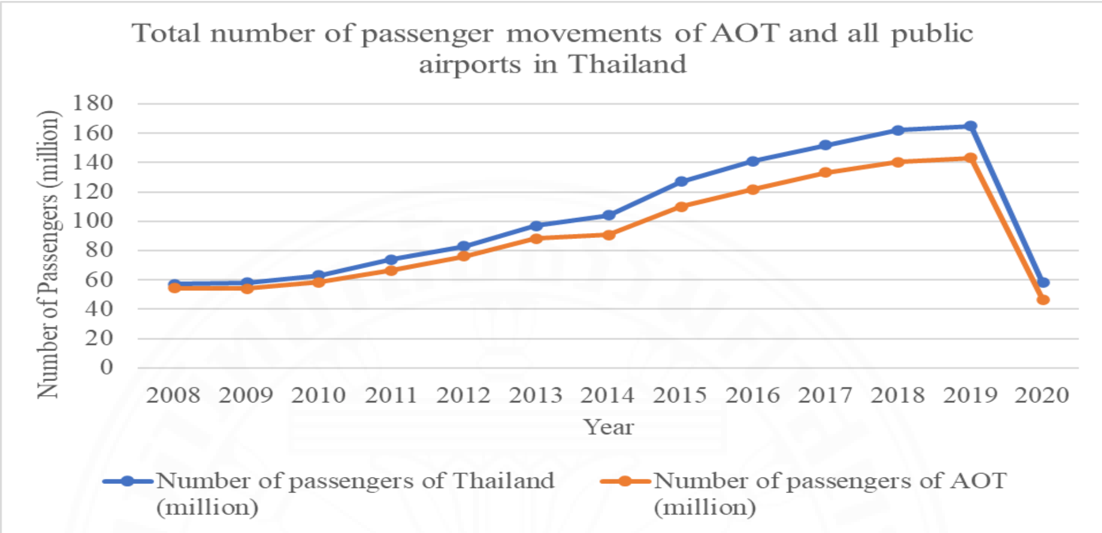
Comparing the total aircraft movements that the 6 main public airports of AOT handled with all public airports in Thailand between 2008 to 2020

Year	Total aircraft movements of AOT (thousand)	Total aircraft movements of Thailand (thousand)	Ratio
2008	371.56	415	89.53%
2009	362.48	422	85.89%
2010	395.10	461	85.71%
2011	449.48	540	83.24%
2012	499.49	593	84.23%
2013	582.41	698	83.44%
2014	624.17	768	81.27%
2015	727.75	894	81.40%
2016	790.35	978	80.81%
2017	833.08	1038	80.26%
2018	887.60	1098	80.84%
2019	893.52	1068	83.66%
2020	395.11	500	79.02%

Note. From CAAT's air transportation statistics between 2017 to 2020 and AOT's air traffic reports between 2015 to 2020.

Figure 2.1

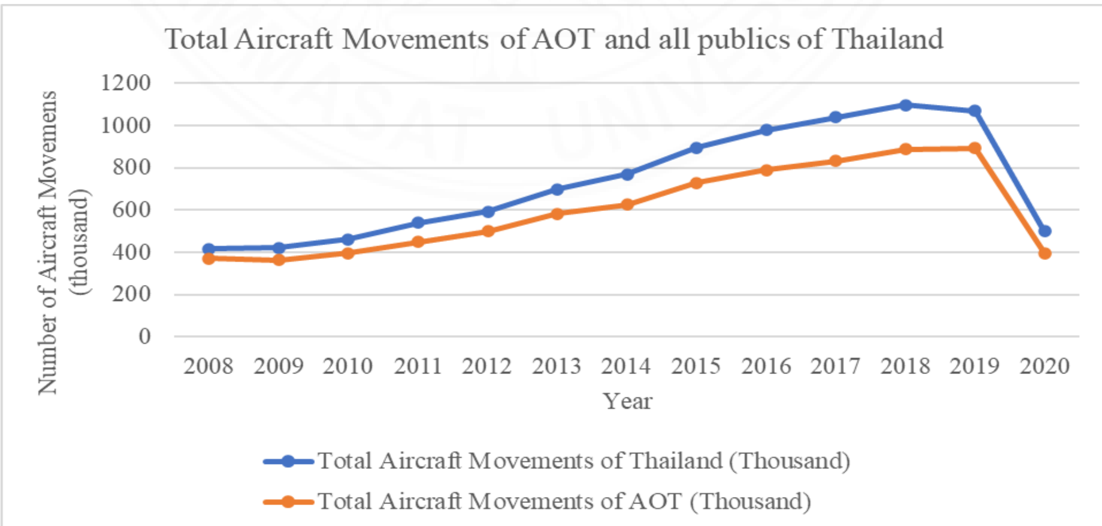
Comparing the total passenger movements that the 6 main public airports of AOT handled with all public airports in Thailand between 2008 to 2020



Note. From CAAT's air transportation statistics between 2017 to 2020 and AOT's air traffic reports between 2015 to 2020.

Figure 2.2

Comparing the total aircraft movements that the 6 main public airports of AOT handled with all public airports in Thailand between 2008 to 2020



Note. From CAAT's air transportation statistics between 2017 to 2020 and AOT's air traffic reports between 2015 to 2020.

2.1 Background of AOT

Airports of Thailand Public Company Limited (AOT) is a public limited company and a leader of Thailand's airport business operator. Thailand Ministry of Finance holds stocks of AOT for 70% or 10 billion stocks. "Thailand Top Companies listed by Market Cap on 1 January 2020" reports that AOT was the second-highest company of Thailand after PTT Public Company Limited and has a value of around 37.711 billion USD. AOT ranked 433th biggest company in January 2020 (Value.Today, 2021). In 2018, AOT was the highest value of all airport companies (Kaohoon, 2018; Chiang Mai News, 2018; Money Buffalo, 2020). Table 2.4 shows the first 10 major shareholders of AOT on 13 December 2019.

Table 2.4

The first 10 major shareholders of AOT as of 13 December 2019

No.	Name	Number of Shares	Percentage of Total Shares
1.	MINISTRY OF FINANCE	10,000,000,000	70.000
2.	THAI NVDR COMPANY LIMITED	704,332,872	4.930
3.	SOUTH EAST ASIA UK (TYPE C) NOMINEES LIMITED	372,348,982	2.606
4.	STATE STREET EUROPE LIMITED	227,276,535	1.591
5.	SOCIAL SECURITY OFFICE	164,542,800	1.152
6.	GIC PRIVATE LIMITED	70,747,700	0.495
7.	SOUTH EAST ASIA UK (TYPE A) NOMINEES LIMITED	58,184,364	0.407
8.	SE ASIA (TYPE B) NOMINEES LLC	56,840,000	0.398
9.	VAYUPAK MUTUAL FUND 1 BY MFC ASSET MANAGEMENT PLC	48,138,700	0.337
10.	VAYUPAK MUTUAL FUND 1 BY KRUNGTHAI ASSET MANAGEMENT PLC	48,138,700	0.337
11.	OTHER SHAREHOLDERS	2,535,149,347	17.747
		14,285,700,000	100.000

Note. From AOT's Annual Report 2020, p.38.

"The main business lines of AOT are managing, operating, and developing airports. Currently, AOT has 6 international airports under responsibility i.e., Suvarnabhumi Airport (BKK), Don Mueang International Airport (DMK), Phuket International Airport (HKT), Chiang Mai International Airport (CNX), Hat Yai International Airport (HDY), and Mae Fah Luang-Chiang Rai International Airport (CEI).

All airports of AOT handle both domestic and international freights. AOT's main revenue is derived from 2 main channels. Aeronautical revenue includes landing charge, parking charge, passenger service charge, and aircraft service charge. Non-Aeronautical revenue includes concession revenue, office and real property rents, and service revenues. (AOT's Business Characters, n.d.)"

Before BKK opened in 2006, "DMK was the main international airport of Thailand between 1924 to 2006 and transitioned in 2007 to become the low-cost airlines' hub for Bangkok (Suvarnabhumi Airport, n.d.)". DMK was known as "Bangkok International Airport". This airport is considered as "one of the world's oldest international airports and Asia's oldest operating airports. It was officially opened as a Royal Thai Air Force base on 27 March 1914. Commercial freights began in 1924, making it one of the world's oldest commercial airports. In September 2006, DMK was closed and replaced by the BKK, before reopening on 24 March 2007 after renovations. Since the opening of BKK, DMK has become a regional commuter freight hub and the low-cost carriers (LCCs) hub (Don Mueang International Airport, n.d.)". In 2015 and 2017, DMK became the world's largest low-cost carriers airport (CAPA CENTRE FOR AVIATION, 2015; MGR ONLINE, 2015; CAPA CENTRE FOR AVIATION, 2018).

BKK covers an area of 8,000 acres, making it "one of the biggest international airports in Southeast Asia and a regional hub for aviation. The airport is also a major cargo air freight hub (20th busiest in 2019), which has a designated Airport Free Zone, as well as road links to the East Economic Corridor (EEC) on Motor way 7. In 2019, ACI reported BKK was the 19th busiest airport in the world. BKK was 21th

Ref. code: 25646204040080WKG

busiest airport between 2017 to 2018 and 20th in 2016. (Suvarnabhumi Airport, n.d.; List of busiest airports by passenger traffic, n.d.)"

The average ranking of Thailand's busiest airports of AOT between 2009 to 2019 is following as BKK, DMK, HKT, CNX, HDY, and CEI. BKK, DMK, HKT, CNX, and HDY were 1st, 2nd, 3rd, 4th, and 5th busiest of all airports in Thailand, respectively. CEI was the 9th busiest airport in Thailand after Krabi International Airport (KBV), Samui International Airport (USM), and Udon Thani International Airport (UTH), respectively (List of the busiest airports in Thailand, n.d.). USM is operated by Bangkok Airways Public Company Limited, while KBV and UTH are operated by Thailand's Department of Airports.

2.2 Airports of AOT long term development projects

In the part of factors affecting future operation in AOT's Annual Report 2020, it has been reported about the phase 2 development plan of BKK. There have been "95% progress in the construction of Midfield Satellite building 1 (SAT-1). Currently, it is in the stage of the architecture, interior design, and landscaping and installation of the building's systems. Apart from this, the installation of the Automated People Mover (APM) is approximately 71% in progress and the baggage handling system is 76% in progress. The construction of airline offices and the eastern car parks are expected to be completed in 2020. The installation of building's systems for the car park is expected to be completed around 2021 (AOT's Annual Report, 2020, p.144-145)."

"AOT plans to increase revenue during the 2021 aviation crisis by raising income from non-aeronautical revenue such as a pre-export product quality certification center or Certify Hub, as well as Suvarnabhumi Airport City, AOT's subsidiaries and application of AOT's airports. This will allow AOT to provide a complete range of airport services. It will make Thailand being center for trade, investment, enhance competitiveness, and tourism growth. It will also be enabling the country's economy

Ref. code: 25646204040080WKG

to recover once the spread of COVID-19 is under control and make Thailand becoming the region's leading aviation and air cargo hub (AOT's Annual Report, 2020, p.145)."

For the long term development projects of the 6 airports, "the airport development master plans of the 6 airports under AOT's responsibility have been developed in consideration of the necessity for airport capacity expansion to accommodate a continuous increase in air traffic volume and maintain the country's opportunities for economic growth, trade, investment, tourism, and services as well as connectivity of transport network systems in different modes (land, rail, and sea). In the context of national development, changes vary according to the environment and diverse modes and purposes of travel/transport. As such, the development of Airport Development Master Plans must be considered based on the national transport systems development in various types that connect transport networks to AOT's transports (AOT's Annual Report, 2020, p.158)."

For Suvarnabhumi Airport (BKK) Development Master Plan, BKK is currently developing as project phase 2 that can increase the capacity of this airport to handle 60 million passengers per year. This project consists of the construction of the Midfield Satellite 1 (SAT-1), installation of the Automated People Mover (APM) to connect the main Passenger Terminal, the baggage handling system, and the construction of the Airline Office Building and the east car park. All of these are expected to complete within 2021. For the development project in phase 3, BKK will increase capacity to handle 90 million passengers per year. This project includes the construction of the north expansion and will open the 3rd runway in 2023. In phase 4, BKK has a plan to increase capacity to handle 105 million passengers per year by constructing the Midfield Satellite 2 (SAT-2). This project is expected to complete in 2026. The last phase will increase passenger handling capacity from 105 million passengers to 150 million passengers per year. This project will construct the South Passenger Terminal and the 4th runway. This project is expected to complete within 2030.

For Don Mueang International Airport (DMK) Development Master Plan, the third phase is expected to be completed in 2026. This project will increase the capacity of DMK to handle 40 million passengers per year. This project includes the removal of the existing domestic passenger terminal, construction of the Passenger Terminal 3 to handle more than 18 million international passengers per year with the south public utility systems, and improving the Passenger Terminal 1.

Chiang Mai International Airport (CNX) Development Plan is currently in phase 1 between 2020 to 2024. This plan includes the construction of the International Passenger Terminal, improvement of the existing passenger terminal, extension of parking bays, new parallel of taxiway, and the airport support system for increasing passenger handling capacity to 16.5 million passengers per year. Phase 2 will continue after phase 1 is completed. The second phase includes the extension of the passenger terminal and apron to handle 20 million passengers per year.

Hat Yai International Airport (HDY) Development Plan is currently in phase 1 between 2021 to 2025. This plan includes increasing the capacity of the airport to accommodate 10.5 million passengers per year. The project consists of the construction and extension of the passenger terminal, improving the landside road system, improving and extension of the public utility systems, extending the parking bays, and constructing partial parallel taxiways.

Phuket International Airport (HKT) Development Master Plan is currently in phase 2. It consists of the extension of the south apron and the International Passenger Terminal. After completing this project, HKT can handle 18 million passengers per year. This project is expected to complete in 2024.

Mae Fah Luang-Chiang Rai International Airport (CEI) Development Master Plan in phase 1 is between 2024 to 2028. This project includes the extension of the passenger terminal and the construction and extension of the taxiways to increase passenger handling capacity to 4.8 million per year. The second phase is expected to complete within 2033. Phase 2 Development Plan of CEI will be the extension of the passenger terminal and parking bays that can accommodate 5.2 million passengers per year.

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2.3 Problem in 2020

AOT's Annual Report 2020 reported that the impact of the COVID-19 pandemic in 2020 made the revenue of AOT decreased by 50.34% from 2019 to 2020. The profit in 2019 equals 25.026 billion baht declined to 4.320 billion baht in 2020. The profit from 2019 to 2020 had decreased by 82.74%. This report shows that the impact of the COVID-19 pandemic in 2020 made businesses are related to airlines, airports, and tourism faced with the severe problem.

AOT has policies to help concessionaires and airlines affected by the COVID-19 as approved by the Board of Director's meeting in February 2020, April 2020, and July 2020, respectively. At the end of September 2020, the "Board approved the extension of measures to help concessionaries and airlines about rental fees, building service charges, and fixed monthly compensation charges including the fee under the law on air navigation until 31st March 2022 instead of 31st December 2020 as previously specified. This is to lessen the burden of concessionaires and airlines during the crisis period (AOT's Annual Report, 2020, p.137-138)". Table 2.5 shows operating results for the year ended 2020. Table 2.6 shows Aeronautical revenues between 2019 to 2020. Table 2.7 shows Non-Aeronautical revenues between 2019 to 2020. Table 2.8 shows other incomes of AOT between 2019 to 2020. Table 2.9 shows total expenses between 2019 to 2020.

Ref. code: 25646204040080WKG

Table 2.5

Operating results for the year ended 2020

Unit: Million Baht

	2020	2019	Increase (decrease)	% YoY
Revenues from sales or services	31,179.10	62,783.41	(31,604.31)	(50.34)
Aeronautical revenue	*16,625.69*	*35,010.14*	*(18,384.45)*	*(52.51)*
Portion	*53%*	*56%*		
Non-aeronautical revenue	*14,553.41*	*27,773.27*	*(13,219.86)*	*(47.60)*
Portion	*47%*	*44%*		
Other income	2,096.41	1,783.38	313.03	17.55
Total revenues	**33,275.51**	**64,566.79**	**(31,291.28)**	**(48.46)**
Less Total expenses	27,938.93	33,082.48	(5,143.55)	(15.55)
Profit before income tax expense	**5,336.58**	**31,484.31**	**(26,147.73)**	**(83.05)**
Less Income tax expense	1,038.04	6,388.76	(5,350.72)	(83.75)
Net profit for the year	**4,298.54**	**25,095.55**	**(20,797.01)**	**(82.87)**
Profit attributable to:				
Owners of the parent	4,320.68	25,026.37	(20,705.69)	(82.74)
Non-controlling interests	(22.14)	69.18	(91.32)	(132.00)
Earnings per share (Baht)	**0.30**	**1.75**	**(1.45)**	**(82.86)**

Note. From AOT's Annual Report 2020, p.138.

Table 2.6

Aeronautical Revenues between 2019 to 2020

Unit: Million Baht

	2020	2019	Increase (decrease)	% YoY
Office and state property rents	1,838.38	2,296.46	(458.08)	(19.95)
Service revenues	4,550.26	8,009.68	(3,459.42)	(43.19)
Concession revenues	8,164.77	17,467.13	(9,302.36)	(53.26)
Total	14,553.41	27,773.27	(13,219.86)	(47.60)

Note. From AOT's Annual Report 2020, p.139.

Table 2.7

Non-Aeronautical Revenues between 2019 to 2020

Unit: Million Baht

	2020	2019	Increase (decrease)	% YoY
Gain on foreign exchange	141.59	178.65	(37.06)	(20.74)
Interest income	990.89	1,168.24	(177.35)	(15.18)
Gain on sales of assets	3.97	3.40	0.57	16.76
Other	959.96	433.09	526.87	121.65
Total	2,096.41	1,783.38	313.03	17.55

Note. From AOT's Annual Report 2020, p.140.

Table 2.8

Other incomes between 2019 to 2020

Unit: Million Baht

	2020	2019	Increase (decrease)	% YoY
Landing and parking charges	3,788.81	7,425.75	(3,636.94)	(48.98)
Departure passenger service charges	12,351.29	26,742.55	(14,391.26)	(53.81)
Aircraft service charges	485.59	841.84	(356.25)	(42.32)
Total	16,625.69	35,010.14	(18,384.45)	(52.51)

Note. From AOT's Annual Report 2020, p.140.

Table 2.9

Total expenses between 2019 to 2020

Unit: Million Baht

	2020	2019	Increase (decrease)	% YoY
Employee benefit expenses	6,314.23	8,204.21	(1,889.98)	(23.04)
Utilities expenses	2,215.70	2,688.27	(472.57)	(17.58)
Outsourcing expenses	4,030.44	5,893.85	(1,863.41)	(31.62)
Repairs and maintenance	3,045.52	2,802.28	243.24	8.68
State property rental	2,393.31	4,357.48	(1,964.17)	(45.08)
Depreciation and amortisation expenses	5,441.25	5,851.47	(410.22)	(7.01)
Loss (reversal of loss) on impairment of assets	1,228.26	(427.28)	1,655.54	387.46
Other expenses	2,624.02	2,897.67	(273.65)	(9.44)
Financial costs	646.20	814.53	(168.33)	(20.67)
Total	27,938.93	33,082.48	(5,143.55)	(15.55)

Note. From AOT's Annual Report 2020, p.141.

This shows that the unexpected shock from the COVID-19 pandemic in 2020 impacts to decline a lot in revenue, profit, number of passengers, and number of aircraft movements of every airport of AOT. In AOT's Annual Report 2020, the cost of employees had decreased by 23.09% because in 2020, AOT did not set up accrued bonuses for employees. It is the first year in ten years that AOT does not pay the bonus to the employees. Table 2.10 shows total aircraft traffic statistics in the fiscal year 2019-2020 of all airports of AOT. Table 2.11 shows low-cost carriers (LCCs) traffic statistics in the fiscal year 2019-2020 of all airports of AOT. Table 2.12 shows the total number of passenger movement statistics in the fiscal year 2019-2020 of all airports of AOT. Table 2.13 shows only low-cost carriers (LCCs) passenger movement statistics in the fiscal year 2019-2020 of all airports of AOT.

Table 2.10

Total aircraft movements of all 6 airports of AOT in the fiscal year 2019-2020

	FY2019	FY2020	YoY%
BKK	55,337	33,283	(39.85%)
DMK	263,036	159,794	(39.25%)
BKK+DMK	318,373	193,077	(39.36%)
CNX	51,560	33,326	(35.36%)
HDY	21,389	14,255	(33.35%)
HKT	60,862	30,003	(50.70%)
CEI	14,542	9,968	(31.45%)
Total	**466,726**	**280,629**	**(39.87%)**

Note. From AOT's Corporate Presentation 2020, p.5.

Table 2.11

Total low-cost-carriers (LCCs) movements of all 6 airports of AOT in the fiscal year 2019-2020

	FY2019	FY2020	YoY%
BKK	378,882	210,596	(44.42%)
DMK	273,592	166,184	(39.26%)
BKK+DMK	652,474	376,780	(42.25%)
CNX	80,534	47,298	(41.27%)
HDY	27,045	18,250	(32.52%)
HKT	115,525	59,656	(48.36%)
CEI	20,510	13,201	(35.64%)
Total	**896,088**	**515,185**	**(42.51%)**

Note. From AOT's Corporate Presentation 2020, p.5.

Table 2.12

Total number of passenger movements of all 6 airports of AOT in the fiscal year 2019-2020

	FY2019	FY2020	YoY%
BKK	64,710,402	30,750,332	(52.48%)
DMK	41,008,378	22,250,720	(45.74%)
BKK+DMK	105,718,780	53,001,052	(49.87%)
CNX	11,321,459	6,271,652	(44.60%)
HDY	4,028,410	2,478,233	(38.48%)
HKT	17,848,440	9,090,957	(49.07%)
CEI	2,953,088	1,795,794	(39.19%)
Total	**141,870,177**	**72,637,688**	**(48.80%)**

Note. From AOT's Corporate Presentation 2020, p.6.

Table 2.13

Total LCCs passenger movements of all 6 airports of AOT in the fiscal year 2019-2020

	FY2019	FY2020	YoY%
BKK	9,072,537	5,033,625	(44.52%)
DMK	40,624,588	22,220,509	(45.30%)
BKK+DMK	49,697,125	27,254,134	(45.16%)
CNX	7,668,752	4,496,983	(41.36%)
HDY	3,369,484	2,066,589	(38.67%)
HKT	9,076,711	4,149,402	(54.29%)
CEI	2,240,169	1,445,202	(35.49%)
Total	**72,052,241**	**39,412,310**	**(45.30%)**

Note. From AOT's Corporate Presentation 2020, p.6.

CHAPTER 3
THEORETICAL FRAMEWORK

This chapter discusses the theories used for this study. The first part of this chapter begins with the concept of production theory that is represented as sets. The second part emphasizes the theory of distance function that can be applied to both efficiency and productivity measurement. The next section focuses on the theory of efficiency in terms of input and output orientations. The fourth part shows the concept of efficiency in both constant return to scale (CRTS) and decreasing return to scale (DRTS). Next, the fifth part emphasizes measuring the technical efficiency by applying the linear programming model called the "data envelopment analysis (DEA)" model. This part discusses both input- and output-oriented DEA models. The next section discusses the basic idea of total factor productivity (TFP) measurement. TFP change can be decomposed into technical change, technological change, and scale efficiency change. Finally, the last section presents Malmquist's total factor productivity index (MPI) model. This thesis employs the MPI model to measure and decompose the productivity growth in the study periods.

3.1 Theory of Production Economics Using Sets

This section aims to describe the relationship between inputs and outputs that are given by the technology in the production process. Consider a production process consisting of M outputs and K inputs, the output quantities are represented by a nonnegative vector of outputs denoted as $y = (y_1, \dots, y_M) \in R_{+}^{M}$, the output prices are represented by a strictly positive vector of output prices denoted as $p = (p_1, \dots, p_M) \in R_{++}^{M}$, the input quantities are represented by a nonnegative vector of inputs denoted as $x = (x_1, \dots, x_k) \in R_{+}^{K}$, and the input prices are represented by a strictly positive vector of input prices denoted as $w = (w_1, \dots, w_k) \in R_{++}^{K}$.

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Consider a production process that uses multiple inputs with technologies to produce multiple outputs. Production technology (Eq. 3.1) is the set of any feasible input and output vectors in the production process denoted as

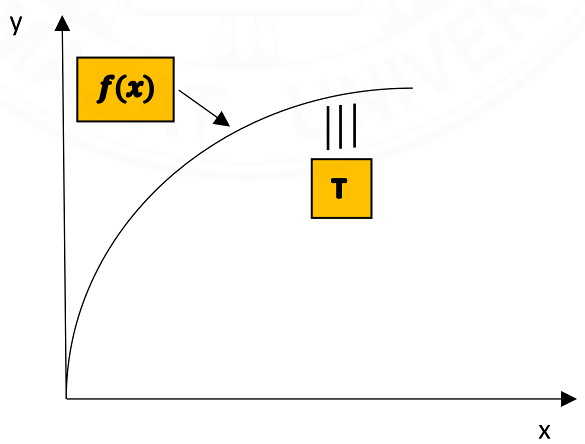
$$T = \{(y, x): x \; can \; produce \; y\} \tag{3.1}$$

The concept of production technology is useful to represent a "production frontier". The production frontier or $f(x)$ (Eq. 3.2) is the maximum output that can be produced by given the input vector. It can be defined by technology set (T), output sets $(P(x))$ or input sets $(L(y))$. Figure 3.1 shows the production frontier curve defined by using the concept of production technology.

$$\begin{aligned} f(x) &= \max\{y: (y, x) \in T\} \\ &= \max\{y: y \in P(x)\} = \max\{y: x \in L(y)\} \end{aligned} \tag{3.2}$$

Figure 3.1

Production frontier curve



Note. From Fare et al. (1996), p.10.

$L(y)$ is the input sets on the interval $[x, \infty]$. It is the sets of input vectors (x) used to produce each output vector (y) and it is denoted as

$$L(y) = \{x: (y, x) \in T\} \quad (3.3)$$

$P(x)$ is the output sets on the interval $[0, y]$. It is the sets of output vectors (y) produced by each input vector (x) and it is denoted as

$$P(x) = \{y: (y, x) \in T\} \quad (3.4)$$

3.2 Production technology with multiple outputs

The distance function is defined to represent a production technology when multiple inputs are used to produce multiple outputs. Noted that the basic production frontier cannot use to describe this production technology. Shephard (1953, 1970) proposed a distance function to describe the structure of production technology with multiple inputs and multiple outputs.

The distance functions have 2 types such as input distance function (D_I) and output distance function (D_o).

For the input distance function (D_I), it is defined as the maximum amount by which a producer's input vector can be radially contracted and remaining feasible for the output vector produces. D_I adopts an input-conserving approach to the measurement of the distance from a producer to the boundary of production possibilities. It can be defined as

$$D_I(y, x) = \max\{\lambda^*: \frac{x}{\lambda^*} \epsilon\, L(y)\} \quad (3.5)$$

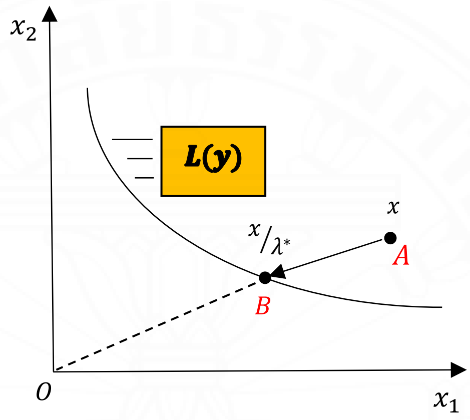
Where $L(y)$ is the input sets, it represents the "isoquant" curve which shows all combinations of all x used to produce a constant quantity of output y. The region of input sets is bounded below by the curve. λ^* is the maximum quantities of input reduced that can be feasible to produce output (y). $\frac{x}{\lambda^*}$ is the minimum of input quantities used to produce constant of output sets $(P(x))$.

Ref. code: 25646204040080WKG

Consider $K = 2$ inputs. Figure 3.2 shows that the input vector x is feasible for output y, but y can be produced with the radially contracted input vector $(\frac{x}{\lambda^*})$. Hence, $D_I(y,x) = \lambda^* = \frac{OA}{OB} \geq 1$.

Figure 3.2

Input distance function (D_I)



Note. From Fare et al. (1996), p.20.

The properties of the input distance function are summarized as follows:

1) $D_I(0,x) = \infty \; and \; D_I(y,0) = 0$
2) $D_I(y,\lambda x) = \lambda D_I(y,x) \; for \; \lambda > 0$
3) $D_I(y,\lambda x) \geq \lambda D_I(y,x) \; for \; \lambda \geq 1$
4) $D_I(\lambda y,x) \leq D_I(y,x) \; for \; \lambda \geq 1$
5) $D_I(y,x) \; is \; concave \; function \; in \; x.$

For the output distance function (D_o), it is defined as the minimum amount by which an output vector can be radially deflated and remaining producible with a given input vector. D_o takes an output-expanding approach to the measurement of the distance from a producer to the boundary of production possibilities. It can be defined as

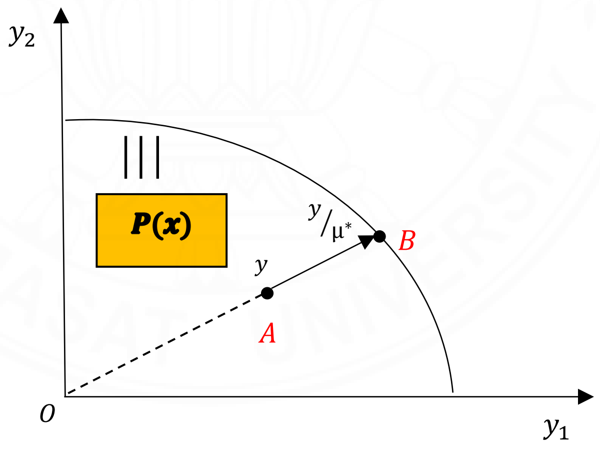
$$D_o(x, y) = \min\{\mu^*: \frac{y}{\mu^*} \epsilon\, P(x)\} \tag{3.6}$$

Where $P(x)$ is the output sets, it represents the "production possibilities curve" which shows the various output combinations that can be produced by using a given input level (x). The region of output sets is bounded above by the curve. μ^* is the minimum quantities of output expanded while using the fixed amounts of input (x). $\frac{y}{\mu^*}$ is the maximum of output quantities produced by using the constant of input sets ($L(y)$).

Consider $M = 2$ outputs. Figure 3.3 shows that the output vector y is producible with the input x, but the radially expanded output vector ($\frac{y}{\mu^*}$) can be also produced by using the input x. Hence, $D_o(x, y) = \mu^* = \frac{OA}{OB} \leq 1$.

Figure 3.3

Output distance function (D_o)



Note. From Fare et al. (1996), p.12.

The properties of the output distance function are summarized as follows:

1) $D_o(x,0) = 0 \; and \; D_o(0,y) = \infty$
2) $D_o(x,\lambda y) = \lambda D_o(x,y) \; for \; \lambda > 0$
3) $D_o(\lambda x,y) \leq D_o(x,y) \; for \; \lambda \geq 1$
4) $D_o(x,\lambda y) \leq D_o(x,y) \; for \; 0 \leq \lambda \leq 1$
5) $D_o(x,y) \; is \; convex \; function \; in \; y.$

3.3 A Measurement of Efficiency

Debreu (1951) and Farrell (1957) defined the technical efficiency measurement into input and output orientations. There can be used to measure the performance of a firm. Technical efficiency can be measured using both production frontier and distance function.

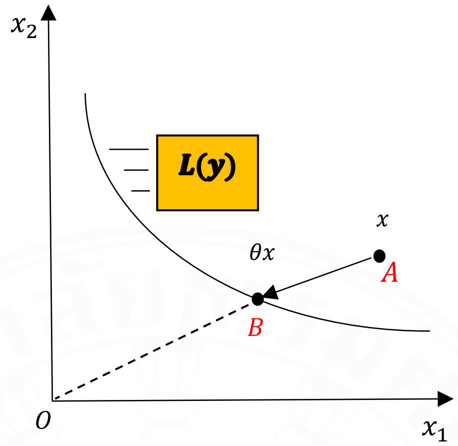
1) Input-oriented technical efficiency (TE_i) reflects the ability of a firm to minimize inputs while still producing the same amount of outputs. Input-oriented technical efficiency equals an inverse of the input distance function (D_I). It is defined as

$$\begin{aligned} TE_i(y,x) &= \min\{\theta: y \leq f(\theta x)\} \leq 1 \\ &= [D_I(y,x)]^{-1} \\ &= \min\{\theta: D_I(y,\theta x) \geq 1\} \end{aligned} \tag{3.7}$$

Where $D_I(y,x)$ is input distance function, and θ is the minimum of all input quantities proportionally reduced to produce the same output quantities. In other words, $\theta = \frac{1}{\lambda^*}$. Figure 3.4 shows the underlying idea of input-oriented technical efficiency.

Figure 3.4

The idea of input-oriented technical efficiency



Note. From Fare et al. (1996), p.20.

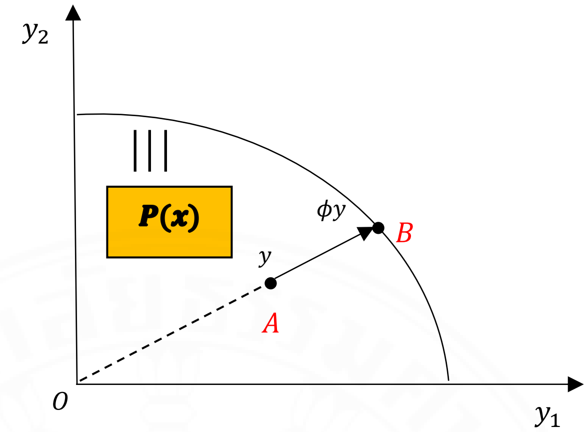
2) Output-oriented technical efficiency (TE_o) reflects the ability of a firm to maximize outputs while still using a fixed amount of the inputs. Output-oriented technical efficiency equals output distance function (D_o). It is defined as

$$\begin{aligned} TE_o(x,y) &= [\max\{\phi: \phi y \leq f(x)\}]^{-1} \leq 1 \\ &= D_o(x,y) \\ &= \max\{\phi: D_o(x,\phi y) \leq 1\} \end{aligned} \tag{3.8}$$

Where $D_o(x,y)$ is output distance function, and ϕ is the maximum of all output quantities proportionally increased by using the same amount of input quantities. In other words, $\phi = \frac{1}{\mu^*}$. Figure 3.5 shows the underlying idea of output-oriented technical efficiency.

Figure 3.5

The idea of output-oriented technical efficiency



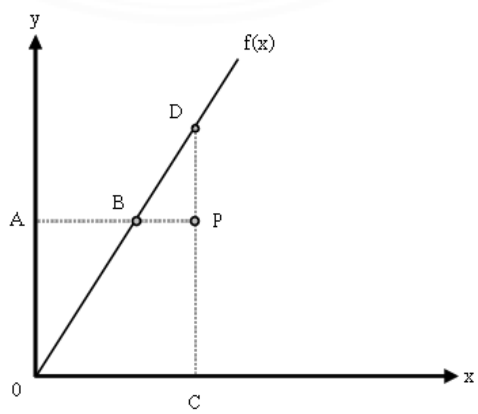
Note. From Fare et al. (1996), p.12.

3.4 Efficiency and Return to Scale.

The relationship between input- and output-oriented technical efficiency is shown in the 2 figures below. Figure 3.6 shows production technology with the constant return to scale (CRTS) assumption. Figure 3.7 shows production technology with the decreasing return to scale (DRTS) assumption (Färe and Lovell, 1978).

Figure 3.6

Input- and Output-Orientated Technical Efficiency Measures and Return to Scale (CRTS)

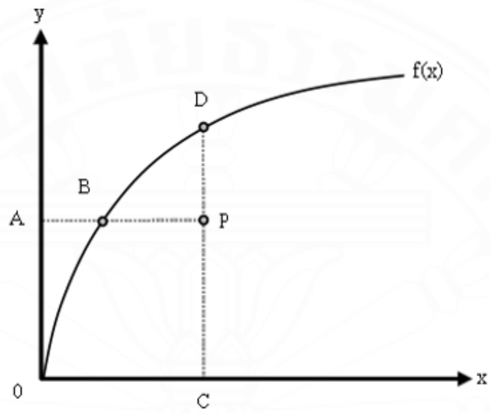


Note. From Coelli et al. (2005), p.55.

The input- and output-oriented technical efficiency under constant return to scale (CRTS) can be measured by $\frac{AB}{AP} = \frac{CP}{CD}$. Therefore, $TE_i = TE_o$.

Figure 3.7

Input- and Output-Orientated Technical Efficiency Measures and Return to Scale (DRTS)



Note. From Coelli et al. (2005), p.55.

The input- and output-oriented technical efficiency under decreasing return to scale (DRTS) can be measured by $\frac{AB}{AP} \neq \frac{CP}{CD}$. Therefore, $TE_i \neq TE_o$.

3.5 Technical Efficiency Measurement by using Data Envelopment Analysis (DEA) model.

The efficiency measurement can be estimated by 2 methods such as the "parametric method" and the "non-parametric method". The parametric method uses the concept of maximum likelihood estimation or "MLE". It can test the hypotheses and exclude any noise from the efficiency scores. On the contrary, the non-parametric method uses the concept of linear programming analysis. It cannot test hypotheses and it includes any noise as part of the efficiency scores.

"Stochastic Frontier Analysis (SFA)" model is the most famous parametric method used to estimate the efficiency levels of firms. This model fits the production technology with only one output and multiple inputs. While the non-parametric method is useful to estimate the efficiency levels using multiple inputs and multiple outputs that is known as the "Data Envelopment Analysis (DEA)" model.

This study uses multiple outputs and multiple inputs to estimate the efficiency levels and productivity changes of the 6 main public airports in Thailand. Therefore, the study employs the DEA model to estimate the results.

3.5.1 Data Envelopment Analysis (DEA) Model

DEA is a linear programming method constructing a non-parametric frontier over the data such that no observed data lie outside the frontier set. For the input orientation, the frontier is constructed using the input set, while the frontier is constructed using the output set for the output orientation.

Under DEA, the firm is referred to as $decision\ makings\ unit\ (DMU)$. DEA is developed to measure relative efficiencies for N homogenous and independent $DMUs$. DEA can be computed by 2 types of orientations such as "the input-oriented DEA model" and "the output-oriented DEA model".

3.5.1.1 Input-Oriented DEA Model

Charnes et al. (1978) proposed a DEA model for measuring technical efficiency (TE) by using input orientation under the assumption of constant return to scale (CRTS). This model is called the "CCR DEA model". CCR stands for "Charnes, Cooper, and Rhodes".

DEA model considers N $DMUs$ where each DMU uses K inputs to produce M outputs. Given i and j are the indexes of DMU where $i, j = 1, \dots, N$. Inputs and outputs can be written in the set forms as

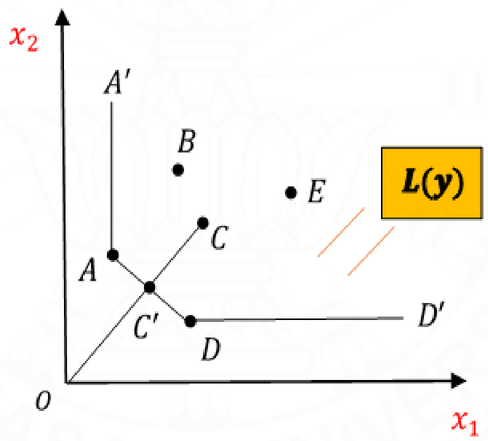
$$\boldsymbol{x}_i = (x_{1i}, \dots, x_{Ki}) \in R_+^K \text{ is input vector of } i^{th}\ DMUs \tag{3.9}$$

$$\boldsymbol{y}_j = \left(y_{1j}, \dots, y_{Mj}\right) \in R_+^M \text{ is output vector of } j^{th}\ DMUs \tag{3.10}$$

Figure 3.8 shows the input-oriented DEA frontier constructed by 5 $DMUs$. The frontier consists of a linear convex combination of $A'A, AD, and\ DD'$. It applies the theory of the input sets ($L(y)$). While point A and point D are operating at the isoquant curve, point B, C, and E do not operate on the curve but bounded inside the input sets ($L(y)$). This means that points A and D are fully efficient because they use minimum inputs to produce the highest amounts of outputs. However, points B, C, and E are operating inefficiently and must be improved their technical efficiencies to operate at the isoquant curve. In other words, they can reduce the amounts of inputs while producing the same amounts of outputs.

Figure 3.8

Input orientation DEA model constructed by 5 $DMUs$



Note. From Rungsuriyawiboon (2015), p.358.

Banker et al. (1984) extended the CCR DEA model with the concept of variable return to scale (VRTS). This model is called the "BCC DEA model". BCC stands for "Banker, Charnes, and Cooper".

The concept of the input-oriented model focuses on whether the firms use inputs efficiently to produce the fixed amounts of outputs. The model constructs the frontier curve by using input sets ($L(y)$). This model applies linear programming to calculate the level of efficiencies of all $DMUs$ and reports how much inefficient they have. The CCR DEA model applies the concept of CRTS. It calculates the efficiency levels at optimum scale or perfectly competitive assumption. While the BCC DEA model uses the concept of variable return to scale (VRTS), it assumes all $DMUs$ do not operate at the optimal point. Under the VRTS, all $DMUs$ are operating under imperfect competition.

Hence, the linear programming model of the input-oriented BCC DEA model can be defined as

$$
\begin{array}{lll}
\text{Min} & \theta_j = \theta^* & \\
\text{Subject to} & \sum_{i=1}^{N} \lambda_{ij}\, x_{ki} \leq \theta_j x_{kj}, & k = 1, \ldots, K \\
 & y_{mj} \leq \sum_{i=1}^{N} \lambda_{ij}\, y_{mj}, & m = 1, \ldots, M \\
 & \lambda_{ij} \geq 0, & i = 1, \ldots, N \\
 & \sum_{i=1}^{N} \lambda_{ij} = 1, & j = 1, \ldots, N
\end{array}
\qquad (3.11)
$$

Where θ_j or θ^* is input-oriented technical efficiency (TE) of the j^{th} DMU.

x_{kj} is input set of the j^{th} $DMUs$.

y_{mj} is output set of j^{th} $DMUs$.

λ_{ij} is the intensity variable representing weights of all $DMUs$ $(i = 1, \ldots, N)$ used to construct frontier for the j^{th} $DMUs$.

$\sum_{i=1}^{N} \lambda_{ij}\, x_{ki}$ is the boundary of input set calculated from λ_i and x_k.

$\sum_{i=1}^{N} \lambda_{ij}\, y_{mj}$ is the boundary of output set calculated from λ_i and y_m.

$\sum_{i=1}^{N} \lambda_{ij} = 1$ is the convexity constraint.

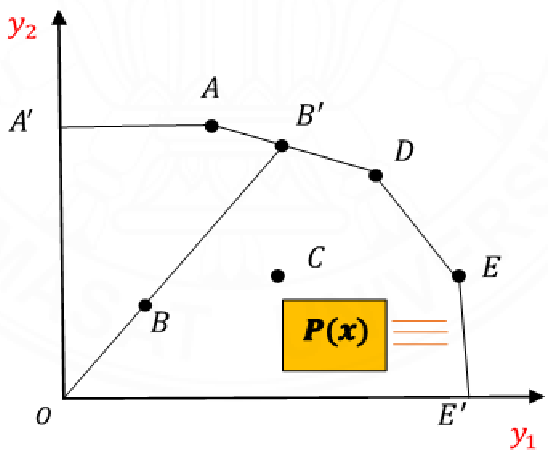
Noted that when assuming $\sum_{i=1}^{N} \lambda_{ij} = 1$, it refers to the BCC DEA model. Otherwise, it is the CCR DEA model.

3.5.1.2 Output-Oriented DEA Model

The concept of the output-oriented DEA model is very similar to the input-oriented DEA model. Figure 3.9 shows the output-oriented DEA frontier constructed by 5 $DMUs$. The frontier consists of a linear convex combination of $A'A, AD, DE, and\ EE'$. It applies the theory of the output sets ($P(x)$). While point A, D, and E are operating at the production possibilities curve, point B and C do not operate on the curve but bounded inside the output sets ($P(x)$). This means that point A, point D, and point E are fully efficient because they produce the highest amounts of outputs by using the limited amounts of the inputs. However, points B and C are operating inefficiently and must be improved their technical efficiencies to operate at the production possibilities curve. In other words, they can produce more outputs by using the same amounts of inputs.

Figure 3.9

Output orientation DEA model constructed by 5 $DMUs$



Note. From Rungsuriyawiboon (2015), p.360.

The output-oriented DEA model focuses on whether firms produce the highest amounts of outputs while still using the same amounts of inputs. The model constructs the frontier curve by using the output sets ($P(x)$). This model applies linear programming to calculate the level of efficiencies of all $DMUs$ and reports how much inefficient they have. The CCR DEA model applies the concept of CRTS. It calculates the efficiency levels at optimum scale or perfectly competitive assumption. On the other hand, the BCC DEA model uses the concept of VRTS that assumes all $DMUs$ operate as imperfect competition.

Hence, the linear programming of the output-oriented BCC DEA model can be defined as

$$
\begin{aligned}
&\text{Max} && \phi_j = \phi^* && \\
&\text{Subject to} && \sum_{i=1}^{N} \lambda_{ij}\, x_{ki} \le x_{kj}, && k = 1, \dots, K \\
& && \phi_j y_{mj} \le \sum_{i=1}^{N} \lambda_{ij}\, y_{mj}, && m = 1, \dots, M \\
& && \lambda_{ij} \ge 0, && i = 1, \dots, N \\
& && \sum_{i=1}^{N} \lambda_{ij} = 1, && j = 1, \dots, N
\end{aligned}
\tag{3.12}
$$

Where $\phi_j \ or\ \phi^*$ is the inverse of output-oriented TE of the j^{th} $DMUs$.

$\sum_{i=1}^{N} \lambda_{ij} = 1$ is the convexity constraint.

Noted that when assuming $\sum_{i=1}^{N} \lambda_{ij} = 1$, it refers to the BCC DEA model. Otherwise, it is the CCR DEA model.

3.6 Productivity Changing Measurement

To estimate the full performances of the firms in any period, a measure of productivity is presented in this section. Productivity considers limited inputs to produce the highest amounts of output and it can be defined as

$$Productivity = \frac{outputs}{inputs} \tag{3.13}$$

When the production process uses multiple inputs to produce multiple outputs, measuring the productivity level is quite complex. The concept of index numbers can be applied to measure productivity by constructing the productivity index. Hence, productivity index measurement can be defined as

$$Productivity\ index = \frac{output\ quntity\ index}{input\ quantity\ index} \tag{3.14}$$

When production technology is measured over the period, “productivity growth” can represent the productivity change of the firm between the first period and second period. Productivity growth between period 1 (first period) and period 2 (second period) can be defined as

$$Productivity\ growth_{12} = \frac{Productivity\ in\ period\ 2}{Productivity\ in\ period\ 1} \tag{3.15}$$

If the value of productivity growth is greater than 1, the firm has “productivity progress” from period 1 to period 2. If the value of productivity growth is smaller than 1, the firm has “productivity regress” from period 1 to period 2.

Total Factor Productivity (TFP) is defined to represent the productivity level when the production process consists of multiple inputs and multiple outputs. TFP growth can be decomposed into 3 components attributing to TFP improvement. These components include technical efficiency changing effect (TEC), scale efficiency changing effect (SEC), and technical changing effect (TC).

TEC refers to the ability of a firm to improve technical or operational efficiency over the periods. In other words, TEC is called “the catching up effect” or the improvement of operating at inefficient to be efficient. SEC refers to the ability of a firm to use the size of the firm operating at the optimal scale over the periods. TC refers to the ability of a firm to adopt new technologies to improve productivity over the periods. It represents the shocks from technological improvements. Figure 3.10 shows the idea of TEC and SEC measurements. Figure 3.11 shows the idea of TC measurement.

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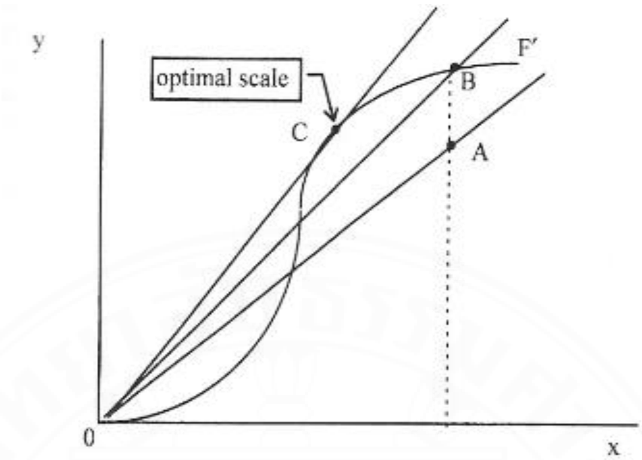
Figure 3.10

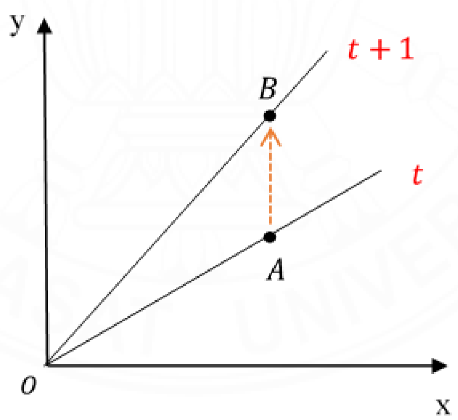
Productivity, Technical Efficiency and Scale Economies



Note. From Coelli et al. (2005), p.5.

Figure 3.11

Technical change effect (TC)



Note. From Fare et al. (1994), p.232.

From Figure 3.10, the line OF' represents a production frontier. Assuming 3 firms such as A, B, and C are operating under this production technology. Firm A is operating beneath the frontier OF' whereas firms B and C are operating on the frontier OF'. This implies that firm A performs inefficient, whereas firms B and C operate as efficient. The productivity of these firms can be measured by the slope of the rays from the origin. At point C, firm C has higher productivity than firm A and B because this point has the highest slope under the production technology. This means that firm C has the highest productivity and operates at the optimal scale because operation at any other point on the production frontier results in lower productivity. Therefore, this point represents "scale economies". Firm A can improve the technical efficiency to obtain a higher level of productivity at the frontier curve as firm B. This effect is called the "technical efficiency changing effect (TEC)" or the "catch-up effect". Firm B can use the size to operate at optimal point to get the highest productivity as firm C, and this effect is called the "scale efficiency changing effect (SEC)".

Figure 3.11 shows that the firm can adopt new technology to improve their productivity level from point A in period t to point B in period $t+1$ while still using the same amounts of input. This figure represents the idea of the "technical changing effect (TC)".

3.7 Malmquist's Total Factor Productivity Index (MPI)

TFP changing over the period can be calculated by employing Malmquist's Total Factor Productivity Index (MPI) model. Caves et al. (1982) and Färe et al. (1994) presented a non-parametric or DEA approach to measure and decompose TFP growth. Färe et al. (1994) defined the Malmquist TFP growth index using output orientation and assuming the CRTS assumption of production technology. MPI can be applied to measure the productivity changes for all firms from period to period and within the starting point and the ending point of the study periods. MPI can be defined by using either the output- or input-oriented assumptions the same as the DEA model.

3.7.1 Output-oriented MPI Model

This model applies the theory of output distance function (D_o). Consider 2 periods (t and $t+1$), the output-oriented MPI model must be calculated in both periods.

3.7.1.1 The period-t Malmquist TFP Index using output orientation.

It is defined as the ratio of output distance function based on period t technology using observed data between period $t+1$ and period t:

$$m_t^o(y_t, y_{t+1}, x_t, x_{t+1}) = \frac{D_t^o(x_{t+1,}y_{t+1})}{D_t^o(x_t, y_t)} \tag{3.16}$$

Where $m_t^o(y_t, y_{t+1}, x_t, x_{t+1})$ is the output-oriented Malmquist's TFP index of period t.

$D_t^o(x_{t+1,}y_{t+1})$ is the output distance function in period t using data of period $t+1$.

$D_t^o(x_t, y_t)$ is the output distance function in period t using data of period t.

3.7.1.2 The period-t+1 Malmquist TFP Index using output orientation.

It is defined as the ratio of output distance function based on period $t+1$ technology using observed data between period $t+1$ and period t:

$$m_{t+1}^o(y_t, y_{t+1}, x_t, x_{t+1}) = \frac{D_{t+1}^o(x_{t+1,}y_{t+1})}{D_{t+1}^o(x_t, y_t)} \tag{3.17}$$

Where $m_{t+1}^o(y_t, y_{t+1}, x_t, x_{t+1})$ is the output-oriented Malmquist's TFP index of period $t+1$.

$D_{t+1}^o(x_{t+1,}y_{t+1})$ is the output distance function in period $t+1$ using data of period $t+1$.

$D_{t+1}^o(x_t, y_t)$ is the output distance function in period $t+1$ using data of period t.

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3.7.1.3 The output-oriented Malmquist TFP Growth Index between period t and t+1.

The output-oriented Malmquist TFP growth is defined as the geometric mean of period t and $t+1$ Malmquist TFP index.

$$m^o_{t,t+1}(y_t, y_{t+1}, x_t, x_{t+1}) = [m^o_t(y_t, y_{t+1}, x_t, x_{t+1}) \times \; m^o_{t+1}(y_t, y_{t+1}, x_t, x_{t+1})]^{1/2}$$
$$= \left[\frac{D^o_t(x_{t+1,}y_{t+1})}{D^o_t(x_t,y_t)} \cdot \frac{D^o_{t+1}(x_{t+1,}y_{t+1})}{D^o_{t+1}(x_t,y_t)}\right]^{1/2}$$
$$= \frac{D^o_{t+1}(x_{t+1,}y_{t+1})}{D^o_t(x_t,y_t)}\left[\frac{D^o_t(x_{t+1,}y_{t+1})}{D^o_{t+1}(x_{t+1,}y_{t+1})} \cdot \frac{D^o_t(x_t,y_t)}{D^o_{t+1}(x_t,y_t)}\right]^{1/2} \quad (3.18)$$

Where $m^o_t(y_t, y_{t+1}, x_t, x_{t+1})$ is the output-oriented Malmquist's TFP index of period t.

$m^o_{t+1}(y_t, y_{t+1}, x_t, x_{t+1})$ is the output-oriented Malmquist's TFP index of period $t+1$.

The value of $m^o_{t,t+1}(y_t, y_{t+1}, x_t, x_{t+1})$ is greater than one indicating that there exists TFP progress from period t to period $t+1$. In other words, the value is smaller than one indicating TFP regress from period t to period $t+1$.

The output-oriented Malmquist TFP growth index between period t and $t+1$ ($m^o_{t,t+1}(y_t, y_{t+1}, x_t, x_{t+1})$) can be decomposed into "output-oriented technical efficiency change (TEC^o)" and "output-oriented technical change (TC^o)".

$\frac{D^o_{t+1}(x_{t+1,}y_{t+1})}{D^o_t(x_t,y_t)}$ = Output-oriented technical Efficiency Change (TEC^o). It measures the change in the technical efficiency between period t and $t+1$. In other words, TEC^o measures the changing of operation efficiency of the firm that contributes to the higher productivity between periods t and $t+1$.

Under the output-oriented MPI model, TEC^o compares the output distance function of the same firm between period t and $t+1$. This measures whether the operational working system of the firm can promote increasing the amounts of outputs while using the same amounts of inputs. In other words, TEC^o measures the efficiency changing of the working system of the firm between 2 periods to produce more outputs while still using the fixed amounts of inputs.

$\left[\frac{D_t^o(x_{t+1},y_{t+1})}{D_{t+1}^o(x_{t+1},y_{t+1})} \cdot \frac{D_t^o(x_t,y_t)}{D_{t+1}^o(x_t,y_t)}\right]^{1/2}$ = Output-oriented technical change (TC^o). It is a geometric mean of the shift in technology in period t and $t+1$ at the same input levels x_t and x_{t+1}. In other words, TC^o measures the ability of the firm to adopt new technology to obtain productivity growth between periods t and $t+1$.

Under the output-oriented MPI model, TC^o compares the performance of the same firm between period t and $t+1$. This measures whether the firm can adopt the new technology to produce more outputs while still using the fixed amounts of inputs.

3.7.2 Input-oriented MPI Model

This model applies the theory of input distance function (D_I). Consider 2 periods (t and $t+1$), the input-oriented MPI model must be calculated in both periods.

3.7.2.1 The period-t Malmquist TFP index using input orientation.

It is defined as the ratio of input distance function based on period t technology using observed data between period $t+1$ and period t:

$$m_t^i(y_t, y_{t+1}, x_t, x_{t+1}) = \frac{D_t^i(x_{t+1,}y_{t+1})}{D_t^i(x_t, y_t)} \tag{3.19}$$

Where $m_t^i(y_t, y_{t+1}, x_t, x_{t+1})$ is the input-oriented Malmquist's TFP index of period t.

$D_t^i(x_{t+1,}y_{t+1})$ is the input distance function in period t using data of period $t+1$.

$D_t^i(x_t, y_t)$ is the input distance function in period t using data of period t.

3.7.2.2 The period-t+1 Malmquist TFP index using input orientation.

It is defined as the ratio of input distance function based on period $t+1$ technology using observed data between period $t+1$ and period t:

$$m_{t+1}^{i}(y_t, y_{t+1}, x_t, x_{t+1}) = \frac{D_{t+1}^{i}(x_{t+1,}y_{t+1})}{D_{t+1}^{i}(x_t, y_t)} \tag{3.20}$$

Where $m_{t+1}^{i}(y_t, y_{t+1}, x_t, x_{t+1})$ is the input-oriented Malmquist's TFP index of period $t+1$.

$D_{t+1}^{i}(x_{t+1,}y_{t+1})$ is the input distance function in period $t+1$ using data of period $t+1$.

$D_{t+1}^{i}(x_t, y_t)$ is the input distance function in period $t+1$ using data of period t.

3.7.2.3 The input-oriented Malmquist TFP Growth Index between period t and t+1.

The input-oriented Malmquist TFP growth is defined as the geometric mean of the period t and $t+1$ Malmquist TFP index.

$$\begin{aligned} m_{t,t+1}^{i}(y_t, y_{t+1}, x_t, x_{t+1}) &= \left[m_t^{i}(y_t, y_{t+1}, x_t, x_{t+1}) \times\ m_{t+1}^{i}(y_t, y_{t+1}, x_t, x_{t+1})\right]^{1/2} \\ &= \left[\frac{D_t^{i}(x_{t+1,}y_{t+1})}{D_t^{i}(x_t,y_t)} \cdot \frac{D_{t+1}^{i}(x_{t+1,}y_{t+1})}{D_{t+1}^{i}(x_t,y_t)}\right]^{1/2} \\ &= \frac{D_{t+1}^{i}(x_{t+1,}y_{t+1})}{D_t^{i}(x_t,y_t)}\left[\frac{D_t^{i}(x_{t+1,}y_{t+1})}{D_{t+1}^{i}(x_{t+1,}y_{t+1})} \cdot \frac{D_t^{i}(x_t,y_t)}{D_{t+1}^{i}(x_t,y_t)}\right]^{1/2} \end{aligned} \tag{3.21}$$

Where $m_t^{i}(y_t, y_{t+1}, x_t, x_{t+1})$ is the input-oriented Malmquist's TFP index of period t.

$m_{t+1}^{i}(y_t, y_{t+1}, x_t, x_{t+1})$ is the input-oriented Malmquist's TFP index of period $t+1$.

The value of $m^i_{t,t+1}(y_t, y_{t+1}, x_t, x_{t+1})$ is greater than one indicating that there exists TFP progress from period t to period $t+1$. In other words, the value is smaller than one indicating TFP regress from period t to period $t+1$.

The input-oriented Malmquist TFP growth index (MPI) between period t and $t+1$ ($m^i_{t,t+1}(y_t, y_{t+1}, x_t, x_{t+1})$) can also be decomposed into "input-oriented technical efficiency change (TEC^i)" and "input-oriented technical change (TC^i)".

$\frac{D^i_{t+1}(x_{t+1}, y_{t+1})}{D^i_t(x_t, y_t)}$ = Input-oriented technical efficiency change (TEC^i). It measures the change in the technical efficiency between period t and $t+1$. In other words, TEC^i measures the changing of operation efficiency of the firm that contributed to the higher productivity growth between period t and $t+1$.

Under the input-oriented MPI model, TEC^i compares the input distance function of the same firm between period t and $t+1$. This measures whether the operation working system of the firm can reduce the amounts of inputs in the production process while still producing the same amounts of outputs. In other words, TEC^i measures the efficiency changing of the working system of the firm between 2 periods about using fewer inputs in the production process while producing the fixed amounts of outputs.

$\left[\frac{D^i_t(x_{t+1}, y_{t+1})}{D^i_{t+1}(x_{t+1}, y_{t+1})} \cdot \frac{D^i_t(x_t, y_t)}{D^i_{t+1}(x_t, y_t)}\right]^{1/2}$ = Input-oriented technical change (TC^i). It is a geometric mean of the shift in technology in time t and $t+1$ at same input levels x_t and x_{t+1}. In other words, TC^i also measures the ability of the firm to adopt new technology to obtain higher productivity growth between period t and $t+1$ as the same as TC^o.

Under the input-oriented MPI model, TC^i compares the performance of the same firm between period t and $t+1$. This measures whether the firm can adopt new

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technology to reduce the inputs in the production process while still producing the same amounts of outputs.

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CHAPTER 4
LITERATURE REVIEW

This chapter aims to discuss previous researches that studied the full performance measurement of the airports. This chapter is divided into 4 sections. The first section discusses the researches applying the parametric and non-parametric methods to measure the operational efficiency of the airports. Section 2 shows researches employing Malmquist's Total Factor Productivity Index (MPI) model to measure the productivity growth of the airports. Section 3 reviews researches studied about Thailand's airports. The last section presents the research gap between researches using Thailand's airports and the other airports in developed countries.

4.1 Measuring technical efficiency of the airports.

Many research papers employed both the parametric method known as stochastic frontier analysis (SFA) and the non-parametric method known as data envelopment analysis (DEA) to measure the efficiency scores of the airports in the studied periods.

Yang (2010) employed the data from 12 international airports in the Asia-Pacific region between 1998 to 2006. This paper defined 3 input variables as the number of employees, number of runways, and operating costs while the operating revenues are defined as the only one output variable. This paper employed both DEA and SFA models to measure the efficiency scores of the individual airports. This paper used DEA-Solver Pro 3.0 to compute the technical efficiency scores of the DEA model and FRONTIER4.1 to estimate the parameters of the SFA model (Yang, 2010, p.700). This paper computed DEA in both terms of the CCR and BCC models. For the SFA model, this paper tested 3 hypotheses and found that technical inefficiency had existed. The result in the SFA model showed that investing more operating costs can help to increase more revenue than human resources. This paper found that the results were obtained

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from both “DEA and SFA were consistent if complementing the DEA model by considering a variable’s significance level obtained from the SFA model (Yang, 2010, p.702)”.

Sarkis (2000) used DEA to estimate the operational efficiencies of 44 U.S. airports. This paper defined four input variables as operating costs, full-time workers, number of gates, and number of runways. For the output variables, this paper used operating revenues, number of aircraft movements, general aviation movements, passenger movements, and amount of cargo shipped. The data used in this paper covered the period between 1990 to 1994. The result showed that the airport hubs performed better than non-airport hubs.

Tsui et al. (2014) applied the DEA model to assess the operational efficiencies of 21 Asia-Pacific airports in the first stage, and then employed the Simar and Wilson bootstrapping regression analysis (Simar and Wilson, 2007) to identify the variations of airport efficiency. This paper measured the operational efficiency of 21 airports between 2002 to 2011. In the first stage, this paper estimated the operational efficiency scores by using the DEA model. They defined four input variables as number of employees, number of runways, total runway length, and passenger terminal area in meter squares. For the output variables, they defined air passenger numbers, air cargo volumes, and the number of aircraft movements. For the second stage, this paper applied Simar-Wilson bootstrapping regression to define the determinants of the efficiency of Asia-Pacific airports (Tsui et al., 2014, p.21). This paper defined DEA efficiency indexes that were obtained from the first stage as a dependent variable in the second stage. For the explanatory variables, the paper defined trend, GDP per capita, percentage of international passengers, airport hub status, airport management, airport operating hours, airport hinterland population, and alliance membership of dominant airline.

Chen et al. (2017) showed that private airports performed better than public airports. This paper obtained data from 14 European and Asia-Pacific countries which had composed of 24 airports. This paper defined 4 output variables as number of passengers, the amount of cargo in ton, number of aircraft movements, and total revenues included in both aeronautical and nonaeronautical activities. For the input

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variables, the paper employed the number of employees, number of gates, number of runways, size of the terminal area (m^2), and length of the runway.

Fernández et al. (2018) employed the SFA model to estimate 35 Spanish airports between 2009 to 2016. The results showed that airports with higher shares of "low-cost carriers (LCCs)" tend to be more efficient airports than airports with lower shares of LCCs. The results also showed that "airports located in high-density touristic areas achieved higher efficiency levels than the non-touristic areas (Fernández et al., 2018, p.56)". This paper defined 3 output variables as the number of passengers, ton of cargo lifted, and airport revenues. For the input variables, they defined capital invested, labor cost, and size of the airports. The interesting point of this paper is that this paper considered the external factor that can be affected the operational efficiency scores of the airports. These factors included low-cost passengers that stimulated the growth of passengers in the touristic areas. The LCCs had increased the airports' operational efficiencies.

Scotti et al. (2010) found that public airports had more efficient than private and mixed airports. This paper included the annual data of 38 Italian airports between 2005 to 2008. For 3 output variables, the paper defined aircraft, passenger, and freight movements. The runway capacity, the total number of aircraft parking positions, the number of baggage claims, and the number of full-time workers were defined as the input variables. The results of this paper showed that "airports with higher intensity of competition were less efficient than those which benefit from local monopoly power (Scotti et al., 2010, p.22)". This paper also suggested that policymakers could improve private airport efficiencies by emphasizing LCCs policy to create new touristic demand.

Oum and Yu (2004) considered data of 76 airports including Asia-Pacific, Europe, and North America. The interesting point of this paper is "this paper provided a summary of the airport's productivities and efficiencies and investigated the relationships between the productivity measures, and airport characteristics and management strategies to better understand the observed differences in airport performances (Oum and Yu, 2004, p.3)". This paper employed variable factor productivity (VFP) to analyze the data. This paper defined 4 output categories such as the number of passengers handled, air cargo in ton handles, the number of aircraft movements handles, and the amount of nonaeronautical service outputs. For the 2 input variables, they defined labor and soft cost inputs. However, Gong et al. (2012) showed that the results of many research papers about airport privatization were still inconclusive. Some privatization programs succeeded to improve airport efficiencies, but many of them were not.

Lin et al. (2013) employed 3 useful models to measure the performance of the North American airports. This paper measured the airport efficiencies by using 3 models such as the productivity index, DEA, and SFA. This paper included the data of 55 U.S. airports and 7 Canadian airports in 2006. The 3 output variables included the number of passengers, air transport movements, and nonaeronautical revenue. For 2 input variables, the paper defined the number of employees and soft cost inputs. The interesting point of this paper is that "the percentage of non-aeronautical revenue, passenger volume, average aircraft size, percentages of international, and connecting traffic are the important factors that significant to airport efficiency (Lin et al., 2013, p.47)".

Karanki and Lim (2020) employed the DEA model in the first stage and Simar and Wilson's method (Simar and Wilson, 2007) in the second stage. This paper employed 59 U.S. airports data covering between 2009 to 2016. They defined five input variables as the number of airport employees, the effective number of standard runways, airport land area, the number of gates, and total operating expenditures minus personal expenditures. For 2 output variables, the paper defined workload unit and nonaeronautical revenue. For the second stage, this paper defined agreement types, hub size, and governance forms as explanatory variables for airport operational efficiency.

Chung et al. (2015) compared the operational efficiencies of the 11 major cargo airports in the Asia-Pacific region between 2009 to 2010. This paper employed the multi-dimensional scaling analysis instead of the DEA and SFA models to measure the airports' operational efficiencies. The aim of this paper studied "the relationships between the efficiency levels and airport characteristics as well as operational strategies for better understanding the observed differences in airport clustering, how different airport group management strategies and how air cargo handling facilities impact on airport group evaluation (Chung et al., 2015, p.86)".

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Pereira et al. (2019) employed both DEA and multiple criteria DEA (MCDEA) models. This paper employed 6 central Brazilian airports data in 2015, the same dataset as Pereira (2015). This paper defined only one input variable which is the total area of the airport size, and 4 output variables such as the number of companies that operate in the airport, the number of certificated departures, the weight of departed cargo load, and the number of departed passengers. This paper computed efficiency scores and applied the new method called "MCDEA". However, the paper did not consider some external factors that can affect airports' efficiency levels as research papers employed Tobit regression or Simar and Wilson regression in the second stage.

Some previous research papers studied the operational efficiencies of the airports in Latin America. They employed both the CCR DEA and BCC DEA models to measure the technical efficiency scores (Perelman and Serebrisky, 2010; Pacheco and Fernandes, 2003; Wanke, 2012). However, they did not consider the external factors that can affect airports' operational efficiencies as the research papers that studied in Europe, Asia-Pacific, and North America.

Lee and Kim (2018) showed that non-aeronautical activities of the airports had a significant effect on airports' efficiency levels. This paper applied the network data envelopment analysis (NDEA) to estimate the efficiency scores of aeronautical, non-aeronautical, and total. For the aeronautical production process, they defined airside capacity that included runway, terminal capacity, and the number of workers as input variables. For output variables, they defined aeronautical revenue, cargo, and passengers. For the non-aeronautical production process, they defined non-airside capacity that included duty-free store size, restaurant size, parking lot capacity, and the number of workers as input variables. Non-aeronautical revenue and passengers were defined as the 2 output variables. This paper employed the data of 14 airports in South Korea between 2011 to 2015. This paper concluded that "the aeronautical efficiency does always guarantee the overall efficiency. Moreover, non-aeronautical sides of the business are becoming critical due to the volatility of airport markets (Lee and Kim, 2018, p.9)".

Ngo and Tsui (2020) employed the slack-based measure (SBM) DEA-window analysis model in the first stage and the instrumental variable (IV)-Tobit regression model in the second stage. SBM DEA-window analysis seems to be fit very well for a small sample than just the normal DEA model. This paper employed the data of 11 New Zealand airports between 2006 to 2017. For the first stage of SBM DEA-window analysis, this research defined 3 input variables as employee expenses, operating expenses, and length of runways. Aeronautical revenues, nonaeronautical revenues, and aircraft movements were defined as the 3 output variables. For the second stage of the IV-Tobit regression model, the paper defined the SBM efficiency scores derived from the first stage as a dependent variable. Arrival, accommodation, number of international destinations connected by airports, number of domestic destinations connected by airports, regional GDP per capita, "a dummy variable that takes 1 for the period of the global financial crisis in 2008/2009 and 0 otherwise (Ngo and Tsui, 2020, p.6)", a dummy for Christchurch earthquakes, a dummy for LCCs, and a dummy for airport privatization were defined as the explanatory variables to estimate whether external factors can affect to efficiency scores of the airports. The results from this paper showed that 6 variables were positively affected the efficiency scores. These variables included arrival, regional GDP per capita, number of domestic destinations connected by airports, airport privatization, LCCs, and Christchurch earthquakes event.

Martín et al. (2009) evaluated the technical efficiencies of the Spanish airports using Markov Chain Monte Carlo (MCMC) simulation to estimate the SFA model (Martín et al., 2009, p.163). This paper employed the data of 37 Spanish airports covering between 1991 to 1997. The paper defined 2 output variables as the air traffic movements and the work-load units. The 3 input variables included labor, capital, and materials.

The work of Ripoll-Zarraga and Raya (2020) is attractive, but the method seems to be complicated. Future research in the field of air transportation can follow the idea of this paper. This paper employed the data of 48 Spanish airports between 2009 to 2013. The paper employed the SFA model in the first stage and tourism indicators related to the location of airports as a regression in the second stage. For the first stage, they defined three input variables as labor costs, operating costs, and depreciation of airside and landside assets, while the output variables included the number of passengers, air traffic movements, cargo, and commercial revenues. For the

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second stage, this paper defined the technical efficiency scores obtained from the first stage as a dependent variable in the second stage. The 8 explanatory variables included the number of hotels, number of campsites, number of apartments, the expenditure in euro spent per day of stay per person, number of employees working in the touristic sector, and “the price index represents the cost of labor working in services (Ripoll-Zarraga and Raya, 2020, p.6)”. “The result from this paper highlighted the relationship between airports’ operations efficiency and the geographical location of airports (Ripoll-Zarraga and Raya, 2020, p.12)”. The interesting point of this paper is that the performances of the airports were analyzed into touristic and non-touristic areas. The main idea from this paper can be useful in the research area of air transportation management in the Thailand context because this paper studied the context and environments of Spain to test the operational efficiencies of the airports through different geographical locations. This paper concluded that “airports located in popular touristic areas will gain from having more passengers subject to having a good travel experience including accommodation (hotels) and leisure activities. Airports located in other areas will make efforts to attract airlines and passengers through price differentiation and quality of the service provided by the airports (Ripoll-Zarraga and Raya, 2020, p.12)”.

Tsui et al. (2014) employed the SBM-DEA and MPI models in the first stage and Simar-Wilson bootstrapping regression analysis (Simar and Wilson, 2000; Simar and Wilson, 2007) in the second stage. This paper included 11 major New Zealand airports data between 2010 to 2012. For the first stage, they defined operating expenses and the number of runways as the input variables. The operating revenues, air passenger movements, and aircraft traffic movements were defined as output variables. The SBM-DEA model can be applied when the traditional DEA model cannot give “any relevant explanation why an airport may become relative efficient or inefficient over time (Tsui et al., 2014, p.79)”. Tone (2001) gave the reason that applying this model will indicate the sources of efficiency and inefficiency. The SBM DEA model requires the number of airport observations must equal or larger than the product of the number of input and output variables for preventing the over airport efficiency scores from this model (Boussofiance and Dyson, 1991; Markovits-Somogyi, 2011; Yang,

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2010). On the other hand, if this requirement is not met, the SBM DEA model will produce a higher efficiency score than reality (Tsui et al., 2014, p.80). For the second stage, Tsui et al. (2014) defined population around the airport, airport hub status, airport operating hours, airport ownership, Christchurch earthquakes, and Rugby World Cup in 2011 as the explanatory variables. The SBM DEA efficiency score obtained from the first stage was defined as a dependent variable in the second stage.

Yu (2004) employed the output-oriented DEA model to measure the efficiency scores of 14 domestic Taiwanese airports. The paper studied between 1994 to 2000. This paper defined four input variables as "runway area, apron area, terminal area, and each airport's number of air routes connecting with the other domestic airports (Yu, 2004, p.298)". For the output variables, the paper had divided the outputs into desirable outputs and undesirable output. The desirable outputs were defined as the number of aircraft traffic movements and the number of passengers where the only undesirable output was defined as aircraft noise.

Many research papers showed that the airports that served a lot of LCCs had more operational efficiencies because they must increase their operational efficiencies to deal with the growth of passengers and air traffic movements. Hong and Domergue (2018) employed the DEA model to measure the technical efficiency scores of Korean LCCs airlines. This paper also compared the efficiency of many types of LCCs airlines.

Lam et al. (2009) employed all 5 DEA models with the 11 major international airports in Asia-Pacific over the period from 2001 to 2005 and compared the efficiency results of these models. This paper defined four input variables as labor, capital, soft input, and trade value. For the output variables, Lam et al. (2009) defined the number of aeronautic movements, passengers, and tons of cargo. All 5 DEA models included the CCR, BCC, SBM, Cost efficiency, and Allocative efficiency models.

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4.2 Measuring productivity growth of the airports.

There were a few studies that employed the MPI model to measure the productivity changing of the airports within the study periods. The MPI model can decompose the productivity changes into the technical efficiency change (TEC) and technological change (TC). TEC reflects whether the airport has technical efficiency improvement, while TC identifies whether the airport can adopt technology to improve the productivity level. Lastly, the product of TEC and TC can be identified whether the airport has total factor productivity (TFP) progress or regress.

Yang and Huang (2014) estimated the efficiencies and productivity change of 12 international airports in the Asia-Pacific region. This paper included the dataset between 1998 to 2006. This paper defined 3 input variables as the number of employees, the length of runways, and the operating costs. The only output variable was operating revenues. This paper employed the SFA model with the Translog production function and specified half-normal distribution to estimate technical inefficiency. This paper also employed MPI to estimate and decompose the productivity changes of the airports.

Abbott and Wu (2002) studied the data of the 12 largest Australian airports between 1989 to 2000. The paper defined 2 output variables as the number of passengers and the amount of freight cargo in ton passing through an airport. For the 3 input variables, they defined the number of staffs, capital stock in dollar, and runway length in kilometers. This paper employed both the MPI and DEA models to analyze the performance of 12 Australian airports.

Abbott (2015) employed the MPI model to analyze the 3 largest New Zealand airports between 1991 to 2012 in the first part of the paper. For the second stage, this paper employed the Tobit regression model “to determine the relationships between the efficiency scores obtained from the first stage as a dependent variable and airport scale and ownership type (Abbott, 2015, p.4)”. In the second stage, the paper defined independent variables as size in terms of aircraft movement, dummy variables for private ownership, joint venture ownership, and single-authority ownership.

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4.3 Previous Studies in Thailand's airports.

A few research papers had studied using data of the airports in Thailand. However, there are no previous studies in the literature investigating the full performances of Thailand's main public airports.

Sopadang and Suwanwong (2016a) employed DEA to assess the operational performances of 19 airports in ASEAN plus 3. This paper defined only one output variable as the number of passengers, and 5 input variables as terminal size, number of runways, length of the runway, number of gates, and check-in desks. This paper employed both the CCR and BCC DEA models to measure the technical efficiency scores.

Rapee and Peng (2014) employed the DEA and analytic hierarchy process (AHP) models to compute the efficiency scores of the 6 main public airports in Thailand in 2013. This paper employed 3 output variables and 3 input variables. The output variables included the number of passengers, number of movements, and amount of cargo. The number of employees, the terminal area, and the number of runways were defined as the input variables.

A paper measured the service quality of CNX, DMK, and HKT. Kratudnak and Tippayawong (2018) collected the data from a satisfaction survey of 300 passengers of the 3 airports that were concerned about the service qualities. This paper applied 2 stages to estimate the results. In the first stage, this paper employed the explanatory factor analysis (EFA) to categorize variables into factors. For the second stage, the AHP model was employed to evaluate the service qualities. The results from this paper showed that the service qualities of the aviation authorities and airport administrators were the key factors to improve service levels of these airports (Kratudnak and Tippayawong, 2018, p.1779).

Karim et al. (2003) emphasized airport development strategies and plans by focusing on Malaysia and Thailand. This paper analyzed strategies and plans for making both Kuala Lumpur International Airport (KUL) and BKK becoming the international hub airports in South-East Asia.

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Sopadang and Suwanwong (2016b) analyzed whether DMK had enough capability to be the biggest LCCs hub in ASEAN by employing the NETSCAN model. This paper emphasized the airport connectivity between DMK and other airports. This paper considered a factor as LCCs because DMK had corporate with the highest LCCs in the world in 2015.

Pandey (2016) focused on the service qualities of 2 DMK and BKK. This paper defined 7 dimensions such as airport service quality measurement by using access, check-in, security, finding your way, facilities, environment, and arrival services. This paper collected data from questionnaires.

Table 4.1 provides a summary of previous researches that measured the efficiency and productivity of the airport in terms of data, types of model, and the selection of input and output variables.

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Table 4.1

Studies of the efficiency and productivity of the airports

Authors	Sample	Models	Inputs	Outputs
Sarkis (2000)	44 U.S. airports from 1990 to 1994	DEA (CCR, BCC, SXEF, AXEF, RCCR, and GTR)	-Operating Costs -No. of full-time workers -No. of gates -No. of runways	-Operating revenues -No. of aircraft movements -No. of general aviation movements -No. of passenger movements -Amount of cargo shipped (ton)
Abbott and Wu (2002)	12 largest Australian airports from 1989 to 2000	-Malmquist total factor productivity index (MPI) -DEA (CCR and BCC)	-No. of staffs -Capital stock in dollar -Runway length (km)	-No. of passengers -Amount of freight cargo (ton)

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Table 4.1

Studies of the efficiency and productivity of the airports (Cont.)

Authors	Sample	Models	Inputs	Outputs
Yu (2004)	14 domestic Taiwanese airports from 1994 to 2000	DEA (CCR)	-Runway area (m^2) -Apron area (m^2) -Terminal area (m^2) -No. of air routes connecting with the other domestic airports	-No. of aircraft movements (desirable output) -No. of passengers (desirable output) -Aircraft noises (undesirable output)
Lam et al. (2009)	11 major international airports in Asia-Pacific from 2001 to 2005	DEA (CCR, BCC, SBM, Cost efficiency, and Allocative efficiency)	-Labor -Capital -Soft inputs -Trade value	-No. of aeronautic movements -No. of passengers -Amount of cargo (ton)

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Table 4.1

Studies of the efficiency and productivity of the airports (Cont.)

Authors	Sample	Models	Inputs	Outputs
Scotti et al. (2010)	38 Italian airports from 2005 to 2008	SFA	-Runway capacity -Total number of aircraft parking positions -No. of baggage claim -No. of full-time workers	-No. of aircraft movements -No. of work-load unit movements
Yang (2010)	12 international airports of Asia-Pacific region from 1998 to 2006	-SFA -DEA (CCR and BCC)	-No. of employees -No. of runways -Operating costs	Operating revenues

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Table 4.1

Studies of the efficiency and productivity of the airports (Cont.)

Authors	Sample	Models	Inputs	Outputs
Lin et al. (2013)	55 U.S. and 7 Canadian airports in 2006	-Index number method -DEA (CCR) -SFA	-No. of employees -Soft cost inputs	-No. of passengers -No. of air transport movements -Nonaeronautical revenue
Rapee and Peng (2014)	6 Thailand main public airports in 2013	-DEA (CCR) -Analytic Hierarchy Process (AHP)	-No. of employees -Terminal area (m^2) -No. of runways	-No. of passengers -No. of aircraft movements -Amount of cargo (ton)

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Table 4.1

Studies of the efficiency and productivity of the airports (Cont.)

Authors	Sample	Models	Inputs	Outputs
Tsui et al. (2014a)	21 Asia-Pacific airports from 2002 to 2011	-DEA (VRS in the first stage) -Simar-Wilson bootstrapping regression (Second stage)	-No. of employees -No. of runways -Total runway length (km) -Passenger terminal area (m^2)	-No. of passengers -Amount of cargo (ton) -No. of aircraft movements
Tsui et al. (2014b)	11 major New Zealand airports from 2010 to 2012	-SBM DEA and MPI (first stage) -Simar-Wilson bootstrapping regression (second stage)	-Operating expenses -No. of runways	-Operating revenues -No. of passengers -No. of aircraft movements

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Table 4.1

Studies of the efficiency and productivity of the airports (Cont.)

Authors	Sample	Models	Inputs	Outputs
Yang and Huang (2014)	12 international Asia-Pacific airports from 1998 to 2006	-SFA -MPI	-No. of employees -Runway length (km) -Operating costs	Operating revenues
Sopadang and Suwanwong (2016)	19 airports in ASEAN plus 3 in 2014	DEA (CCR and BCC)	-Terminal size ($\boldsymbol{m^2}$) -No. of runways -No. of gates -No. of check-in desks	No. of passengers

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Table 4.1

Studies of the efficiency and productivity of the airports (Cont.)

Authors	Sample	Models	Inputs	Outputs
Chen et al. (2017)	24 airports from 14 countries in both Europe and Asia-Pacific between 2001-2013	DEA	-No. of employees -No. of gates -No. of runways -Terminal area (m2) -Length of the runway (km)	-No. of passengers -Amount of cargo (ton) -No. of aircraft movements -Total revenues from aeronautical and nonaeronautical activities
Fernandez et al. (2018)	35 Spanish airports from 2009 to 2016	SFA	-Capital invested -Labor cost -Airport size	-No. of passengers -Amount of cargo (ton) -Airport revenues

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Table 4.1

Studies of the efficiency and productivity of the airports (Cont.)

Authors	Sample	Models	Inputs	Outputs
Lee and Kim (2018)	14 South Korean airports from 2011 to 2015	Network data envelopment analysis (NDEA)	For aeronautical production process: -No. of workers -Runway capacity -Terminal capacity For nonaeronautical production process: -Duty-free store size -Restaurant size -Parking lot capacity -No. of workers	For aeronautical production process: -Aeronautical revenues -No. of passengers -Amount of cargo (ton) For nonaeronautical production process: -Nonaeronautical revenues -No. of passengers

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Table 4.1

Studies of the efficiency and productivity of the airports (Cont.)

Authors	Sample	Models	Inputs	Outputs
Martin et al. (2009)	37 Spanish airports from 1991 to 1997	SFA	-Labor -Capital -Materials	-No. air traffic movements -No. of passengers -Amount of cargo (ton)
Pereira et al. (2019)	6 Brazilian airports in 2015	-DEA -Multiple criteria DEA (MCDEA)	The total area of airport size	-No. of the company operating in the airport -No. pf certificated departures -Weight of departed cargo load -No. of departed passengers

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Table 4.1

Studies of the efficiency and productivity of the airports (Cont.)

Authors	Sample	Models	Inputs	Outputs
Karanki and Lim (2020)	59 U.S airports from 2009 to 2016	-DEA (first stage) -Simar-Wilson (second stage)	-No. of airport employees -No. of runways -Airport area -No. of gates -Total operating expenditures minus personal expenditures	-Work-load unit -Nonaeronautical revenue
Ngo and Tsui (2020)	11 New Zealand airports from 2006 to 2017	-SBM DEA window analysis (first stage) -IV-Tobit regression (second stage)	-Employee expenses -Operating expenses -Length of the runway (km)	-Aeronautical revenues -Nonaeronautical revenues -No. of aircraft movements

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Table 4.1

Studies of the efficiency and productivity of the airports (Cont.)

Authors	Sample	Models	Inputs	Outputs
Ripoll-Zarraga and Raya (2020)	48 Spanish airports from 2009 to 2013	SFA	-Labor costs -Operating costs -Depreciation of airside and landside assets	-No. of passengers -No. of air traffic movements -Amount of cargo (ton) -Commercial revenues

Note. From author's compilation from relevant empirical studies.

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4.4 Research gap

Most research papers before 2010 measured the airport technical efficiency and productivity growth by employing the DEA and MPI models, respectively. Meanwhile, after 2010 most research papers considered some external factors that can affect the operational efficiency scores of the airports. These external factors included LCCs, number of hotels in the same cities of the airports, airport privatization, airport hub status, and the dummy for some events that happened at the studied airports such as earthquake and financial crisis between 2008 to 2009 (Tsui et al., 2014; Ngo and Tsui, 2020; Karanki and Lim, 2020; Ripoll-Zarraga and Raya, 2020).

However, there is no past study that had investigated the full performances and employed the Simar and Wilson method in the second stage for the 6 main public airports in Thailand after the COVID-19 pandemic crisis. Therefore, this thesis aims to close this gap by applying both the DEA and MPI models to measure both efficiency and productivity growth of these airports. In addition, Simar and Wilson Bootstrapping regression is applied to test whether external factors affecting the efficiency level of the airports. Lastly, this thesis is also the first research that employs the basic time-series model forecasting the future performances of the airports.

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CHAPTER 5
MODEL SPECIFICATION

This chapter discusses all models used in this thesis. The theories from chapter 3 applied to be useful models include data envelopment analysis (DEA) and Malmquist's Total Factor Productivity Index (MPI). Both models are non-parametric and linear programming. DEA model is employed to measure and compare the efficiency levels of all airports, while MPI can be employed to measure and decompose productivity growth. This chapter also discusses one of the useful regression methods called as "Simar-Wilson Bootstrapping Regression model (Simar-Wilson, 2007)". This model is employed in the second stage to test whether external factors will affect the efficiency levels of the studied airports.

Lastly, this study applies the autoregressive model (AR) to forecast future trends of the following variables such as number of passengers, number of aircraft movements, and number of employees for the individual airports. This last part will provide the trends of airport performances recovered after the COVID-19 pandemic crisis in the year 2020. Therefore, this basic time-series model also provides the future trend of the Thailand aviation industry.

Moreover, this study employs the input orientation in both DEA and MPI models because the output variables of the airports do not solely depend on the production process of the airports. The number of aircraft movements, passenger movements, and amounts of cargo shifted in the individual airports depend on the comparative advantage of each province in Thailand. The airports locate in Chiang Mai, Phuket, and Bangkok have higher chances to handle more tourists than other provinces because these provinces are the 3 largest hubs of international tourists who have traveled to Thailand. Hence, this study employs the input orientation to test whether the 6 main public airports in Thailand can spend the amounts of inputs efficiently with the amounts of outputs obtained.

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5.1 The input-oriented CCR DEA Model to estimate the technical efficiency levels of the airports.

For the first model, this study employs "the input-oriented CCR DEA" model to calculate the operational efficiencies of all 6 Thailand's main public airports. This model applies the concept of input distance function (D_I) and input sets ($L(y)$) to construct the frontier as discussed in chapter 3. The concept of the input-oriented model focuses on whether the airports use inputs efficiently to produce the fixed amounts of outputs. This method applies linear programming to calculate both the technical efficiency and inefficiency scores of the airports in the study periods.

To estimate the technical efficiency of the individual airports for each period, linear programming of the input-oriented CCR DEA model can be defined as

$$\begin{array}{lll} \text{Min} & \theta_j = \theta^* & \\ \text{Subject to} & \sum_{i=1}^{N} \lambda_{ij}\, x_{ki} \le \theta_j x_{kj}, & k = 1, \dots, K \\ & y_{mj} \le \sum_{i=1}^{N} \lambda_{ij}\, y_{mj}, & m = 1, \dots, M \\ & \lambda_{ij} \ge 0, & i = 1, \dots, N \end{array} \tag{5.1}$$

Where θ_j or θ^* is input-oriented TE of the j^{th} airports.

x_{kj} is input set of the j^{th} airports.

y_{mj} is output set of j^{th} airports.

λ_{ij} is the intensity variable representing weights of all airports ($i = 1, \dots, N$) used to construct frontier for the j^{th} airports.

The CCR DEA model applies the concept of CRTS where it calculates the efficiency levels at the optimum scale or perfectly competitive assumption.

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This study assumes all 6 airports are perfect competition because all 6 airports locate in different regions. They use the same operation working system, technologies and serving many low-cost carriers (LCCs) airlines. Lastly, they are international airports that serve tourists from all around the world who travel to Thailand with different objectives.

This thesis employs 3 output variables and 4 input variables to estimate the technical efficiencies of the individual airports between 2007 to 2020. The 3 output variables include the number of passenger movements, total aircraft movements, and the amounts of cargo shifted in ton. The input variables compose of the number of employees, number of runways, apron area in meter squares (m^2), and terminal area in meter squares (m^2). The 14 years data of 6 airports are studied. Hence, the number of $DMUs$ will be 84 ($N = 84$), the number of input variables equals 4 ($K = 4$), and the number of output variables equals 3 ($M = 3$).

5.2 The input-oriented MPI model to decompose the productivity changing of the airports in the studied periods.

Next, Malmquist's Total Factor Productivity Index (MPI) is employed to calculate the productivity changes of the airports in the studied periods. The MPI model is the DEA model that extends to estimate the productivity growth of the airports.

The MPI model can also be decomposed into the specific subjects as the "input-oriented technical efficiency changing (TEC^i)" and the "input-oriented technological changing (TC^i)". TEC^i reflects whether any airport can improve their operation working system efficiently to get more productivity growth. TC^i reflects whether any airport can adjust their organization wisely by adopting new technology to improve their productivity growth. Some airports can improve their productivity growth by emphasizing either TEC^i or TC^i, or both.

To measure and decompose productivity changing between period t and $t + 1$, the input-oriented MPI model ($m^i_{t,t+1}(y_t, y_{t+1}, x_t, x_{t+1})$) can be defined as

$$m^i_{t,t+1}(y_t, y_{t+1}, x_t, x_{t+1}) = \left[m^i_t(y_t, y_{t+1}, x_t, x_{t+1}) \times m^i_{t+1}(y_t, y_{t+1}, x_t, x_{t+1})\right]^{1/2}$$
$$= \left[\frac{D^i_t(x_{t+1,}y_{t+1})}{D^i_t(x_t,y_t)} \cdot \frac{D^i_{t+1}(x_{t+1,}y_{t+1})}{D^i_{t+1}(x_t,y_t)}\right]^{1/2}$$
$$= \frac{D^i_{t+1}(x_{t+1,}y_{t+1})}{D^i_t(x_t,y_t)}\left[\frac{D^i_t(x_{t+1,}y_{t+1})}{D^i_{t+1}(x_{t+1,}y_{t+1})} \cdot \frac{D^i_t(x_t,y_t)}{D^i_{t+1}(x_t,y_t)}\right]^{1/2} \quad (5.2)$$

Where $m^i_t(y_t, y_{t+1}, x_t, x_{t+1})$ is the input-oriented Malmquist's TFP index of the individual airports in period t.

$m^i_{t+1}(y_t, y_{t+1}, x_t, x_{t+1})$ is the input-oriented Malmquist's TFP index of the individual airports in period $t + 1$.

$D^i_t(x_t, y_t)$ is the input distance function in period t using data of the individual airports in period t.

$D^i_{t+1}(x_t, y_t)$ is the input distance function in period $t + 1$ using data of the individual airports in period t.

$D^i_t(x_{t+1,}y_{t+1})$ is the input distance function in period t using data of the individual airports in period $t + 1$.

$D^i_{t+1}(x_{t+1,}y_{t+1})$ is the input distance function in period $t + 1$ using data of the individual airports in period $t + 1$.

The value of $m^i_{t,t+1}(y_t, y_{t+1}, x_t, x_{t+1})$ is greater than one indicating a TFP of the airport has progressed from period t to period $t + 1$, whereas the value is smaller than one indicating that TFP of the airport has regressed from period t to $t + 1$.

The input-oriented MPI model is derived from the calculation of the 4 input distance functions including $D^i_t(x_t, y_t)$, $D^i_t(x_{t+1,}y_{t+1})$, $D^i_{t+1}(x_t, y_t)$, and $D^i_{t+1}(x_{t+1,}y_{t+1})$.

5.2.1 The input distance function in period t using data of period t ($D_t^i(x_t, y_t)$)

$D_t^i(x_t, y_t)$ measures the input-oriented technical efficiency of the j^{th} airports which can be calculated by employing linear programming as

$$D_t^i(x_t, y_t) = \text{Min } \theta_j = \theta^*$$

$$\text{Subject to} \quad \sum_{i=1}^{N} \lambda_{ij}\, x_{ki,t} \leq \theta_j x_{kj,t}\,, \qquad k = 1, \ldots, K$$

$$y_{mj,t} \leq \sum_{i=1}^{N} \lambda_{ij}\, y_{mj,t}\,, \qquad m = 1, \ldots, M$$

$$\lambda_{ij} \geq 0, \qquad i = 1, \ldots, N \tag{5.3}$$

Where θ_j or θ^* is input-oriented TE of the j^{th} airports. In other words, it is the input distance function in period t using data of each airport in period t.

$x_{kj,t}$ is input set of the j^{th} airports at period t.

$y_{mj,t}$ is output set of j^{th} airports at period t.

λ_{ij} is the intensity variable representing weights of all airports ($i = 1, \ldots, N$) used to construct frontier for the j^{th} airports.

5.2.2 The input distance function in period t using data of period $t+1$ ($D_t^i(x_{t+1,} y_{t+1})$)

$D_t^i(x_{t+1,} y_{t+1})$ measures the input-oriented technical efficiency of the j^{th} airports which can be calculated by employing linear programming as

$$D_t^i(x_{t+1,} y_{t+1}) = \text{Min } \theta_j = \theta^*$$

$$\text{Subject to} \quad \sum_{i=1}^{N} \lambda_{ij}\, x_{ki,t} \leq \theta_j x_{kj,t+1}\,, \qquad k = 1, \ldots, K$$

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$$y_{mj,t+1} \leq \sum_{i=1}^{N} \lambda_{ij}\, y_{mj,t}, \qquad m = 1, \dots, M$$

$$\lambda_{ij} \geq 0, \qquad i = 1, \dots, N$$

(5.4)

Where θ_j or θ^* is input-oriented TE of the j^{th} airports. In other words, it is the input distance function in period t using data of each airport in period $t+1$.

$x_{kj,t+1}$ is input set of the j^{th} airports at period $t+1$.

$y_{mj,t+1}$ is output set of j^{th} airports at period $t+1$.

5.2.3 The input distance function in period $t+1$ using data of period t ($D_{t+1}^{i}(x_t, y_t)$)

$D_{t+1}^{i}(x_t, y_t)$ measures the input-oriented technical efficiency of the j^{th} airports which can be calculated by employing linear programming as

$$D_{t+1}^{i}(x_t, y_t) = \text{Min } \theta_j = \theta^*$$

Subject to

$$\sum_{i=1}^{N} \lambda_{ij}\, x_{ki,t+1} \leq \theta_j x_{kj,t}, \qquad k = 1, \dots, K$$

$$y_{mj,t} \leq \sum_{i=1}^{N} \lambda_{ij}\, y_{mj,t+1}, \qquad m = 1, \dots, M$$

$$\lambda_{ij} \geq 0, \qquad i = 1, \dots, N$$

(5.5)

Where θ_j or θ^* is input-oriented TE of the j^{th} airports. In other words, it is the input distance function in period $t+1$ using data of each airport in period t.

5.2.4 The input distance function in period $t+1$ using data of period $t+1$ ($D_{t+1}^{i}(x_{t+1,}y_{t+1})$)

$D_{t+1}^{i}(x_{t+1,}y_{t+1})$ measures the input-oriented technical efficiency of the j^{th} airports which can be calculated by employing linear programming as

$$D_{t+1}^{i}(x_{t+1,}y_{t+1}) = \text{Min } \theta_j = \theta^*$$

Subject to
$$\sum_{i=1}^{N} \lambda_{ij}\, x_{ki,t+1} \leq \theta_j x_{kj,t+1}\,, \qquad k = 1, \dots, K$$

$$y_{mj,t+1} \leq \sum_{i=1}^{N} \lambda_{ij}\, y_{mj,t+1}\,, \qquad m = 1, \dots, M$$

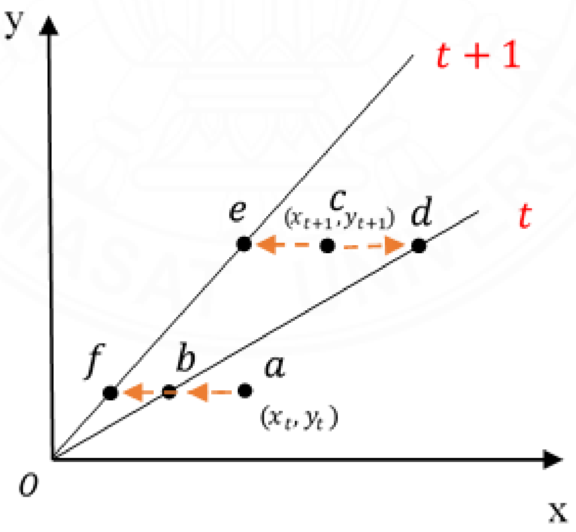
$$\lambda_{ij} \geq 0, \qquad i = 1, \dots, N$$

(5.6)

Where θ_j or θ^* is input-oriented TE of the j^{th} airports. In other words, it is the input distance function in period $t+1$ using data of each airport in period $t+1$.

Figure 5.1

The basic idea to estimate $D_t^i(x_t, y_t)$, $D_t^i(x_{t+1,}y_{t+1})$, $D_{t+1}^i(x_t, y_t)$, and $D_{t+1}^i(x_{t+1,}y_{t+1})$



Note. From Rungsuriyawiboon (2015), p.444.

Figure 5.1 shows the basic idea for calculating all 4 input distance functions of the input-oriented MPI model ($m_{t,t+1}^i(y_t, y_{t+1}, x_t, x_{t+1})$). Consider the technology in period t and $t+1$, the input and output variables in period t (x_t, y_t), and the input and output variables in period $t + 1$ $(x_{t+1,} y_{t+1})$. Therefore, $D_t^i(x_t, y_t)$ can be defined by $\frac{oa}{ob}$. $D_t^i(x_{t+1,} y_{t+1})$ can be defined by $\frac{oc}{od}$. $D_{t+1}^i(x_t, y_t)$ can be defined by $\frac{oa}{of}$. Lastly, $D_{t+1}^i(x_{t+1,} y_{t+1})$ can be defined by $\frac{oc}{oe}$. All 4 input distance functions are applied to measure TC^i and TEC^i.

5.2.5 Input-oriented Technical Efficiency Changing (TEC^i) Measurement.

"The more talent density you have the less process you need. The more process you create the less talent you retain."

Reed Hastings (CEO of Netflix)

TEC^i or $\frac{D_{t+1}^i(x_{t+1,} y_{t+1})}{D_t^i(x_t, y_t)}$ measures the changing in the input-oriented technical efficiency between periods t and $t + 1$. Under the input-oriented MPI model, TEC^i measures whether the operational efficiency of the airport uses the limited inputs quantities efficiently while serving the same amounts of outputs.

If TEC^i is greater than 1, it indicates the progress of the technical efficiency of the airport between period t to $t + 1$. This means that the airport can improve their working system and environment of workplace efficiently to support the production processes by reducing the inputs used between period t to $t + 1$. The examples to improve the technical efficiency scores are the airports adapt their working systems by setting the new working systems such as LEAN, AGILE, and Talent Density instead. Figure 5.2 shows the theory of the LEAN system and Figure 5.3 shows the concept of the AGILE system.

If TEC^i is lower than 1, it indicates the regress of the technical efficiency of the airport between period t to $t + 1$. This means that the airport operates on working

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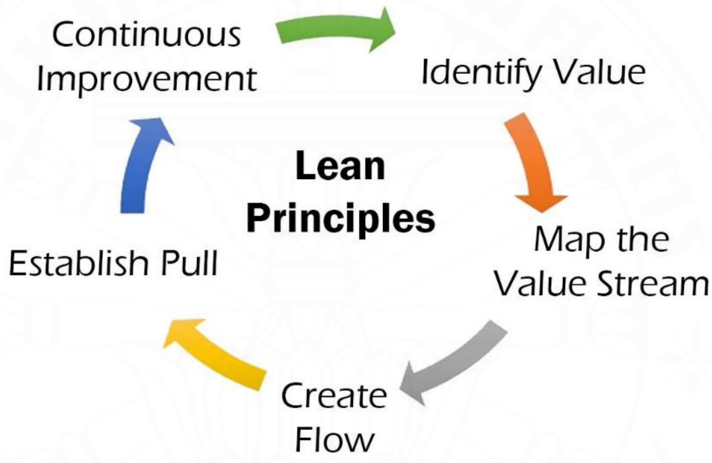
systems inefficiently and wastes inputs using in the production processes between period t to $t+1$. An example is the old working systems in terms of labor at the airports cannot support productivity growth anymore and also obstruct the sustainable growth of the airports.

Figure 5.2

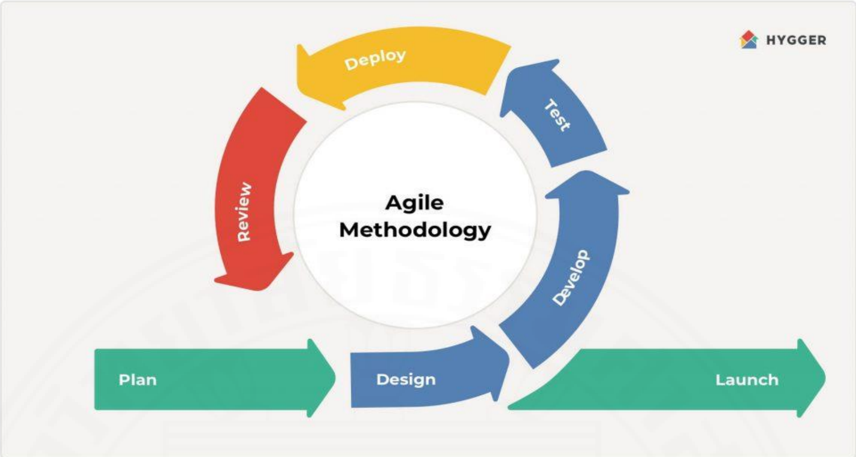
The LEAN system



Note. From https://kanbanzone.com/2019/lean-management/

Figure 5.3

The AGILE system



Note. From https://hygger.io/guides/agile/

5.2.6 Input-oriented Technical Changing (TC^i) Measurement.

Under the input-oriented MPI model, TC^i or $\left[\frac{D_t^i(x_{t+1},y_{t+1})}{D_{t+1}^i(x_{t+1},y_{t+1})}\cdot\frac{D_t^i(x_t,y_t)}{D_{t+1}^i(x_t,y_t)}\right]^{1/2}$ measures the ability of the airports taking advantage of new technology to promote productivity growth between period t and $t+1$.

If TC^i is greater than 1, it indicates the progress of technology adoption of the airport between period t to $t+1$. This means that the airport can adapt their organization smoothly with new technology to reduce the wasted inputs between period t to $t+1$. For example, smart airports can adopt new technologies such as Big data, Artificial Intelligent (AI), self-service check-in kiosks, the internet of things (IOT), and face recognition to replace unskilled employees at the airports. These new technologies can reduce some costs spent in training at particular positions. The new technologies can help smart airports to keep only high-skilled employees and operate their businesses productively. Figure 5.4 shows the example of a smart airport from Beijing Daxing International Airport, China. This airport was successful to be a smart airport by using new technologies such as the face recognition machine, virtual and physical robots, and self-check-in kiosks by radio frequency identification (RFID). Figure 5.5 shows the biometric facial recognition machine. Figure 5.6 shows the AR assistant application. This application can show the map of the entire airport. Figure 5.7 shows the robot assistant at the airport. Some airports such as Heathrow Airport, England and Incheon Airport, South Korea use this machine to convenient the passengers. All these technologies can stimulate the productivity growth of airports in the long run.

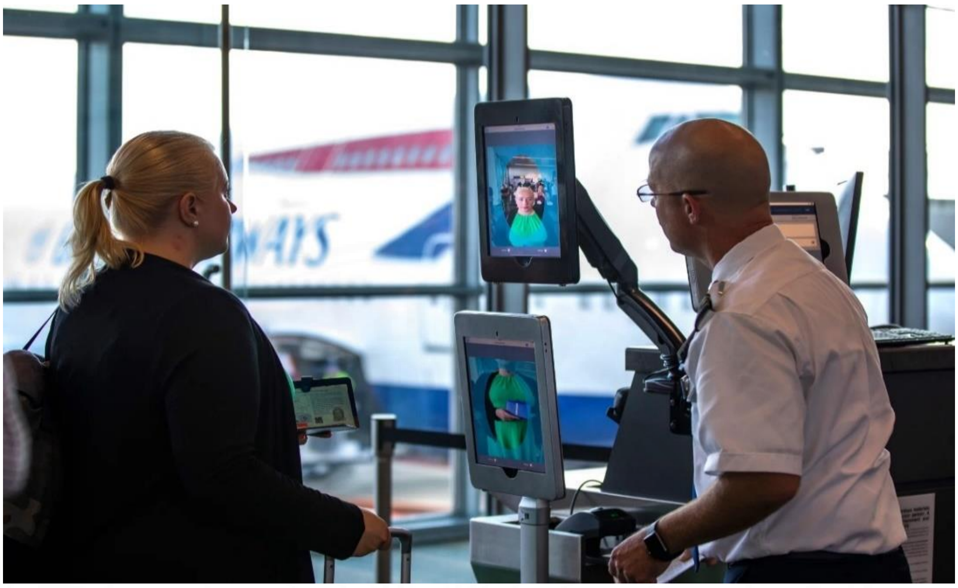
Figure 5.4

Beijing Daxing International Airport

Note. From https://www.mhesi.go.th/index.php/en/all-media/book/3073-2021-01-22-16-46-51.html

Figure 5.5

The Biometric Facial Recognition



Note. From https://globalnews.ca/news/4567183/facial-recognition-technology-u-s-airports/

Figure 5.6

AR Assistant at the airport

Note. From https://www.dailygizmo.tv/2019/12/02/5-airport-technology/

Figure 5.7

The Robot Assistant at Incheon Airport

Note. From http://koreabizwire.com/incheon-airport-introduces-airstar-passenger-aiding-robot/121298

If TC^i is lower than 1, it indicates the regress of technological adoption of the airport between period t to $t+1$. This means that the airport cannot adapt their working systems wisely with new technology to reduce the wasted inputs quantities used between period t to $t+1$. For example, the airport lacks to adapt their environment of workplaces and working systems with the rapid development of new technologies. This shows that the airport cannot take the advantage of new technologies to help them reduce the wasted inputs and convenience to the passengers.

This thesis defines all input variables and output variables of the input-oriented MPI model to measure productivity growths of the airports are the same as in the input-oriented CCR DEA model.

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5.3 Simar and Wilson Bootstrapping Regression Model

The efficiency scores of the 6 airports obtained from the input-oriented CCR DEA model will be employed in the second stage to test whether the external factors in Thailand and the global contexts within the study periods will affect the technical efficiency levels of the 6 airports.

According to Tsui et al. (2014), the Tobit regression method did not give reliable results as the Simar and Wilson's method (Simar and Wilson, 2007). Hence, the authors employed the Simar-Wilson Bootstrapping regression analysis in the second stage after obtaining the results from the DEA model in the first stage.

This thesis employs the Simar and Wilson Bootstrapping Regression technique to test in the second stage whether the external factors will affect the operational efficiencies of the 6 main public airports in Thailand.

"According to Simar and Wilson (2007), the Simar-Wilson Bootstrapping regression model can be written as follow:

$$\theta_j^* = \alpha + z_j\beta + \varepsilon_j \quad where\ j = 1,2,3, \dots n \tag{5.7}$$

Where θ_j^* is the CCR DEA efficiency index of airport j.

α is the constant.

z_j is a vector of observation independent variables that are expected to affect the airport j's efficiency scores.

β is a vector of parameters.

ε_j is the error term.

To applying the Simar-Wilson bootstrapping approach, the distribution of ε_j will be limited to the condition of $\varepsilon_j \geq 1 - \alpha - z_j\beta$. Thus, the distribution of ε_j becomes $\varepsilon_j \sim iidN(0, \sigma_\varepsilon^2)$ (Tsui et al.,2014, p.18)".

All external factors are employed in this thesis include 9 independent variables such as a dummy for airport hub status (AHS), a dummy for the global financial crisis between 2008 to 2009 (GFC), a dummy for People's Alliance for

Democracy occupied DMK and BKK for a short period at the end of the year 2008 or in the fiscal year 2009 (PAD), a dummy for DMK was flooded at the end of the year 2011 or fiscal year 2012 (FLOOD), a dummy for Thailand's political conflict between 2013 to 2014 or in the fiscal year 2014 (TPC), percent of international low-cost carriers (LCCs) passengers of the individual airports (PILCCS), percent of domestic LCCs passengers of the individual airports (PDLCCS), percent of international passengers of the individual airports (PIP), and a dummy for the COVID-19 pandemic in 2020 (COVID).

Table 5.1 shows all independent variables have employed in the second stage. GFC and COVID represent the dummy of macro impacted variables. The global financial crisis in 2008-2009 and the COVID-19 pandemic in 2020 provided a huge negative impact on the global economy. AHS, FLOOD, TPC, and PAD represent micro impacted variables. Airport hub status is defined as the airports that handle a large number of tourists within each year more than 10 million passengers. Currently, Thailand has 4 airport hubs such as BKK, DMK, HKT, and CNX. These 4 micro dummy variables represent the events that happened only in Thailand in the studied periods. However, PILCCS, PDLCCS, and PIP are not dummy variables. Appendix B shows all the abbreviation names of all independent variables.

Table 5.1

List of all independent variables

Name of all independent variables	Symbol	Type of variable
Airport hub status	AHS	Dummy variable
Global financial crisis between 2008 to 2009	GFC	Dummy variable
People's Alliance for Democracy occupied DMK and BKK in 2008	PAD	Dummy variable
Flooding at DMK in 2011	FLOOD	Dummy variable

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Table 5.1

List of all independent variables (Cont.)

Name of all independent variables	Symbol	Type of variable
Thailand's political conflict between 2013 to 2014	TPC	Dummy variable
COVID-19 pandemic in 2020	COVID	Dummy variable
Percent of international low-cost carriers of the individual airports	PILCCS	Non-dummy variable
Percent of domestic low-cost carriers of the individual airports	PDLCCS	Non-dummy variable
Percent of international of the individual airports	PIP	Non-dummy variable

Note. From author's compilation and AOT's Corporate Presentations between 2007 to 2020.

5.4 Autoregressive (AR) Model

For the last part of the analysis, this thesis employs an autoregressive model (AR) to forecast the future data and applies all of them to estimate the future performances of all 6 airports in the post-COVID-19 period between 2021 to 2030.

AR model can be used to predict future data based on past data. The process of AR prediction is a linear combination of past values of the variable. AR model indicates that it is a regression of the variable against itself. The AR model of order p can be defined as:

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$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \varepsilon_t \tag{5.8}$$

Where y_t is forecast value in period t.

$y_{t-1}, y_{t-2}, \ldots, y_{t-p}$ are the lag values from period $t-1$ to $t-p$.

c is a constant.

$\phi_1, \phi_2, \ldots, \phi_p$ are the parameters of the model.

ε_t is white noise.

This thesis applies $AR(1)$ model to forecast 2 output variables such as the number of passengers and total aircraft movements of the individual airports between 2024 to 2030, and only one input variable as the number of employees between 2021 to 2030. The $AR(1)$ model is autoregressive with order 1 or called "first-order autoregressive". This model can be defined as:

$$y_t = c + \phi_1 y_{t-1} + \varepsilon_t \tag{5.9}$$

Where y_t is forecast value in period t.

c is a constant.

ϕ_1 is the parameter of the model.

y_{t-1} is the lag value of y_t from period $t-1$.

ε_t is white noise. (Hyndman and Athanasopoulos, 2013; Stephanie, 2015)

All forecasting data will be employed to estimate the future performances of the airports in the post-COVID-19 period. The results in this part show the recovery trends of the technical efficiency scores and productivity growths of the 6 main public airports in Thailand after the unexpected shock from the COVID-19 pandemic in 2020.

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CHAPTER 6
DATA

This chapter discusses all data employed in this thesis. All data focus on the 6 main public airports of Thailand. They include Suvarnabhumi Airport (BKK), Don Mueang International Airport (DMK), Phuket International Airport (HKT), Chiang Mai International Airport (CNX), Hat Yai International Airport (HDY), and Mae Fah Luang-Chiang Rai International Airport (CEI).

The first part explains data between 2007 to 2020 that covers the big shock events such as the global financial crisis between 2008 to 2009, flooding in Thailand in 2011, and the COVID-19 pandemic that started in early 2020. These data are employed to measure the technical efficiencies and productivity growths of the airports in the first stage. In the second stage, this thesis applies the Simar and Wilson method within this study period to test which external factors will affect the technical efficiency scores of the airports. This part discusses all input and output variables defined to the efficiency and productivity measurement in the first stage, and it also includes all independent variables in the second stage.

The latter part of this chapter includes data between 2007 to 2030. In this part, this thesis employs the basic time-series method called the "Autoregressive (AR) model" to forecast the airport's future data between 2021 to 2030. This part tries to forecast the recovery trends of these airports for the next 10 years after the crisis in 2020. These data are employed to predict the future performances in both terms of efficiency changes and productivity growths of the airports. This part also discusses some limitations of the data used within this period.

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6.1 Data used for analyzing the full performances of the 6 main public airports in Thailand between 2007 to 2020.

In the first stage, all variables are employed to estimate the airports' technical efficiency scores and productivity levels between 2007 to 2020, the pre-COVID-19 pandemic period. Table 6.1 shows descriptive statistics of all data employed to estimate DEA and MPI between 2007 to 2020.

Table 6.1

Descriptive statistics of all data using in first stage estimation between 2007 to 2020

Input/ Output	Variables	Maximum	Minimum	Average	Std. Dev.
Input	Number of employees	3,514.00	105.00	807.50	958.05
Input	Number of runways	2.00	1.00	1.33	0.47
Input	Apron area (m^2)	1,033,000.00	28,800.00	359,842.83	420,876.08
Input	Terminal area (m^2)	563,000.00	14,656.00	158,653.19	206,740.06
Output	Number of passengers	64,711,010.00	648,783.00	14,801,188.39	18,057,737.28
Output	Number of aircraft movements	378,886.00	5,546.00	97,642.17	109,452.34

Table 6.1

Descriptive statistics of all data using in first stage estimation between 2007 to 2020 (Cont.)

Input/ Output	Variables	Maximum	Minimum	Average	Std. Dev.
Output	Cargo volumes (tons)	1,500,139.00	1,271.00	226,424.48	468,657.60

Note. From author's summary.

This thesis defines 3 output variables such as the number of passengers, total aircraft movements, and amount of cargo volumes in tons of the individual airports to measure the input-oriented CCR DEA technical efficiency scores and Malmquist's total factor productivity growths in the first stage (Sarkis, 2000; Lam et al., 2009; Lin et al., 2013; Tsui et al., 2014; Tsui et al., 2014; Sopadang and Suwanwong, 2016; Chen et al., 2017; Ripoll-Zarraga and Raya, 2020). For 4 input variables, this thesis employs the number of employees, the number of runways, terminal area (in meter squares), and apron area (in meter squares) (Sarkis, 2000; Yu, 2004; Yang, 2010; Lin et al., 2013; Tsui et al., 2014; Tsui et al., 2014; Sopadang and Suwanwong, 2016; Chen et al., 2017; Kaaranki and Lim, 2020; Ripoll-Zarraga and Raya, 2020).

All 3 output variables and the number of employees are derived from AOT's annual reports between 2007 to 2020. The number of runways and the terminal area (m^2) of the individual airports are obtained from AOT's corporate presentation between 2007 to 2020. Lastly, the apron area (m^2) is derived from AOT's SET56-1 Form between 2008 to 2020.

It is worthy to note that previous researches defined operating revenues and operating costs as the output and input variables (Yang, 2010; Tsui et al., 2014b; Yang and Huang, 2014). This thesis cannot use these variables because AOT's annual reports did not collect these data separately for the individual airports. According to Scotti et al. (2010), Tsui et al. (2014a), and other researches, they didn't consider these variables as inputs and outputs. However, most of them defined the number of passenger movements, air traffic movements, and the amount of air cargo shifted as the output variables. For the input variables, they defined the number of employees, runways, the terminal size, and the total area of the airports (Abbott and Wu, 2002; Lam et al. 2009; Rapee and Peng, 2014).

Table 6.1 shows that the number of employees ranges between 105 to 3,514 and has an average of 807.50 people. The BKK has the highest number of employees of 3,514 in 2020, and the CEI has the lowest number of employees of 105 in 2008. The number of runways ranges between 1 and 2. Only BKK and DMK have 2 runways. The BKK has the largest apron area of 1,033,000 m^2 , while the CEI has the smallest area of 28,800 m^2. The average apron area in meter squares is 359,842.83. The average terminal area in meter squares is 158,653.19, while the BKK has the largest terminal area of 563,000 m^2 and the HDY has the smallest terminal area of 14,656 m^2. The number of passengers ranges between 648,783 to 64,711,010, and it has an average and standard deviation of 14,801,188.9 and 18,057,737.28 people, respectively. The number of aircraft movements has a maximum of 378,886 and a minimum of 5,546. The average is 97,642.17 and the standard deviation is 109,452.34. The BKK handled the highest amount of cargo shifted in 2018 of 1,500,139 tons, while the CEI handled the smallest amount of this output in 2020 of 1,271 tons. The average is 226,424.48 tons and the standard deviation is 468,657.20 tons.

For the second stage, this thesis defines a dependent variable as DEA's efficiency scores between 2007 to 2020 derived from the first stage. This stage employs 9 independent variables to test whether external factors in both terms of micro and macro variables can affect the efficiency levels of the airports. These variables include the 6 dummy variables and 3 non-dummy variables. The dummy variables include a dummy for airport hub status, a dummy for the global financial crisis event that happened between 2008 to 2009, a dummy for the COVID-19 pandemic in 2020, a

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dummy for the People's Alliance for Democracy (PAD) occupied DMK and BKK for the short period at the end of 2008 (the fiscal year 2009), a dummy for DMK was flooded at the end of 2011 (the fiscal year 2012), and a dummy for Thailand's political conflict between 2013 to 2014 (the fiscal year 2014). The non-dummy variables include the percent of international low-cost carriers (LCCs), percent of domestic LCCs, and percent of international passengers at the individual airports (Tsui et al., 2014; Fernandex et al., 2018; Karanki and Lim, 2020; Chung et al., 2015; Ngo and Tsui, 2020; Tsui et al., 2014).

BKK, CNX, and HKT have been holding airport hub status since 2007 while DMK became the airport hub after 2009. This thesis has obtained the percent of international LCCs, percent of domestic LCCs, and percent of international passengers from AOT's corporate presentations between 2007 to 2020. Table 6.2 shows the descriptive statistics of all independent variables employed in the second stage.

A dummy of airport hub status represents the big airports that handle more than 10 million passenger movements per year. One indicates that the airport has the airport hub status, and zero otherwise. This variable has an average of 0.62 and a standard deviation of 0.49. A dummy of the global financial crisis between 2008 to 2009 has an average of 0.14 and a standard deviation of 0.35. The percent of international LCCs has a maximum of 41 percent and a minimum of 0 percent. Some airports did not handle the international LCCs such as DMK between 2007 to 2011, CEI between 2007 to 2016, and HDY in 2009. The percent of domestic LCCs has an average of 0.42 and a standard deviation of 0.28. The maximum and minimum are 0.98 and 0, respectively. DMK had the largest share of the domestic LCCs in 2011 by 97%, but the smallest share was the BKK in 2014 and 2015 that this airport did not handle domestic LCCs. This thesis employs a dummy of the PAD occupied DMK and BKK at the end of 2008, the average is 0.02 and the standard deviation is 0.15. At the end of 2011, DMK was flooded, so a dummy of DMK was flooded is employed in this model. Between the end of 2013 until mid of 2014, Thailand had a political conflict again. A dummy of Thailand's political conflict between 2013 to 2014 is also applied in this model. Lastly, the world had faced with the beginning period of the COVID-19 pandemic in 2020. This thesis employs a dummy of the COVID-19 pandemic in 2020. The average and standard deviation are 0.07 and 0.26, respectively.

Table 6.2

Descriptive statistics of all independent variables used in stage 2

Explanatory Variables	Maximum	Minimum	Average	Std. Dev.
Airport hub status	1.00	0.00	0.62	0.49
Global financial crisis	1.00	0.00	0.14	0.35
Percent of international low-cost carriers	0.41	0.00	0.09	0.09
Percent of domestic low-cost carriers	0.98	0.00	0.42	0.28
PAD occupied BKK and DMK in 2008	1.00	0.00	0.02	0.15
Thailand political conflict between 2013 to 2014	1.00	0.00	0.07	0.26
Percent of international passengers	0.77	0.00	0.20	0.27

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Table 6.2

Descriptive statistics of all independent variables used in stage 2 (Cont.)

Explanatory Variables	Maximum	Minimum	Average	Std. Dev.
Flooding at DMK in 2011	1.00	0.00	0.01	0.11
COVID-19	1.00	0.00	0.07	0.26

Note. From author's summary.

6.2 Data used for analyzing the full performances of the 6 main public airports in Thailand between 2007 to 2030.

To forecast the performance of the 6 main public airports in Thailand between 2021 to 2030, this analysis covers the data from 2007 to 2030. Due to the limitation of data on the amounts of cargo volumes, this thesis uses $AR(1)$ model to forecast 2 output variables such as the number of passengers and total aircraft movements of an individual airport between 2024 to 2030. Since data on the number of runways, terminal area, and apron area are unchanged over the period, only one input variable such as the number of employees is used in this stage.

In 2020, the news agencies reported all airports of AOT are going to handle 446,986 of total aircraft movements and 47.91 million passengers in 2021. In 2022, there will be 776,763 aircraft movements and 110.88 million people of the total number of passengers. In 2023, both the passenger and aircraft movements of the individual airports will be recovered to a similar level of 2019 (The Standard, 2020; Thairath, 2020; Prachachat, 2020).

There are 2 limitations of this part. Firstly, the forecasting trend for the amounts of cargo volumes cannot be obtained from any sources. The analysis of this

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part excludes the amount of cargo shifted from the output variables. Secondly, the terminal area and apron area are still difficult to forecast. Hence, this thesis assumes the size of the terminal and apron area of the individual airports between 2021 to 2030 remain unchanged as in 2020. Therefore, the analysis of this part forecasts only 2 output variables such as the number of passengers and number of aircraft movements, and one input variable such as the number of employees to predict the future airports' technical efficiency scores and productivity growths in the post-COVID-19 pandemic period (Yu, 2004; Sopadang and Suwanwong, 2016).

According to the AOT's Corporate Presentation in 2020, it shows that between the fiscal year 2019 to 2020, the total number of passenger movements of the BKK was decreased by 52.48% because of the affecting of the COVID-19 pandemic. HKT was the second-worst airport that decreased by 49.07%. The number of passenger movements at DMK had decreased from 41,008,378 in 2019 to 22,250,720 in 2020. The CNX had also declined by 44.60%. The CEI and HDY had declined by 39.19% and 38.48%, respectively. This report shows that the average decreasing rate of the 6 main public airports from 2019 to 2020 was 48.80 percent.

According to AOT's annual report in 2020, BKK was 41% and 42% of the ratio of total air traffic movements and the total number of passenger movements of all airports of AOT, respectively. DMK was 32% and 31%. HKT was 12% and 13%. CNX was 9% and 9%. HDY was 4% and 3%. Lastly, CEI was 3% and 2% of these 2 output variables. This thesis uses the proportions in the year 2020 of all airports to forecast the number of passengers and the total number of aircraft movements of the individual airports between 2021 to 2022. The thesis assumes the number of passengers and aircraft movements of each airport in 2023 will be the same as in 2019 (The Standard, 2020; Thairath, 2020; Prachachat, 2020). Between 2024 to 2030, this thesis employs the $AR(1)$ model to forecast the 2 output variables.

CAAT (2021) forecasted the 3 scenarios of the recovery trends of all airports between 2021 to 2029 by assuming that the COVID-19 pandemic has spread only in phase one. These scenarios include best case, moderate case, and worst case. Figures 6.1-6.6 show forecasting the number of passengers between 2021 to 2030 of all

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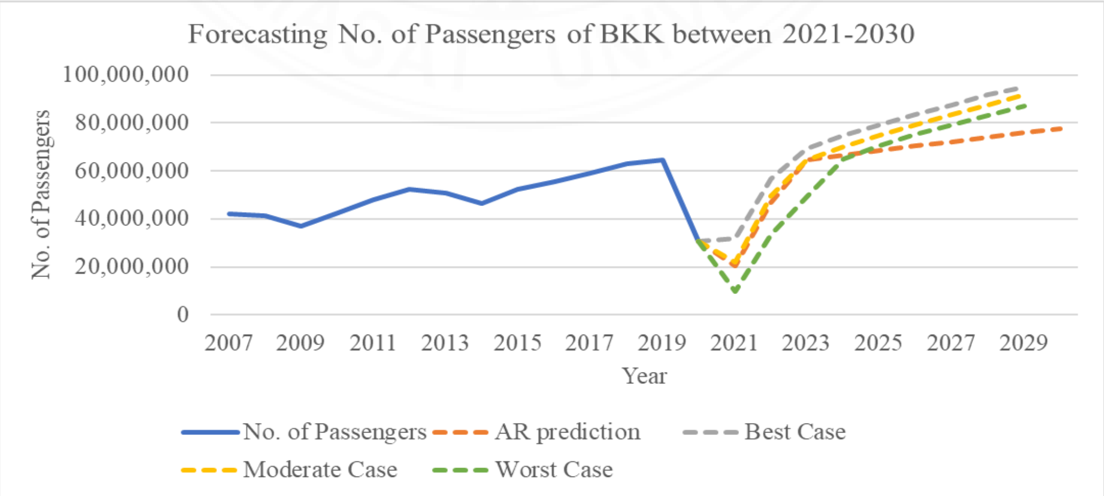
airports by applying the forecasted trends of CAAT (2021) and the AR (1) model. Due to another limitation, Thailand currently faces phase four of a pandemic, and the original COVID-19 virus has mutated to alpha, beta, gamma, and delta variants, respectively. The new forecasting trends of Thailand's aviation sector do not publish yet. During the writing of this thesis, Thailand has a total number of COVID-19 patients of 736,522 people. The total number of deaths is 6,066 people (Bangkok Post, 2021).

It is worthy to note that BKK has plans to open a third runway in 2023 and a fourth runway in 2030. Between 2023 to 2029, this thesis assumes BKK has 3 runways, and it will increase to 4 runways in 2030.

The $AR(1)$ model shows that the number of passenger movements of the individual airports will increase again after 2022 when the normal situation is brought back and have the same levels as 2019 in 2023. The results from this model are similar to the moderate and worst cases. The best case shows that all airports will start to recover in 2021 and have the same levels as 2019 in 2022.

Figure 6.1

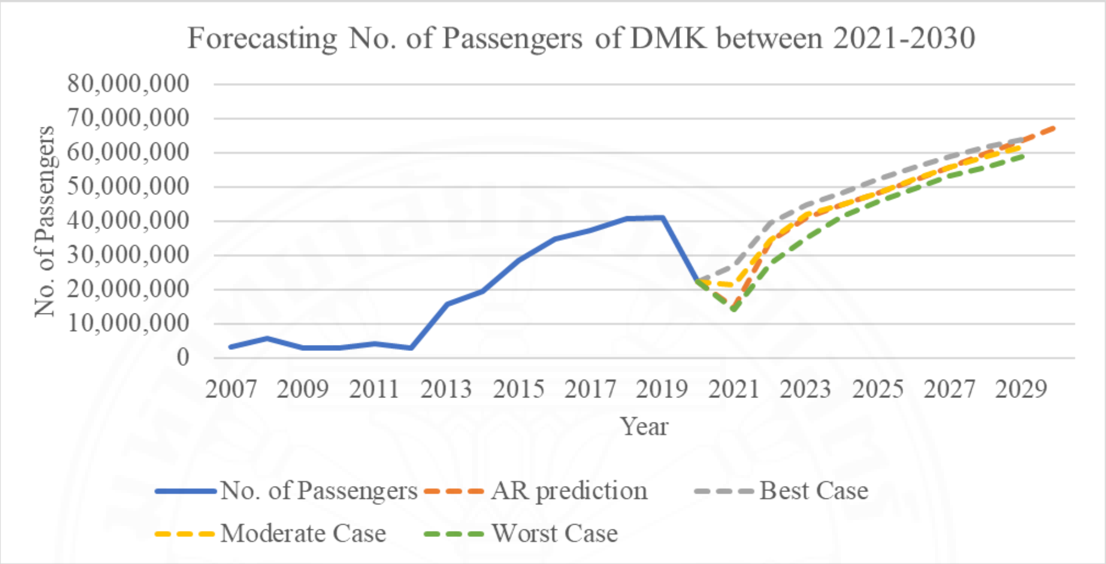
Forecasting the number of passengers of Suvarnabhumi Airport (BKK) between 2021 to 2030



Note. From author's estimation and CAAT (2021).

Figure 6.2

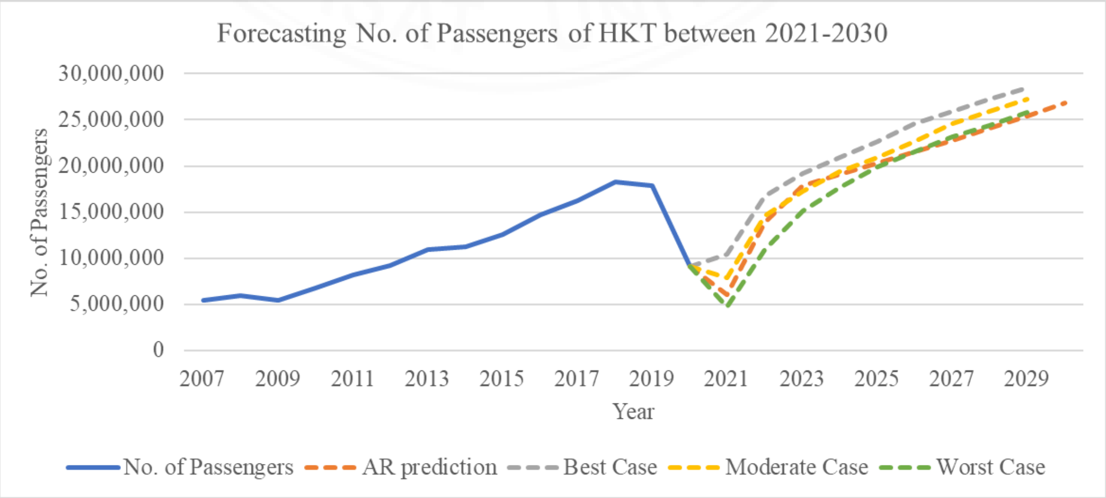
Forecasting the number of passengers of Don Mueang International Airport (DMK) between 2021 to 2030



Note. From author's estimation and CAAT (2021).

Figure 6.3

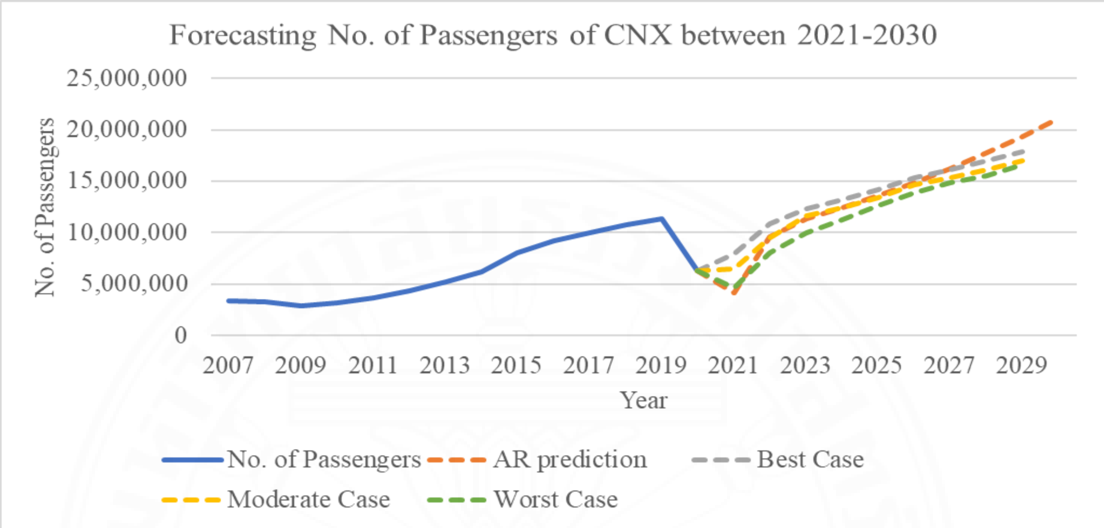
Forecasting the number of passengers of Phuket International Airport (HKT) between 2021 to 2030



Note. From author's estimation and CAAT (2021).

Figure 6.4

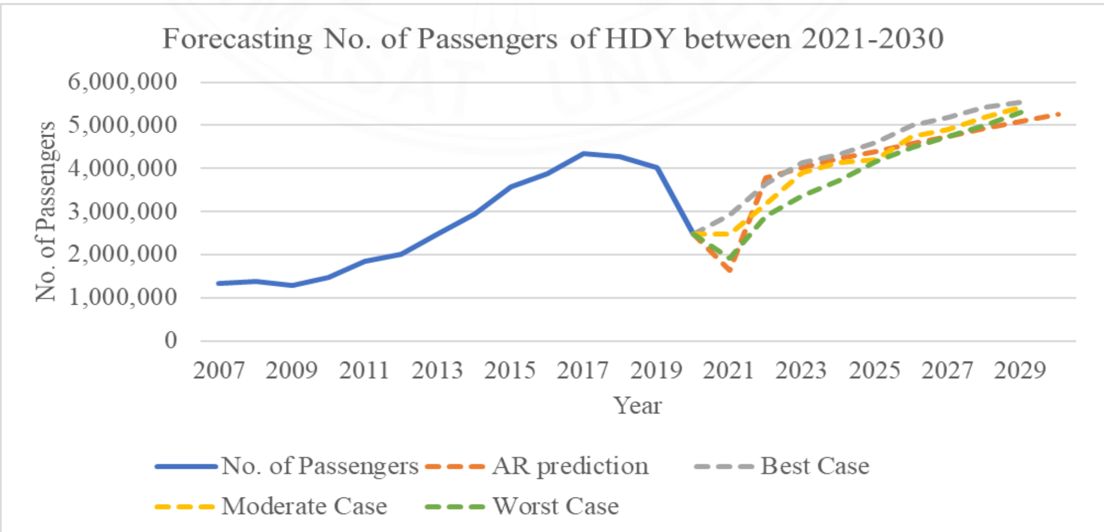
Forecasting the number of passengers of Chiang Mai International Airport (CNX) between 2021 to 2030



Note. From author’s estimation and CAAT (2021).

Figure 6.5

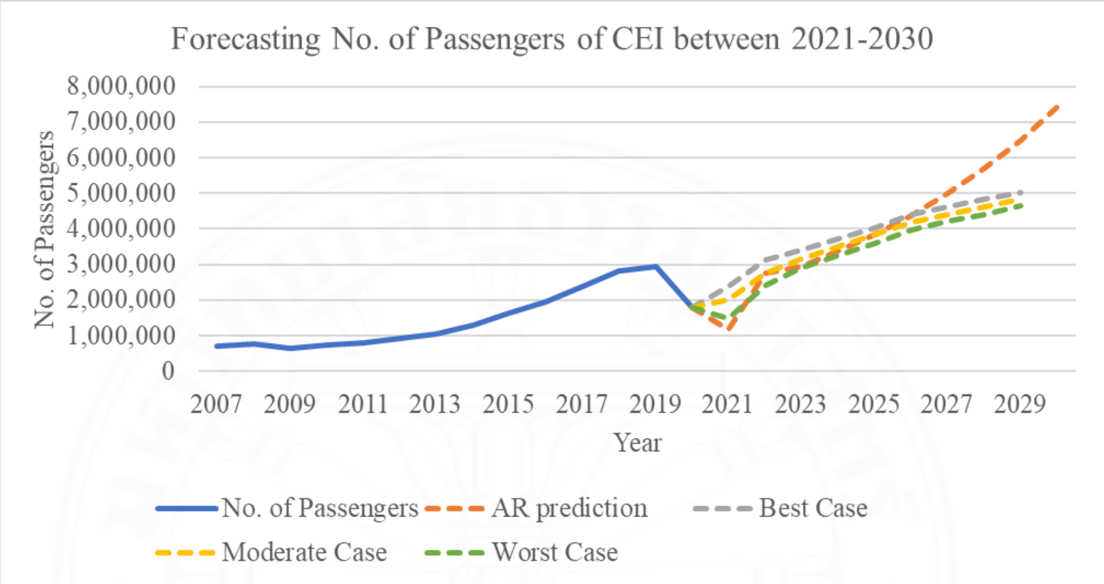
Forecasting the number of passengers of Hat-Yai International Airport (HDY) between 2021 to 2030



Note. From author’s estimation and CAAT (2021).

Figure 6.6

Forecasting the number of passengers of Mae Fah Luang-Chiang Rai International Airport (CEI) between 2021 to 2030



Note. From author's estimation and CAAT (2021).

AOT's Corporate Presentation in 2020 reports that between the fiscal year 2019 to 2020, the effect of the COVID-19 pandemic made the total number of aircraft movements of the HKT decreased by 48.36%. BKK was the second-worst airport that decreased by 44.42%. The number of aircraft movements of DMK had decreased from 273,592 in 2019 to 166,184 in 2020. This equals -39.26 percent. The CNX had also declined by 41.27%. The CEI and HDY had declined by 35.64% and 32.52%, respectively. This report shows that the average decreasing rate of the 6 main public airports in this output variable from 2019 to 2020 was 42.51 percent.

Figures 6.7-6.12 show forecasting the total aircraft movements between 2021 to 2030 of all airports by applying the forecasted trends of CAAT (2021) and the AR (1) model. CAAT (2021) forecasted the domestic and international movements between 2021 to 2029 by assuming the 3 recovery scenarios in the period of the COVID-19 pandemic, such as a best case, moderate case, and worst case.

This thesis employs the same proportions of this variable in 2020 to forecast the total aircraft movements between 2021 to 2022. AOT's annual report in 2020 reported that BKK was 41% of total air traffic movements of all airports under AOT. DMK, HKT, CNX, HDY, and CEI were 32%, 12%, 9%, 4%, and 3%, respectively. In 2023, this thesis assumes all airports will be back to the normal situation.

The AR (1) model reports that the air traffic movements will be recovered after 2021 and have the same levels as 2019 in 2023. All airports except BKK have recovery trends that are similar to the moderate and worst cases of CAAT (2021). The BKK is the only airport in this analysis that has the same levels of total aircraft movements between 2021 to 2022 as the best case from CAAT (2021). The results from AR (1) forecasted are quite similar in the recovery trends to the forecasted from CAAT (2021) except BKK after 2023, HDY after 2025, and CEI after 2027.

This thesis is the first research that applies the time-series method to predict the future performances of airports. Hence, the thesis employs the results from the AR (1) model to estimate the future efficiency scores and productivity growths of the airports. Future research can employ other models to forecast and compare with the results from CAAT (2021).

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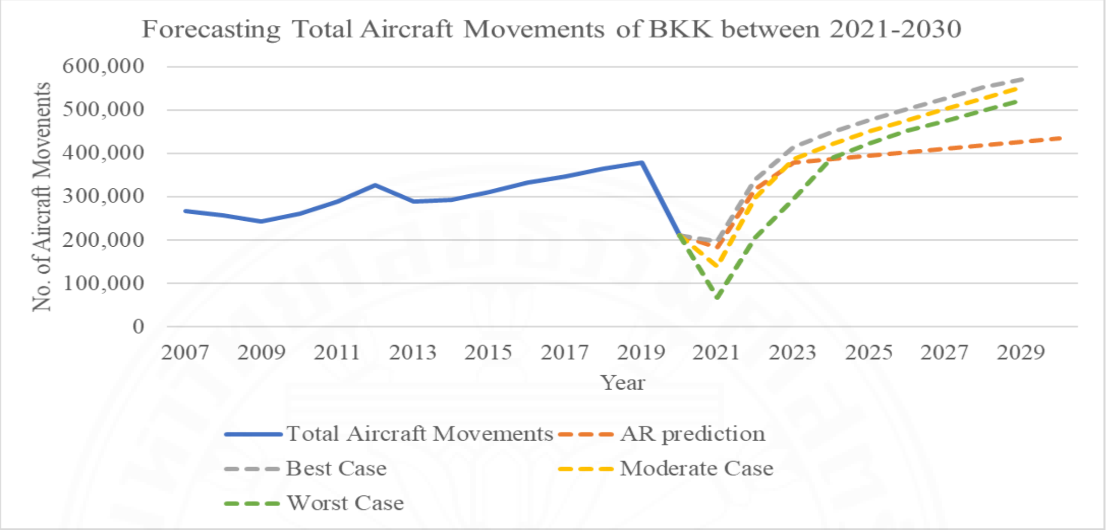
Figure 6.7

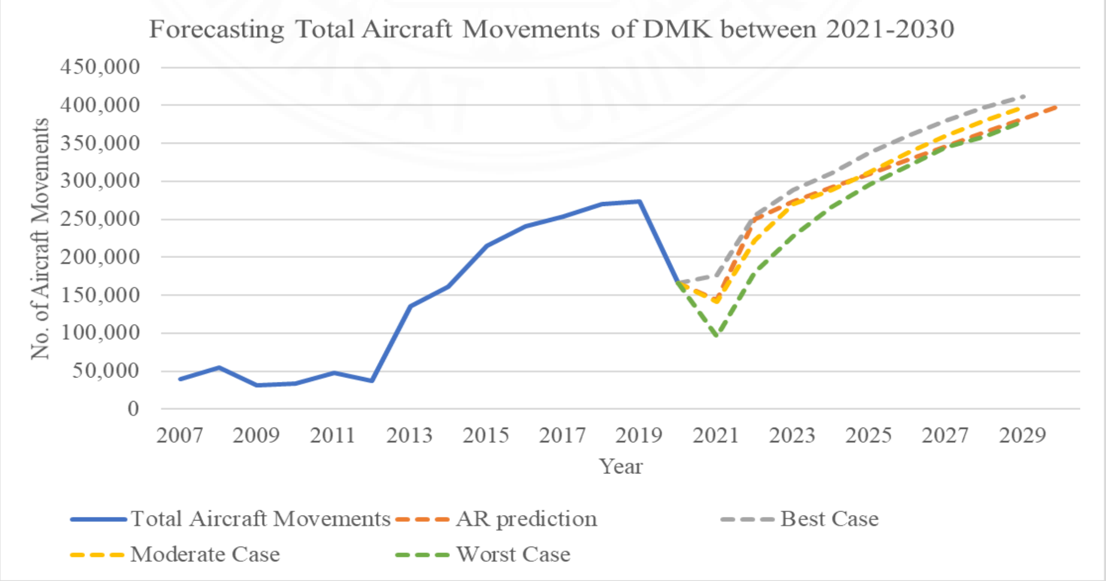
Forecasting total aircraft movements of Suvarnabhumi Airport (BKK) between 2021 to 2030



Note. From author's estimation and CAAT (2021).

Figure 6.8

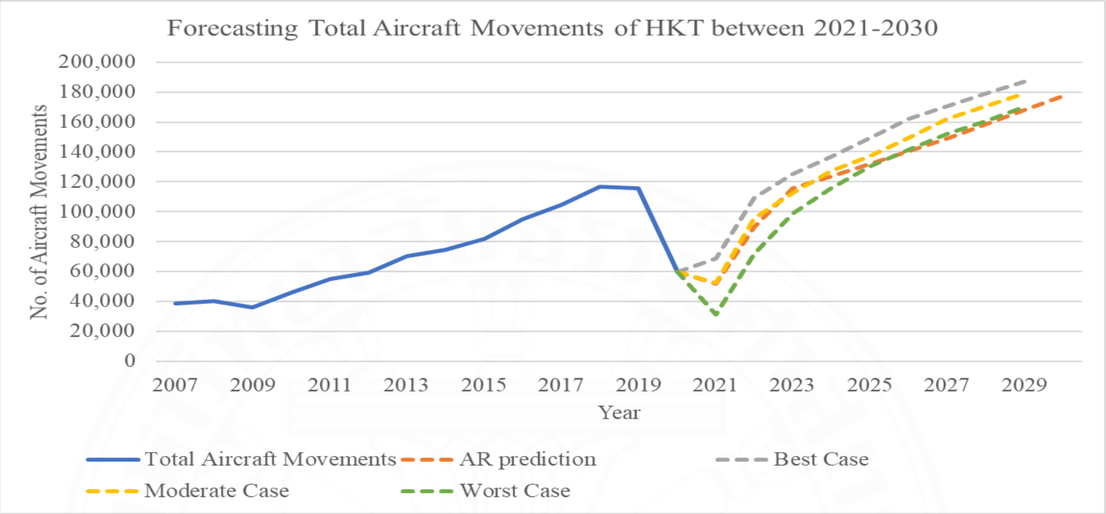
Forecasting total aircraft movements of Don Mueang International Airport (DMK) between 2021 to 2030



Note. From author's estimation and CAAT (2021).

Figure 6.9

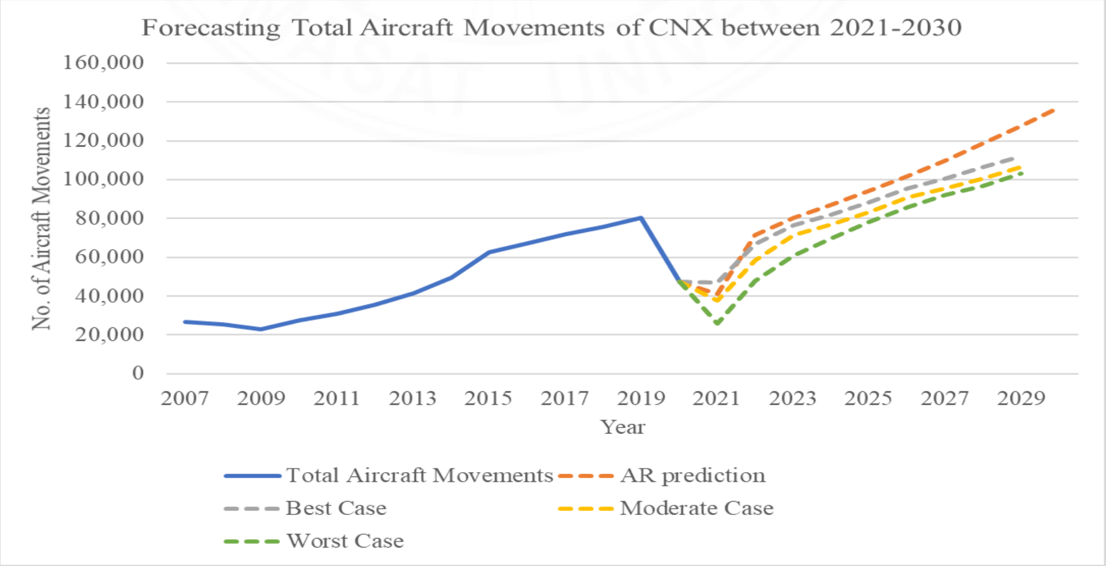
Forecasting total aircraft movements of Phuket International Airport (HKT) between 2021 to 2030



Note. From author's estimation and CAAT (2021).

Figure 6.10

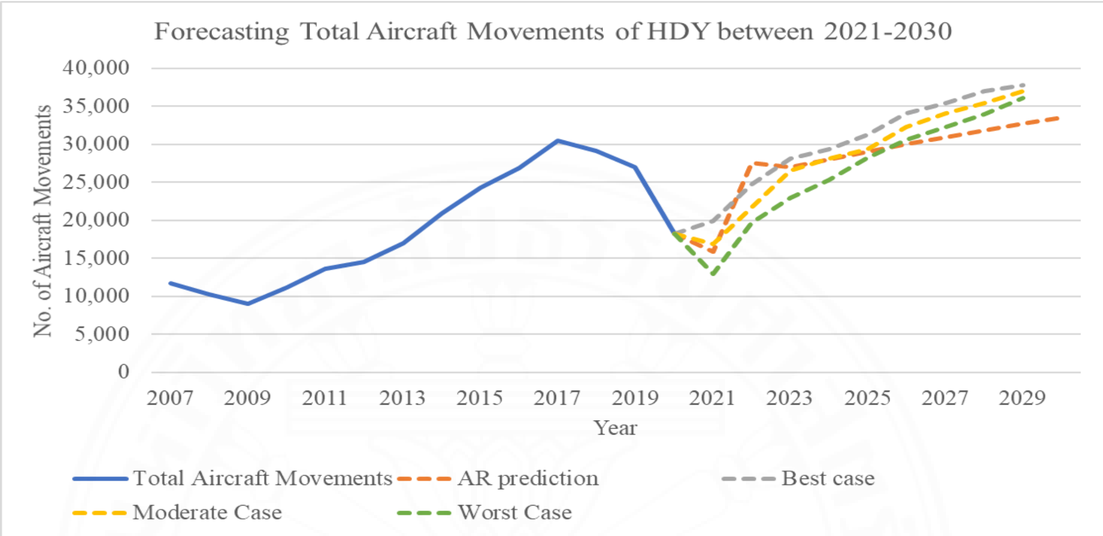
Forecasting total aircraft movements of Chiang Mai International Airport (CNX) between 2021 to 2030



Note. From author's estimation and CAAT (2021).

Figure 6.11

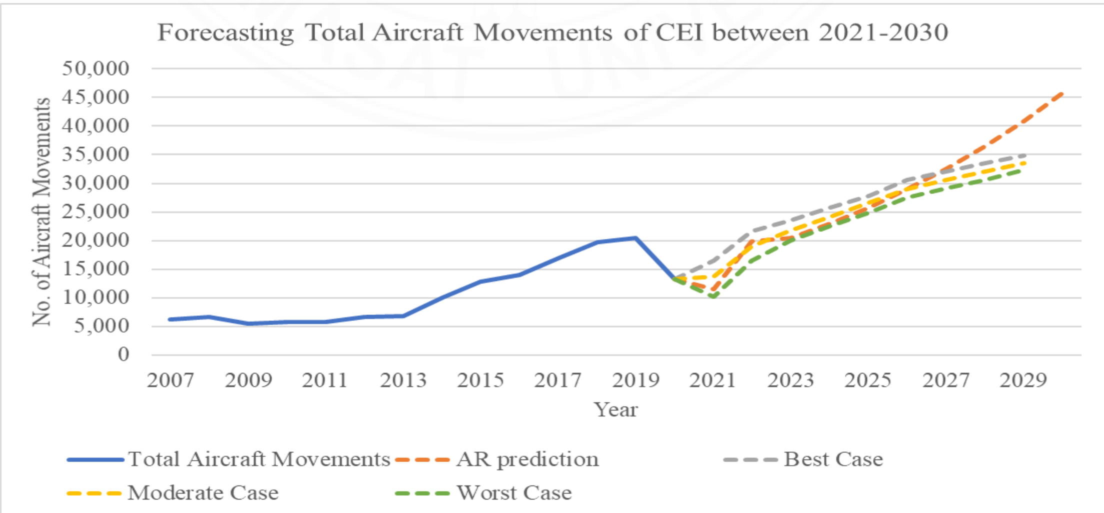
Forecasting total aircraft movements of Hat-Yai International Airport (HDY) between 2021 to 2030



Note. From author's estimation and CAAT (2021).

Figure 6.12

Forecasting total aircraft movements of Mae Fah Luang-Chiang Rai International Airport (CEI) between 2021 to 2030



Note. From author's estimation and CAAT (2021).

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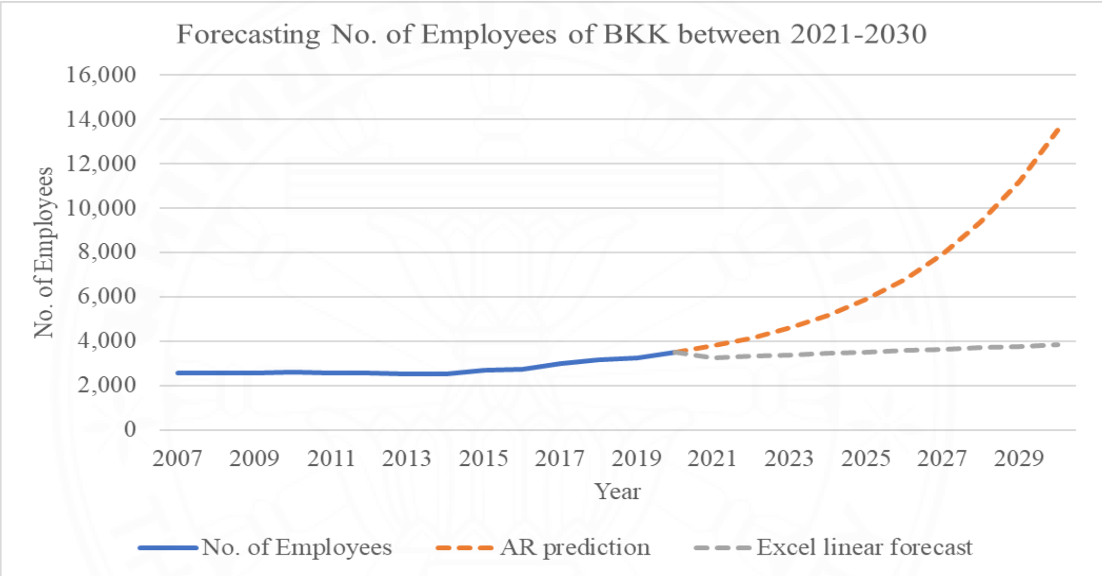
Figures 6.13-6.18 show forecasting the total number of employees between 2021 to 2030 of the individual airports by employing the AR (1) model and Excel Linear Forecast function. According to the AOT's annual report (2020), it shows that every airport had the number of employees increased from 2019 to 2020 except HDY and CEI that decreased by 21 and 8 people, respectively.

Firstly, this thesis has expected to employ the AR (1) model to forecast the number of employees of the individual airports between 2021 to 2030. The one of limitations is the thesis assumes that the number of employees will increase every year according to the AR (1) results. The results after employing the AR (1) model show that the BKK's number of employees will be overestimated after 2026 that is the number of employees will be increased by 2,000 people per year. After 2028, the number of workers at BKK will be over 10,000 people and reached almost 14,000 people in 2030. According to the AR (1) results, DMK's forecasted the number of workers faces the same problem as BKK in the forecasting process. HKT and CNX have also faced the same problems. The number of employees of CEI and HDY will be smoothly increased year by year. The results show that it is difficult to trust the AR (1) model to forecast this variable of the airport hubs. Hence, the Excel Linear Function is employed. The results from the Excel Linear Forecast function show the number of employees of all airports will be smoothly increased between 2021 to 2030. Only HDY has the number of employees forecasted by the Excel Linear Function is higher than the AR (1) model, and CEI has the same levels in both methods. Appendix A reports forecasting and comparing the growth of the number of employees at the individual airports between 2021 to 2030 by the AR (1) model and the Excel Linear Forecast function.

All airports except BKK have a limited area to expand. However, there are not possible that the airports such as DMK, HKT, and CNX will have the total number of employees of over 5,000 people, 2,000 people, and 1,000 people in the next 10 years. BKK has plans to build new constructions in the future, but there is not possible that the number of employees will be higher than 5,000 after 2023 because the size of the airport cannot be increased that much (AOT's annual report, 2020) within a short period. In summary, this thesis will employ the forecasted data from the Excel Linear Forecast function to analyze the DEA and MPI models between 2007 to 2030.

Figure 6.13

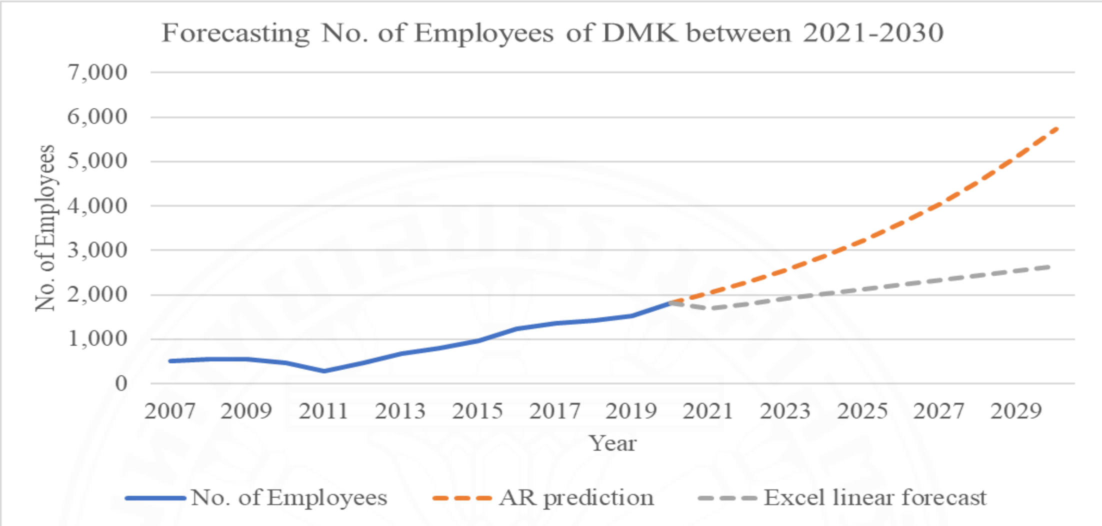
Forecasting the total number of employees of Suvarnabhumi Airport (BKK) between 2021 to 2030



Note. From author's estimation.

Figure 6.14

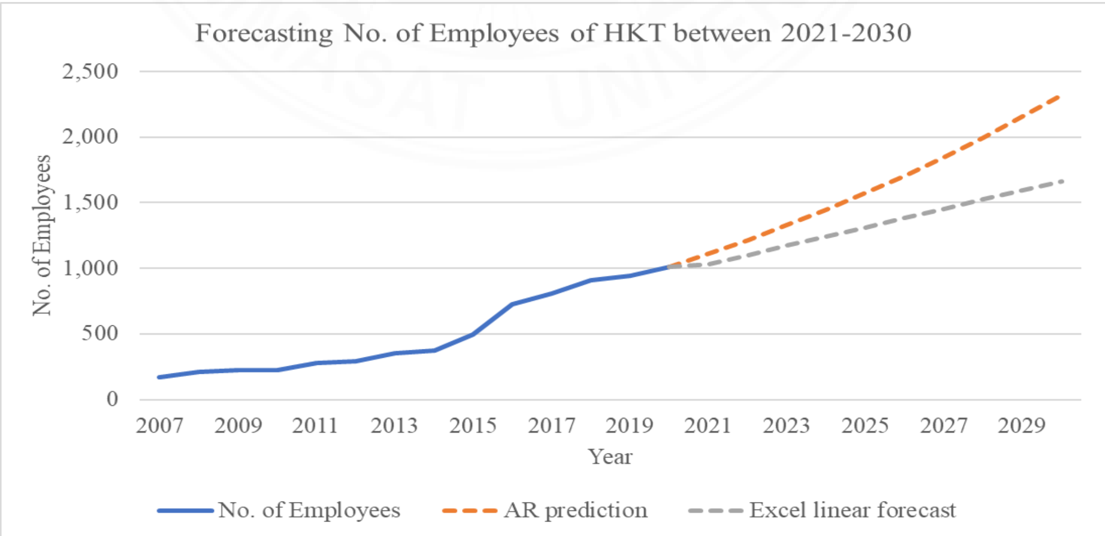
Forecasting the total number of employees of Don Mueang International Airport (DMK) between 2021 to 2030



Note. From author’s estimation.

Figure 6.15

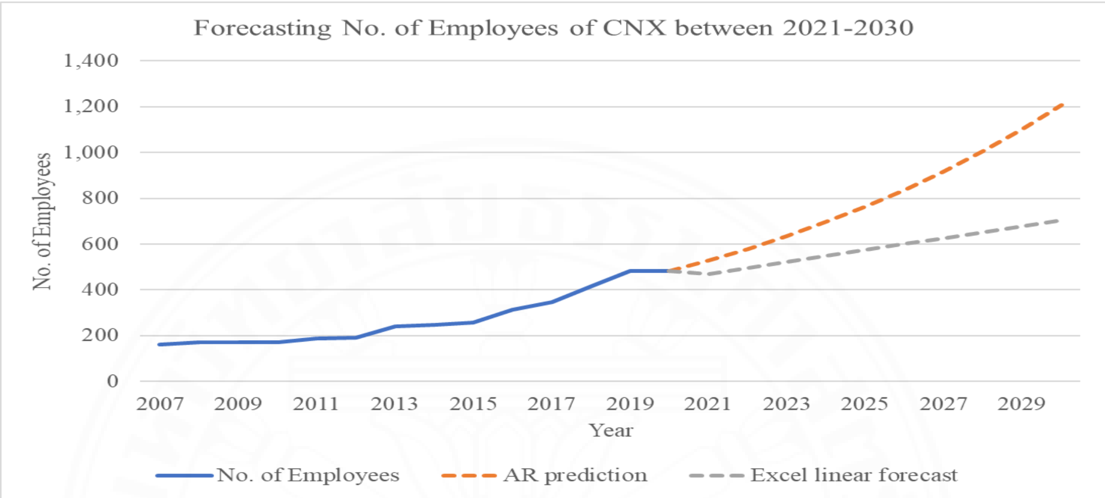
Forecasting the total number of employees of Phuket International Airport (HKT) between 2021 to 2030



Note. From author’s estimation.

Figure 6.16

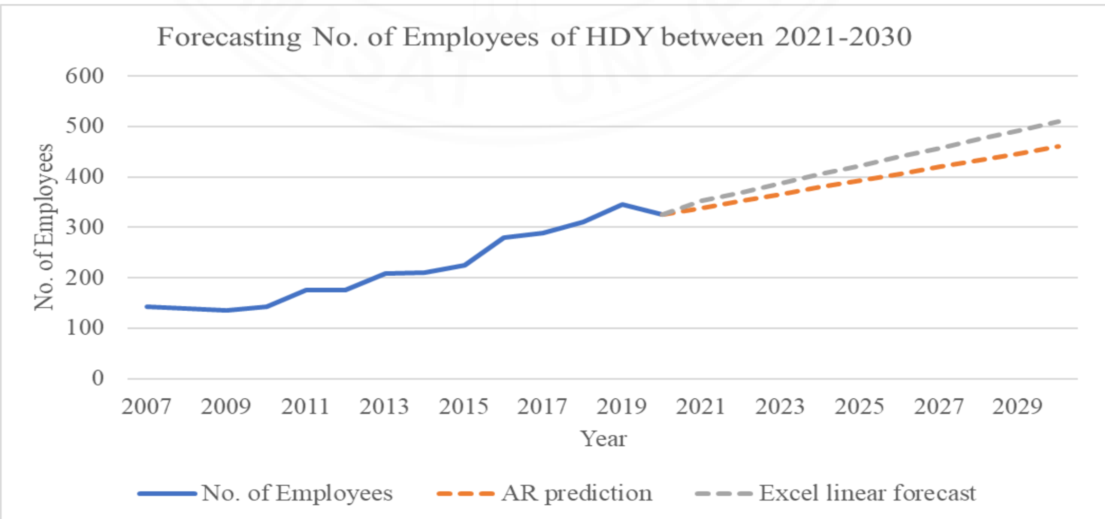
Forecasting the total number of employees of Chiang Mai International Airport (CNX) between 2021 to 2030



Note. From author's estimation.

Figure 6.17

Forecasting the total number of employees of Hat-Yai International Airport (HDY) between 2021 to 2030



Note. From author's estimation.

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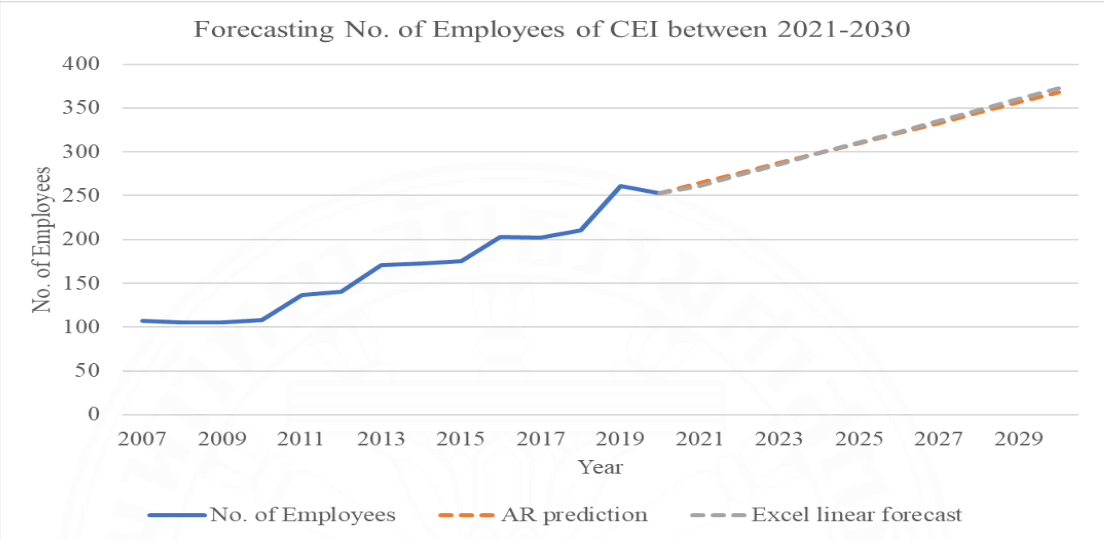
Figure 6.18

Forecasting the total number of employees of Mae Fah Luang-Chiang Rai International Airport (CEI) between 2021 to 2030



Note. From author's estimation.

Table 6.3 shows the descriptive statistics of all input and output variables employed to measure the technical efficiency scores and productivity growths of the airports between 2007 to 2030.

Table 6.3

Descriptive statistics of all input and output variables used to estimate DEA and MPI between 2007 to 2030

Input/ Output	Variables	Maximum	Minimum	Average	Std. Dev.
Input	Number of employees	3,827.00	105.00	1,054.00	1,089.86
Input	Number of runways	4.00	1.00	1.40	0.62

Table 6.3

Descriptive statistics of all input and output variables used to estimate DEA and MPI between 2007 to 2030 (Cont.)

Input/ Output	Variables	Maximum	Minimum	Average	Std. Dev.
Input	Apron area (m^2)	1,033,000.00	28,800.00	359,842.83	419,823.63
Input	Terminal area (m^2)	563,000.00	14,656.00	159,968.04	201,148.29
Output	Number of passengers	77,644,350.00	648,783.00	19,388,900.95	21,665,516.62
Output	Number of aircraft movements	434,521.00	5,546.00	124,287.94	127,972.59

Note. From author's Summary.

To measure the technical efficiency changes and productivity growths of the individual airports between 2007 to 2030, this thesis employs only 2 output variables such as the aircraft and passenger movements. For the 4 input variables, they include the number of employees, the number of runways, the apron area (m^2) and the terminal area (m^2). The number of employees ranges between 3,827 and 105.

The Excel Linear Forecast shows that in 2030 the BKK's number of workers will be 3,827. The average is 1,054.44 people and the standard deviation is 1,089.86 people. The number of runways ranges within 1 to 4 by BKK will open the 3rd and 4th runway in 2023 and 2030, respectively. The average terminal area is 359,842.83 m^2 and the standard deviation is 159,968.04 m^2. According to the AR (1) results, BKK will handle the passenger movements of 77,644,350 people in 2030. The mean of this variable is 19,338,900.95 people and the standard deviation is

21,665,516.62 people. This shows the range of passenger movements between each airport is very broad. Lastly, the total number of aircraft movements has a maximum of 434,521 and a minimum of 5,546. The average is 124,287.94 and the standard deviation is 127,972.59.

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CHAPTER 7
RESULT

This chapter is divided into 2 parts. The first part presents 2 two-stage measurements of airports' performances. The first stage measures the full performances of Thailand's 6 main public airports in terms of efficiency scores and productivity changes between 2007 to 2020. The second stage employs the Simar and Wilson bootstrapping regression model to test which external factors in both micro and macro variables will affect the technical efficiencies of the airports in this study period.

The second part uses the forecasting data to measure the future performances of these airports between 2021 to 2030. This part aims to predict the recovery trends of Thailand's main public airports in the post-COVID-19 pandemic period.

7.1 Performance Measurement of Thailand's 6 main public airports between 2007 to 2020.

This section reports the technical efficiency scores and productivity growths of the airports between 2007 to 2020. This period covers the events such as the global financial crisis between 2008 to 2009, flooding in Thailand in 2011, and the beginning period of the COVID-19 pandemic in 2020. This section also tests that which external factors in both terms of micro and macro variables affect the technical efficiency scores.

Section 7.1.1 measures the technical efficiency scores of the airports by employing the input-oriented CCR DEA model between 2007 to 2020. Section 7.1.2 measures productivity changes of the airports between 2007 to 2020 by employing the MPI model. Section 7.1.3 employs the Simar and Wilson bootstrapping regression to test which external factors affect the efficiency scores obtained from section 7.1.1.

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7.1.1 Results of technical efficiency scores of 6 main public airports of Thailand between 2007 to 2020.

This section reports technical efficiency scores obtained from the input-oriented CCR DEA model of the individual airports over the study period of 2007-2020. These results allow to measure and compare the performances of Thailand's 6 main public airports.

Table 7.1

Technical efficiency scores of the 6 main public airports of Thailand between 2007 to 2020

Year	BKK	DMK	HKT	CNX	HDY	CEI	Mean
2007	0.878	0.332	1.000	0.850	0.423	0.279	0.627
2008	0.934	0.437	0.877	0.690	0.393	0.299	0.605
2009	0.741	0.246	0.773	0.670	0.381	0.248	0.510
2010	0.931	0.287	0.982	0.796	0.463	0.255	0.619
2011	0.987	0.694	0.947	0.812	0.532	0.245	0.703
2012	1.000	0.326	1.000	0.909	0.576	0.286	0.683
2013	0.976	0.870	1.000	0.724	0.571	0.263	0.734
2014	0.927	0.895	1.000	0.839	0.578	0.357	0.766
2015	0.951	1.000	1.000	1.000	0.540	0.461	0.825
2016	0.988	0.978	0.929	0.985	0.590	0.512	0.830
2017	0.994	0.972	0.963	1.000	0.669	0.595	0.866
2018	1.000	1.000	1.000	1.000	0.641	0.684	0.888
2019	1.000	1.000	0.992	1.000	0.594	0.711	0.883
2020	0.676	0.607	0.512	0.587	0.401	0.458	0.540
Mean	0.927	0.689	0.927	0.847	0.525	0.404	0.720

Note. From author's calculation. The names and code names of the airports are following as Suvarnabhumi Airport (BKK), Don Mueang International Airport (DMK),

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Phuket International Airport (HKT), Chiang Mai International Airport (CNX), Hat-Yai International Airport (HDY), and Mae Fah Luang-Chiang Rai International Airport (CEI).

Table 7.1 reports the technical efficiency scores of all 6 airports between 2007 to 2020. The average efficiency score of all airports is 72 percent in this period. The average efficiency of all airports was above 60 percent in 2007-2008 and decreased to 51 percent in 2009, the period of the global financial crisis. Between 2010 to 2011, the recovery period after the crisis, the results show that the average efficiency score returned to higher than 60 percent again and reached 70 percent in 2011. At the end of the year 2011, Thailand faced a big flooding in many provinces and the DMK was flooded. This made the efficiency score of DMK in 2012 was dropped to 32.6 percent, in other words, the technical inefficiency score was 67.4 percent. The result shows that flooding at the end of 2011 affected only DMK's efficiency score. The average efficiency in 2012 had dropped a little bit to 68.3 percent. After 2012, the average efficiency scores were higher than 70 percent every year and higher than 80 percent between 2013 to 2019. Between 2013 to 2019, a lot of tourists traveled to Thailand. This made the 6 main public airports had to improve their qualities and operational efficiencies to bear with the high growth of the tourism sector. At the end of 2019, the beginning period of the COVID-19 pandemic from Wuhan, China, this pandemic made the world faced a severe problem in terms of life, employment, and economy. So, the shock from this pandemic affected the decreasing of air traffic and passenger movements because many countries had a lockdown policy in 2020. The average efficiency score in 2020 decreased to 54 percent. The average efficiency scores of each year in Table 7.1 have been plotted on a graph in Figure 7.1.

Figure 7.1 shows the overall means of efficiency between 2007 to 2020. The result shows that the trend of main public airports' efficiency scores was increased from 2007 to 2019, and it was dropped in 2009, 2012, and 2020. Declines in technical efficiency scores in these periods can be explained by the following events. In 2009, the world faced a global financial crisis. The total number of passenger movements of the airports had declined from 58 million people in 2008 to 50 million in 2009. The amount of cargo shifted was dropped to 10.4 million tons in 2009, while in 2008, the amount of cargo movement was 13.4 million tons. Tsui et al. (2014) and Voltes-Dorta and Pagliari (2012) showed the global financial crisis declined the airports' efficiency levels between 2009 to 2010.

At the end of 2011 (the fiscal year 2012), Thailand faced a big flooding in many provinces, and Don Mueang International Airport (DMK) was flooded. This event made the total number of passenger movements of DMK had declined from 39 million people in the fiscal year 2011 to 27 million people in the fiscal year 2012. The effect of this event made the average airports' technical efficiency score in 2012 was dropped by 20 percent from 2011.

In 2020, there was the beginning period of the COVID-19 pandemic crisis. The total number of passenger movements of the airports was dropped from 141 million people in 2019 to 72 million people in 2020. The total aircraft movements were dropped to 51 million. This macro shock affected the average airports' technical efficiency score was dropped by more than 30 percent from 2019 to 2020.

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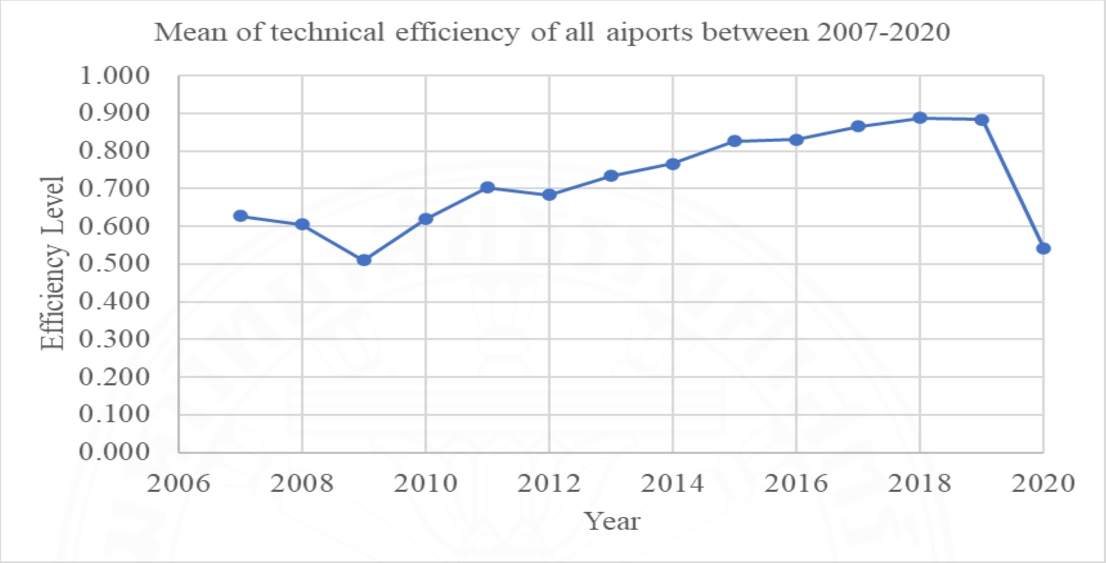
Figure 7.1

Means of technical efficiency of the 6 main public airports of Thailand between 2007 to 2020



Note. From author's calculation.

After 2009, the result shows the recovery trends after the global financial crisis. The average technical efficiency scores of all airports increased to almost 90 percent in 2018-2019 but dropped to below 60 percent in 2020. The average efficiency scores of the individual airports between 2007 to 2020 have been plotted as a bar chart in Figure 7.2.

Figure 7.2 shows the average technical efficiency levels of the individual airport between 2007 to 2020.

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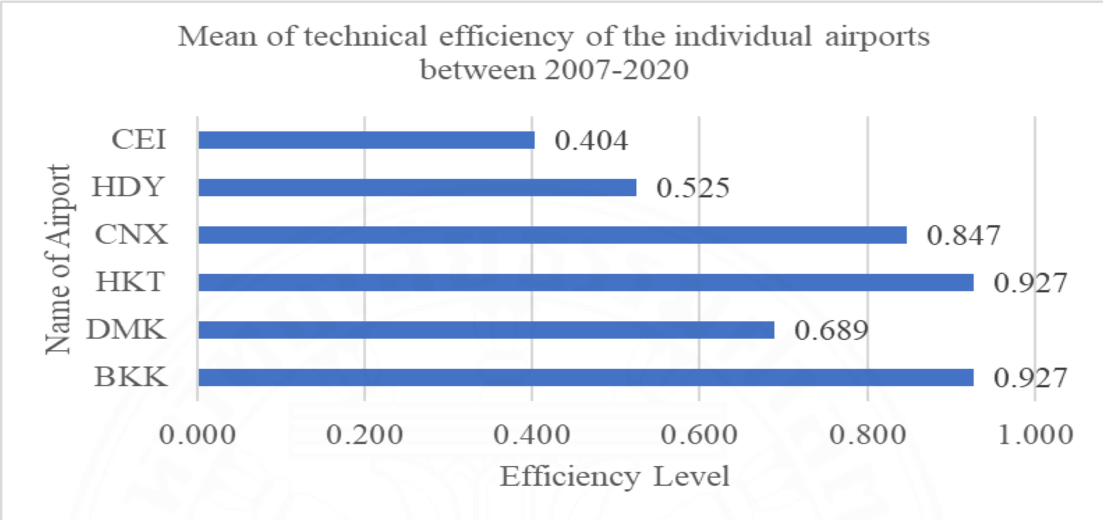
Figure 7.2

Means of technical efficiency of the individual airports between 2007 to 2020



Note. From author's calculation. The names and code names of the airports are following as Suvarnabhumi Airport (BKK), Don Mueang International Airport (DMK), Phuket International Airport (HKT), Chiang Mai International Airport (CNX), Hat-Yai International Airport (HDY), and Mae Fah Luang-Chiang Rai International Airport (CEI).

Figure 7.2 shows that BKK and HKT had the highest efficiency scores of 92.7 percent. In other words, BKK and HKT had technical inefficiencies of 7.3 percent. BKK and HKT are the big airports and have airport hub status. Phuket is a popular province that many international tourists around the world visit every year. Bangkok is the capital of Thailand and BKK is the center of the international air traffic airport of Thailand. A lot of international freights and passengers were landing and taking off at these airports. Between 2007 to 2019, the number of international passenger movements of BKK and HKT had increased by average 1.6 million and 688 thousand people per year, while CNX, HDY, and CEI had increased by only 232 thousand, 16 thousand, and 28 thousand people a year, respectively. DMK had increased by average 1.4 million people per year, but a high growth of passengers started in 2013. For the domestic passenger movements, DMK had the highest average increase of 1.7 million per year. CNX had increased by an average of 430 thousand people per year, and HKT had increased by 342 thousand people per year. BKK had increased by 230 thousand per year because DMK was the main airport that handled the domestic passenger movements in Bangkok. HDY had increased by an average of 207 thousand passengers per year. The lowest one was CEI. This airport had increased by an average of 158 thousand people per year. Hence, both BKK and HKT handled a large number of international passenger and aircraft movements every year since 2007, this made the airports had the highest average efficiency scores.

Between 2007 to 2020, CNX had a technical efficiency of 84.7 percent, while DMK had 68.9 percent. CNX and DMK are the airport hubs. CNX had the growth of passenger movements after 2009 and handled 10 million passengers in 2017. CNX had a lot of Chinese tourists visited between 2014 to 2019 which the international passengers were above 1 million people. DMK started to be the airport hub after 2012, the recovery period after the big flooding.

HDY and CEI have no airport hub status because Songkhla and Chiang Rai provinces are not the popular places where tourists visited. Both airports handled the number of passengers lower than 500,000 people a year. Considering the periods between 2007 to 2020, the average number of passengers of HDY had increased by 87 thousand people per year and 83 thousand people by CEI. The airport hubs such as DMK, HKT, and CNX had an average increase of passengers over 200 thousand people per year. Within this period, the average increase of passengers of BKK was negative because the total number of passenger movements was declined by 33 million at the beginning period of the COVID-19 pandemic in 2020. The result shows that HDY had an average efficiency score between 2007 to 2020 of 52.5 percent. CEI had the lowest technical efficiency comparing with the other 5 airports. The result shows that CEI had a technical inefficiency of almost 60 percent within this period. Between 2007 to 2012, CEI had passenger movements below 100,000 people. After 2012, the number of passengers had increased every year and reached 300,000 people in 2019. This supports the result that the efficiency scores of CEI had been increased every year and above 70

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percent in 2019 and dropped to less than 50 percent again in 2020, the period of the COVID-19 pandemic. This thesis analyzes 4 airport hubs and 2 non-airport hubs. The results support that the airport hubs have higher technical efficiency scores than non-airport hubs.

Turning to the performance measurement of the individual airports, Figures 7.3-7.8 show the technical efficiency scores of each airport over the study period. Figure 7.3 shows the efficiency levels of BKK between 2007 to 2020. BKK is a big airport hub that opened in 2007. The number of passenger movements was higher than 40 million between 2007 to 2011 except in 2009, the period of the global financial crisis, the total passenger movements were 37 million. After 2011, the number of passenger movements was above 50 million every year except in 2014, the period of Coup d'etat and Thailand's political conflict, and 2020, the period of the COVID-19 pandemic.

In the period of the global financial crisis, the result shows that the efficiency had declined to 74.1% and recovered to more than 90% in 2010. BKK performed fully efficiently every year between 2011 to 2019 except in 2013-2015, the period of Thailand's political conflict and Coup d'etat in 2014. In 2020, the world had faced a big shock from the COVID-19 pandemic, the technical efficiency of BKK dropped to 67.6 percent. The result shows that in 2020, BKK had the lowest efficiency score in 14 years.

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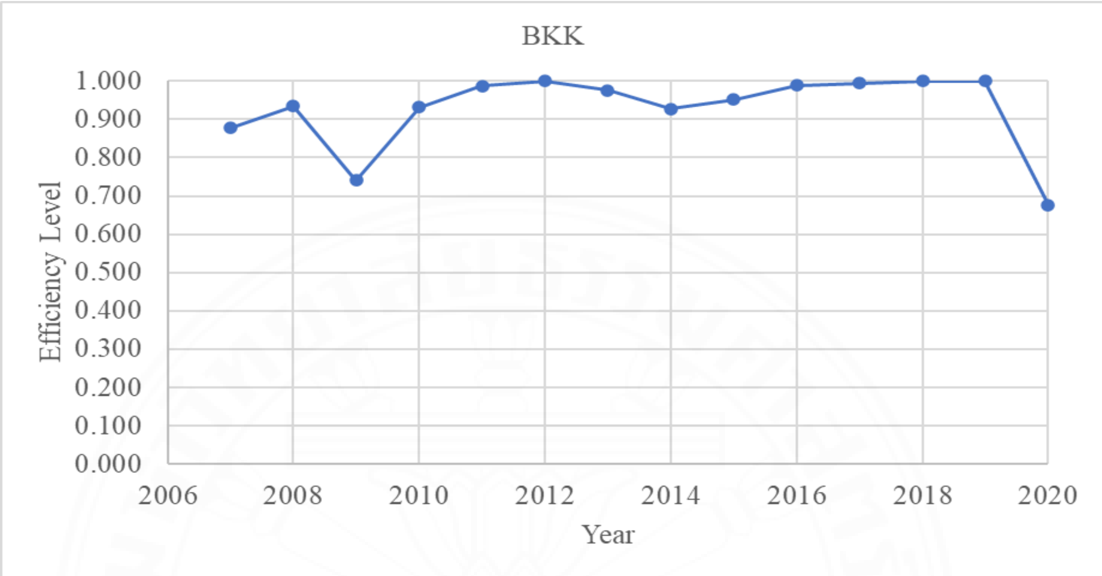
Figure 7.3

Efficiency levels of Suvarnabhumi Airport (BKK) between 2007 to 2020



Note. From author's calculation.

Since 2010, DMK has been focusing on low-cost carriers (LCCs) in both domestic and international freights. This policy made DMK handled the highest number of LCCs in the world in 2015 (Sopadang and Suwanwong, 2016).

Figure 7.4 shows the technical efficiencies of DMK between 2007 to 2020. Between 2007 to 2009, the responsibility of DMK overlapped with BKK. DMK closed for a short period in 2007. The efficiency scores were lower than 50 percent within this period. In 2009, DMK had a technical inefficiency of 75.4 percent, the lowest in the study period. In 2010, Thailand's government defined the new responsible for DMK to handle only low-cost carriers. This made DMK had the efficiency score increased to 69.4 percent in 2011. The effect of this policy contributed to DMK became the biggest low-cost carrier airport in 2015. DMK had been flooded from the end of 2011 to the early of 2012. The efficiency score dropped to 32.6 percent in 2012. After the flooding, DMK recovered the technical efficiency to almost 90% and performed fully efficiently

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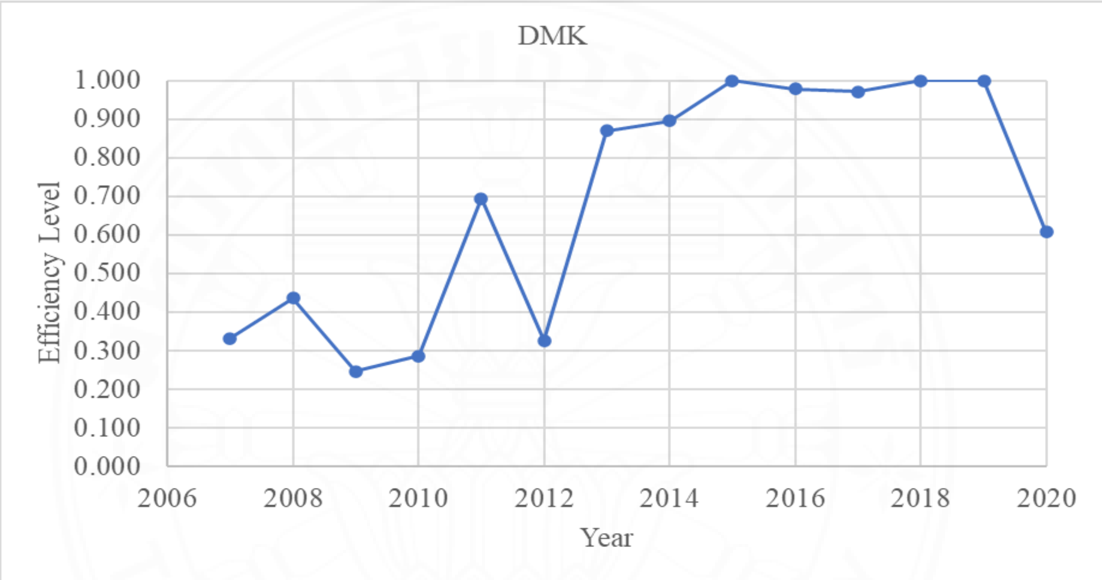
in 2015, 2018, and 2019, respectively. The result shows that in the beginning period of the COVID-19 pandemic, the efficiency scores fell to 60.7 percent.

Figure 7.4

Efficiency levels of Don Mueang International Airport (DMK) between 2007 to 2020



Note. From author's calculation.

Figure 7.5 shows the technical efficiencies of HKT between 2007 to 2020. HKT is the airport hub of Thailand where international tourists around the world visit Phuket province every year. The number of passengers had increased since 2009. Between 2007 to 2012, the passenger movements were above 5 million but below 10 million. After 2012, the number of passengers who visited this airport was over 10 million and almost 20 million in 2018-2019. The result shows that HKT performed fully efficiently every year except 2008-2009 and 2020.

In 2008 and 2009, HKT was affected by the global financial crisis. The inefficiency scores were 12.3 and 22.7 percent, respectively. After the crisis, HKT performed fully efficiently almost every year until 2020. In the beginning period of the COVID-19 pandemic, the technical efficiency dropped to 51.2 percent, the lowest

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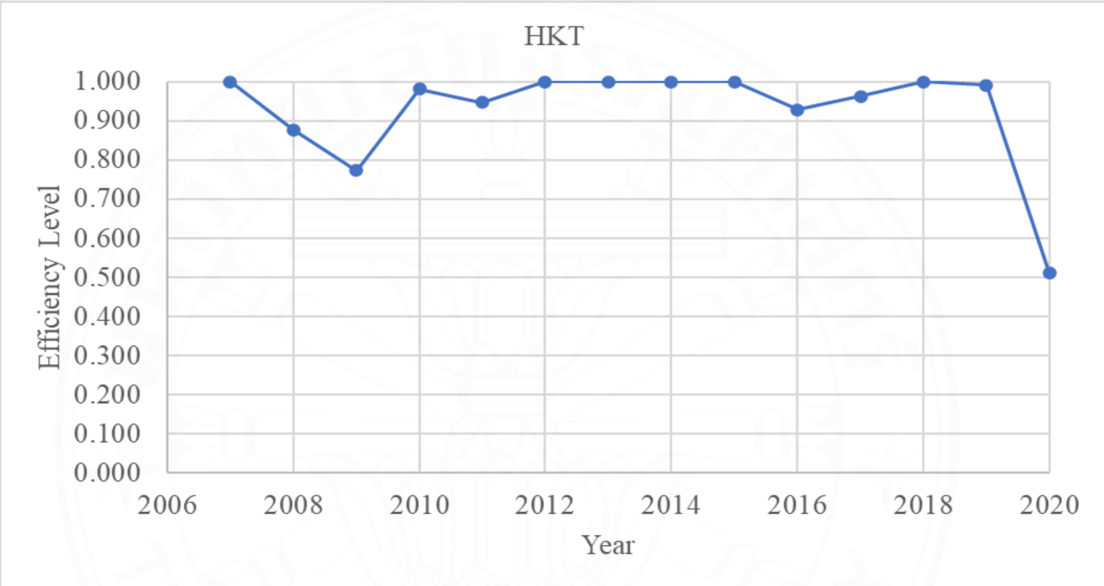
efficiency score in the study period. This shock made a huge impact on this airport more than the financial crisis.

Figure 7.5

Efficiency levels of Phuket International Airport (HKT) between 2007 to 2020



Note. From author's calculation.

Figure 7.6 shows the technical efficiencies of CNX between 2007 to 2020. Between 2007 to 2012, the number of passenger movements was below 5 million and the number of aircraft movements was below 40,000 times. The passenger movements had increased every year and handled more than 10 million passengers after 2017 because many Chinese tourists visited Chiang Mai province. AOT's annual reports between 2007 to 2020 report that the number of passenger and aircraft movements of CNX had been increased every year except in 2020, the beginning period of the COVID-19 pandemic. The amounts of cargo shifted were higher than 20,000 tons between 2007 to 2012 and dropped to 18,451 tons in 2013. CNX handled the cargo shifted around 18,000 to 19,000 a year since 2013 except in 2019 and 2020, the cargo

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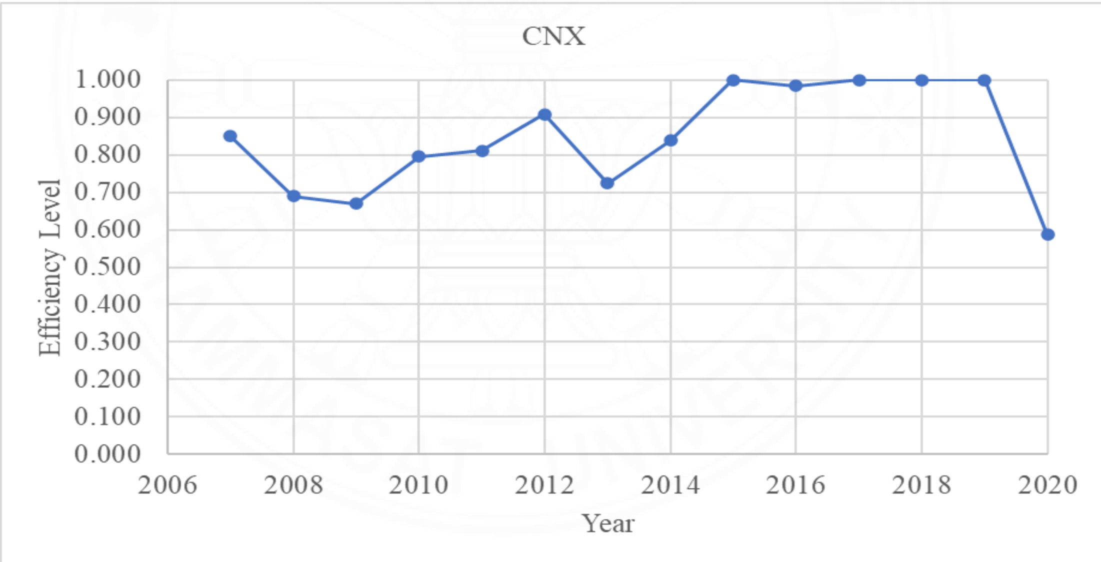
volumes were 13,032 and 6,605 tons, respectively. These made the technical efficiency scores of CNX increased after 2013 and reached fully efficient after 2014.

In 2007, the technical efficiency was 85 percent. In the global financial crisis period, the efficiency score dropped to below 70 percent. Between 2010 to 2014, the efficiency scores ranged within 80 to 90 percent. Since 2014, CNX was performing fully efficient almost every year until 2020 that the efficiency level dropped to 58.7 percent. A shock from the COVID-19 pandemic also affected the efficiency level of this airport to perform the highest inefficient in the study period.

Figure 7.6

Efficiency levels of Chiang Mai International Airport (CNX) between 2007 to 2020



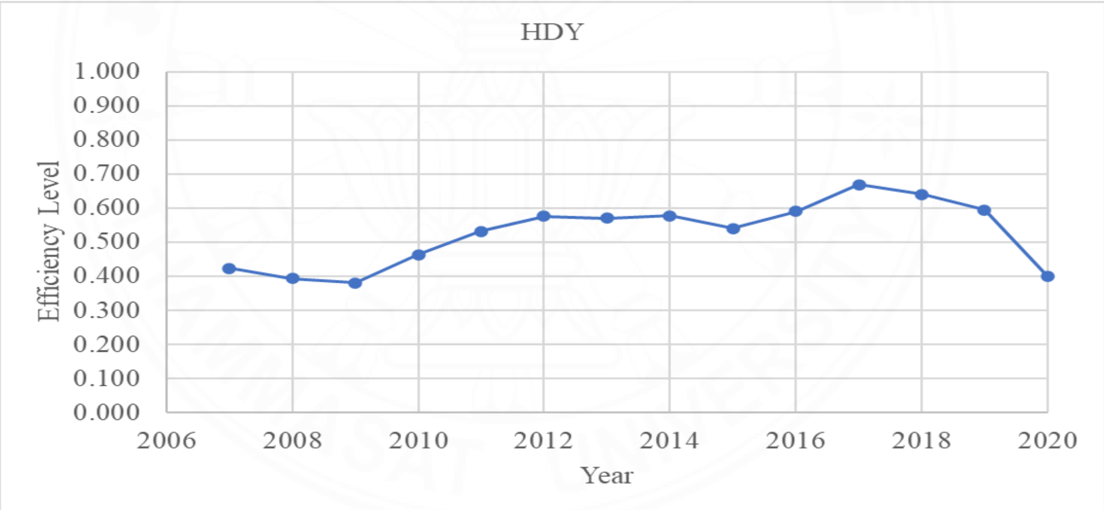
Note. From author's calculation.

Figure 7.7 shows the technical efficiencies of HDY between 2007 to 2020. HDY is a non-airport hub. The number of passengers was lower than 5 million a pear by the international passengers were not above 350,000 people. The number of aircraft movements was below 30,000 times a year by the number of international aircraft movements was below 3,000 times except in 2018. The amount of cargo shifted was below 15,000 tons a year. These made the HDY's efficiency scores were quite stable at 50 percent in this study period.

The efficiency levels had slightly decreased between 2008 to 2009 and increased to almost 50 percent in 2010. Between 2011 to 2019, the efficiency scores ranged within 50 to 70 percent. In 2017, the technical efficiency was 0.669. It was the highest efficiency in the study period. In the beginning period of the COVID-19 pandemic, this airport had a technical inefficiency of 59.9 percent. Comparing with the other airports, the result shows that HDY performed the worst in 2020 (Table 7.1).

Figure 7.7

Efficiency levels of Hat-Yai International Airport (HDY) between 2007 to 2020



Note. From author's calculation.

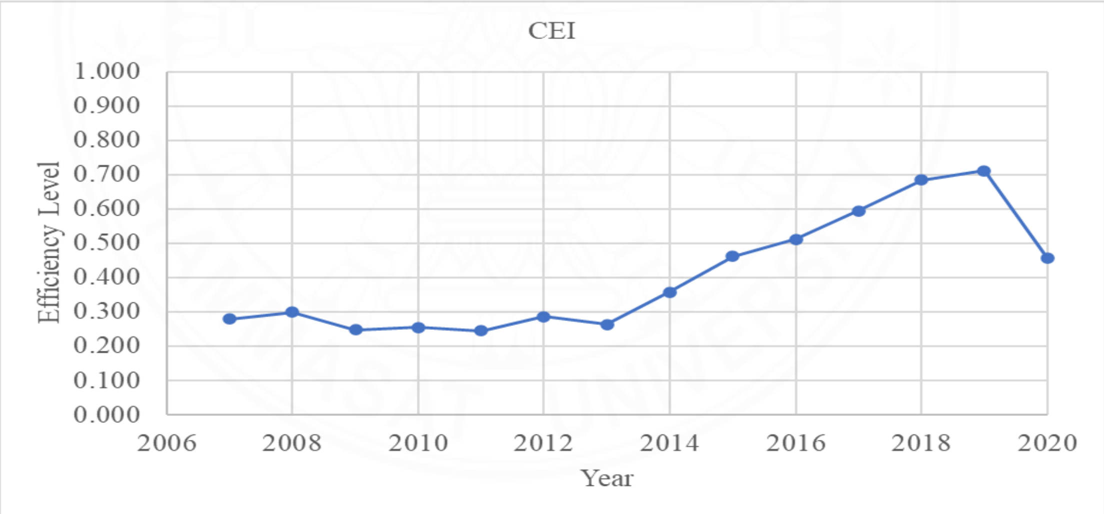
Figure 7.8 shows the technical efficiencies of CEI between 2007 to 2020. CEI is another non-airport hub. The result shows that the efficiency scores of CEI were below 30 percent between 2007 to 2013. After 2013, the technical efficiencies of the airport had increased every year and reached 71.1% in 2019. In 2020, CEI's technical inefficiency rose to 54.2 percent.

Between 2007 to 2013, the total number of air traffic movements every year was below 10,000 times. The number of passenger movements was lower 1 million except in 2013. The cargo volume was lower than 5,000 tons. These made the CEI's efficiency scores were below 30 percent within this period.

Between 2013 to 2019, the number of total aircraft movements and the number of passengers had increased from 6,882 to 20,511 and 1,053,863 to 2,953,093, respectively (AOT's Annual Report, 2013, 2019). Because the number of employees had slightly increased, this made CEI performed better within this period.

Figure 7.8

Efficiency levels of Mae Fah Luang-Chiang Rai International Airport (CEI) Between 2007 to 2020



Note. From author's calculation.

7.1.2 Result of productivity changes of 6 main public airports of Thailand between 2007 to 2020.

This thesis employs Malmquist's Total Factor Productivity Index (MPI) model to measure the productivity growths of the airports between 2007 to 2020. The MPI model allows one to explain what sources are attributed to productivity change of the airport industry such as technical efficiency change (TEC) and technical change (TC). TEC measures whether the working systems in labors at the airports can handle more the passenger movements, the aircraft movements, and the amount of cargo shifted while keeping a low number of employees. An example of TEC improvement is the number of employees is increased at a low rate while handling a high growth of passenger movements. TC measures whether the airports can take the advantage of new technologies to help them promote productivity levels. An example of TC improvement is the adoption of new technologies such as self-check-in desks and check-in by using smartphones to prevent crowded situations at the airports by reducing the check-in counters and labors at the terminal zone.

Table 7.2 reports the productivity growths of the overall airports from 2007 to 2008 until 2019 to 2020. Table 7.3 shows the productivity growths of the individual airports between 2007 to 2020.

Table 7.2

The overall airport's productivity changes from 2007 to 2008 until 2019 to 2020

Period	TEC	TC	TFPC
2007 – 2008	1.023	0.972	0.995
2008 – 2009	0.958	0.885	0.847
2009 – 2010	0.931	1.260	1.172
2010 – 2011	1.133	1.086	1.231
2011 – 2012	0.891	1.076	0.958
2012 – 2013	1.164	0.974	1.133
2013 – 2014	1.049	1.037	1.088
2014 – 2015	1.034	1.036	1.072
2015 – 2016	1.073	0.947	1.016
2016 – 2017	1.014	1.051	1.067
2017 – 2018	0.996	1.040	1.037
2018 – 2019	0.985	0.990	0.976

Table 7.2

The overall airport's productivity changes from 2007 to 2008 until 2019 to 2020 (Cont.)

Period	TEC	TC	TFPC
2019 – 2020	1.041	0.551	0.574
Geometric Mean	1.020	0.978	0.998

Note. From author's calculation.

The analysis between 2007 to 2020 shows that the average total factor productivity (TFP) growth index of the 6 main public airports equals 0.998. This means that the average productivity level of these airports had declined by 0.2 percent a year in this study period. The reason was the average of technical change (TC) had regressed by 2.2 percent a year, while the average of technical efficiency change (TEC) had progressed by 2 percent a year. This means that within this study period, the 6 main public airports cannot take advantage of new technologies to promote productivity growth. They emphasized the working system at the airports, but the TEC cannot overwhelm the TC to make the TFP growth higher than 1.

From 2008 to 2009, the period of the global financial crisis, the overall airports faced the regress of both TEC and TC of 4.2% and 11.5%, respectively. These made the TFP was regressed by 15.3 percent. This shows that the global financial crisis affected both the working systems and the adoption of new technologies at the airports.

From 2009 to 2010, the recovery period after the crisis, TC had progressed by 26%, but TEC had declined by 6.9%. The result shows that during this period the TFP of the overall airports had progressed by 17.2 percent. After the crisis between 2008 to 2009, the overall airports performed better because of taking advantage of new technologies. In this period, the international passenger and aircraft movements were recovered because the world air transportation was back to the normal situation again.

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These made the airports' technical changes were increased by 26 percent because the airports used the machines more efficiently to handle a lot of tourists.

After 2010, Table 7.2 shows that the technical efficiency changes of the overall airports were progressing until 2017 except between 2011 to 2012, the period of Thailand was flooded.

Between 2011 to 2012, the effect of flooding made the average TEC of these airports declined by 10.9 percent, but the average technological adoption rate increased by 7.6 percent. Because of the affected by flooding at the end of the year 2011, the average TFP of the airports had declined by 4.2 percent. The technical efficiency change had regressed because the flooding obstructed the working process at the airports. The airports tried to use machines instead of workers in some parts that there were affected by flooding. This shows that the airports can take advantage of technologies to offset the inefficiency at the airports' working systems but there was not enough to improve the productivity. The shock from flooding in 2011 made the TFP of the airports declined again.

The average TEC from 2017 to 2018 declined by 0.4%, but the average TC increased by 4%. This made the TFP of this period had regressed by 3.7 percent.

From 2018 to 2019, the TFP had regressed by 2.4 percent. By the technical efficiency and technical changes regressed by 1.5 and 1 percent, respectively. This period shows that both TEC and TC had declined. This means that the old working system at the airports cannot promote productivity growth anymore. And the airports lacked to adopt new technologies to support the production processes.

Between 2019 to 2020, the beginning period of the COVID-19 pandemic, the TFP had regressed by 42.6 percent. The TEC had increased by 4.1percent, while the TC had regressed by 44.9 percent. The result shows that the COVID-19 pandemic hurt the technology adoption of the airports but had a positive impact on the technical efficiency improvement. The TEC had increased because the airports cannot take advantage of new technologies in this period. This means that the airports emphasized the operational systems of workers to offset productivity regress instead of adopting new technologies to promote productivity growth because Thailand had a lockdown during this period. The total number of passengers had declined more than 45 percent from 2019 to 2020. This shock had declined the technological adoption rate by almost 45 percent.

Table 7.3

Productivity growths of the individual airports between 2007 to 2020

Airport Name (code name)	TEC	TC	TFPC
Suvarnabhumi Airport (BKK)	1.000	0.972	0.972
Don Mueang International Airport (DMK)	1.065	0.978	1.042
Phuket International Airport (HKT)	1.000	0.972	0.972
Chiang Mai International Airport (CNX)	1.000	0.975	0.975
Hat-Yai International Airport (HDY)	1.024	0.955	0.977
Mae Fah Luang-Chiang Rai International Airport (CEI)	1.032	1.019	1.051

Table 7.3

Productivity growths of the individual airports between 2007 to 2020 (Cont.)

Airport Name (code name)	TEC	TC	TFPC
Geometric Mean	1.020	0.978	0.998

Note. From author's calculation.

Table 7.3 shows the productivity changes of all airports between 2007 to 2020. Every airport except CEI had an average TC lower than 1. The average TEC of these airports was 2 percent a year. The TEC was higher than 1, this means that within this study period, the operating system at the airports was good to stimulate productivity levels. The results show that these airports concentrated on the using of labor instead of taking the innovation wisely. Within this study period, only CEI, the lowest number of aircraft and passenger movements, had the highest productivity growth.

Only DMK and CEI have no productivity regress in the study period between 2007 to 2020. This could be explained that DMK still faced the highest number of domestic passengers of almost 15 million people in 2020. The number of both international and domestic passenger movements had declined by around 9 million people from 2019 to 2020. CEI had the lowest number of passengers that was declined by 1.2 million people between 2019 to 2020 because this airport is not the airport hub. The number of international passenger movements had declined by only 230 thousand people.

Considering the pre-COVID-19 period, between 2007 to 2019, all airports had the TFP progress where DMK had TFP progress of 10.3 percent a year and CEI had the highest rate of TFP progress by 10.4 percent a year. A non-airport hub as HDY had a rate of TFP progress by 4.4 percent a year. Hence, the shock from the COVID-19 pandemic affected all airports had productivity regressed in 2020, but in the analysis between 2007 to 2020, Table 7.3 shows that only DMK and CEI still had TFP progressed of 4.2% and 5.1% per year, respectively. BKK and HKT had the same TFP regressed. They regressed at 2.8% per year. CNX and HDY also had TFP regressed of 2.5% and 2.3% per year, respectively.

Table 7.3 shows that BKK and HKT were the highest productivity regressed airports. When considered between 2007 to 2020, the result shows CEI was the highest productivity progress airport. The technical efficiency changes of all 6 airports report that they had no regress, but only DMK, HDY, and CEI had the progress in efficiency changes. This means that the workers of these airports performed more efficiently to promote productivity growth especially DMK that had the highest TEC progressed.

CEI was the only airport between 2007 to 2020 that had the progress in the technological adoption rate by 1.9% per year. CEI performed better in operational efficiency improvement and adapted the working system wisely with new technologies in this period. Table 7.5 shows that both TEC and TC are higher than 1. There made the CEI had productivity progressed.

HDY was the worse in TC by regressing at 4.5 percent, but this airport performed better in the operation. The TEC was 1.024. In other words, this airport had a TEC progressed of 2.4 percent a year. The TFP of HDY had regressed by 2.3 percent per year because of a lack of technological adoption rate.

BKK and HKT had the same TC that regressed by 2.8% per year. The TEC had also no change. This means that BKK and HKT did not perform better in the operational process at the airports, and they lacked to adaptive their working process smoothly with new technologies to promote productivity. These airports are the airport hubs, but they cannot use technologies efficiently to handle the passengers.

DMK had a TC regressed by 2.2% per year. DMK became an airport hub again after 2010 and was the LCCs largest airport in 2015. This made DMK had the highest TEC airport. DMK did not take advantage of technologies efficiently, but the airport still had the TFP progressed by a high TEC improvement.

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CNX had no change in TEC, but the TC had declined by 2.5 percent a year. So, the productivity had regressed by 2.5 percent a year.

The result shows that the airport hubs such as BKK, HKT, and CNX had no improvement in efficiency changes and cannot adaptive their organizations wisely with new technologies between 2007 to 2020. These made the productivity levels had declined more than 2 percent a year in this study period.

There was an airport hub as DMK and a non-airport hub as CEI can promote productivity growth in this study period.

7.1.3 Stage 2: Simar-Wilson Bootstrapping Regression.

This thesis employs the Simar and Wilson bootstrapping regression model in the second stage to test whether the external factors in terms of micro and macro variables affect the airport's efficiency scores derived from the first stage. These external factors represent the events that happened in Thailand between 2007 to 2020.

Tsui et al. (2014a, 2014b) and Karanki and Lim (2020) employed the Simar-Wilson model (Simar and Wilson, 2007) to test which external factors in the second stage affected the operational efficiency scores of the airports that derived from the first stage. On the other hand, Ripoll-Zarraga and Raya (2020) employed the ordinary least squares (OLS) model in the second stage. There was no conclusion that which model was the best to employ in the second stage. Some research suggested that Simar and Wilson bootstrapping regression model was the best model to use in the second stage to test which external factors affected the airports' efficiency scores. According to Tsui et al. (2014a), the research showed that the Simar and Wilson Bootstrapping regression model is the best model to estimate in the second stage because the traditional regression models will be biased when applying with the DEA's efficiency scores. Hence, this thesis follows the Simar and Wilson bootstrapping regression model to interpret the results.

Appendix B defines the abbreviation names of all variables. Appendix C shows that all variables employed in this stage have no problems of collinearity and variance inflation factor (VIF). Appendix D shows all estimation results of the ordinary

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least squares (OLS), Simar and Wilson Bootstrapping regression, fixed effect, and random effect models. The signs of all independent variables of these models are the same but different in scales. This thesis employs Hausman's test to obtain the most appropriate panel estimation model. The result shows that the random effect model is the best one. However, a few research in this field employed panel estimation methods to test in the second stage.

This thesis uses the input-oriented technical efficiencies obtained from the first stage as a dependent variable. For the 9 independent variables, they include a dummy for airport hub status, a dummy for the global financial crisis between 2008 to 2009, a dummy for the PAD occupied DMK and BKK in 2008, a dummy for Thailand's political conflict between 2013-2014, a dummy of flooding at DMK in 2011, percent of international LCCs, percent of domestic LCCs, percent of international passengers, and a dummy for the COVID-19 pandemic in 2020.

Figure D.1 in Appendix D reports the result of the OLS model, the R^2equals 86.84 percent. The airport hub status had the 1% positively significant on the airport's technical efficiency by 33.9%, while the global financial crisis had a negative impact by 10.3%. The percent of international LCCs was 5% positively significant and increased the technical efficiencies by 53.7%. The percent of international passengers increased the efficiency scores of the airports by 29.7 percent. The flooding in 2011 declined the DMK's efficiency score by 41.9 percent. The COVID-19 pandemic in 2020 decreased the airports' efficiency scores by 27.4% and was significant at 5%. The percent of domestic LCCs, the PAD occupied DMK and BKK in 2008, and a political conflict in Thailand in the fiscal year 2014 had insignificant in this model. Table 7.4 shows the Simar-Wilson Bootstrapping regression result between 2007 to 2020.

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Table 7.4

Simar-Wilson Bootstrapping regression result between 2007 to 2020

Explanatory variables	Coefficient	z-value	Significant
Constant	0.382	6.430	***
Airport hub status	0.290	6.290	***
Global financial crisis	-0.098	-2.300	**
Percent of international low-cost carriers	1.008	3.410	***
Percent of domestic low-cost carriers	0.123	1.420	
PAD occupied BKK and DMK in 2008	-0.179	-1.900	*
Thailand political conflict between 2013 to 2014	-0.044	-0.710	
Percent of international passengers	0.492	3.990	***
Flooding at DMK in 2011	-0.365	-2.850	***
COVID-19	-0.333	-5.850	***

Note. From author's calculation. Number of observations = 68, number of efficient $DMUs$ = 16, Wald-Chi^2 = 190.38, p-value = 0.0000, *** = 1% significant, ** = 5% significant, and * = 10% significant.

Table 7.4 reports that the $Wald - Chi^2$ equals 190.38. The airport hub status was 1% positive significant and had a coefficient of 29%. The percent of international LCCs increased the airports' efficiency scores by more than 100 percent, while the percent of international passengers increased the technical efficiencies by 49.2 percent. The flooding in 2011 declined the DMK's efficiency score by 36.5% in 2012. The COVID-19 pandemic decreased the airports' efficiency levels by 33.3% in 2020. The global financial crisis was 5 percent significant and declined the efficiency levels by 9.8 percent. PAD occupied BKK and DMK was 10 percent significant and had declined the airports' efficiency scores by 17.9 percent. In this model, the percent of domestic LCCs and Thailand political conflict between 2013 to 2014 had no relationship with the airports' technical efficiencies.

The result of this part supports the previous research (Gillen and Lall, 1997; Lin and Hong, 2006; Perelman and Serebrisky, 2010; Tsui et al., 2014; Abbott, 2015). They showed that the airport hub status and the global financial crisis had a positive and negative effect on the airports' efficiencies, respectively. The airport hub status had a positive effect on the airports' efficiency scores. This means that the airport hubs performed better than non-airport hubs. The global financial crisis between 2008 to 2009 declined the performances of the airports because the effect from this shock declined the passenger and aircraft movements in this period. The percent of international LCCs had a positive impact on the airports' efficiency scores by more than 100 percent in the Simar-Wilson model and 50 percent in the OLS model (Figure D.1 in Appendix D). The percent of international passengers had also positively significant. This means that the airports that handled a higher number of international passenger movements performed better than the others. The flooding at the end of 2011 at DMK made a big negative impact on this airport. This shock affected the operational working process on this airport to perform inefficiently. Lastly, the shock from the COVID-19 pandemic in 2020 declined the airports' efficiency scores more than the shock from the global financial crisis between 2008 to 2009. This shock declined the number of passenger movements by 45.30 percent and the number of aircraft movements by 39.87 percent (AOT's Annual Report, 2020). The result shows that the shock from the

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COVID-19 pandemic made the 6 main public airports of Thailand performed the worst in 11 years (Table 7.1).

In this thesis, the Simar and Wilson model is the most appropriate model employing to define which external factors affect the airports' technical efficiency scores in Table 7.1. The impacts of new technologies are excluded in this analysis. The reason is the proxies of new technologies cannot be defined easily in the Simar-Wilson model because the airports adopted these technologies vary over time. For closing this gap, the technical changes (TC) in Section 7.1.2 can measure the effectiveness of the technology shocks to the airports' performances within the study period most accurately.

7.2 Performance Measurement of Thailand's 6 main public airports between 2007 to 2030.

This part aims to forecast the future performances of the airports after the COVID-19 pandemic happened in early 2020. The scope of study ranges between 2007 to 2030 by assuming that the period from 2020 to 2030 is the post-COVID-19 pandemic period. The objective of this section is to predict the recovery trends of the airports after the shock and designing future policies to transform the old version airports into smart airports within 10 years.

Section 7.2.1 forecasts the future technical efficiency scores of the airports between 2021 to 2030 by employing the input-oriented DEA model. This section compares the technical efficiency scores of the airports between the pre-and post-COVID-19 pandemic periods. This section also discusses the impact of the COVID-19 pandemic during the lockdown period between 2020 to 2021.

The last section employs the MPI model to predict productivity growths of the airports after the pandemic ended. This section compares the airports' productivity changes between the pre-and post-COVID-19 pandemic periods and shows the effect of the COVID-19 pandemic on the lockdown period. This section shows the difference in the operating systems between the first and second periods. The first period emphasized the number of workers to promote productivity growth. This thesis predicts that the airports will take advantage of new technologies instead in the second period.

7.2.1 Result of technical efficiency scores of 6 main public airports of Thailand between 2007 to 2030.

This thesis forecasts the future technical efficiencies of the airports after the COVID-19 pandemic in 2020. This part employs the forecasting data between 2021 to 2030 derived from the news agencies, the $AR(1)$ model, and the Excel Linear Forecast function to measure the future airports' efficiency scores.

Table 7.5 reports the technical efficiencies of all 6 airports between 2007 to 2030. Figure 7.9 shows the mean of airports' efficiencies between 2007 to 2030.

Table 7.5

Technical efficiency scores of the 6 main public airports of Thailand between 2007 to 2030

Year	BKK	DMK	HKT	CNX	HDY	CEI	Mean
2007	0.682	0.324	1.000	0.738	0.369	0.255	0.561
2008	0.656	0.415	0.877	0.607	0.327	0.279	0.527
2009	0.620	0.237	0.773	0.602	0.301	0.230	0.461
2010	0.660	0.287	0.697	0.718	0.349	0.232	0.536
2011	0.738	0.694	0.936	0.753	0.366	0.197	0.614
2012	0.834	0.326	1.000	0.860	0.388	0.223	0.605
2013	0.783	0.870	0.991	0.700	0.396	0.203	0.657
2014	0.758	0.895	0.979	0.825	0.483	0.283	0.704
2015	0.778	1.000	0.831	1.000	0.513	0.357	0.747
2016	0.834	0.957	0.688	0.943	0.467	0.347	0.706
2017	0.874	0.947	0.741	0.931	0.516	0.419	0.738

Table 7.5

Technical efficiency scores of the 6 main public airports of Thailand between 2007 to 2030 (Cont.)

Year	BKK	DMK	HKT	CNX	HDY	CEI	Mean
2018	0.929	0.977	0.813	0.852	0.465	0.473	0.752
2019	0.957	0.953	0.789	0.805	0.394	0.439	0.723
2020	0.527	0.525	0.395	0.471	0.280	0.284	0.414
2021	0.457	0.474	0.341	0.418	0.227	0.245	0.360
2022	0.794	0.797	0.589	0.695	0.379	0.423	0.613
2023	0.726	0.841	0.745	0.753	0.361	0.432	0.643
2024	0.736	0.869	0.782	0.784	0.374	0.482	0.671
2025	0.746	0.896	0.818	0.816	0.387	0.540	0.701
2026	0.762	0.920	0.855	0.850	0.400	0.606	0.732
2027	0.779	0.942	0.891	0.885	0.413	0.684	0.766
2028	0.796	0.963	0.927	0.922	0.428	0.776	0.802
2029	0.813	0.982	0.964	0.960	0.443	0.881	0.841
2030	0.741	1.000	1.000	1.000	0.457	1.000	0.866
Mean of all periods	0.749	0.754	0.821	0.787	0.395	0.429	0.656
Mean of Pre-COVID-19	0.777	0.683	0.876	0.795	0.410	0.303	0.641
Mean of Post-COVID-19	0.716	0.837	0.755	0.778	0.377	0.578	0.673
During the lock-down period	0.492	0.500	0.368	0.445	0.254	0.265	0.387

Note. From author's calculation. The names and code names of the airports are following as Suvarnabhumi Airport (BKK), Don Mueang International Airport (DMK), Phuket International Airport (HKT), Chiang Mai International Airport (CNX), Hat-Yai International Airport (HDY), and Mae Fah Luang-Chiang Rai International Airport (CEI).

Table 7.5 shows that the average efficiency of the overall airports equals 41.4% in 2020. The overall mean of the technical efficiency scores equals 65.6 percent in all periods. In other words, the average technical inefficiency score is 34.4 percent between 2007 to 2030. In 2021, the average of technical efficiencies will decline to 36 percent. This thesis predicts that the average efficiency score will be recovered to almost 61.3% by the end of 2022, the beginning of the recovery period after the crisis. After 2027, the result shows that the average efficiency will be higher than 80 percent. The individual airports must take at least 6 years to recover the average efficiency scores to be the same levels as in 2019.

This thesis also calculates the means of technical efficiency scores of the pre- and post-COVID-19 pandemic periods and during the lockdown period between 2020 to 2021. The average technical efficiency score of the overall airports was 64.1 percent during the pre-COVID-19 pandemic period. During the post-COVID-19 pandemic period, the average efficiency score is 67.3 percent. This means that after the pandemic ends, the airports will perform better than in the previous period. The result shows that only DMK and CEI can perform better in the post-COVID-19 pandemic period. CEI will perform better than the first period more than 27 percent. BKK, HKT, CNX, and HDY will perform better in the pre-COVID-19 pandemic period because these airports must take a lot of time to recover the number of passenger and aircraft movements to be the same level as in 2019.

During the lockdown period, the average technical efficiency score is 38.7 percent. This means that the COVID-19 pandemic makes the airports perform inefficiently at 61.3 percent. DMK performs the best, while HDY performs the worst.

Figure 7.9 shows that the 6 main public airports in Thailand must spend 7 years to recover the technical efficiencies be the same levels as 2019.

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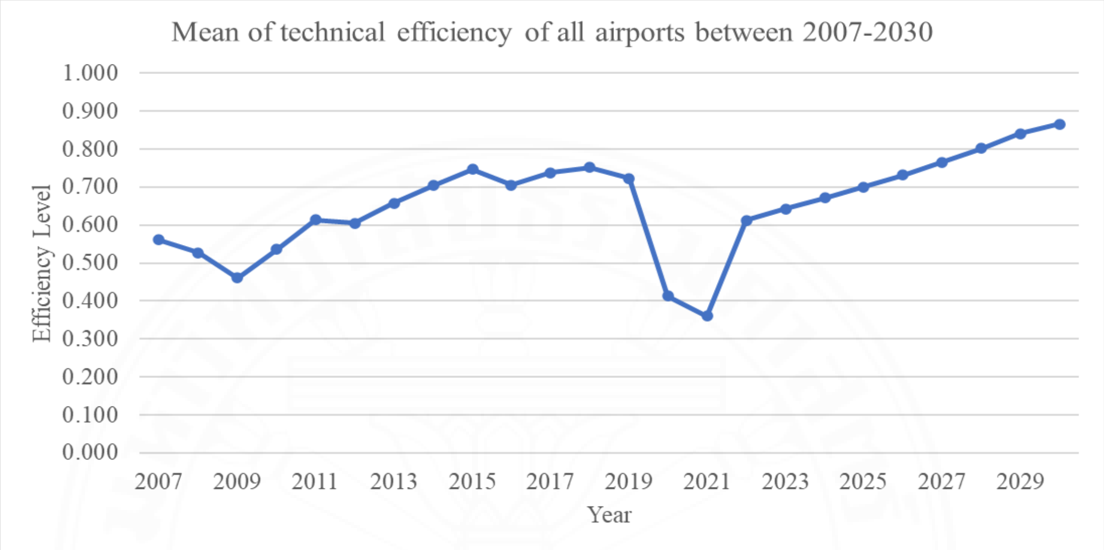
Figure 7.9

Mean of technical efficiency of the 6 main public airports of Thailand between 2007 to 2030



Note. From author's calculation.

Figure 7.10 shows the average technical efficiency scores of the individual airport between 2007 to 2030. The result shows that the HKT has the highest efficiency score at 82.1 percent. The CNX will be the second-highest efficient airport. The BKK and DMK have efficiency scores of 74.9 and 75.4 percent, respectively. The CEI has a technical efficiency of 42.9 percent. The HDY performs the worse in this period and has an efficiency score of 39.5 percent.

Figure 7.10 also shows the average technical efficiencies of the individual airports in the periods of the pre-and post- COVID-19 pandemic. Only CEI and DMK will perform better in the post- COVID-19 pandemic period. CEI will perform better in this period by the average technical efficiency score is 57.8 percent. DMK's average efficiency score is 83.7 percent, while in the pre-COVID-19 pandemic, the average efficiency score was 68.3 percent.

In the post-COVID-19 pandemic period, BKK, HDY, HKT, and CNX will perform worse than in the pre-COVID-19 pandemic period. HDY will have an average efficiency score lower in the post- COVID-19 pandemic of 37.7 percent. The average technical efficiency score was 41 percent in the pre-COVID-19 pandemic period. In the first period, CNX had an average efficiency score of 79.5 percent. CNX's average efficiency score will decline to 77.8 percent in the second period. The average efficiency score of HKT will be 75.5 percent between 2020 to 2030. While in the pre-COVID-19 pandemic period, the average efficiency score was 87.6 percent. Lastly, BKK had an average efficiency score of 77.7 percent in the period of the pre-COVID-19 pandemic. BKK's average efficiency score will drop to 71.6 percent in the post-COVID-19 pandemic period.

During the lockdown period, HDY performs the worst in the average technical efficiency score by 25.4 percent. CEI has 25.4 percent. HDY has 36.8 percent. CNX performs at 44.5 percent. BKK has 49.2 percent. DMK performs the best. The average technical efficiency score is 50 percent.

The results during the lockdown period show that the airport hubs still perform better than non-airport hubs. Domestic aircraft and passenger movements are the main factors to drive the efficiency scores. All airports' average efficiency scores are lowest when compared with other periods.

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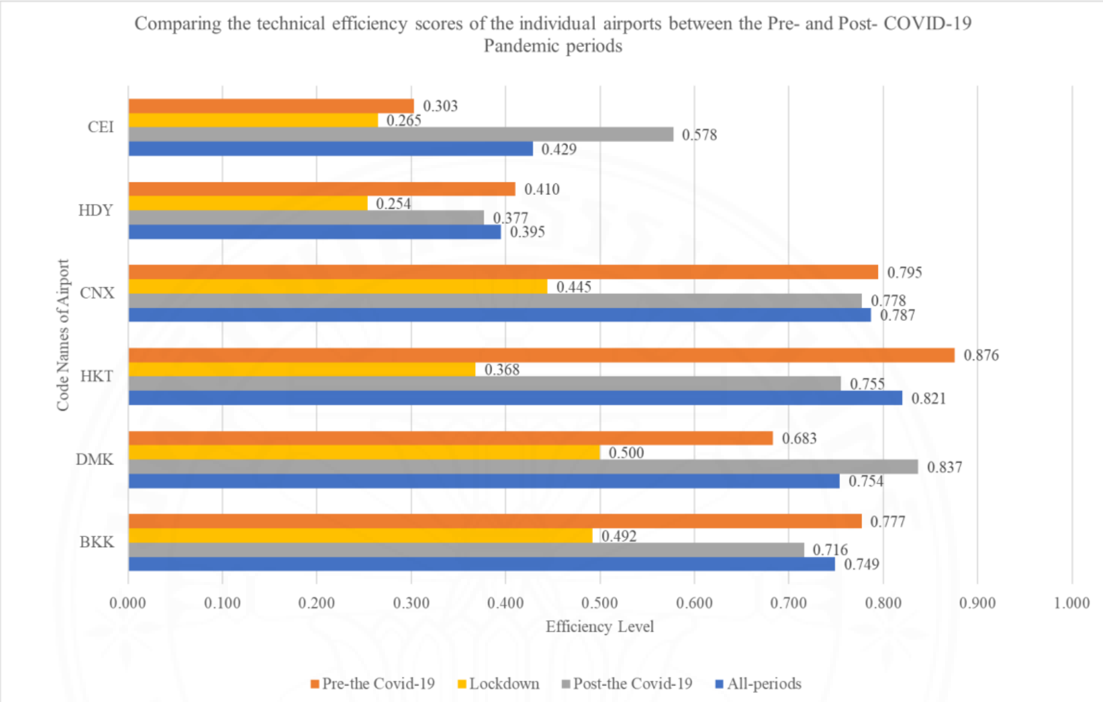
Figure 7.10

Comparing the technical efficiencies for the individual airports between the pre-and post-COVID-19 pandemic periods



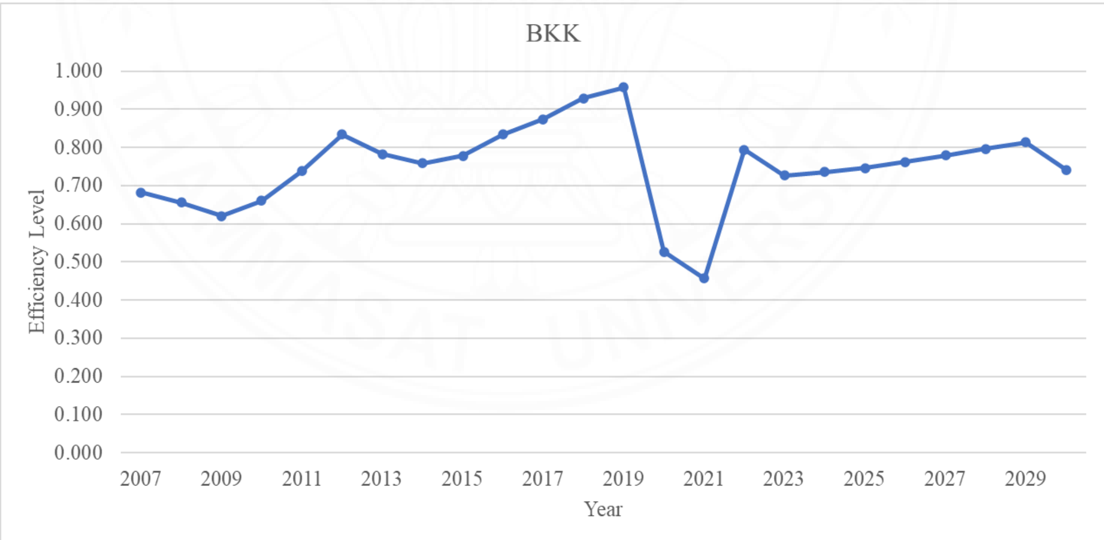
Note. From author's calculation. The names and code names of the airports are following as Suvarnabhumi Airport (BKK), Don Mueang International Airport (DMK), Phuket International Airport (HKT), Chiang Mai International Airport (CNX), Hat-Yai International Airport (HDY), and Mae Fah Luang-Chiang Rai International Airport (CEI).

Figures 7.11 to 7.16 show the technical efficiencies of all airports between 2007 to 2030. The results show that the 6 main public airports of Thailand must spend at least 6 years to recover the technical efficiency scores to be the same levels as in 2019 after the shock from the COVID-19 pandemic in 2020.

Figure 7.11 shows the technical efficiency scores of BKK between 2007 to 2030. This thesis assumes BKK will follow the plans to open the 3rd runway in 2023 and the 4th runway in 2030. All airports except BKK have less space to build new constructions. BKK is the only airport that has development plans for the next decade (AOT's annual report, 2020). In 2021, the technical efficiency of BKK will drop to 45.7 percent. This means that the technical inefficiency in the second year of the COVID-19 pandemic has 54.3 percent. In 2022, this thesis forecasts that the efficiency score will be back to higher than 75 percent. BKK will open the 3rd runway in 2023. This makes the efficiency level in 2023 dropped to 72.6 percent. Between 2024 to 2029, the efficiency scores will increase every year and in 2029, the technical efficiency score will be higher than 80 percent. In 2030, the BKK has a plan to open the 4th runway, the efficiency score will be dropped to 74.1 percent. If the number of passenger and aircraft movements is not increased more than the forecast in this thesis, the technical efficiency scores will not be recovered to be the same level as in 2019 again for the next 10 years.

Figure 7.11

Efficiency levels of Suvarnabhumi Airport (BKK) between 2007 to 2030

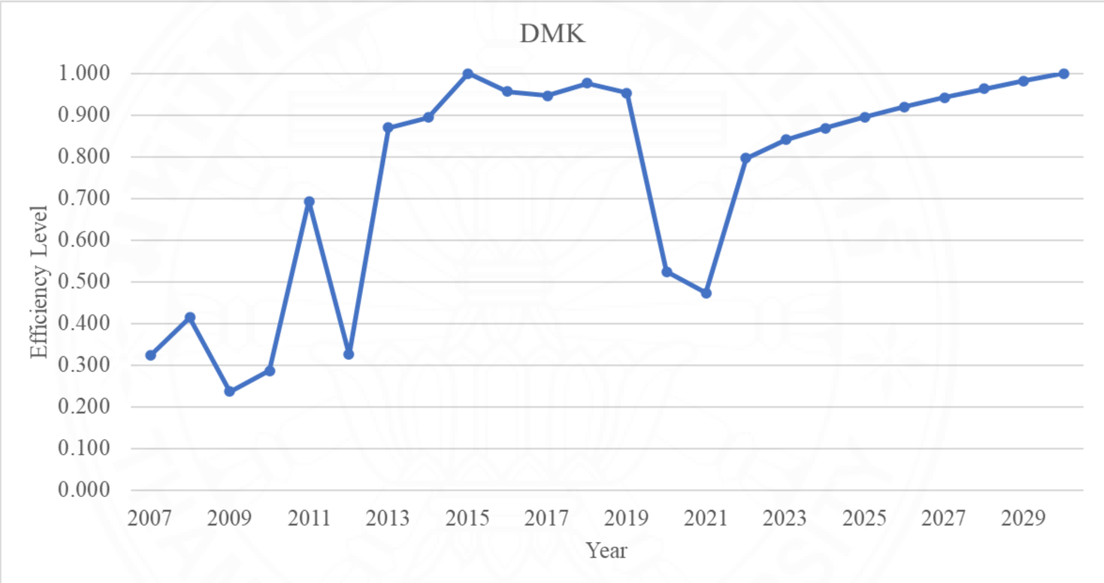


Note. From author's calculation.

Figure 7.12 shows the technical efficiency scores of DMK between 2007 to 2030. The technical efficiency of DMK in the second year of the COVID-19 pandemic will be dropped to 47.4 percent. The efficiency score will be recovered to higher than 80 percent in 2023 and performed above 90 percent again after 2025. The results show that DMK must spend 9 years to recover the efficiency score to be at the same level as in 2019. This thesis forecasts that DMK will perform fully efficiently again in 2030.

Figure 7.12

Efficiency levels of Don Mueang International Airport (DMK) between 2007 to 2030

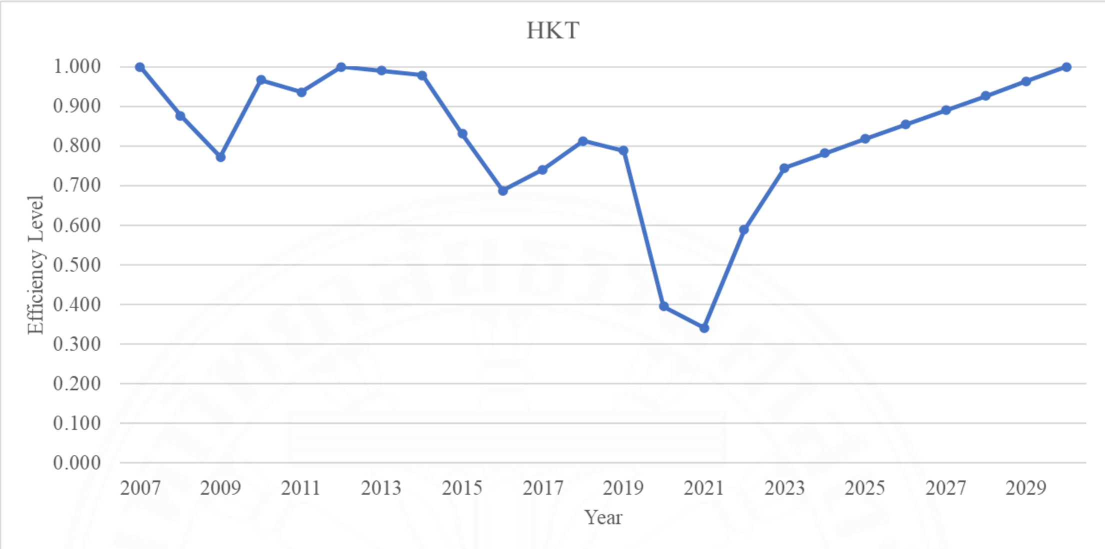


Note. From author's calculation.

Figure 7.13 shows the technical efficiency scores of HKT between 2007 to 2030. In 2021, the HKT's efficiency score will be dropped to 34.1 percent. This means that in 2021, the efficiency score will be the lowest in this study period. In 2022, the beginning of the recovery period after the crisis, the technical efficiency will back to 58.9 percent. Between 2023 to 2024, the efficiency scores will be higher than 70 percent and above 90 percent after 2027. In 2030, this thesis predicts that the HKT will perform fully efficiently again. The result shows that HKT must spend 6 years to recover the operational efficiency score to be the same as in 2019.

Figure 7.13

Efficiency levels of Phuket International Airport (HKT) between 2007 to 2030

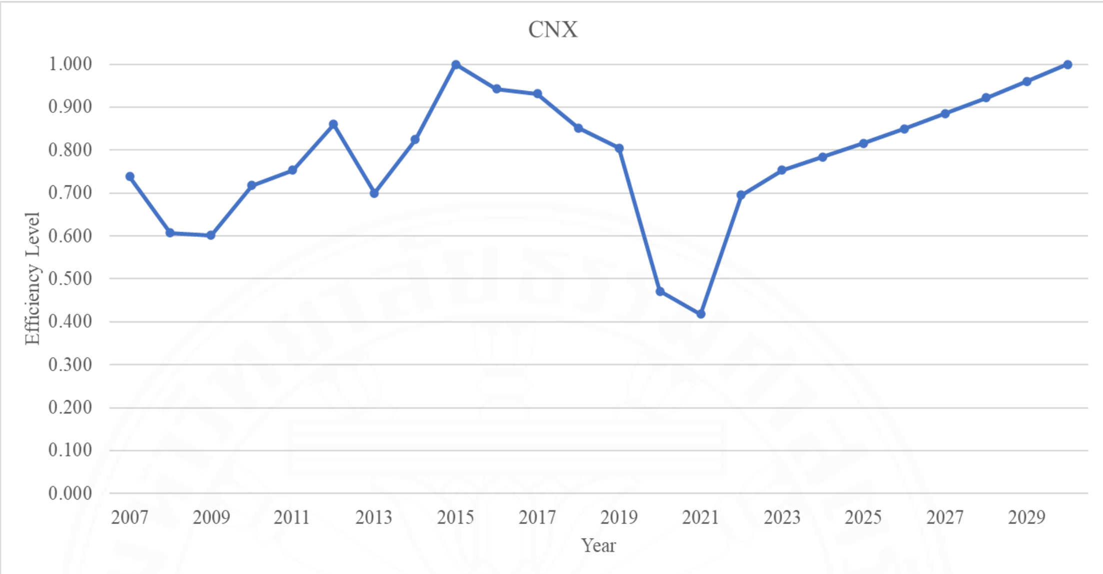


Note. From author's calculation.

Figure 7.14 shows the technical efficiency scores of CNX between 2007 to 2030. The CNX will have an efficiency score below 45 percent in 2021. The highest technical inefficient in 24 years. In 2022, the technical efficiency will back to almost 70 percent. Between 2025 to 2027, the CNX's efficiency scores will be higher than 80 percent and 90 percent after 2027. This thesis forecasts that the CNX will perform fully efficiently again in 2030. The result shows that CNX must spend 6 years to recover the efficiency score to be the same level before the COVID-19 pandemic begin.

Figure 7.14

Efficiency levels of Chiang Mai International Airport (CNX) between 2007 to 2030

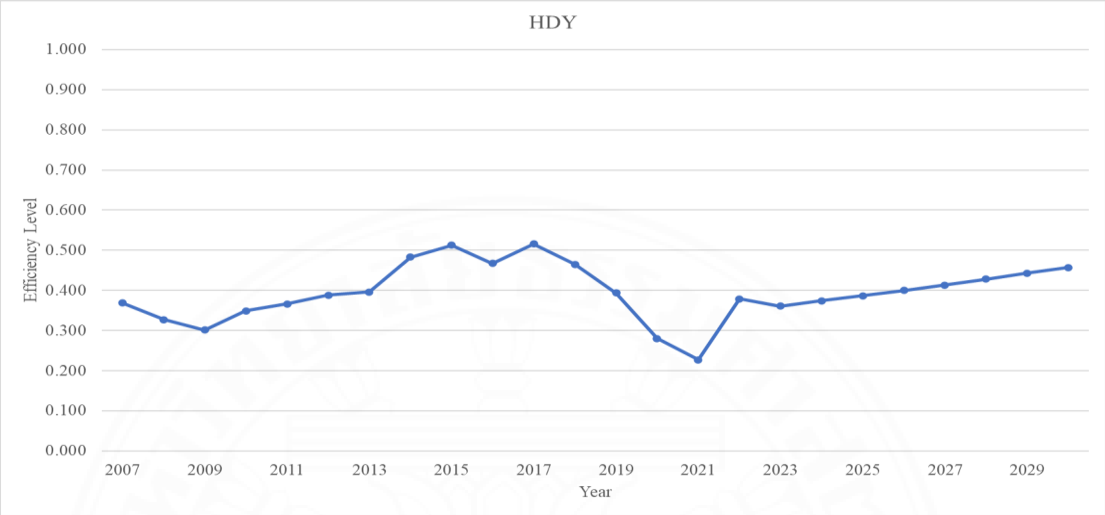


Note. From author’s calculation.

Figure 7.15 shows the technical efficiency scores of HDY between 2007 to 2030. In 2021, HDY will have a technical efficiency of 22.7 percent, the period that this airport will perform the worst. The technical inefficiency of HDY during the lockdown period will be greater than in the period of the global financial crisis. In 2022, the HDY’s efficiency score will increase to 37.9 percent. This thesis forecasts that between 2025 to 2030, the efficiency scores will be increased every year but there will be lower than 50 percent. The result shows that the efficiency score of HDY will not back to the same level as 2017, the technical efficiency had higher than 50 percent.

Figure 7.15

Efficiency levels of Hat-Yai International Airport (HDY) between 2007 to 2030

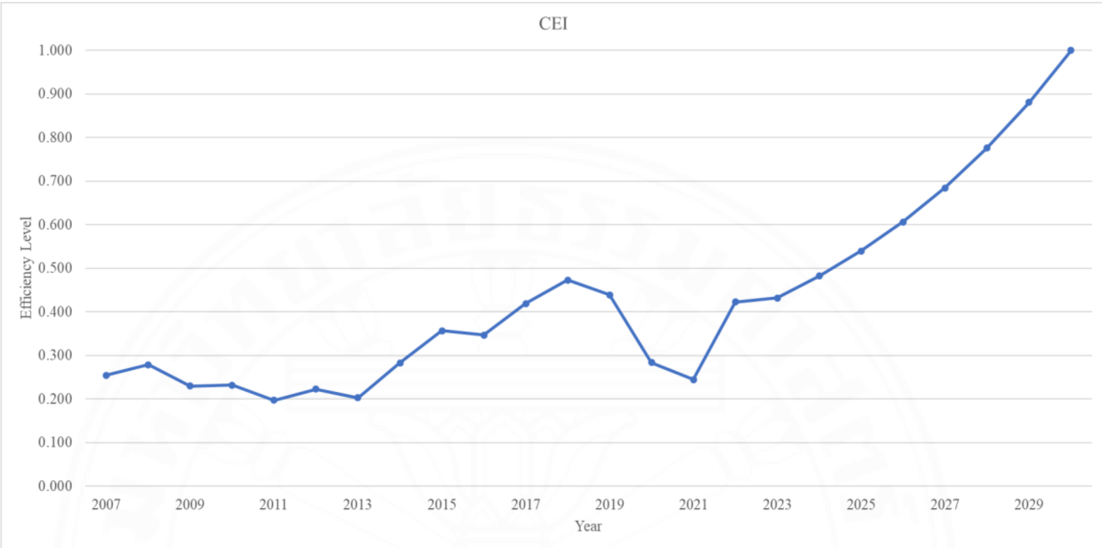


Note. From author's calculation.

Figure 7.16 shows the technical efficiency scores of CEI between 2007 to 2030. In 2021, CEI will have an efficiency score of 24.5 percent. The technical efficiency will be recovered to more than 40 percent in 2022. After 2023, the efficiency scores will be increased every year and reached 100 percent in 2030. This thesis forecasts that this airport will handle the number of passenger movements more than 5 million people after 2027, and there will handle more than 7 million passengers in 2030. The aircraft movements will be higher than 35,000 times after 2028. These will make the efficiency scores of this airport increased every year, and its make CEI will perform fully efficiently in 2030.

Figure 7.16

Efficiency levels of Mae Fah Luang-Chiang Rai International Airport (CEI) between 2007 to 2030



Note. From author's calculation.

The result from this part shows that the technical efficiency scores of all 6 main public airports will start to recover in 2022. In 2021, the situation will be severe than in 2020. The airport hubs except BKK must take 9 years to perform fully efficiently in 2030. The technical efficiency scores of BKK will not be higher than 90 percent after the COVID-19 pandemic crisis passed and tend to decrease after open the 4th runway in 2030. After recovering from the crisis in 2022, HDY will perform stable around 40 percent. CEI will have good progress every year and perform fully efficiently for the first time in 2030.

It is worthy to note that this section has a limitation. This section employs only 2 output variables such as total aircraft and passenger movements because the forecasting amount of cargo shifted cannot find from a reliable source. This section must exclude this variable. Hence, this makes the technical efficiency scores of the airports between 2007 to 2020 on Table 7.5 are less than Table 7.1. Both tables have the same trends but different scales.

7.2.2 Result of productivity changes of 6 main public airports of Thailand between 2007 to 2030.

This section also employs the MPI model to forecast the future productivity growths of the airports between 2021 to 2030, the period after the COVID-19 pandemic happened. Table 7.6 shows the productivity changes of overall airports from 2007 to 2008 until 2029 to 2030. Table 7.7 shows the productivity changes of the individual airports between 2007 to 2030.

Table 7.6

The overall airports' productivity changes from 2007 to 2008 until 2029 to 2030

Period	TEC	TC	TFPC
2007 – 2008	0.994	0.995	0.989
2008 – 2009	0.931	0.895	0.833
2009 – 2010	0.932	1.244	1.159
2010 – 2011	1.135	1.085	1.232
2011 – 2012	0.895	1.074	0.961
2012 – 2013	1.179	1.004	1.184
2013 – 2014	1.107	1.028	1.138
2014 – 2015	1.038	1.055	1.096
2015 – 2016	1.055	0.967	1.021
2016 – 2017	1.024	1.050	1.075
2017 – 2018	0.999	1.049	1.048
2018 – 2019	0.982	1.008	0.991
2019 – 2020	1.039	0.536	0.557
2020 – 2021	1.000	0.763	0.763
2021 – 2022	1.000	1.984	1.984
2022 – 2023	0.962	1.147	1.104
2023 – 2024	1.000	1.061	1.061
2024 – 2025	0.998	1.064	1.062

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Table 7.6

The overall airports' productivity changes from 2007 to 2008 until 2029 to 2030 (Cont.)

Period	TEC	TC	TFPC
2025 – 2026	0.993	1.068	1.060
2026 – 2027	0.994	1.065	1.059
2027 – 2028	0.995	1.063	1.057
2028 – 2029	0.995	1.063	1.057
2029 – 2030	0.974	1.063	1.035
Geometric Mean of all periods	1.008	1.034	1.042
Geometric Mean of Proe-COVID-19	1.019	1.035	1.055
Geometric Mean of Post-COVID-19	0.991	1.104	1.094
Geometric Mean of during the lockdown period	1.019	0.640	0.652

Note. From author’s calculation.

Table 7.6 shows that the geometric mean of TFP growth of the airports between 2007 to 2030 is 4.2 percent per year. This table also compares the geometric means of TEC, TC, and TFPC of the airports between the pre-and post-COVID-19 pandemic periods and during the lockdown period.

In the period of the pre-COVID-19 pandemic, the geometric means of TEC, TC, and TFP had increased by 1.9, 3.5, and 5.5 percent per year, respectively.

For the post-COVID-19 pandemic period, the geometric mean of TEC will decline by 9 percent a year. The geometric mean of TC will increase by 10.4 percent per year. This means that in the post-COVID-19 pandemic period, the airports will take advantage of new technologies more efficiently to improve the growth of productivity. In contrast, the old working system at the airports will prevent productivity improvement. The result shows that the TFP of the airports will increase by 9.4 percent a year in the post-COVID-19 pandemic period.

During the lockdown period, the result shows that the geometric of TEC has increased 1.9 percent per year. The geometric mean of TC is regressed by 36 percent a year. These make the geometric mean of TFP declined by 34.8 percent per year. The airports perform the worst within this period when compared with other periods.

Table 7.6 shows that between 2020 to 2021, the second year of the COVID-19 pandemic, the overall TFP change of the airports will be declined again by 23.7 percent. The TEC has no change, but the technological adoption rate has declined by 23.7 percent.

Between 2021 to 2022, the recovery period after the pandemic, the TFP will be increased by 98.4 percent because of the increase of the technical change. The TEC has no change in this period.

The technical efficiency change will be dropped again between 2022 to 2023, while the technical change will be increased by 14.7 percent. These make the TFP has increased by 10.4 percent.

Between 2024-2025 to 2028-2029, the result shows that the productivity growths of the 6 main public airports will be higher than 5% per year because of the progress of technological improvements. Within these periods, overall airports will be regressed in technical efficiency changes.

Between 2029 to 2030, Table 7.6 shows that the technical efficiency change will be dropped by 2.6 percent, and the technological adoption rate will be increased by 6.3 percent. These make the average productivity change of the airports in this period has inclined by 3.5 percent.

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This thesis shows that the average TFP change of the airports will increase by an annual 4.2 percent between 2007 to 2030. The average technological adoption rate has increased by 3.4% a year. The technical efficiency change has increased only 0.8% a year. After 2021, the forecasted productivity growths of the airports show that all airports do not worry about adopting new technologies to improve their performances. The average operational efficiency of the airports tends to decline after 2024. The results show that the airports will use new technologies effectively to improve productivity, but these airports must concern about the working processes at the airports by adopting new operating systems to improve the technical efficiency change in the long run.

Table 7.7

Productivity growths of the individual airports between 2007 to 2030

Airport Name (code name)	TEC	TC	TFPC
Suvarnabhumi Airport (BKK)	0.987	1.020	1.006
Don Mueang International Airport (DMK)	1.036	1.025	1.062
Phuket International Airport (HKT)	1.000	1.025	1.025
Chiang Mai International Airport (CNX)	1.001	1.031	1.033
Hat-Yai International Airport (HDY)	0.995	1.040	1.035

Ref. code: 25646204040080WKG

Table 7.7

Productivity growths of the individual airports between 2007 to 2030 (Cont.)

Airport Name (code name)	TEC	TC	TFPC
Mae Fah Luang-Chiang Rai International Airport (CEI)	1.028	1.066	1.095
Geometric Mean	1.008	1.034	1.042

Note. From author's calculation.

Between 2007 to 2030, Table 7.7 shows that the BKK will have the TFP progress of 0.6% per year by the efficiency change will decrease by 1.3% per year. The average technological adoption rate increases an annual 2 percent.

CEI will be the highest TFP progress airport that has the TFP progressed by 9.5% a year. The TEC and TC will increase by 2.8% and 6.6% per year, respectively. This means that CEI will be the best in technology adoption when compared with the other airports.

DMK will have the TEC increased by 3.6% a year in this period. The TC will increase by an annual 2.5 percent. These make the DMK has a productivity growth of 6.2 percent a year.

The TFP growth of HDY will increase by 3.5% a year between 2007 to 2030. The TC is going to increase by 4% a year, while the TEC will decrease by 0.5% a year.

CNX will have the TEC increased only 0.1 percent a year and the TC increased by 3.1 percent a year. Table 7.8 shows that between 2007 to 2030, CNX will have the TFP progressed by an annual 2.5 percent.

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HKT will have no change in the TEC, but the technological adoption rate will increase by 2.5% a year. So, the TFP has progressed by an annual 2.5 percent between 2007 to 2030.

The result shows that all airports will take the advantage of new technology to improve the productivity growths and the total factor productivity will be progressed. HKT has no change in operational improvement. Only BKK and HDY must concern about the airports' operational processes.

This thesis also calculates the TEC, TC, and TFP changes of the individual airports between the pre-and post-COVID-19 pandemic periods and during the lockdown period. Figure 7.17 shows comparing the technical efficiency changes of the individual airports between the pre-and post-COVID-19 pandemic periods and during the lockdown period. Figure 7.18 shows comparing the technical changes of the individual airports between the pre-and post-COVID-19 pandemic periods and during the lockdown period. Figure 7.19 shows comparing the total factor productivity changes of the individual airports between the pre-and post-COVID-19 pandemic periods and during the lockdown period.

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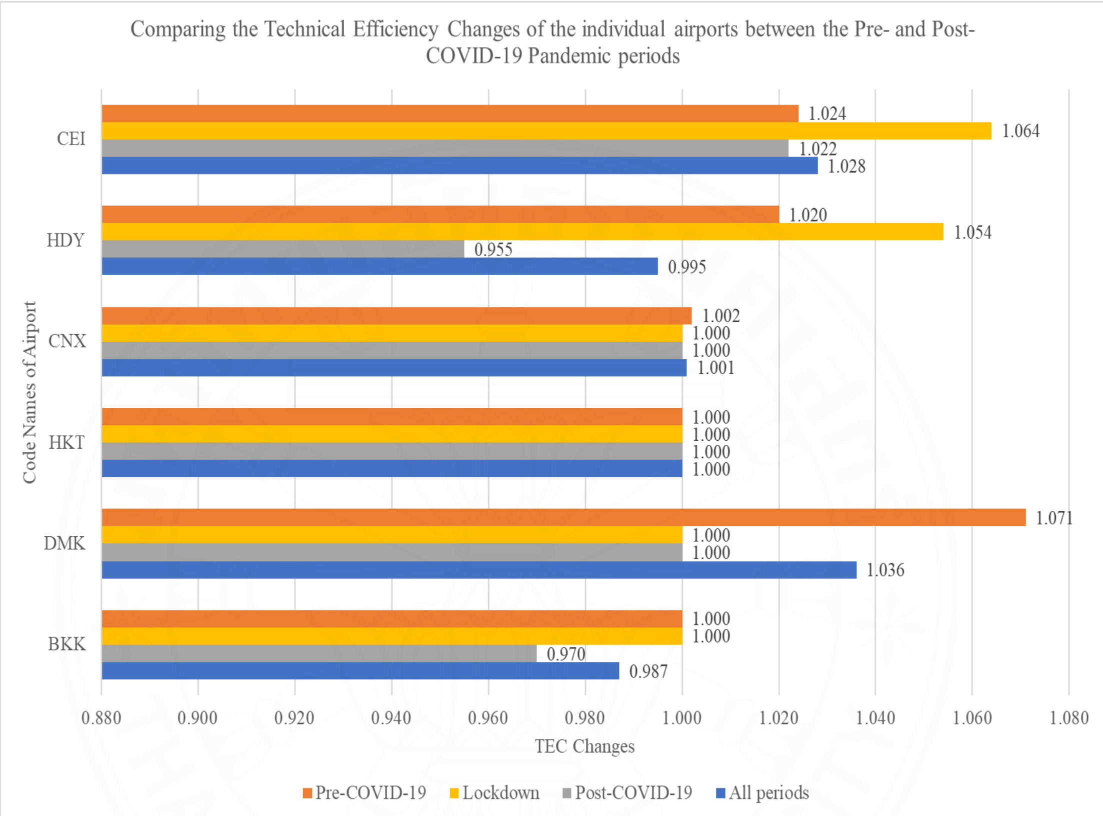
Figure 7.17

Comparing the technical efficiency changes of the individual airports between the pre- and post-COVID-19 pandemic periods



Note. From author's calculation. The names and code names of the airports are following as Suvarnabhumi Airport (BKK), Don Mueang International Airport (DMK), Phuket International Airport (HKT), Chiang Mai International Airport (CNX), Hat-Yai International Airport (HDY), and Mae Fah Luang-Chiang Rai International Airport (CEI).

The results from Figure 7.17 show that every airport except HKT will perform poorer in the working system in the post-COVID-19 pandemic period. The geometric mean of TEC at CEI in the pre-COVID-19 pandemic period had increased by 2.4 percent a year. In the second period, the geometric mean of TEC will increase only 2.2 percent a year. This means that the operating system in the post-COVID-19 pandemic period at CEI still promotes productivity growth but performs worse than in the first period. During the lockdown period, the geometric mean of TEC has increased by 6.4 percent a year. The result shows that CEI has the highest geometric mean of TEC in this period.

In the lockdown period, HDY has the geometric mean of TEC is progressed by 5.4 percent a year. In the post-COVID-19 pandemic period, the geometric mean of TEC at HDY will decline by 4.5 percent a year. On the opposite, the geometric mean of TEC had increased by 2 percent a year in the first period. This means that HDY can perform better in the working system at the airport in the first period. For the second period, the old operating system cannot promote productivity growth anymore.

The geometric mean of TEC at CNX will not change much in the second period. The geometric mean will be 1. While in the pre-COVID-19 pandemic period, the geometric mean had increased by 0.2 percent a year. The results show that the same working system at CNX will not promote productivity growth anymore in the post-COVID-19 pandemic period, but there will not interrupt productivity growth. During the lockdown period, the geometric mean of TEC has no change.

The geometric means of TEC at HKT between the first and second periods and during the lockdown period will be the same at 1. This implies that the airport's working system cannot promote productivity growth anymore in both the first and second periods.

In the post-COVID-19 pandemic period and during the lockdown period, the geometric mean of TEC at DMK will have no change. But in the first period, the geometric mean had increased by 7.1 percent a year. DMK also performs worse in the second period.

In the second period, BKK will have the TEC regressed by 3 percent a year. While in the pre-COVID-19 pandemic period, the geometric mean of TEC was 1.000. This means that the operating system at this airport is not good enough to promote productivity growth in both the first and second periods. But in the post-COVID-19

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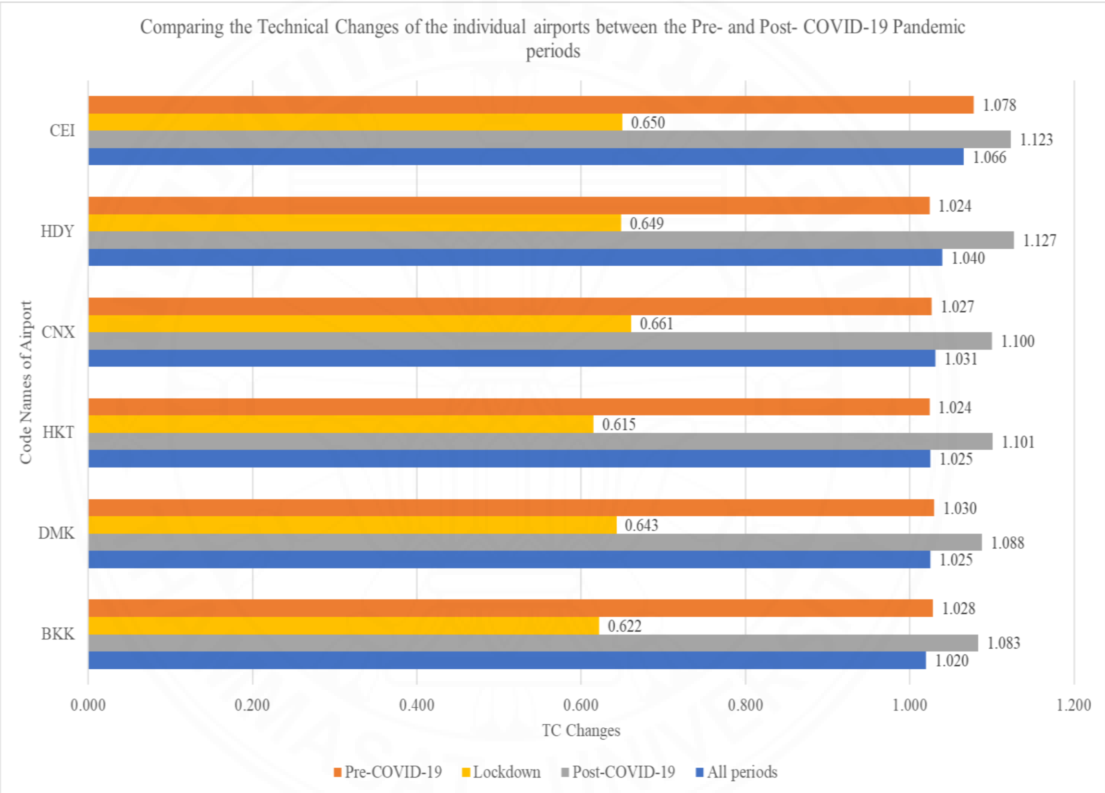
pandemic period, the old working system will obstruct productivity improvement. During the lockdown period, the geometric mean of TEC also has no change.

Figure 7.18

Comparing the technical changes of the individual airports between the pre-and post-COVID-19 pandemic periods



Note. From author's calculation. The names and code names of the airports are following as Suvarnabhumi Airport (BKK), Don Mueang International Airport (DMK), Phuket International Airport (HKT), Chiang Mai International Airport (CNX), Hat-Yai International Airport (HDY), and Mae Fah Luang-Chiang Rai International Airport (CEI).

Figure 7.18 shows all airports can take advantage of new technologies to promote productivity growth in the post-COVID-19 pandemic period than the pre-COVID-19 pandemic period. This means that new technologies will be the most important factor to promote productivity growths of the airports in the period of the post-COVID-19 pandemic. This thesis shows that every airport can take benefit from new technologies in this period by the geometric mean of the TC will progress at least 8 percent a year.

CEI will have the geometric mean of TC progressed by 12.3 percent per year in the post-COVID-19 pandemic period. While in the first period, the TC had progressed by 7.8 percent a year. During the lockdown period, the geometric mean of TC is regressed by 35 percent a year.

In the second period, HDY will have the highest TC progressed when compared with other airports. The technological adoption rate will increase by 12.7 a year. Between 2007 to 2019, this airport had a TC that progressed only 2.4 percent a year. While during the lockdown period, the TC has declined by an annual 35.1 percent.

Within the lockdown period, CNX has the geometric mean of TC is regressed by 33.9 percent a year. In the pre-COVID-19 pandemic period, CNX had the geometric mean of TC progressed by 2.7 percent a year. After the COVID-19 pandemic happened in 2020, the result shows that CNX will adopt technology wisely to promote productivity growth by the TC will progress by 10 percent per year between 2020 to 2030. Within the lockdown period, the geometric mean of TC is regressed by 33.9 percent a year.

In the first period, HKT can adopt new technology to promote productivity growth by TC progressed at 2.4 percent a year. But in the second period, HKT will perform better. The geometric mean of TC will increase by 10.1 percent per year. In the lockdown period, HKT has the geometric mean of TC has declined by 38.5 percent a year.

During the lockdown period, DMK has the geometric mean of TC is regressed by 35.7 percent a year. Between 2007 to 2019, DMK also adopted new

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technologies to promote productivity growth. The TC had increased by 3 percent a year. In the post-COVID-19 pandemic period, DMK's geometric mean of TC will increase by 8.8 percent per year.

For the BKK, the geometric mean of the TC will increase by 8.3 percent in the second period, the lowest TC progressed when compared with the other airports. In the pre-COVID-19 pandemic period, the TC had progressed by only 2.8 percent. In the lockdown period, the geometric mean of TC has declined by 37.8 percent.

The result shows that every airport can use new technologies to help them perform better in the period after the COVID-19 pandemic happened. During the lockdown period, all airports have the lowest geometric mean of TC when compared with other periods. The shock of the COVID-19 pandemic prevents the airports adopt new technologies smoothly.

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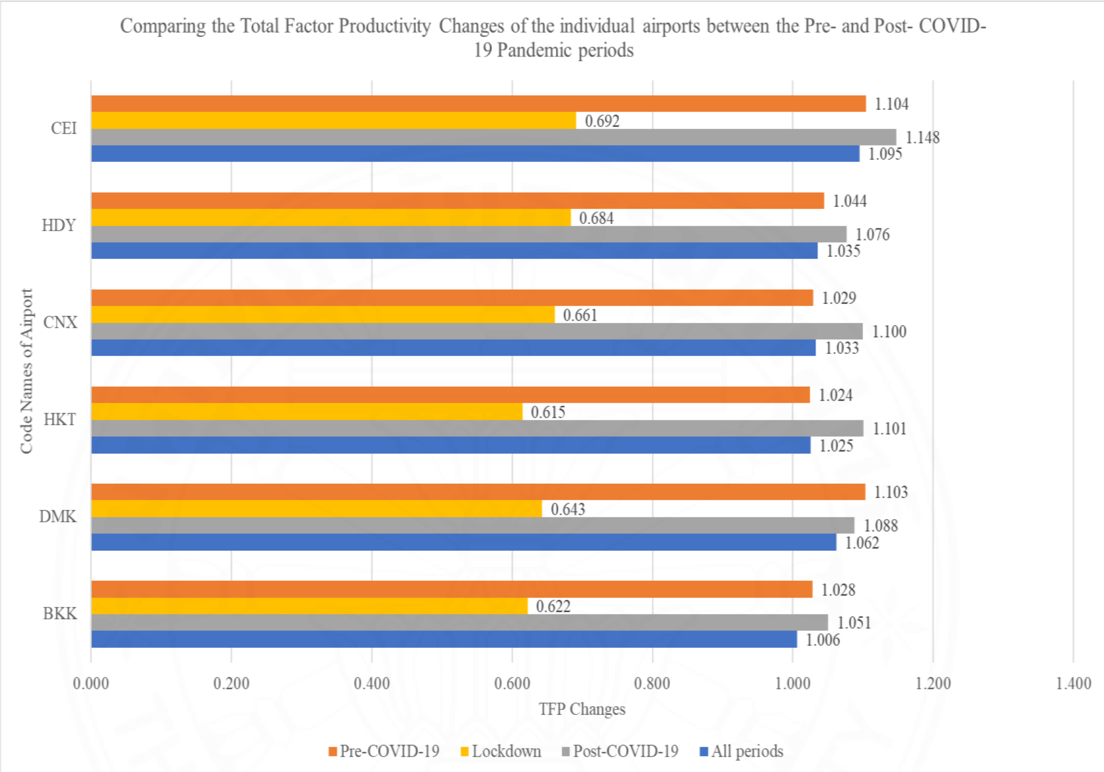
Figure 7.19

Comparing the total factor productivity changes of the individual airports between the pre-and post-COVID-19 pandemic periods



Note. From author's calculation. The names and code names of the airports are following as Suvarnabhumi Airport (BKK), Don Mueang International Airport (DMK), Phuket International Airport (HKT), Chiang Mai International Airport (CNX), Hat-Yai International Airport (HDY), and Mae Fah Luang-Chiang Rai International Airport (CEI).

Figure 7.19 shows all airports except DMK will have the TFP growth higher in the post-COVID-19 pandemic period. CEI will have the highest TFP progressed by 14.8 percent a year in this period. In the pre-COVID-19 pandemic period, the TFP had progressed by 10.4 percent per year. While during the lockdown period, the TFP is regressed by 30.8 percent a year.

HKT will be the second-highest of TFP progressed. HKT's productivity growth will progress by 10.1 percent a year in the second period. For the pre-COVID-19 pandemic period, the productivity growth of HKT had increased by 2.4 per year. During the lockdown period, HKT has the TFP is regressed by an annual 38.5 percent.

CNX will be the third-highest of TFP progressed. The TFP is going to progress by 10 percent per year in the post-COVID-19 pandemic period. Between 2007 to 2019, the TFP increased by only 2.9 percent a year. Within the lockdown period, the TFP is declined by 33.9 percent a year.

In the pre-COVID-19 pandemic period, HDY had a productivity growth of 4.4 percent a year. While in the post-COVID-19 pandemic period, HDY will perform better. The TFP change will increase by 7.6 percent per year. For the lockdown period, the TFP has regressed by an annual 31.6 percent.

For BKK, the productivity growth had increased by only 2.8 percent in the first period. Between 2020 to 2030, this thesis predicts that the TFP growth of this airport will incline by 5.1 percent a year. During the lockdown period, the TFP has declined by 37.8 percent per year.

Lastly, DMK will be the only airport that has the TFP progressed in the second period less than in the first period. The productivity growth will increase by 8.8 percent per year in the post-COVID-19 pandemic period. In the pre-COVID-19 pandemic period, this thesis calculates that the TFP growth of DMK increased by 10.3 percent a year. During the lockdown period, the TFP is regressed by 35.7 percent a year.

The result shows that all airports except DMK will perform better in the post-COVID-19 pandemic period. During the lockdown period, the airports have the TFP changes regressed more than 30 percent a year. The reasons are the airports do not take advantage of new technologies and the decline of the number of passenger and aircraft movements.

As mentioned in section 7.2.1, the analysis between 2007 to 2030 employs 2 output variables such as the number of aircraft and passenger movements. The

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productivity changes from 2007 to 2020 shown in Table 7.6 are different from Table 7.2. Both tables have very close TFP changes. Only 3 periods have distinctive differences. Between 2007 to 2008, Table 7.2 reports that the TEC of the airports was progressed by 2.3 percent, while in Table 7.6, the TEC had declined by 0.6 percent. Between 2012 to 2013, Table 7.2 reports the TC had declined by 2.6 percent, while Table 7.6 reports the TC had increased by only 0.4 percent. Lastly, between 2018 to 2019, Table 7.2 reports the TC had regressed by 10 percent, but Table 7.6 reports the TC had progressed by only 0.8 percent.

This thesis assumes that the number of workers in each airport will be increased every year and BKK will follow the plans to open the 3rd runway in 2023 and the 4th runway in 2030. BKK is the only airport that can be installing the new runways. The other 5 airports have no space to install a new runway. BKK must concern about the inputs used and the outputs derived in the future. If the total passengers and aircraft movements have increased more than the numbers that this thesis forecasts, the efficiency scores of this airport will be higher than the result shown in Table 7.5 and the productivity growths will be higher than 0.6 percent a year.

The technical efficiency changes in the post-COVID-19 pandemic period of all airports will be lower. The average TEC of BKK and HDY will decline by 1.3 and 0.5 percent, respectively. Therefore, BKK and HDY must reorganize the working processes to perform more efficiently and concern about the number of employees working at the airports urgently than other airports.

CHAPTER 8
DISCUSSION

This chapter includes 3 parts. The first part discusses the policy implications. This part refers to the past performances of the airports and suggests future policies for the policymakers to improve the productivity growths of the airports in the long run. This thesis emphasizes how to adopt new technology and design a new working system to transform classical airports into smart airports. There will discuss the details more specifically in this part.

The second part discusses the limitations of this thesis. They include the data used in this thesis and the method to forecast the variables.

The last part shows the research gap after this thesis has been published. What the future researchers have left to do in this field and the trend of the research in the air transportation of Thailand? The answer will be given in this part.

8.1 Policy implications

This thesis is the first work in Thailand that analyzes the full performances of the 6 main public airports of Thailand operated by AOT for the longest period. This thesis analyzes the past performances and forecasts the future performances of the airports.

This thesis analyzes the past performances in terms of the technical efficiency scores and the productivity growths of the airports from the year BKK opened until the year of the COVID-19 pandemic started. The results show that airport hubs performed better than non-airport hubs. The percent of international passengers in both terms of normal and low-cost-carriers passengers affected the efficiency levels of the airports. The external shocks such as the global financial crisis in 2008-2009, the big flooding in Thailand in 2011, and the COVID-19 pandemic started in 2020 had negative impacts on airports' efficiency scores especially the airport hubs because these airports handled a lot of international passengers. This means that in the future if the world faces a big shock again, the technical efficiency scores and productivity levels of the international airports will be declined. This thesis can conclude that the number of international passengers has very significant to improve technical efficiency scores and productivity growths of the airports. The non-airport hubs can promote their growth by encouraging tourism in the provinces that the airports locate.

For the analysis between 2021 to 2030, this thesis assumes the growth of employees at the individual airports will increase at a very low rate between 2021 to 2030. The results show that the performances of the overall airports will be recovered in 2022 and taken at least 6 years to have the same efficiency levels as in 2019. The number of international passenger and aircraft movements has a very significant to promote the efficiency and productivity levels. BKK will open the 4^{th} runway in 2030. If the passenger and aircraft movements increase as the AR (1) model forecasted, the efficiency score of BKK tends to decline in 2030. DMK, HKT, and CNX will perform fully efficiently in 2030. If these airports have higher growths of passenger and aircraft movements than the results from the AR (1) model, their efficiency scores and productivity growths can be looked better than this thesis estimated. The result shows that if the passenger and aircraft movements of CEI have increased like the AR (1) model predicted, eventually this airport will perform fully efficiently in 2030. HDY can be performed fully efficiently like CEI if tourism of Songkhla province has high growth every year after the pandemic.

According to the findings obtained in this thesis, the foremost recommendations to efficiency and productivity improvements are presented as follows:

1. The airports must concern about the inputs wasted in the future if the number of aircraft and passenger movements is recovered equal or less than the prediction in this thesis. If the number of passenger and traffic movements at the airports is increased more than the forecast in this thesis, there is possible that the technical efficiency scores and

productivity growths will be higher. Otherwise, these values will be declined again.

2. BKK must focus on the inputs used in the future because BKK in the post-COVID-19 period will not have the technical efficiency scores recovered as the same as in the pre-COVID-19 period again. The reasons are the number of employees will increase, and the 3rd and 4th runway will be opened. If the number of aircraft and passenger movements is increased more than this thesis predicted in the post-COVID-19 period, the technical efficiency scores will be higher, and opening the 3rd runway in 2023 and the 4th runway in 2030 will be good strategies. Otherwise, BKK tends to waste inputs to handle a few outputs.
3. All airports will be recovered after 2021, but only DMK, CNX, HKT, and CEI will perform fully efficiently in 2030. These airports must take at least 6 years to recover the efficiency scores to be the same as in 2019. Policymakers can help to reduce the recovery time in 2 ways. Firstly, they must lay off some of the employees at the airports. This will help them to reduce the wasted labor because the size of the airports cannot be reduced. Secondly, Thailand must open the country as soon as possible by injecting the vaccines to people on a mass scale within early 2022. The confidence of international tourists is matters. Injecting the good vaccines to 70 percent of people who live in Thailand can make more confidence to international tourists traveling to Thailand again. If the world's situation is better, the world's aviation sector will be possible back to normal in the next few years.
4. The non-airport hubs such as CEI and HDY can be transformed into airport hubs by promoting tourism for Chiang Rai and Songkhla provinces. These airports can create more routes that connect with the other airports of nearby countries.
5. The technical change is a major factor for driving sustainable growth in the aviation industry for the post-COVID-19 period. The airports

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should consider in adopting new technologies by transforming the traditional airports into smart airports for the future.

6. Thailand is the big hub of international tourists. Hence, the aviation industry should not only rely on the international market. There should be able to diversify risk or uncertainty events that may be occurred in the future.

Since the technical change will be a major factor in driving sustainable growth in the aviation industry in Thailand, the suggestions for transforming the traditional airports into smart airports are presented as follows:

1. All airports should adopt the new working systems such as agile, lean, and hire only talented workers. These will help them to reduce low-skilled employees and be replaced by specialists instead.
2. All airports should adopt new technologies such as the biometric facial recognition machine, new applications, internet of things (IOT), artificial intelligence (AI), Robot Assistants, and big data to promote productivity and reduce the wasted inputs such as low-skilled workers at the airports. These will help them to keep a low number of workers while handling the same amounts of passengers. Big data and AI can help policymakers to manage the schedule of the flights wisely. These technologies can help to promote air traffic movements on time by reducing buffering time.
3. The airports must set new strategies to create a new environment for the working system. They can hire the data analyst team, the data science team, and the data engineer team who can work with a lot of data and new technologies wisely to design sustainable policies. These will help the airports keep very low talented employees because the size of the airports cannot be reduced. The few talented employees can replace many low-skilled employees, while the productivity and efficiency that the airports can be derived will be higher. Successful companies around

the world employ these strategies to improve their efficiency, productivity, and profits in the long run.

4. The world after the COVID-19 will be the world that companies must adapt themselves to new technologies immediately. The data teams can help the airports to inspect some defections in the working processes at the airports and design strategies to fix them suddenly. This can be done by applying the internet of things (IOT). This technology can reduce the number of employees at the airports because it can detect every problem at the airports and report them to the responsible workers immediately. Although the new technologies will be the main factor to drive long-run productivity growths at the airports, the workers are going to be significant. The new working systems and technologies can support the slower increase of employees at the airports to handle future air transportation movements.

The suggestions above will help to transform Thailand’s airports into smart airports within the short period after the COVID-19 pandemic has ended. These suggestions can help the main public airports to save costs and raise the aeronautical and non-aeronautical revenues in the long run after the new working systems have been set.

8.2 Limitations

This thesis has 7 main limitations. Firstly, during writing this thesis, Thailand faces phase four of the COVID-19 pandemic by the delta variant. The original COVID-19 from Wuhan, China has mutated to the alpha, beta, gamma, and delta variants. Thailand has a problem with the shortage of vaccines in the first half of 2021 (CNA, 2021). The new forecasting recovery trends from news agencies and CAAT do not publish yet. CAAT (2021) and news agencies (2020) forecasted the number of aircraft and passenger movements after the COVID-19 pandemic happened in 2020 by assuming Thailand faces only phase one of a pandemic. Hence, this thesis still assumes

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to use the data to be consistent with what news agencies and CAAT (2021) had forecasted.

Secondly, this thesis is the first work that employs the time-series model to forecast the growths of passenger and aircraft movements of the 6 Thailand's main public airports. This thesis employs the forecasting data between 2021 to 2030 from the AR (1) model and the Excel Linear Forecast function to estimate the productivity growths and the efficiency scores at the airports. The AR (1) model is employed to predict the recovery trends of the 2 output variables such as total passenger and aircraft movements at the airports between 2024 to 2030. Between 2021 to 2023, this thesis uses the forecasting data from AOT (The Standard, 2020; Thai Rath, 2020) by assuming that in 2023, the passenger and aircraft movements will be back to the same level as in 2019. The Excel Linear Forecast function is employed to forecast the growths of the number of employees of the airports because the results from the AR (1) model are overestimated in the airport hubs such as BKK, DMK, HKT, and CNX. The total space of all airports except BKK is limited. Only BKK has a large space left to create new constructions, but the number of employees could not be possible to over 13,000 people in 2030. HKT is a fully developed airport. That would not be possible that HKT will have employees over 2,000 people in the next 10 years. Hence, this thesis assumes the number of workers in each airport will slowly increase and the Excel Linear Forecast function gives trustworthy results.

Thirdly, this thesis assumes the terminal and apron areas are fixed in the post-COVID-19 period. All airports except BKK have less space to expand the sizes. Only BKK has plans to build more constructions in the next 10 years, but the size of this airport cannot be predicted.

Fourth, the results from the AR (1) model forecasted the number of aircraft movements and the passenger movements are different from the forecasted from CAAT's report (CAAT, 2021). CAAT (2021) forecasted the trends of passenger and aircraft movements of the 6 main public airports after the COVID-19 pandemic happened to 3 scenarios. They are best case, moderate case, and worst case. The results from AR (1) model are different from the best case but they are quite similar to moderate and worst cases in some years. This thesis does not consider the data from CAAT (2021) to estimate the efficiency scores and productivity growths. Future research in this field can use these data to estimate the future performances of airports and compare them with this thesis.

Fifth, the forecasting trends of the cargo shifted at the airports cannot find from any reliable source. Hence, this variable must be excluded from the output variables in the analysis period between 2007 to 2030. This makes the technical efficiency scores and productivity growths of the airports between 2007 to 2020 in sections 7.1.1 and 7.2.1 are different.

Sixth, this thesis assumes the BKK will follow the development projects in the third phase and fifth phase to open the 3rd and the 4th runway in 2023 and 2030, respectively. The other airports have no space to create a new runway (AOT's annual report, 2020). They can do only renovate their buildings. Only CNX has a plan to build the International Passenger building to handle more international tourists in the future.

Seventh, this thesis focuses on the 6 main public airports in Thailand operated by AOT. Currently, Thailand has 39 public airports across the country. This is the first research that focuses on Thailand's airports with the longest period of data. Hence, this thesis focuses on the 6 largest airports of Thailand. Future research can find the data of the other 33 public airports to analyze and compare the performances with these 6 airports.

8.3 Future research in this field

This thesis employs the input-oriented CCR DEA and the Malmquist total factor productivity index (MPI) models to measure the technical efficiency scores and the productivity growths of the airports, respectively. This thesis employs only nonparametric models. Future research can employ another model such as the BCC DEA model and parametric method to estimate the airports' efficiency scores. They can employ other DEA and MPI models to compare the results. They can use the data that

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CAAT (2021) forecasted to estimate the efficiency levels and productivity changes and compare them for all cases.

This thesis is the first research that uses the time-series method so called the autoregressive (AR) model to forecast the data and estimate the future performances of the airports. Future research can employ other time-series models such as moving average (MA), autoregressive integrated moving average (ARIMA), vector autoregressive (VAR), and artificial neural network (ANN) to forecast and compare the results. These will help the policymakers to confirm the most appropriate model for predicting the growth of this industry.

Lastly, future research can collect the data from all airports in Thailand across the country to measure the full performances of all Thailand's airports. Since all data from different sources are collected in various ways, it will take more time to combine all data in the consistent format.

It is worth noting that this thesis is the first research in the air transportation field of Thailand. There exist some gaps to be filled in the future. Future research can extend the boundary of the knowledge in this field more broadly.

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CHAPTER 9
CONCLUSION

"If you never miss a plane, you're spending too much time at the airport."

George Stigler (1911-1991)

This thesis measures the full performances of the 6 main public airports of Thailand operated by the Airports of Thailand Public Company Limited between 2007 to 2020 and forecasts the future performances between 2021 to 2030. This is the first research in Thailand that employs the input-oriented CCR DEA and the Malmquist total factor productivity index (MPI) models to measure the technical efficiency scores and productivity growths of the airports, respectively. This is also the first work that employs the Simar and Wilson bootstrapping regression model to test which external factors in both micro and macro variables affect the efficiency levels of the airports within the study period. This thesis also considers the future performances of the airports by employing the autoregressive model to forecast the future performances after the COVID-19 pandemic occurred in 2020.

The findings indicate that the airport hubs performed better than the non-airport hubs. The external shocks from the global financial crisis, the big flooding in Thailand in 2011, and the COVID-19 pandemic had negative impacts on the airports' efficiency scores and productivity levels. The percent of international passengers in both normal and low-cost-carriers passengers had positive effects to promote the technical efficiency levels. The analysis between 2007 to 2020 shows that the 6 main public airports of Thailand had an average technical efficiency change progressed by 2 percent per year, but the technical change regressed by 2.2 percent a year. These made the total factor productivity of the airports declined by 0.2 percent a year. These findings can be concluded that the airports performed better in the operation than adopting new technologies to improve productivity between 2007 to 2020.

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After the pandemic from the COVID-19 occurred in 2020, this thesis forecasts that the overall efficiency scores and productivity growth will increase again in 2022. In 2021, the overall situation will be worse than in 2020. The airport hubs except BKK will use at least 6 years to recover the efficiency levels to be the same in 2019. BKK will not operate fully efficient again. DMK, HKT, CNX, and CEI will perform fully efficient in 2030. CNX and DMK will take 15 years to perform fully efficient again, while HKT will take 16 years. CEI will perform perfectly efficient in 2030, the first time in 24 years. HDY will not perform over 50 percent again between 2021 to 2030. The results show that all airports have no problem in adopting new technologies to improve productivity growth. Only BKK and HDY tend to use wasted inputs for handling the passenger and aircraft movements. These 2 airports must keep a low number of employees if the total passenger movements are recovered as predicted in this study. These will help to improve the technical efficiency scores.

After 2023, this thesis shows that the average technological adoption rate of the overall airport will progress by 6 percent a year. Between 2024 to 2030, the technical efficiency change will be regressed every year. This implies that the 6 main public airports of Thailand must concern about the operating system and the wasted inputs. This problem can be solved by setting the new working systems such as agile, lean, and talent density. These systems can help the airports to reduce expenses for hiring many employees because the size of the airports cannot be reduced.

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APPENDICES

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Appendix A
Forecasting the number of employees at the individual airports between 2021 to 2030

Table A.1

Forecasting and comparing the number of employees at Suvarnabhumi Airport (BKK) by employing the AR (1) model and the Excel Linear Forecast function

Year	AR (1)	% of change	Excel Linear Forecast	% of change
2020	3,514		3,514	
2021	3,795	8.00%	3,254	-7.39%
2022	4,150	9.36%	3,318	1.96%
2023	4,599	10.81%	3,381	1.92%
2024	5,166	12.33%	3,445	1.88%
2025	5,882	13.87%	3,509	1.85%
2026	6,787	15.39%	3,572	1.81%
2027	7,931	16.85%	3,636	1.78%
2028	9,376	18.22%	3,700	1.75%
2029	11,202	19.47%	3,763	1.72%
2030	13,509	20.59%	3,827	1.69%

Note. From author’s calculation.

Table A.2

Forecasting and comparing the number of employees at Don Mueang International Airport (DMK) by employing the AR (1) model and the Excel Linear Forecast function

Year	AR (1)	% of change	Excel Linear Forecast	% of change
2020	1,823		1,823	
2021	2,044	12.15%	1,699	-6.81%
2022	2,293	12.14%	1,805	6.26%
2023	2,571	12.14%	1,911	5.89%
2024	2,883	12.13%	2,018	5.56%
2025	3,233	12.13%	2,124	5.27%
2026	3,625	12.12%	2,230	5.00%
2027	4,064	12.12%	2,336	4.77%
2028	4,556	12.12%	2,443	4.55%
2029	5,108	12.11%	2,549	4.35%
2030	5,727	12.11%	2,655	4.17%

Note. From author's calculation.

Table A.3

Forecasting and comparing the number of employees at Phuket International Airport (HKT) by employing the AR (1) model and the Excel Linear Forecast function

Year	AR (1)	% of change	Excel Linear Forecast	% of change
2020	1,014		1,014	
2021	1,113	9.73%	1,031	1.66%
2022	1,217	9.41%	1,101	6.84%
2023	1,328	9.13%	1,172	6.40%
2024	1,446	8.88%	1,242	6.02%
2025	1,572	8.66%	1,313	5.68%
2026	1,704	8.46%	1,384	5.37%
2027	1,846	8.28%	1,454	5.10%
2028	1,995	8.11%	1,525	4.85%
2029	2,154	7.97%	1,595	4.63%
2030	2,323	7.83%	1,666	4.42%

Note. From author's calculation.

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Table A.4

Forecasting and comparing the number of employees at Chiang Mai International Airport (CNX) by employing the AR (1) model and the Excel Linear Forecast function

Year	AR (1)	% of change	Excel Linear Forecast	% of change
2020	483		483	
2021	529	9.58%	470	-2.70%
2022	580	9.58%	496	5.54%
2023	636	9.58%	522	5.24%
2024	696	9.58%	548	4.98%
2025	763	9.58%	574	4.75%
2026	836	9.58%	600	4.53%
2027	916	9.58%	626	4.34%
2028	1,004	9.59%	652	4.16%
2029	1,101	9.59%	678	3.99%
2030	1,206	9.59%	704	3.84%

Note. From author's calculation.

Table A.5

Forecasting and comparing the number of employees at Hat-Yai International Airport (HDY) by employing the AR (1) model and the Excel Linear Forecast function

Year	AR (1)	% of change	Excel Linear Forecast	% of change
2020	325		325	
2021	339	4.21%	353	8.48%
2022	352	4.03%	370	4.95%
2023	366	3.86%	387	4.72%
2024	380	3.70%	405	4.51%
2025	393	3.56%	422	4.31%
2026	406	3.43%	440	4.13%
2027	420	3.30%	457	3.97%
2028	433	3.19%	475	3.82%
2029	447	3.08%	492	3.68%
2030	460	2.97%	510	3.55%

Note. From author’s calculation.

Table A.6

Forecasting and comparing the number of employees at Mae Fah Luang-Chiang Rai International Airport (CEI) by employing the AR (1) model and the Excel Linear Forecast function

Year	AR (1)	% of change	Excel Linear Forecast	% of change
2020	483		483	
2021	529	9.58%	470	-2.70%
2022	580	9.58%	496	5.54%
2023	636	9.58%	522	5.24%
2024	696	9.58%	548	4.98%
2025	763	9.58%	574	4.75%
2026	836	9.58%	600	4.53%
2027	916	9.58%	626	4.34%
2028	1,004	9.59%	652	4.16%
2029	1,101	9.59%	678	3.99%
2030	1,206	9.59%	704	3.84%

Note. From author's calculation.

Appendix B

Defining the abbreviations of the variables used in the second stage

Table B.1

The abbreviations of the variables using in the second stage between 2007 to 2020

Variable Name	Abbreviation
Technical efficiency score	te
Airport hub status	ahs
Global financial crisis	fc
Percent of international low-cost carriers	pilcc
Percent of domestic low-cost carriers	pdlcc
PAD occupied BKK and DMK in 2008	mob
Thailand political conflict between 2013 to 2014	pc
Percent of International passengers	pip
Flooding at DMK in 2011	flood
COVID-19	covid

Note. From author's compilation.

Ref. code: 25646204040080WKG

Appendix C

Checking the Collinearity and Variance Inflation Factor (VIF)

Figure C.1

Checking Collinearity

```
. pwcorr te ahs fc flood mob pilcc pdlcc pc pip covid
```

	te	ahs	fc	flood	mob	pilcc	pdlcc
te	1.0000						
ahs	0.8216	1.0000					
fc	-0.2546	-0.1001	1.0000				
flood	-0.1660	0.0861	-0.0448	1.0000			
mob	-0.1357	-0.0383	0.3825	-0.0171	1.0000		
pilcc	0.5616	0.5170	-0.2463	-0.1058	-0.0892	1.0000	
pdlcc	-0.4441	-0.5698	-0.0876	-0.1615	-0.0747	0.0505	1.0000
pc	0.0491	0.0272	-0.1132	-0.0304	-0.0433	0.0470	0.0502
pip	0.5765	0.5652	-0.0283	-0.0688	0.0842	0.0473	-0.7985
covid	-0.1914	0.0272	-0.1132	-0.0304	-0.0433	0.1367	0.1027

	pc	pip	covid
pc	1.0000		
pip	0.0152	1.0000	
covid	-0.0769	-0.0126	1.0000

Note. From author's estimation.

Ref. code: 25646204040080WKG

Figure C.2

Checking Variance Inflation Factor (VIF)

. **vif**

Variable	VIF	1/VIF
pdlcc	3.88	0.257545
pip	3.49	0.286331
ahs	2.81	0.355686
pilcc	1.91	0.523224
fc	1.32	0.758676
flood	1.21	0.827180
mob	1.20	0.835467
covid	1.06	0.947504
pc	1.03	0.967556
Mean VIF	1.99	

Note. From author's estimation.

Ref. code: 25646204040080WKG

Appendix D

The regression results of the second stage

Figure D.1

Ordinary Least Squares (OLS) result

```
. reg te ahs fc flood mob pilcc pdlcc pc pip covid
```

Source	SS	df	MS
Model	4.94847322	9	.549830358
Residual	.74980434	74	.010132491
Total	5.69827756	83	.068653947

Number of obs	=	84
F(9, 74)	=	54.26
Prob > F	=	0.0000
R-squared	=	0.8684
Adj R-squared	=	0.8524
Root MSE	=	.10066

te	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ahs	.3392331	.0379217	8.95	0.000	.2636724	.4147937
fc	-.1026321	.036034	-2.85	0.006	-.1744314	-.0308327
flood	-.4192866	.1113419	-3.77	0.000	-.6411402	-.1974331
mob	-.1252582	.0788154	-1.59	0.116	-.2823014	.0317849
pilcc	.5369968	.1619033	3.32	0.001	.2143974	.8595962
pdlcc	.1220162	.0768212	1.59	0.116	-.0310533	.2750857
pc	-.0337584	.0433548	-0.78	0.439	-.1201446	.0526279
pip	.29726	.0774145	3.84	0.000	.1430082	.4515117
covid	-.2744786	.0438111	-6.27	0.000	-.3617742	-.1871831
_cons	.3939982	.0520617	7.57	0.000	.2902629	.4977335

Note. From author's compilation.

Figure D.2

Simar and Wilson Bootstrapping regression result

```
. simarwilson te ahs fc flood mob pilcc pdlcc pc pip covid

Simar & Wilson (2007) eff. analysis      Number of obs             =        68
(algorithm #1)                           Number of efficient DMUs  =        16
                                         Number of bootstr. reps   =      1000
inefficient if te < 1                    Wald chi2(8)              =    190.38
twosided truncation                      Prob > chi2(8)            =    0.0000

Data Envelopment Analysis:                        externally estimated scores
```

efficiency	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Percentile [95% Conf.	Interval]
te						
ahs	.2899521	.0460993	6.29	0.000	.2041569	.3862678
fc	-.0980792	.0427281	-2.30	0.022	-.1829089	-.016488
flood	-.3653747	.1281572	-2.85	0.004	-.634107	-.1454633
mob	-.1794091	.0943529	-1.90	0.057	-.3670002	.0136279
pilcc	1.008156	.2955224	3.41	0.001	.4159657	1.627077
pdlcc	.1229162	.0865837	1.42	0.156	-.0627683	.2770246
pc	-.0440081	.0620499	-0.71	0.478	-.1573551	.0784968
pip	.4921661	.1232722	3.99	0.000	.2432397	.7287832
covid	-.3328086	.0568949	-5.85	0.000	-.4396542	-.2171726
_cons	.3815705	.0593335	6.43	0.000	.2744163	.5017696
/sigma	.1075905	.0106129	10.14	0.000	.077737	.1198869

Note. From author's compilation.

Figure D.3

Setting the panel data

```
. sort ID Year

. xtset ID Year,yearly
       panel variable:  ID (strongly balanced)
        time variable:  Year, 2007 to 2020
                delta:  1 year
```

Note. From author's compilation.

Figure D.4

Running by the fixed effect model

```
. xtreg te ahs fc flood mob pilcc pdlcc pc pip covid,fe

Fixed-effects (within) regression               Number of obs     =         84
Group variable: ID                              Number of groups  =          6

R-sq:                                           Obs per group:
     within  = 0.7631                                         min =         14
     between = 0.7988                                         avg =       14.0
     overall = 0.7031                                         max =         14

                                                F(9,69)           =      24.70
corr(u_i, Xb)  = -0.8647                        Prob > F          =     0.0000

------------------------------------------------------------------------------
          te |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         ahs |   .2914195   .0788131     3.70   0.000     .1341917    .4486473
          fc |  -.0757885   .0332007    -2.28   0.026     -.142022    -.009555
       flood |   -.274067   .1182843    -2.32   0.023    -.5100377   -.0380964
         mob |  -.0741096   .0735479    -1.01   0.317    -.2208337    .0726146
       pilcc |   .7841443   .2012185     3.90   0.000     .3827244    1.185564
       pdlcc |     .18172   .0737474     2.46   0.016     .0345979    .3288421
          pc |   -.046217   .0387244    -1.19   0.237    -.1234701     .031036
         pip |   1.245873   .3218596     3.87   0.000     .6037803    1.887965
       covid |  -.2723686   .0393523    -6.92   0.000    -.3508742   -.1938629
       _cons |   .1767992   .0875928     2.02   0.047     .0020564    .3515421
-------------+----------------------------------------------------------------
     sigma_u |  .25414919
     sigma_e |  .08935799
         rho |  .88998047   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(5, 69) = 4.98                       Prob > F = 0.0006
```

Note. From author's compilation.

Figure D.5

Storing the result of the fixed effect model

```
. estimates store fixed
```

Note. From author's compilation.

Figure D.6

Running and storing the result of the random effect model

```
. xtreg te ahs fc flood mob pilcc pdlcc pc pip covid,re

Random-effects GLS regression                   Number of obs     =         84
Group variable: ID                              Number of groups  =          6

R-sq:                                           Obs per group:
     within  = 0.7276                                         min =         14
     between = 0.9657                                         avg =       14.0
     overall = 0.8684                                         max =         14

                                                Wald chi2(9)      =     488.38
corr(u_i, X)   = 0 (assumed)                    Prob > chi2       =     0.0000

------------------------------------------------------------------------------
          te |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         ahs |   .3392331   .0379217     8.95   0.000     .2649079    .4135582
          fc |  -.1026321    .036034    -2.85   0.004    -.1732574   -.0320067
       flood |  -.4192866   .1113419    -3.77   0.000    -.6375128   -.2010605
         mob |  -.1252582   .0788154    -1.59   0.112    -.2797336    .0292172
       pilcc |   .5369968   .1619033     3.32   0.001     .2196721    .8543215
       pdlcc |   .1220162   .0768212     1.59   0.112    -.0285505    .2725829
          pc |  -.0337584   .0433548    -0.78   0.436    -.1187322    .0512154
         pip |     .29726   .0774145     3.84   0.000     .1455303    .4489896
       covid |  -.2744786   .0438111    -6.27   0.000    -.3603468   -.1886104
       _cons |   .3939982   .0520617     7.57   0.000     .2919591    .4960373
-------------+----------------------------------------------------------------
     sigma_u |          0
     sigma_e |  .08935799
         rho |          0   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. estimates store random
```

Note. From author's compilation.

Figure D.7

Employing the Hausman's test

```
. hausman fixed random

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
         ahs |    .2914195     .3392331      -.0478136        .0690901
          fc |   -.0757885    -.1026321       .0268436               .
       flood |    -.274067    -.4192866       .1452196        .0399268
         mob |   -.0741096    -.1252582       .0511487               .
       pilcc |    .7841443     .5369968       .2471475         .119483
       pdlcc |      .18172     .1220162       .0597038               .
          pc |    -.046217    -.0337584      -.0124587               .
         pip |    1.245873       .29726       .9486127         .312411
       covid |   -.2723686    -.2744786       .0021101               .
------------------------------------------------------------------------------
                         b = consistent under Ho and Ha; obtained from xtreg
          B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(9) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       13.96
                Prob>chi2 =      0.1237
                (V_b-V_B is not positive definite)
```

Note. From author's compilation.

It is worthy to note that if we employ the panel estimations, the p-value of the Hausman's test is higher than 0.05. It can be concluded that the random effect is a more appropriate model to test in the second stage than the fixed effect model.

Ref. code: 25646204040080WKG

BIOGRAPHY

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