4-2021

Cost Optimization Modeling for Airport Capacity Expansion Problems in Metropolitan Areas

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COST OPTIMIZATION MODELING FOR AIRPORT CAPACITY EXPANSION PROBLEMS IN METROPOLITAN AREAS

By

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A Dissertation Submitted to the College of Aviation
in Partial Fulfillment of the Requirements for the Degree of
Doctor of Philosophy in Aviation

Embry-Riddle Aeronautical University
Daytona Beach, Florida
April 2021

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This Dissertation was prepared under the direction of the candidate's Dissertation Committee Chair, Dr. Dothang Truong, and has been approved by the members of the dissertation committee. It was submitted to the College of Aviation and was accepted in partial fulfillment of the requirements for the
Degree of
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ABSTRACT

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Institution: Embry-Riddle Aeronautical University

Degree: Doctor of Philosophy in Aviation

Year: 2021

The purpose of this research was to develop a cost optimization model to identify an optimal solution to expand airport capacity in metropolitan areas in consideration of demand uncertainties. The study first analyzed four airport capacity expansion cases from different regions of the world to identify possible solutions to expand airport capacity and key cost functions which are highly related to airport capacity problems. Using mixed-integer nonlinear programming (MINLP), a deterministic optimization model was developed with the inclusion of six cost functions: capital cost, operation cost, delay cost, noise cost, operation readiness, and airport transfer (ORAT) cost, and passenger access cost. These six cost functions can be used to consider a possible trade-off between airport capacity and congestion and address multiple stakeholders' cost concerns.

This deterministic model was validated using an example case of the Sydney metropolitan area in Australia, which presented an optimal solution of a dual airport system along with scalable outcomes for a 50-year timeline. The study also tested alternative input values to the discount rate, operation cost, and passenger access costs to review the reliability of the deterministic model. Six additional experimental models were tested, and all models successfully yielded optimal solutions. The moderating effects of

financial discount rate, airport operation cost, and passenger access costs on the optimal solution were quantitatively the same in presence of a deterministic demand profile.

This deterministic model was then transformed into a stochastic optimization model to address concerns with the uncertainty of future traffic demand, which was further reviewed with three what-if demand scenarios of the Sydney Model: random and positive growth of traffic demand, normal distribution of traffic demand changes based on the historical traffic record of the Sydney region, and reflection of the current COVID-19 pandemic situation. This study used a Monte Carlo simulation to address the uncertainty of future traffic demand as an uncontrollable input. The Sydney Model and three What-if Models successfully presented objective model outcomes and identified the optimal solutions to expand airport capacity while minimizing overall costs. The results of this work indicated that the moderating effect of traffic uncertainties can make a difference with an optimal solution. Therefore, airport decision-makers and airport planners should carefully consider the uncertainty factors that would influence the airport capacity expansion solution.

This research demonstrated the effectiveness of combining MINLP and the Monte Carlo simulation to support a long-term strategic decision for airport capacity problems in metropolitan areas at the early stages of the planning process while addressing future traffic demand uncertainty. Other uncertainty factors, such as political events, new technologies, alternative modes of transport, financial crisis, technological innovation, and demographic changes might also be treated as uncontrollable variables to augment this optimization model.

DEDICATION

I dedicate my dissertation works to many airport operators who are devoted to providing aviation stakeholders and passengers with safe and convenient mobility and operational environment. Their persistent and passionate efforts to accommodate the growing or sometimes fluctuating air traffic demand have motivated this research.

ACKNOWLEDGEMENTS

Many helped me along the way on this long and exciting journey. I wish to take a moment to appreciate their dedicated supports and valuable guidance for me to journey in the right direction and present this dissertation to the public.

First, I would like to express my deepest appreciation to my academic supervisor as well as dissertation chair, Professor Dothang Truong, who has been providing me with substantial efforts throughout my Ph.D. study: he has continuously supported and motivated me to be professional and improve my research skills. I also wish to thank my dissertation committee. Without their strong guidance, I would not have achieved the goals of this study. Dr. Bruce Conway and Dr. Isaac Martinez served as wise and supportive committee members, and Dr. Rafael Echevarne, my lifetime academic and professional mentor, went above and beyond to help me to reach my goal. Their immense knowledge and plentiful experience have encouraged me in shaping my research methods and concluding results. I also express my heartfelt gratitude to the faculty of the Ph.D. in Aviation program, Susan Sprowl. and Katie Esquerra. for their consistent and warm support during my two years' residence on the ERAU campus.

To my old friends who are working at Incheon Airport, Changi Airport, and many other major airports who shared me their concerns and thoughts with airport capacity problems: I hope to have time now to reconnect with each of them. I am also indebted to my colleagues who are working with me on the new Western Sydney Airport project. Their passionate and dedicated efforts to tackle the capacity issue of the Sydney metropolitan area in such an innovative approach have much influence on my study. I would like to extend my sincere thanks to Eli Walter and Jamie Atkins for the kind help and support that have made my study and life in Sydney a wonderful time. Special thanks to Steve Cornell, a great friend and a superb airport guru who has been part of my professional life in the aviation industry. His continuous encouragement and professional knowledge brought a significant contribution to this research.

Finally, to my beloved wife, Yumi, and my dearest two sons, Theo and Juo: their warm love and trust in me helped a lot throughout the challenging times, keeping me going through with this difficult study. They earned this degree right along with me.

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INTRODUCTION

World Air Transport Statistics 2019, published by the International Air Transport Association (IATA), showed that global air traffic had reached 8.8 billion passengers in 2018 and was forecasted to double by 2037 and would reach 19.7 billion passengers by 2040 (IATA, 2019). While the recent dramatic plunge in air traffic demand was due to the COVID-19 pandemic (IATA, 2020), limited airport capacity has long been a challenge for many metropolitan regions worldwide, impeding the mobility of people and goods. Hamzawi (1992) showed that aircraft operation delays at airports exponentially grow when the traffic demand starts to exceed approximately 80% of the airport capacity. Therefore, in general, attempts to resolve airport congestion largely focus on finding methods to increase airport capacity.

There are multiple solutions to increasing airport capacity, but the planning process is inherently cumbersome in large metropolitan areas (Sismanidou & Tarradellas, 2017). As a popular option, expanding existing airports is usually constrained by three major factors: investment capability, community concerns on environmental issues, and availability of land (Organization for Economic Co-Operation and Development [OECD], 2014). If existing airports cannot be expanded, developing a new airport within a reasonable distance from population centers can be an alternative solution. However, creating sufficient land for the new airport in a remote location and providing connectivity to population centers requires extensive investments in surface transport and infrastructure development (OECD, 2014). Furthermore, the relocation of resources to the new airport imposes extra costs on airlines and other aviation stakeholders.

According to the IATA and Airports Council International (ACI) (2017), as shown in Figure 1, 45 of the 100 busiest airports in the world, as measured by passenger traffic, have been experiencing over-capacity problems either with the runway or terminal facilities, during 2016. By ACI's 2018 Policy Brief (ACI, 2018), though a group of 50 countries introduced a USD 355 billion airport investment plan between 2018 and 2022, it is anticipated that more than USD 433 billion will be required to meet the expected air traffic demand by 2022. This gap indicates the critical importance of investment planning and stakeholders' decision-making in increasing airport capacity.

Figure 1

Worldwide Airport Overcapacity Problem with 100 Busiest Airports

Note. 45 out of the 100 busiest airports in the world exceeded either runway or terminal facility design capacity in 2016. Adapted from "IATA-ACI NEXTT Program Brochure" by IATA (2017, p. 2).

In 2019, based on its bi-annual survey, Airports Council International-North America (ACI-NA) predicted that the total capital costs of U.S. airports between 2019 and 2023 would be more than USD 128 billion (ACI-NA, 2019). As shown in Table 1, the majority of necessary capital costs are planned for allocated to large hub airports in metropolitan areas. Compared to ACI-NA's 2017 report (ACI-NA, 2017), which predicted costs of about $100 billion, this projection showed a significant increase. Meanwhile, the approximate average annualized capital cost of USD 25.6 billion between 2019 and 2023 appears to be significantly higher than the funding available through Airport Improvement Program (AIP) grants, Passenger Facility Charge (PFC) revenue, and net income from airport operations (ACI-NA, 2018). The current funding system in the United States is not sufficient to support the demand for expanding its airport capacity in a timely manner, which is essential for a safe and efficient air transport system.

When airport facilities fail to meet the demand needs either of the society or global economy, there might be challenges in the economic growth of the cities, states, and regions. Thus, developing an optimal solution to increase airport capacity appears to be of critical importance not only for the stakeholder working for the airport and aviation industry but also for many different parties who are related to urban planning and policy making. As a famous example, the British Chambers of Commerce have consistently called for a third Heathrow runway development to keep the UK economy competitive and they also warned that repeated delays and losing efficiency could cost the UK economy more than £30bn between 2020 and 2030, with the country losing out on trade to Germany and France (Burridge, 2019).

Table 1

U.S. Airport Capital Cost Projection per Year and Category ($ in Millions)

Airport Type	2019	2020	2021	2022	2023	Total	Percent
Large hub	20,129	16,776	16,549	13,982	13,630	81,066	63.3%
Medium hub	3,142	2,705	3,313	3,441	4,935	17,537	13.7%
Small hub	2,385	1,999	1,651	2,043	1,319	9,398	7.3%
Non-hub	1,099	1,115	1,132	1,149	1,166	5,660	4.4%
Other [a]	2,809	2,851	2,893	2,937	2,981	14,471	11.3%
Total	29,563	25,446	25,539	23,551	24,032	128,131	100.0%

Note. Data from ACI-NA annual publication in 2019. Extracted from https://airportscouncil.org/wp-content/uploads/2019/02/2019TerminallyChallenged-Web-Final.pdf. [a] ‘Other’ category includes non-commercial service airports and seven proposed new airports based on the FAA’s NPIAS report (2019-2023).

In many metropolitan areas, as shown in Table 2, the planned airport capacity improvement programs have not been implemented in a timely manner (Santos & Antunes, 2014), mainly due to significant extensions of the initial planning phase. Among many factors, the options for capacity expansion, whether to expand existing airports or to develop a new airport, appear to be a dominant factor that causes delays in the planning and decision-making process. Also, environmental concern to expand the existing airport infrastructure or developing a new airport site has been another major issue to delay the decision-making.

Table 2

Example Cases of Major Airport Project Delays in Metropolitan Areas

Metropolitan City	Airport	Type of Expansion	Plan Initiated	Major Issues	Current Status	(Planned) Finish
Munich, Germany	Munich	Greenfield Development	1963	Location, Traffic forecast, Environmental effects	Operation / Expansion Planning	1992
Berlin, Germany	Branden-burg	Greenfield Development	1992	Location, Design changes, Cost overrun	Construction / Activation	2020
Ho Chi Minh, Vietnam	Long Thanh	Greenfield Development	2006	Financial Feasibility, Financing	Design	2025
Pusan, Korea	Kimhae	Mega-Expansion	2000	Expansion vs. New Airport, Conflict among stakeholders	Planning / Suspension	2026
London, UK	Heathrow	Mega-Expansion	1968	Expansion vs. New Airport, Conflict among stakeholders	Planning / Suspension	2026
Sydney, Australia	Western Sydney	Greenfield Development	1972	Remote Location, Conflict with the existing airport	Design	2026
Chicago, USA	South Suburban	Greenfield Development	1968	Politics, Conflict with O'Hare and Midfield airports	Planning	Not Confirmed

Note. The cases above were selected and analyzed by the researcher. The information on the expected finish year is retrieved from the latest announcement by the concerned airport authorities.

To better understand the complex nature of planning airport capacity expansion in metropolitan areas, the background and major causes of long-term delays must be analyzed. Among the projects shown in Table 2, three projects that have been delayed for several decades and are not yet complete were reviewed: Western Sydney Airport development in Australia, London Heathrow Airport expansion in the United Kingdom, and Long Thanh Airport development in Vietnam.

Like many other metropolitan regions, Sydney has long experienced an airport capacity problem associated with its single airport situation. The Kingsford Smith Airport is located 8 km away from the central business district (CBD) at a small coastal site of 907 hectares (2,241 acres) (OECD, 2014). While air traffic demand has rapidly increased for the last 2 decades, the airport's night-time curfew and proximity to the CBD make it difficult to utilize the existing infrastructure extensively or to develop further capacity. For several decades, the Australian government has evaluated multiple solutions to build a new airport infrastructure. The critical issues that complicated the decision-making process were related to site location, air traffic networks, and airline marketing and competition (OECD, 2014). Finally, the Western Sydney Airport project commenced in 2018 and is expected to be completed by the end of 2026. Because this new airport will be located about 45 km from the CBD, accessing it will be less convenient for passengers and airlines. Furthermore, transforming the current single airport operational model into a multi-airport system may prove problematic. Meanwhile, it is expected to resolve the environmental concerns of the communities regarding both noise and air pollution (Western Sydney Airport Co., 2014).

Another well-known case, the expansion of Heathrow airport, provides important lessons that can help with understanding the complex environment of airport capacity planning. There had been lengthy debates on whether to develop a new airport or to expand existing airports to tackle the airport capacity issue of the London metropolitan area. Considering the potential economic benefits and severe competition with other major hub airports, the capacity expansion of Heathrow airport has been the British government's preferred option since the 1990s. After almost 30 years of prolonged review, the government gave the go-ahead to a third runway plan at Heathrow Airport. It launched a public consultation process as part of its masterplan and proposed a phased airport expansion plan: the runway construction will be completed by 2026, and the rest of the airport infrastructure, including new terminals, are to be completed by around 2050 (Burridge, 2019). However, the British Court of Appeal recently ruled the Heathrow third runway expansion plan is unlawful due to increasing climate change concerns, and this expansion plan is unlikely to re-start in the short-term (Tophem, 2020).

Long Thanh International Airport in Viet Nam is proposed to become an international hub airport in Ho Chi Minh City. The proposed site is located approximately 40 km east of the city center, covering about 5,000 hectares (12,355 acres). The new airport site has been prepared to accommodate four runways in the final phase and handle beyond 100 million passengers per annum. This scale of the airport would become one of the largest airports in the world. It plans to have three major expansion phases over three decades; the first phase is scheduled for completion by 2025, and the next two phases are to be completed between 2030-2035 and 2040-2050, respectively. While the National Assembly approved this ambitious plan in 2015, a decision was made that the investor would use its funds and that the government could not guarantee any loan taken for the project. Due to the investment requirements of USD 4.8 billion and potential competition with the existing Than Son Nath Airport, funding for the project has made it uncertain whether the project will be completed on time (Center for Asia Pacific Aviation [CAPA], 2019).

From reviewing these three cases, it is apparent that airport capacity problems at the municipal level have caused complex situations and delayed definitive decision-making. Several critical reasons for this issue can be summarized: limited financial and land availability, lumpy capital investment requirements under uncertain traffic demand which means airport infrastructure cannot be acquired in small increments but must be obtained in large and discrete units, conflicting stakeholders' interests over multiple solutions, and the future environmental impact on the metropolitan areas. The lessons learned from these cases supported the development of the research questions and objectives of this study.

Many factors affect the decision of whether to expand the existing airport(s) or to build a new airport, and it is apparent that different stakeholders pursue their own interests (Martín & Voltes-Dorta, 2011b). Among the various factors delaying the stakeholders' decision-making, the financial concern is a significant aspect, as it can easily override the future benefits from timely capacity expansion (Xiao et al., 2017). This is mainly because airport expansion works typically involve massive investment based on future infrastructure needs forecasted by uncertain traffic demand.

According to IATA (2020), air passenger traffic as measured by revenue passenger kilometer dropped 94.3% year-on-year in April 2020, which was the largest decrease in history caused by the large-scale worldwide lockdowns linked to the COVID-19 pandemic, and it was still down 75.3% in August 2020. This decline has shown across all regions. As stated by the ACI media release article (ACI, 2020), the recovery of overall air traffic demand is anticipated to take up to 18 months to reach pre-crisis traffic volume. However, with the uncertainty of the further impact of the current situation, there is a likelihood of re-evaluation of necessity and timeline for airport capacity expansion plans for the majority of airports.

Meanwhile, the environmental costs associated with community concerns can also complicate the planning and decision-making processes for airport capacity expansion in metropolitan regions (OECD, 2014). Community concerns usually include noise level, air and water pollution, loss of wildlife habitats, traffic congestion, and a host of other environmental concerns (OECD, 2014). A recent decision of the British Court of Appeal to ruled the Heathrow third runway expansion plan as unlawful, which was made primarily because the expansion plan did not take climate commitments into account. The ruling occurred while public concerns about climate change were rapidly rising, and the government passed legislation with the target of net zero emissions by 2050 (Tophem, 2020).

Therefore, to develop capacity planning for airport infrastructure projects, it is of critical importance to involve not only financial factors but also consider various non-financial factors such as social, environmental, congestion, and technical aspects. It is also vital to study other related stakeholder costs, such as airlines, communities, and passengers, so that the decision can be supported by the related stakeholders.

Three significant areas of literature have been found regarding airport capacity expansion problems: airport site location study (Daskin, 1995; Hammad & Akbarnezhad, 2017; ReVelle & Eiselt, 2005; Yang et al., 2016), airport capacity expansion model (Marshall, 2018; Martin & Voltes-Dorta, 2011; Sun & Schonfeld, 2015), and airport network design (Clark et al., 2018; Santos & Antunes, 2014; Wandelt et al., 2017). Those studies aimed to maximize the traffic throughput or operational efficiency of the concerned airports, and little attention has been paid to assessing multiple solutions at a metropolitan level to decide airport capacity investment.

A review of existing literature, as shown in chapter two, reveals the limitations of assessing the complex dynamics of cost functions to expand airport capacity under future traffic uncertainty. Moreover, previous research that studied the relationship between cost functions and airport capacity focused on a few major cost elements in the development and operation of airport infrastructure without sufficiently considering an overall framework and the multi-faceted cost mechanism over time. Therefore, this research, which focused on the comprehensive cost functions of airport development and operations, attempted to address these significant literature gaps and proposed a cost optimization model that can be used in considering future airport capacity expansion in large metropolitan areas.

Statement of the Problem

The existing literature (Marshall, 2018; Martin & Voltes-Dorta, 2011; Sun & Schonfeld, 2015) regarding airport capacity expansion problems has primarily addressed the costs and benefits of investing in an individual airport without assessing multiple solutions for the overall airport system of metropolitan areas. While such measures may result in locally improved solutions for a particular airport, they are often sub-optimal for the airport systems of metropolitan areas. Thus, they do not sufficiently support effective decision-making during the early planning stages.

Another major problem with the acquisition of airport capacity and future airport operations is associated with potential fluctuations in air traffic demand (Luke & Walters, 2013). Under the current liberalization and cost-competitive business environment, airport capacity expansion planning at a metropolitan level requires careful consideration of future demand uncertainty. Hence, the airport capacity decision-making process needs to take into account the dynamics and possible trade-off among cost functions, associated with the uncertainty of future air traffic demand.

Purpose Statement

This research intended to develop a quantitative optimization model that can help determine optimal solutions for airport capacity expansion in large metropolitan areas. Using a mixed-integer nonlinear programming (MINLP) method, it aimed to develop an optimization model to identify the optimal solution for expanding airport capacity with a specific interest in minimizing the total costs over time. After the development of the general optimization model with a deterministic approach, the effects of uncertainties of air traffic demand and unexpected events on capacity planning were examined using a Monte Carlo simulation method. This approach helped to analyze various what-if scenarios in major metropolitan areas by simulating key objective functions or constraint variables.

Significance of the Study

This study aimed at expanding the understanding of capacity expansion planning for transportation infrastructure by building an optimization model specifically tailored to the airport system in large metropolitan areas. Theoretically, this optimization model improved the body of knowledge by assessing various solutions for expanding airport capacity as a system within metropolitan areas. Moreover, by adding a what-if simulation framework to the deterministic optimization model, it could address uncontrollable input variables such as air traffic demand and catchment population. The optimization model also provided a foundation for future research questions related to specific cases in metropolitan areas.

Practically, the results of this research will provide airport authorities and planners with an evidence-based assessment model to scrutinize solutions for airport capacity expansion concerning their competitive outcomes, connectivity, and overall user benefits. By changing an objective function, decision-makers can also modify and customize the optimization model to choose an optimal solution based on their specific needs and priority functions. The key contributions of this work can be elaborated as below:

(1) analysis of various cost functions for airport capacity expansion and the formulation of cost assessment models along with the nonlinear traffic growth effects;

(2) an optimization model for assisting aviation authorities in their strategic decisions regarding the expansion of the airport capacity of large metropolitan areas in consideration of multiple capacity expansion solutions; and

(3) provision of several model enhancements under different what-if scenarios for modifying the presented solution through a series of computational tests.

Research Questions

This study was designed to answer the question of what are the critical costs for expanding airport capacity in metropolitan areas and how airport stakeholders can identify the optimal solution that helps to minimize overall costs under the future air traffic demand uncertainty. More specifically, this research aimed to help to answer the following three questions:

Q1. What are the key cost functions related to airport capacity expansion, and how are they related to traffic change over time?

Q2. Using the identified key cost functions, how can an optimum solution for the airport capacity expansion be determined in terms of minimizing related costs?

Q3. How can the optimum solution be decided in consideration of various factors that may impact future traffic demand?

Delimitations

This study focused on the impact of acquisition and environmental costs directly incurred in the expansion of airport capacity in large metropolitan areas. Because the modeling outcomes from one airport or metropolitan area may not be generalized to another airport, multiple sources were used to collect required data from various airports in Asia, the USA, Oceania, and Europe. The selected instances helped establish cost parameters to build an MINLP model. Therefore, the optimization model obtained can be generalizable to most metropolitan areas worldwide, thus becoming a useful tool for supporting the decision-making process.

In order to produce a generalizable optimization model, any specific factors that can vary depending on geographical and business environments such as ownership structure and governance of airports were not considered in this research. Also, it did not produce a model that captures political and economic factors, such as taxations and revenues both from aeronautical and non-aeronautical activities. Moreover, it did not address induced costs or benefits such as job creation, quality of services, and economies of scale, which may be related to many compounding variables that cannot be controlled within this study. In the meantime, expanded operational considerations such as cost of initial operational inefficiency, training, and relocation, which could cost more at a new airport than an existing airport, are addressed with the Operation Readiness and Airport Transfer (ORAT) cost.

Limitations and Assumptions

The airport capacity expansion problems of metropolitan areas usually engage many different variables and uncertainties, which can vary depending on geographical, social, political, and economic conditions. Therefore, developing plausible scenarios and assumptions that apply to most metropolitan areas is essential to ensure the validity of the research outcomes. Thus, the proposed optimization model utilized information and parameters from multiple metropolitan cases and global practices.

However, it was also essential to understand the limitations of the information collected from the case studies and existing literature, which have different operational conditions and geographical factors. Therefore, it was imperative to limit the scope of the model by simplifying its assumptions and input parameters by considering generally applicable industrial practices, as shown below:

(1) The time horizon of the study is aligned with the typical planning and development period of airport capacity expansion projects.

(2) Having a macro-level analysis, the researcher considered expanding entire airport facilities rather than prioritizing any specific component of the airport. Therefore, sub-components such as airfield, cargo, and passenger terminal of an airport system were not modeled into the optimization model.

(3) Among various demands, annual passenger traffic was taken as a primary parameter in the development of this optimization model. Other traffic profiles, such as cargo traffic or aircraft movement, were not considered.

(4) This research did not consider political or socio-economic factors that can be influenced by different local conditions.

(5) In this study, traffic demand was associated with the origin and destination passengers, and transfer traffic demand was not considered as a discrete input variable.

Summary

Due to complex stakeholder structures and lumpy investment requirements, the capacity expansion of airports for accommodating the growing air traffic demand has become one of the key challenges in many metropolitan areas. Several solutions exist to solve this issue, either with a multi-airport or single airport scenario. It has been a pervasive industrial practice to take a qualitative approach influenced by political factors or assess each of these solutions individually to make a decision. However, with the presence of multiple decision factors and uncertainties in traffic demand, budget, airport location, and network, the decision-making process for airport capacity expansion has often resulted in social conflicts and prolonged delays. These delays often negatively impact the sustainable growth of the air transportation industry.

The researcher intended to evaluate these various solutions quantitatively and developed a useful optimization model for airport capacity expansion. The outcomes of this research established a hypothetical scenario and modeling parameters to evaluate and compare the various solutions for capacity expansion, with a focus on minimizing the costs of airport capacity expansion. The optimization model presented is expected to help decision-makers determine an optimal solution with a focus on both cost and time efficiency.

Definitions of Terms

Aeronautical revenue	Airport user charges generated by flight operations.
Air Cargo	Commercial freight, including express packages and mail, transported by passenger or all-cargo airlines.
Air Carrier	An airline providing scheduled air service for the commercial transport of passengers or cargo.
Airfield	A defined area on land or water including any buildings, installations, and equipment intended to be used either wholly or in part for the arrival, departure, or movement of aircraft.
Airport	An area of land or water that is used or intended to be used for the landing and takeoff of aircraft, and includes its buildings and facilities, if any.
Airport Access Plans	Includes the proposed routing of airport access to the central business district and to points of connection with existing or planned ground transportation arteries.
Airport Authority	Similar to a port authority but with the single purpose of setting policy and management direction for airports within its jurisdiction.

Airport Master Plan	A document presenting the planner's conception of the ultimate development of a specific airport. It presents the research and logic from which the plan was evolved and displays the plan in a graphic and written format.
Airport-To-Airport Distance	The great-circle distance, measured in statute miles, between airports.
Capacity	A measure of the maximum number of aircraft operations that can be accommodated on the airport component in an hour.
Catchment area	A geographic area from where a large proportion of an airport's outbound passengers originate. A geographical area is considered a catchment area of an airport if it controls at least 25 % of the passengers originating from that area (UK CAA, 2011).
Charter	A nonscheduled flight offered by either a supplemental or certificated air carrier.
General Aviation	All civil aviation operations other than scheduled air services and non-scheduled air transport operations for remuneration or hire.
Ldn	Day-night sound levels; a method of measuring noise exposure.

Non-aeronautical revenue	Airport charges that are not directly related to flight operations.

List of Acronyms

ACI	Airport Council International
AIP	Airport Improvement Program
ARC	Aerodrome Reference Code
CBD	Commercial Business District
CPI	Consumer Price Index
ERAU	Embry-Riddle Aeronautical University
FAA	Federal Aviation Administration
GA	General Aviation
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
ILP	Integer Linear Programming
IRB	Institutional Review Board
LOS	Level of Service
LP	Linear Programming
MAP	Million Annual Passenger
MAS	Multi Airport System
MILP	Mixed Integer Linear Program
MINLP	Mixed Integer Non-linear Programming
NSW	New South Wales
OECD	Organization for Economic Co-operation and

	Development
ORAT	Operation Readiness and Airport Transfer
RAAF	Royal Australian Air Force
SACL	Sydney Airport Corporation Limited
SARP	Standards and Recommended Practices
WLU	Work Load Units

CHAPTER II

REVIEW OF THE RELEVANT LITERATURE

This chapter presents the existing literature related to four main categories: (1) the capacity planning of transportation infrastructure, (2) airport capacity and network modeling, (3) airport capacity expansion solutions and cost functions, and (4) the theoretical foundation for optimization and simulation modeling. Each section details the importance and theoretical framework of the capacity planning of airport infrastructure based on existing literature.

Furthermore, this chapter focuses on various research methods used for airport capacity planning and their practical applications in supporting the decision-making processes of airport stakeholders. For developing an optimization model for airport capacity planning, this research primarily focuses on the development of linear programming and a Monte Carlo simulation model. Hence, this chapter also provides the rationales, model parameters, and independent variables that are necessary to develop an optimization model, how they can be treated, and the applicable algorithms for this study.

Capacity Planning for Transportation Infrastructure

Capacity planning is the process of determining the future capacity provision levels of specific facilities over a planning horizon (Sun, & Schonfeld, 2015). In the context of expected long-term demand growth, the core of this process is to determine the optimal timing and level of capacity acquisition or expansion. A large body of literature can be found on capacity planning in transportation sectors, such as logistics (Crainic et al., 2009; Darayi et al., 2019), railway (Anoop et al., 2018; Burdett, 2016; Lai & Shih, 2013), highway (Lu & Meng, 2017), aviation (Clark et al., 2018; Marshall, 2018; Martin

& Voltes-Dorta, 2011; Sun & Schonfeld, 2015; Wandeltet al., 2017), seaport (Dong et al, 2015), and multi-modal network design (Bevrani et al. 2017; Pimentel et al., 2013).

In transportation capacity planning, it is common to engage long lead times to adapt capacity. The initial development of a new highway, high-speed railway, or airport may take ten years or more, which requires demand forecasts for the next 10-30 years (Proost & van der Loo, 2010). Regarding the challenge of the long-term demand forecast in transport, Proost and van der Loo (2010) described two major streams of literature. First, traffic demand is stochastic in that it is difficult for stakeholders to know the aggregate level of future demand or the required capacity. Second, traffic demand has a macroeconomic uncertainty, and the demand levels are unknown to the planner. Therefore, one of the most crucial areas in the capacity planning process of transportation infrastructure is demand forecasting. As large-scale projects usually require massive and lumpy investment, demand forecasting is an essential part of the planning process (Solak et al., 2009). Its most critical difficulty is associated with the unpredictability of the long-term demand that cannot be justified due to the uncertainty of the future (Xiao et al., 2013). The existing literature presents several areas of methodological improvement that can tackle the challenges of demand forecasting.

First, sensitivity analysis can be used to deal with future uncertainty as it can suggest more reliable outcomes based on different market scenarios (Burghouwt, 2007; Sismanidou & Tarradellas, 2017). Second, improvement can also be achieved by incorporating multiple decision factors from the broad spectrum of stakeholders into the planning and decision-making processes (Armstrong and Green, 2005; Burghouwt, 2007). Each stakeholder can have different interests and considerations, so engaging multiple stakeholders in the forecasts can also be a safeguard against prejudices associated with infrastructure project planning. Finally, freeing the planning process from political influences is a complicated matter; therefore, forecast analyses may often end up with wrong figures to meet the regulators' expectations. Thus, when it comes to capacity planning for major transportation infrastructure projects, it is necessary to involve various non-economic factors—such as social, environmental, congestion, and technical aspects—along with financial feasibility.

Transportation network design, an essential topic in transportation studies, has been recently studied to optimize throughput and productivity. While a paper by Farahani et al. (2013) covered its definitions, formulations, classifications, and solutions based on a deterministic model, the effects of uncertainties such as demand were analyzed either with stochastic programming (Liu et al., 2009; Ukkusuri and Patil, 2009) or robust optimizations (Lou et al., 2009; Sharma et al., 2009; Yin et al., 2009). Lai and Shih (2013) proposed a stochastic model to select capacity expansion projects for North American freight railroad networks. While Lai and Shih (2013) made significant progress, their study had significant limitations. For instance, the capacity increment resulting from implementing one project is difficult to estimate due to the complex interactions among various railroad system components. More importantly, the penalty costs due to congestion effects should be nonlinear to demands, contrary to the assumed linear relation.

Proost and van der Loo (2010) recommended considering the competition among multiple transportation modes when it comes to capacity planning for transportation infrastructure in metropolitan areas. When there are more than two competing modes without monopolistic conditions such as competition between railways and airlines, alternative objectives and how they may lead to changes in airport behavior under demand uncertainty must be considered. This recommendation gave great importance to this study because multiple airports that serve one metropolitan area may be in a competitive position.

Airport Capacity and Network Modeling

Within the airport business and engineering field, there is abundant literature highlighting the importance of capacity expansion planning. While applications in other industrial domains can shed light on the airport capacity expansion problem, there is a particularly important factor in the airport industry that needs to be addressed. By nature, as long as traffic demand is growing, airport facilities are subject to congestion (Sun & Schonfeld, 2015), and complex relations between demand and delay costs need to be considered. Therefore, from the planning perspective, it is desirable to secure excess capacity in advance to mitigate potential delays with limited capacity. The insufficient consideration of congestion effects can result in the underestimation of capacity needs, increasing delay costs.

In contrast, the literature dealing with airport expansion and construction problems at the network level is meager (Santos & Antunes, 2015). Optimizing airport capacity and network in a metropolitan area is of critical importance because the airports are not functionally or managerially independent. Many researchers (Burghouwt, 2007; Sismanidou & Tarradellas, 2017; Szyliowicz & Goetz, 1997; Xiao et al., 2013) have stated that more flexible and practical approaches will improve the conventional study models of master planning and financial feasibility.

As shown in Table 3, three areas of study on airport capacity and network problems were found in the existing literature: airport site location (Hammad et al., 2017; Yang, Yu, & Notteboom, 2016), airport capacity expansion model (Marshall, 2018; Martin & Voltes-Dorta, 2011; Sun & Schonfeld, 2015), and airport network design (Clark et al., 2018; Magnanti & Wong, 1984; Wandelt et al., 2017). Each is relevant to the study. It must be noted that the previous studies emphasized the importance of airport planning in terms of the capacity expansion of a single airport or network efficiency from the regional perspective. However, discussions of airport expansion at the network level within the metropolitan area are relatively meager, particularly in the field of optimization (Santos & Antunes, 2014).

To develop the framework of the study, the researcher reviewed three recent studies that developed optimization models for airport capacity and network problems. Santos and Antunes (2014) introduced an optimization model to support the decision-making process in long-term airport network expansion. Using an application example case, they aimed to maximize passenger throughput within the airport network. The researchers first tested a hypothetical small-scale system and expanded the study into the evolution of major airport networks in the United States.

Table 3

Recent Aviation Research for Airport Capacity and Network Problems

Author	Year	Purpose	Variables	Sample	Methodology	Finding
Hammad, Rey, and Akbarnezhad	2017	To solve the problem of airport location and environmental impact	Noise, catchment areas, and total travel time	Transport network composed of 12 nodes and 28 links	Mixed-integer linear program (MILP) model	Airport location could significantly affect the total noise levels.
Marshall	2018	To explore airport expansion, planning, the links to national geographies, and the issues	None	UK Airports	Case study	Climate change movements find new strengths; financing is a key factor for airport expansion problems.
Martín & Voltes-Dorta	2011a	To explore the problem of airport capacity expansions under MAS	Labor, materials, and capital expenditures	161 airports worldwide	Bayesian inference and Markov chain Monte Carlo methods	Cost efficiency at a system level is significantly lower than the observed at the individual airports.
Santos and Antunes	2014	To support the decision-making to maximize passenger throughput	Throughput, capacity, impact of travel costs	28 metropolitan areas in the USA	Optimization model	An optimization model for airport expansion, while complying with a given budget.
Sun and Schonfeld	2015	To analyze how capacity expansion decisions for airport systems should be made	Capital cost, operating cost, and delay cost	None, Scenario-based	Deterministic total cost minimization model	Computational tests demonstrate the validity of developed models and proposed algorithms.
Sun and Schonfeld	2016	To optimize facility development decisions for airport systems in the presence of demand uncertainty	Capital cost, operating cost, and delay cost	None, Scenario-based	Mixed-integer nonlinear program (MINLP)	Demonstrate the capability of the proposed MINLP model and the computational efficiency of the solution method.
Xiao, Fu, & Zhang	2013	To analyze the effects of demand uncertainty on airport capacity planning and choices	Commercial revenue, capital cost, and airport operation cost	None, Scenario-based	Linear programming	Optimal airport capacity under uncertainty will be larger than the case with deterministic mean demand.
Xiao, Fu, Oum, & Yan	2017	To develop a multi-stage game model that identifies the optimal airport capacity to be invested	Capacity, service charge, demand, capital cost, reserve cost	None, Scenario-based	Linear programming	Using real options in capacity planning can be a valuable tool for airports to battle uncertainty.
Yang, Yu, & Notteboom	2016	To solve an airport location problem as a function of accessibility considerations	Spatial area, population, and social consumption level	101 Chinese airports	Structural equation model	Optimal airport location pattern ranges from a single airport to a multiple airport network.

Sun and Schonfeld (2014) developed a deterministic optimization model to expand airport capacity within a single airport system, with a focus on minimizing costs and transformed the model into a stochastic model. They developed an optimization model based on the outer-approximation technique to solve airport expansion decision-making problems by considering capital costs, operating costs, and delay costs. Computational tests with airfield systems, terminals, and cargo facilities demonstrated the validity of the airport expansion models and the efficiency of the algorithms. As a result, the optimal model reduced the total costs by 18.8% with the numerical example (Sun & Schonfeld, 2014).

Hammad and Akbarnezhad (2017) studied the problems of airport facility location and environmental impact and used a mixed-integer linear programming (MILP) method. Focusing on optimizing noise impact, the coverage of catchment areas, and the required passenger travel time on the existing road network, they suggested changes to traffic on the road network and solved airport location problems for the Sunshine Coast network in Queensland, Australia. The results indicated that the airport location could significantly affect the total noise levels of the surrounding population centers and the passengers' travel time on the road network.

Airport Capacity Expansion Solutions and Cost Functions

The airport capacity problem can be mitigated with various aviation stakeholders, such as aviation administration, municipalities, and airlines, by using different measures (Santos & Antunes, 2014). Useful short-term tools may include demand management, such as airline slot re-allocation and congestion charges for de-peaking traffic, or advanced process management systems, such as off-airport check-in and the United

States NextGen (FAA, 2012). On the other hand, long-term solutions such as expanding the existing infrastructure or developing a new airport are essential to meet increases in future demand.

Cost Functions for Airport Capacity Expansion

While there have been quite a few studies on the cost functions of the air transport industry (Caves et al., 1980), insufficient financial data on airport capacity expansion limits the choice of model specification and estimation methodology (Martín & Voltes-Dorta, 2011a). Consequently, there have been limited efforts to standardize an airport-specific cost estimation methodology.

Expanding the capacity of airports in metropolitan areas is a complex undertaking that requires significant capital expenditure, often under uncertain conditions. In this study, the six major costs were identified to be significantly related to airport capacity problems and analyzed to develop an optimization model.

Capital Costs. In infrastructure development, capital costs are significant in making an investment decision due to its massive and lumpy investment requirement (Xiao et al., 2017). In the airport domain, the capital costs can be categorized by the following sub-groups:

(1) Land acquisition. Land purchasing, soil investigation, grading, fencing, drainage system, etc.

(2) Access infrastructure. Highway, airport access road, railway, and traffic control system, etc.

(3) Utility installation. A power station, electricity, water, communication, water, waste, etc.

(4) Civil works. Movement of land, runway, taxiways, lay-bys, aprons, etc.

(5) Building works. A control tower, terminal building, fire and rescue service building, power plant, other buildings, etc.

(6) Navigational aids. Ground lighting. Approach lighting, radar, control tower, transmitter center, etc.

(7) Special airport systems. Security, flight information, baggage handling, airport operation database, deicing, passenger boarding bridge, etc.

Operation Costs. To date, passenger movement, aircraft movement, and air freight have been used as prominent output measures to develop cost functions in the existing literature. The existing research generally considers a unit passenger or aircraft movement would require similar costs to handle (Keeler, 1970; Main et al., 2003, Oum et al., 2008). However, multiple researchers have challenged this monolithic and unitized cost assessment approach because the same volume of passenger and freight does not necessarily require a similar level of resources in physical or financial terms (Martín & Voltes-Dorta, 2011b).

In the meantime, existing literature generally agrees on the presence of the economy of scale in airport operations (Martín & Voltes-Dorta, 2011b) and recommends the use of broad and representative data for a proper estimation of airports' cost function. Hence, the researcher used actual benchmarked cost information from the industry in terms of type and size of airports and developed the operation cost function.

Delay Costs. Delay at airports happens as a consequence of the rapidly growing air traffic in comparison to the supplied airport capacity, which has been one of the most severe concerns of the industry (Karaman, 2018). Many major hub airports accommodate air traffic volume beyond capacity during peak-demand seasons, which causes congestion and delays at the airports. For redistributing the traffic at the peak-hours to off-peak hours, major hub airports charge differentiated landing fees based on the extent of airport congestion. This is a standard industry practice used to encourage airlines to shift small and inefficient fleets away during peak traffic time (Hu et al., 2018). The delay costs are generally nonlinear (Sun & Schonfeld, 2015). There is plenty of literature on airport congestion pricing and capacity financing/cost recovery (Gillen et al., 1987; Gillen et al., 1989; Morrison, 1987; Oum and Zhang, 1990; Verhoef, 2017; Zhang and Zhang, 2001; Zhang and Zhang, 2003).

Noise Costs. Environmental concerns have been increasingly highlighted in air transport, especially in densely populated metropolitan areas. Major airports that are adjacent to local communities have developed and managed specific measures, such as noise mitigation procedures, curfew, noise surcharges, and noise penalties, to mitigate environmental problems (Morrell & Lu, 2000). The aircraft noise surcharge has been increasingly used by major airports adjacent to population centers to encourage the operation of environmentally friendly aircraft and to cover the costs for implementing noise management programs.

In 2014, Lu developed a systematic aircraft noise charge scheme, based on noise social costs, for application in Taiwan by attempting to put noise nuisance into monetary terms. He suggested that the total and average noise social cost per flight at one airport is different from another, depending mainly on the size of the noise contour and the number of residents affected.

The schemes for applying these charges vary significantly from country to country and even among airports within the same country. Noise-related costs generally have several charging mechanisms, based on the noise charge mechanisms chosen and the variables used in the noise charge formulas, as listed below:

(1) percentages of surcharges/discounts based on landing fee;

(2) landing fee according to aircraft acoustic category;

(3) noise surcharges based on noise levels, and aircraft weight and noise surcharges based on aircraft acoustic categories; and

(4) night surcharges.

Passenger Access Costs. A large number of studies found accessibility to airports, including access time, costs, and convenience, to be one of the critical factors affecting the passengers' choice of airport transport (Budd et al., 2011; Carstens, 2014; Pels et al., 2003; Tsamboulas & Nikoleris, 2008). Airport accessibility determines whether it is convenient for passengers to travel to the airport by road or railway. It can be measured by travel distance, time, or cost (Yang et al., 2016). It is becoming increasingly important to plan multiple modes of transportation connecting population centers to major airports to provide passengers more choices for their airport trips and reduce access costs and time (Akar, 2013).

Operational Readiness and Airport Transfer (ORAT) Costs. The process of taking a newly built airport facility and turning it into a fully functioning airport requires careful and sensitive management (Martín & Voltes-Dorta, 2011a). An ORAT program is critical in the formulation of new processes, staff training, and testing of each new system and procedure, from passenger and baggage handling to security and airside operations. If the existing airport is to be closed once the new airport opens, there will be decommissioning costs as well. This program requires thorough cost planning at the onset of the project. In this research, ORAT costs were expected to differentiate the costs between a new airport and an existing airport. Despite the importance of the ORAT costs in expanding airport capacity, literature that studies the cost functions of airport commissioning and de-commissioning is scarce.

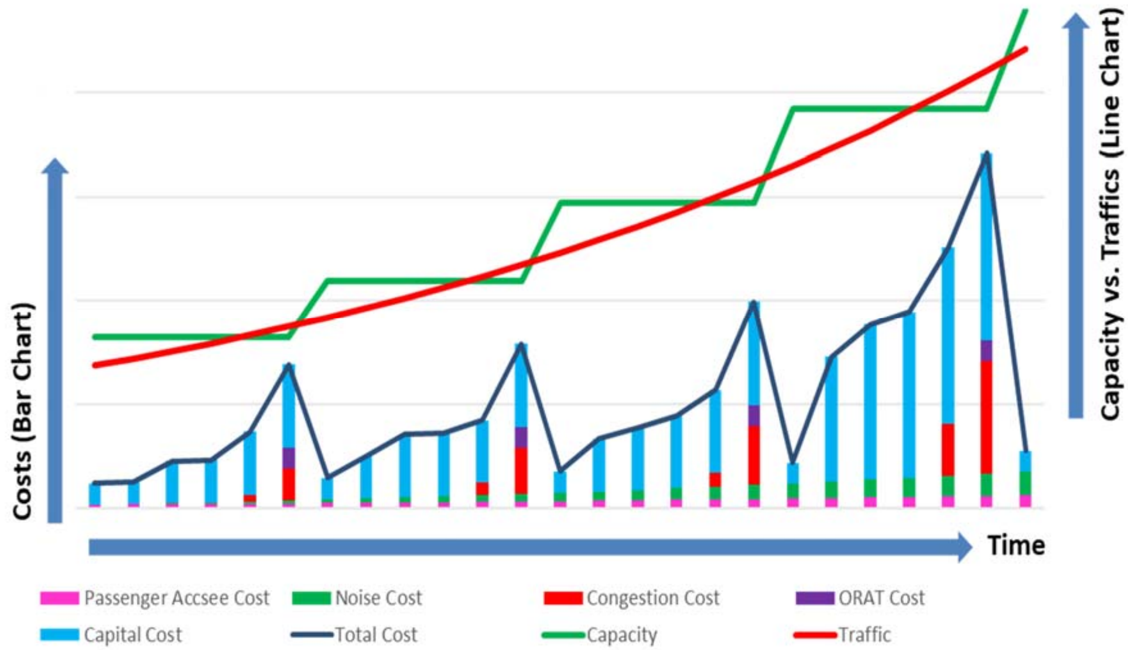
Integrated Cost Pattern with Time Series

Cost functions for airport capacity expansion are closely related to its time frame, which is associated with long-lead project time and future traffic uncertainty. While delaying capital investments in airport infrastructure by multiple years can be worthwhile, the early investment in airport capacity can prevent airports from falling short of the demand. Several solutions can be considered to measure these costs and benefits before actual capital investment.

Under a single airport condition, each aforementioned cost function is connected to traffic patterns and airport capacity. These cost functions have direct and indirect relationships primarily with airport capacity and traffic demand over time, which is illustrated in Figure 2. While capital costs and capacity expansion follow a step-curve, noise costs and passenger access costs are proportional to a non-linear passenger traffic growth line. Passenger traffic beyond the airport capacity incurs delay costs until additional capacity is added to the airport.

Figure 2

Simplified Cost Pattern for Airport Capacity Expansion on Time Series



Note. Bar graphs for cost functions and line graphs for airport capacity comparing to annual passenger traffics. No consideration for operational expenses and revenue. Non-scale and schematic representation developed by the researcher based on Martín & Voltes-Dorta (2011a), Sun & Schonfeld (2015), and Xiao et al. (2013).

Gaps in the Literature

Through the literature review, the researcher found that existing studies on airport capacity planning and decision making have certain deficiencies:

(1) Previous studies mostly emphasized the importance of airport planning in the development and capacity expansion of a single airport or specific components of the airport, such as the passenger terminal (Solak et al., 2009), runway system (De Neufville & Odoni, 2003), baggage reclaim (Young & Jeong, 2015) and boarding gate (Chen &

Schonfeld, 2013). Optimization models that considered multiple solutions to solve the capacity problem in metropolitan areas were not found.

(2) Within an optimization approach, traffic demand uncertainty has not been adequately studied in the investigations of airport capacity planning and optimization models. The use of a simulation method is expected to develop a quantifiable optimization model and help solve this complex planning problem.

(3) Existing studies regarding airport capacity expansion show limited cost profiles that are primarily related to airport authorities' activities with operations and construction works. Costs to be borne by other stakeholders, such as airlines, passengers, and communities, were barely studied. In this optimization model, other cost functions such as noise, ORAT, and passenger access costs are included to address multiple stakeholders' needs.

(4) Correlations between demand changes, increases in infrastructure capacity, and the associated cost profile over time have not been discussed. For instance, existing studies did not adequately address the capacity constraints and associated congestion effects while considering non-linear cost functions over time. Both linear and non-linear methods were used in this study to explain these relationships and solve the associated problems.

Theoretical Foundation for Modelling

Optimization Method

The optimization method primarily deals with the maximization or minimization of mathematical functions and has contributed to solving complex problems in many diverse fields, such as applied science, engineering, economics, transportation, logistics, finance, and statistics, both practically and academically. Today, decision-making for complex systems is very complicated and beyond human capability.

The aviation industry was one of the first domains to apply operations research and optimization methodology on a large scale (Cynthia & Lavanya, 2009). As early as the late 1950s, operations researchers were beginning to study how the developing fields of mathematical programming could be used to address many diverse and complicated problems faced by the aviation industry (Bazargan et al., 2013). Since then, many aviation-related issues have been the focus of active research.

Historical optimization-based approaches involved a sequential process and the assumption that future operation conditions would be known and deterministic, which resulted in solutions that were generally sub-optimal and myopic (Barnhart & Marla, 2009). For instance, the day-to-day operations of the aviation industry often face unexpected events such as crew disability, mechanical failure, and congestion at airports, which require alternative plans. To overcome this, researchers have taken to robust optimization approaches that reflect the stochastic nature of the aviation industry and developed extended optimization models that integrate many related factors and variables (Jiang & Barnhart, 2009). Table 4 shows recent aviation research that used optimization modeling to systematically address dynamic or complex problems of the industry.

Table 4

Recent Aviation Research Using Optimization Modeling

Author(s)	Area of Study	Year
Guo, Y., Wood, J., Pan, W., & Meng, Q.	Inventory optimization of airport perishable emergency supplies	2018
Ribeiro, N. A., Jacquillat, A., Antunes, A. P., Odoni, A. R., & Pita, J. P.	An optimization approach for airport slot allocation	2018
Updegrove, J. A., Jafer, S., Jessica Updegrove, & Shafagh Jafer	Optimization of air traffic control training	2017
Samà, M., D'Ariano, A., D'Ariano, P., & Pacciarelli, D.	Scheduling models for optimal aircraft traffic control at busy airports	2017
Rosenow, J., Lindner, M., & Fricke, H.	Impact of climate costs on airline network and trajectory optimization	2017
Ren, H., Chen, X., & Chen, Y.	Reliability-based aircraft maintenance optimization and applications	2017
Zhang, M., Yu, H., Yu, J., & Zhang, Y.	Dispatching plan based on the route optimization model	2016
Lernbeiss, R.	Arrival time optimization at hubs of network airlines	2016
Weiszer, M., Chen, J., & Locatelli, G.	Integrated airport ground operations	2015
Zhivov, A., Schad, S., Herron, D., Fiedler, L., Liesen, R. J., Steitz, P., & Shepherd, N.	Airport energy consumption optimization	2014
Dunbar, M., Froyland, G., & Wu, C.	Aircraft routing, crew pairing, and re-timing.	2014
Yang, S. W., & Tong, M.	Optimization of airport capacity dynamic system	2014
Inoue, H., Kato, Y., & Sakagami, T.	Airline network optimization	2013
Raj, A. J., Nithyanandam, G. K., & Jayaraj, S.	Airline revenue management	2012
Zhang, M., Guo, S., & Li, T.	The express aviation network hub optimization	2011
Zachary, D. S., Gervais, J., & Leopold, U.	Reduction of aviation noise and emissions	2010

Airport Industry and Optimization Method. The air transport sector greatly relies on the available capacity of the airport infrastructure to accommodate future growth in traffic demand. Simultaneous operations of aircraft ground movement, as well as passenger and baggage flow in time-sensitive environments at airports, increase operational complexity and safety concerns. Moreover, due to the complicated stakeholder structure and increasing non-aeronautical business activities, the theoretically available capacity of an airport cannot effectively be utilized (Sun & Schonfeld, 2015).

Under this environment, decision-making for both capacity expansion and operation planning becomes incredibly complex. Therefore, optimization modeling can be a useful and powerful tool for preparing systematic plans in advance and enhancing operational efficiency at airports, while maintaining high-level safety procedures in all foreseeable conditions.

Linear Programming. Linear programming (LP) is a mathematical technique designed to support the optimization method and help operation managers determine the best way to utilize limited resources to reach the desired objective of either maximizing the benefit or minimizing the costs (Tiwari & Kumar, 2018). There are different methods for solving LP problems, from the simplex method and Big M method to integer programming, non-linear programming, dynamic programming, stochastic programming, and goal programming (Rama et al., 2017).

Integer linear programming (ILP) is a subset of the broader field of LP. Both methods seek optimal values either by minimizing or maximizing an objective function of a set of decision variables. The transportation problem is an excellent example of a real integer linear programming problem (Price & Carter, 2017). In LP, the decision variables are continuous, whereas, in ILP, the decision variables are restricted and can take only discrete values (Rama et al., 2017). In other words, if the decisions have to be discrete, such as the number of passengers at an airport, the ILP method needs to be used. On the other hand, if some other decisions are continuous, such as the water usage of a city, LP modeling is suitable. In case there are multiple variables mixed between discrete and constant values, a mixed-integer linear programming (MILP) method can solve the problems. For instance, in a simple manufacturing problem, MILP can determine the number of check-in counters and staff at an airport that should serve the passengers for a certain period to maintain the promised level of service. If the MILP model needs to deal with both continuous and discrete variables, and nonlinear functions are embedded in the objective function, as in the study, then mixed-integer nonlinear programming (MINLP) can be used.

Simulation Model

Simulation modeling has been a widely used and popular method in operations research and management science to evaluate complex systems (García, 2017). The simulation method considers a series of assumptions to operate a specific system, which support the development of mathematical and logical relationships among its components to investigate various issues in the system. Simulation models are such widely used tools to understand the potential effects of changes in existing systems or the behavior of new systems. Using the simulation method has the following benefits (García, 2017):

(1) New policies, rules, and procedures can be tested without changing the existing systems; hence, fewer resources and costs are required compared to the actual implementation.

(2) A simulation model can investigate the behavior of non-existent or newly invented systems.

(3) The model can respond to what-if questions and deal with the uncertainty of the system's environment. This is particularly useful for this study, as it can help explore different future operational scenarios.

Simulation modeling has been actively used in the airline and airport industry in recent years (Bazargan et al., 2013). Future traffic demand forecasting cannot be accurate due to many compounding factors and complicated mechanisms that can generate uncertainty in the future demand forecast (Seger & Kisgyorgy, 2018). Therefore, it is risky to take a single measure of future traffic without consideration of the uncertainty. Moreover, under the current deregulated and highly competitive air transportation market conditions, airlines can and do make sudden changes to fares, flight schedules, and service networks (Sun & Schonfeld, 2015). For instance, the introduction of low fare services can very quickly generate a substantial increase in traffic at an airport; however, the traffic decreases when an airline collapses or abandons hub operations at the airport. Such radical changes affect both major and small airports significantly. As shown in Table 5, research using simulation modeling in the aviation domain encompasses a wide range of activities, including planning, engineering, procurement, day-to-day operations, and business management.

Table 5

Recent Aviation Research Using Simulation Modeling

Author(s)	Area of Study	Year
He, C. & Wang, C.	Airport access transport mode	2018
Verma, A., Tahlyan, D., & Bhusari, S.	Passenger service time	2018
Storer, L. N., Williams, P. D., & Joshi, M. M.	Clear-Air turbulence to climate change	2017
Zheng, J., Qiao, H., & Wang, S.	The effect of a carbon tax in the aviation industry	2017
Das, K. P., & Dey, A. K.	Risk of aviation accidents	2016
Hang Li Xiao-Bing Hu Xiaomei Guo Zhen Xu P.H.A.J.M.van Gelder.	The vulnerability of civil aviation network system to spatially localized hazards	2016
Felix, M., & Reis, V.	Performance of check-in in airports	2016
Mori, R.	Airport ground and runway performance	2015
Li, T.	General aviation demand forecasting models	2014
Khodayari, A., Olsen, S. C., & Wuebbles, D. J.	Aviation NO x -induced effects forecast	2014
Sari, D., Ozkurt, N., Akdag, A., Kutukoglu, M., & Gurarslan, A.	Level of aircraft noise	2014
Zou, X., Cheng, P., & Cheng, N.	Airport runway capacity estimation	2014
Huszar, P., Teyssèdre, H., Michou, M., Voldoire, A., Olivié, D. J. L., Saint-Martin, D., Halenka, T.	Future impact of aviation on climate	2013
Ivannikova, V., & Kryshkevych, K.	Manpower planning of airlines	2013
Boril, J., Jalovecky, R., & Ali, R.	Human-machine interaction used in aviation	2012
Ashford, N. J., Mumayiz, S., & Wright, P. H.	Airport landside operation	2011
Graf, M., & Kimms, A.	Option-based revenue management of airline alliance	2011
Vera-Morales, M., & Hall, C.	Aircraft performance and emission	2010
Sudars, M.	Aircraft guidance system	2009
Foyle, D. C., & Hooey, B. L.	Aviation human performance	2008
Lee, L. H., Lee, C. U., & Tan, Y. P.	Flight scheduling	2007

The Airline Industry. In airlines that operate and manage immense resources and staff, simulation models must come out of a solid strategy that considers the complex business environment and incorporates their current operation status, potential changes, and future directions. Simulation modeling can help make appropriate decisions in the following areas:

(1) fare structure (discount, normal, or luxury) for meeting customer demands;

(2) promotion and advertising budgets and the recruitment of salespeople;

(3) the fleet size, acquisition plan, and setting of a maintenance policy;

(4) fuel procurement planning, hedging, and budgeting;

(5) route scheduling to serve customer demands;

(6) a roster, training, and compensation system; and

(7) currency plans, dividends, and cash management that increase profitability.

The Airport Industry. Airports have faced multiple challenges with dynamic market environments of constant operational changes, such as demand fluctuation, deployment of new technology, and capacity expansion (An & Yang, 2013). In a competitive and dynamic environment, simulation tools can deal with the change in operational/physical conditions. Recently, advancements in computer technologies, software systems, and data processing techniques have strengthened simulation technologies by adding sophisticated data analytics and machine learning-based models.

Irvine, Budd, & Pitfield (2015) used Monte Carlo simulation to quantify and compare various solutions to solve a capacity problem in the London metropolitan region with three key candidate solutions: a new international airport development in the Thames Estuary; additional runways at Heathrow, Gatwick, or Stansted; and improving operational procedures at Heathrow. The simulation results suggested that it will be financially and environmentally challenging to develop the mega-infrastructure in a remote area, even though developing the new airport would be the most effective way to increase capacity on a large scale. New runways at Heathrow, Gatwick, and Stansted would provide more modest capacity increases in airport capacity in the London metropolitan area.

Currently, many major airport operators have used simulation modeling to estimate the impact of potential changes with various passenger traffic, aircraft traffic, baggage movements, and other sub-processes. Quite a few simulation studies are found in airport master planning, airspace procedures, terminal passenger flow analysis, curbside capacity studies, and airport environmental impact analysis.

Summary

Optimizing airport capacity and network in a metropolitan area can be of critical importance to ensure sustainable development of the aviation industry. While literature is abundant on airport site selection, airport capacity expansion model, and airport network designs, literature that discusses airport expansion at a metropolitan level as part of the overall transportation system is relatively meager, particularly in the field of optimization (Santos & Antunes, 2014). Therefore, this study attempt to fill the gap by presenting an optimization model for the capacity planning of the airport system at a metropolitan level as an integrated decision-making framework.

The MILP method has been widely used, demonstrating that it can provide an optimization model to address the complex environment of capacity planning, which engages multiple variables mixed between discrete and continuous values. Because the MILP model developed by this work aimed to handle optimization problems that include nonlinear functions, the MINLP was considered the most suitable method to solve the problem. Furthermore, to address the unpredictability of future traffic, different areas of methodological improvement using simulation methods as well as varying scenarios of the market have been identified in the existing literature to deal with the limitations of forecasting.

The review of the cost functions related to airport capacity expansion and congestion in metropolitan areas revealed several key aspects: (1) Airport capacities are limited mainly due to massive investment requirements and constraints of the land; (2) The type of capital expenditure and ORAT costs required to expand airport capacity can vary depending on the type of projects, such as developing a new airport or expanding existing airports; (3) Considerable time is needed to implement a capacity expansion project and increase the planned capacity; (4) The performance functions such as delay as a function of the facility utilization rate and associated delay costs are essentially nonlinear; and (5) Social and environmental costs can be mitigated by developing optimized airport networks under a multi-airport system.

Therefore, this research addresses the following aspects of the problem: (1) Focusing on cost minimization, various solutions to expand airport capacity should be modeled to optimize airport capacity planning; (2) The nonlinear response of congestion to the system capacity utilization rate should be handled with effective methods; and (3) Special considerations for future traffic demand uncertainty must be included in an airport capacity planning model intended to be practically useful.

CHAPTER III

METHODOLOGY

Due to the complexity of the problems discussed and the uncertainty of future traffic demand, this research required a robust mathematical modeling process. A combination of the MINLP and the Monte Carlo analysis helped develop a useful optimization model that can identify the optimal solution for expanding airport capacity under uncertain market conditions.

Research Method Selection

To develop an optimization model for airport capacity expansion in metropolitan areas, the researcher used a quantitative research method in the form of an optimization model. This helped deal with the cost minimization of mathematical functions to expand the airport capacity and solve complex problems at the metropolitan level. The key to this optimized decision model was to transform both controllable inputs and uncontrollable inputs into projected results, which were one of the outcomes of this research. An LP method was used to find the optimal solution that can fulfill the intended objective, subject to the given constraints.

As discussed in chapter two, LP is a mathematical technique designed to support the optimization method and help operation managers determine the best way to utilize available resources and achieve the required objective of either maximizing benefit or minimizing costs. As this research needed to handle multiple variables mixed between discrete and continuous values, some of which have nonlinear functions, the MINLP method can solve the problems.

After the development of the general MINLP model, a Monte Carlo method simulated potential values for the uncontrollable input variables. More specifically, the simulation analyzed a variety of combinations of these inputs over time, such as passenger traffic level and traffic growth. This simulation process yielded a range of possible outcomes, based on the specific traffic demand scenarios to define probability distribution.

Population and Sample

Metropolitan areas are the target population of this research. While there are many different ways to list global metropolitan areas, such as by population and urban area size, the air traffic profile of the cities was primarily used to determine the population for this study. Airbus, one of the major aircraft manufacturers defined an industrial term "Aviation Mega City" (2019), which serves over 10,000 daily long-haul passengers. These aviation mega-cities are expected to rise from 66 cities in 2018 to 83 cities in 2028 and 95 cities in 2038. In 2018, the 66 aviation mega-cities handled 40% of all passengers, over 70% of long-haul passengers, and 35% of short-haul passengers. Many of these aviation megacities developed the need for more than one airport, and some have even three or four today (Airbus, 2019).

These aviation mega-cities have been and will serve as centers for long-haul air travel. Although they have a potential for future growth as global hub airports, they are exposed to significant risks with major airlines' decisions with their hubbing strategy and potential relocation to another airport. Because of their crucial roles as global aviation hubs and the constant expansion of airport capacity they require, the 66 aviation megacities shown in Table 6 comprise the population of this study.

Table 6

Aviation Mega Cities in 2018

City Name	Region Name	City Name	Region Name
Abu Dhabi	Middle East	Los Angeles	North America
Addis Ababa	Africa	Madrid	Europe
Amsterdam	Europe	Manchester	Europe
Atlanta	North America	Manila	Asia/Pacific
Auckland	Asia/Pacific	Melbourne	Asia/Pacific
Bangkok	Asia/Pacific	Mexico City	Latin America
Barcelona	Europe	Miami	North America
Beijing	Asia/Pacific	Milan	Europe
Bogota	Latin America	Montreal	North America
Boston	North America	Moscow	CIS
Brisbane	Asia/Pacific	Mumbai	Asia/Pacific
Brussels	Europe	Munich	Europe
Buenos Aires	Latin America	New York City	North America
Chicago	North America	Osaka	Asia/Pacific
Dallas	North America	Panama	Latin America
Delhi	Asia/Pacific	Paris	Europe
Denpasar	Asia/Pacific	Perth	Asia/Pacific
Doha	Middle East	Reykjavik	Europe
Dubai	Middle East	Rome	Europe
Dublin	Europe	San Francisco	North America
Frankfurt am Main	Europe	Santiago	Latin America
Guangzhou	Asia/Pacific	Sao Paulo	Latin America
Hong Kong	Asia/Pacific	Seattle	North America
Honolulu	North America	Seoul	Asia/Pacific
Houston	North America	Shanghai	Asia/Pacific
Istanbul	Middle East	Singapore	Asia/Pacific
Jakarta	Asia/Pacific	Sydney	Asia/Pacific
Jeddah	Middle East	Taipei	Asia/Pacific
Johannesburg	Africa	Tokyo	Asia/Pacific
Kuala Lumpur	Asia/Pacific	Toronto	North America
Lima	Latin America	Vancouver	North America
Lisbon	Europe	Washington, D.C.	North America
London	Europe	Zurich	Europe

Note. Data retrieved from "2019-2038 GMF – Data spreadsheet" by Airbus, 2019, https://www.airbus.com/aircraft/market/global-market-forecast.html

Each aviation mega-city has unique characteristics and dynamics regarding air traffic demand, catchment, airport infrastructure capacity, and costs for airport capacity expansion. Therefore, representative sample cities were selected for case studies to collect the necessary data and establish practical considerations for the optimization model. Each case study helped to understand the significance and dynamics of different cost functions for the four proposed solutions, providing vital information to develop a deterministic cost optimization model.

Sampling Frame

For selecting representative samples, it was critical to identify all the relevant solutions that can resolve airport capacity problems. As illustrated in Figure 3, the capacity limitation issue can be alleviated using four solutions:

Solution 1. Expanding the capacity of an existing airport.

Solution 2. Developing a new airport and closing down the existing airport.

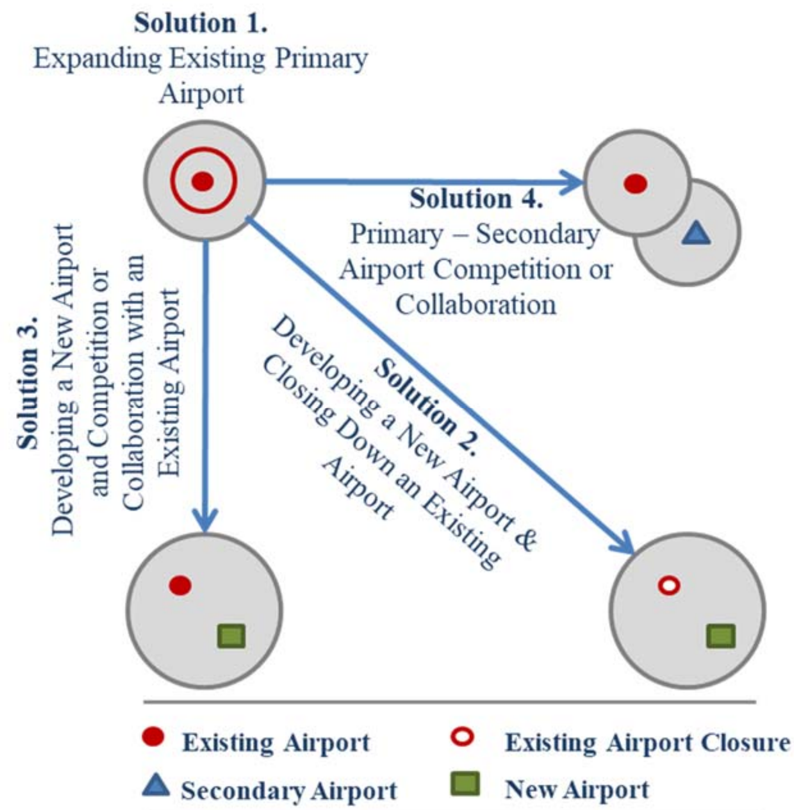
Solution 3. Developing a new airport and pairing it with the existing airport.

Solution 4. Modernizing or expanding secondary airports to collaborate with a primary airport.

Expanding the capacity of existing airport facilities is the most common method used to accommodate increasing demands (Martín & Voltes-Dorta, 2011a). However, community agreements generally constrain this due to environmental issues such as noise and air pollution. Moreover, shortages of available land and problems with existing infrastructure have often made expansions difficult. Moreover, capacity expansion projects may disrupt the day-to-day operations of the airport, thus decreasing the airports' throughput and productivity.

Figure 3

Major Solutions for Airport Capacity Expansion in Metropolitan Regions



Note. Conceptualized airport capacity expansion scenarios sketched by the researcher. The solution 1 and 2 are regarded as a single airport operation system, while the solution 3 and 4 are under a multi-airport system.

Developing a new airport adjacent to the population center and closing down the existing airport can be a feasible solution to supply additional capacity without interfering in the existing airport operations. However, building or relocating an airport on green-field sites may not be a simple solution. Massive investment is required to acquire and prepare the new airport site preparation, and the development of access infrastructure for airport users may be cost prohibitive (OECD, 2014).

Another solution is to operate a multi-airport system (MAS) by integrating the existing airport with either a new or existing secondary airport that has idle capacity. Many metropolitan regions serving more than 10 million passengers per annum have several airports under the MAS framework (De Neufville, 1995). The typical MAS features a primary airport that serves as a gateway or international hub for the major network carriers, with secondary airports focusing on domestic, short-haul, and low-cost traffic (Martín & Voltes-Dorta, 2011a). Table 7 shows major cities from around the world to exemplify these four solutions.

Four case studies were conducted to review the cost mechanism for expanding airport capacity in metropolitan areas:

Case 1: Hong Kong – Hong Kong International Airport (Solution 1);

Case 2: Munich – Munich Airport (Solution 2);

Case 3: Seoul – Incheon and Gimpo airports (Solution 3); and

Case 4: New York – JFK, Newark, and La Guardia airports (Solution 4).

By analyzing and comparing the four cases and incorporating the outcomes into the optimization model, the outcomes from this study can be used to solve any type of airport capacity expansion problems. As each case city shows specific constraints and conditions to expand its airport capacity, the case studies helped construct a deterministic optimization model as well as expand the model into stochastic what-if models under various operational scenarios. Localized cost factors such as statutory costs and taxation were not considered because they can vary by country. None of these cases was preferable to the others because the nature and value of each case have been shaped by the different strategic approaches and locational decisions made in response to various socio-economic and political situations.

Table 7

Example Cases of Airport Capacity Expansion in Major Cities

Type	City		
	Americas	Europe	Asia / MENA
Solution 1. Expansion of Existing Airport	Atlanta, San Diego, Boston, Vancouver	Madrid, Lisbon, Amsterdam, Zurich, Dublin	Hong Kong, Jakarta, Hanoi, Delhi, Abu Dhabi
Solution 2, Developing a New Airport and Closing an Existing Airport	Denver, Mexico City	Munich, Berlin, Istanbul	Doha, Jeddah, Kuala Lumpur
Solution 3. Developing a New Airport and Competition or Collaboration with an Existing Airport	Houston, Washington, Montreal	London, Paris, Milano	Dubai, Seoul, Bangkok, Beijing, Shanghai, Ho Chi Minh, Osaka, Mumbai
Solution 4. Primary-Secondary Airports Competition or Collaboration	New York, LA, San Francisco, Chicago, Dallas, Miami, Toronto	Brussel, Frankfurt, Rome, Barcelona	Manila, Tokyo, Singapore, Melbourne

Note. Cities having passenger volumes greater than 20 million are selected. Data collected by the researcher in 2019.

Design and Procedures

The researcher assessed an optimal solution for metropolitan areas that may involve various solutions and be solved through complete enumeration. The research process, as shown in Figure 4, begins with an analysis of the airport cost functions for expanding airport capacity and operating ground infrastructure under multiple, plausible airport capacity expansion solutions.

The researcher used data collected from relevant case studies to formulate the decision variables, related parameters, and constraints and to develop a standard cost optimization MINLP model. A general model was further developed and validated by using the case of Sydney's metropolitan region, which is introduced in this chapter. Then, LINGO 18.0 software was used to identify an optimal solution and required investment profile over the planning horizon.

As a final step, What-if analyses were conducted to evaluate changes in the coefficients and their effects on the optimal solution. Three scenarios were considered to develop the what-if models, as below.

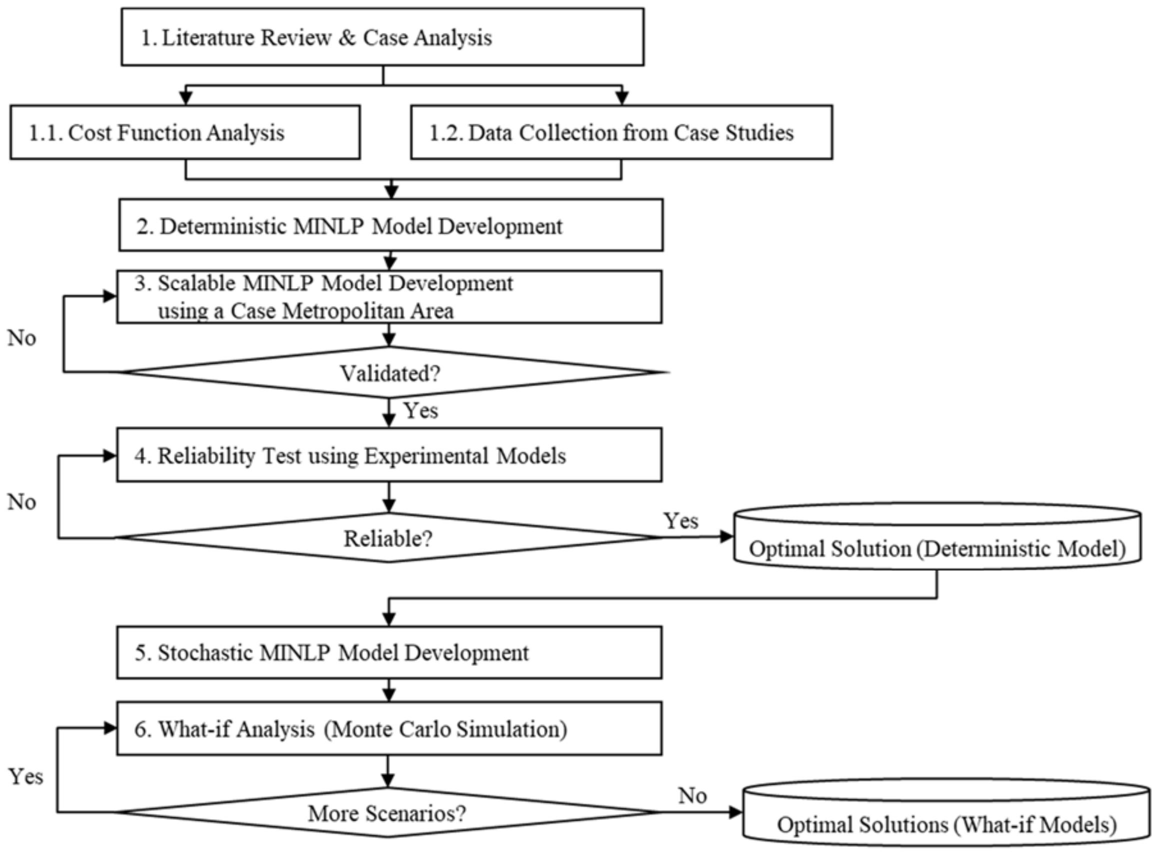
(1) Annual growth rates of passenger traffic demand are randomly selected using a Monte Carlo simulation method;

(2) A major airline changes with its business strategy and relocates its hub-base to another city – Permanent decrease of the traffic demand; and

(3) A pandemic disease causes a strong downturn in passenger traffic demand and will show resilience after several years from the event – Temporal decrease of the traffic demand.

Figure 4

MINLP and Simulation Model Flowchart



Note. Research procedure for identifying an optimal solution to expand airport capacity in metropolitan areas.

Data Sources

As the outcomes of this study aimed to help establish a decision-making framework to expand airport capacity in metropolitan areas, both industrial practices and a theoretical foundation from existing academic research are required. Along with the literature's established cost models for developing and operating airport infrastructure, recent cases of airport capacity expansion projects were reviewed and analyzed. Four recent cases on airport capacity expansion policy-making and project delivery and the OECD's study "Expanding airport capacity under constraints in large urban areas" (OECD, 2013) were used as the primary sources of reference. All this data is publicly available from each source's respective websites.

As discussed in the literature review, only a few studies were found to deal with the cost of airport capacity development and operations. The researcher referred to the mathematical formula from the cost function analysis conducted by Martín and Voltes-Dorta (2011a), Sun and Schonfeld (2015), and Xiao et al. (2013) to build the cost model after verifying the data obtained from the case study in this step. Table 8 exhibits the cost elements that were identified from the literature review and selected four cases, which were used to build a cost optimization model. Detailed review of the case studies and cost function analysis are shown in Chapter 4.

Ethical Considerations

This research involved neither human subject testing nor data collection or experimentation involving human subjects. Therefore, it does not require Institutional Review Board (IRB) approval. The archival data from existing research and selected case projects were used as the primary method of data collection to develop the MINLP model and conduct the Monte Carlo simulation.

Table 8

Airport Expansion Cost Functions for Each Solution

Solutions	Description	Cost Elements
I	Expanding the existing airport	• Operation and delay costs • Noise costs • Capital costs: Airport expansion costs • Access costs

II	Developing a new airport and closing the existing airport	• Operation and delay costs
		• Capital costs
		  o Land acquisition,
		  o Airport development, and
		  o Access infrastructure costs
		• ORAT costs
		• Access costs
		• Airport decommissioning costs

III	Developing a new airport and pairing it with the existing airport	• Operation and delay costs
		• Noise costs
		• ORAT costs
		• Capital costs
		  o Land acquisition,
		  o Airport expansion, and
		  o Access infrastructure development
		• Access cost

IV	Primary – Secondary airport collaboration	• Operation and delay costs
		• Noise costs
		• ORAT costs
		• Capital costs
		  o Airport expansion, and
		  o Access infrastructure development
		• Access costs

Model Development and Constructs

Mathematical Optimization Model Development

After the required data were collected, the cost functions and input variables were identified to define the objective function. In this stage, it should be clearly defined how the model behaves and what are the basic requirements and information necessary to develop the model in the next step.

A mathematical MINLP model was constructed considering the non-linear nature of air traffic growth and traffic-associated costs at a macro-planning level. It is essential as well as challenging to plan the future airport capacity to meet the long-term traffic demand in a changing environment with various uncertainties (Sun & Schonfeld, 2015). The demand fluctuations under deregulated market conditions add another layer of complexity to the decision-making process. Thus, a deterministic optimization model was developed and then expanded to a stochastic optimization model to address the concerns with future traffic demand uncertainty.

Sydney as a Case Metropolitan Region

The applicability of the proposed model was tested using a case metropolitan region. In this study, the Sydney metropolitan area was taken as a case region to validate the mathematical optimization model.

Current Operations. Sydney has reached a stage where no spare capacity is left. Kingsford Smith Airport (KSA), as a primary gateway to Australia, has begun to experience excessive demand. Passenger traffic demand has been anticipated to rise at about 3.4% per annum, and the aircraft movement growth would be at a rate of 1.2% (Joint Study, 2012). KSA is sensitive to weather conditions. Storms and strong winds often prevent KSA from full capacity operations. Without any disruptive event like the COVID-19 pandemic, all slots between 6 AM and 12 PM and between 4 PM and 7 PM on weekdays were expected to be reserved unless a capacity increase is made in a timely manner (Joint Study, 2012). By 2027, no more slots would be available for new flights (OECD, 2014). Before the Covid-19 pandemic, it was challenging for airlines to secure additional slots at popular time windows, even when weather conditions are benign.

Delay Level and Limitation at KSA. In 2014, arrival delays were about six minutes and departure delays were about twelve minutes on average during peak periods (OECD, 2014). As another constraint, flight procedures at KSA need to comply with an operational plan that can distribute aircraft noise across different suburbs.

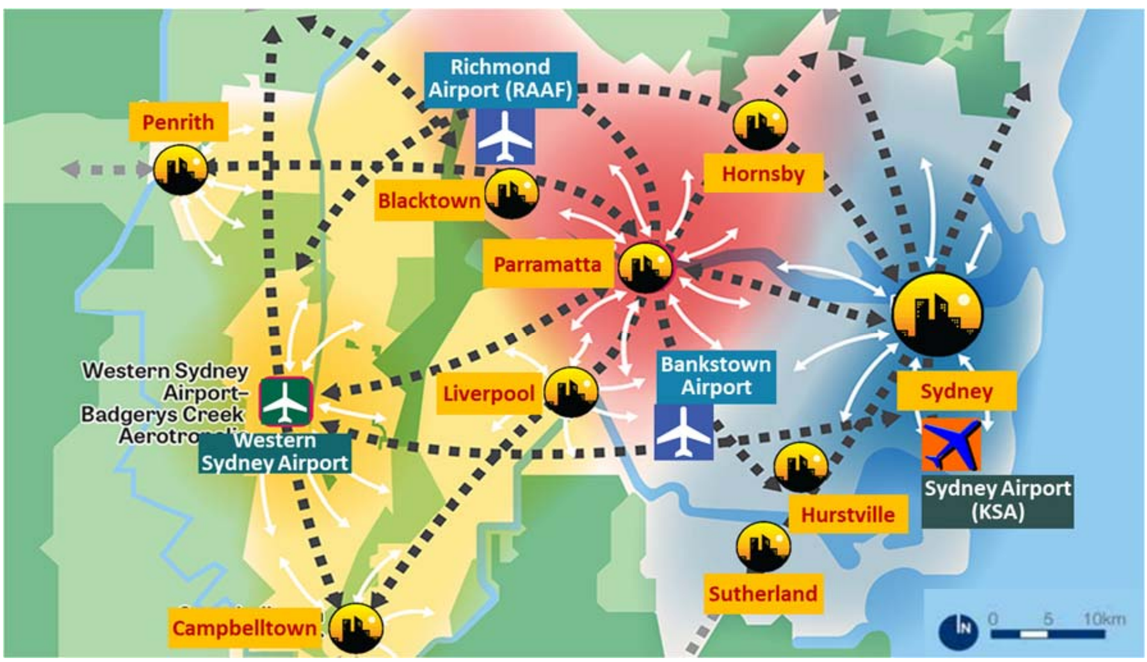
Currently, KSA has an operational limit of flight at 80 movements per hour. However, KSA can deal with a maximum of 87 movements under good weather conditions (Joint Study, 2012). Because the airport site is relatively small, there are currently only a few ways in which the airport can expand its capacity to tackle the challenges.

Other Existing Airports in Sydney. Two existing airport sites have the potential to provide Sydney with additional airport capacity: Bankstown Airport, which is the main general aviation airport, and Richmond Air Force Base. Bankstown Airport is located in the west part of Sydney and can handle regional aircraft as it has a small and constrained site. Infrastructure modernization and better connectivity to Sydney Airport for transit passengers are the keys to make this option viable. Another option is to transform the Richmond Air Force Base into a commercial airport by developing a long runway, which enable it to accommodate commercial flights. However, transforming the airbase into a commercial airport and improving connectivity to population centers will require a massive investment.

New Airport Opportunity. Western Sydney Airport (WSA) has been investigated by the Australian government for several decades as an attractive option for the government's urban development plans in the western part of the Sydney region. As substantively expanding KSA would be complicated and replacing it completely would be difficult, WSA can be a feasible solution for the sustainable growth of Sydney's aviation market in the long term. A site was selected near WSA at Badgery's Creek area, which is located about 45 km from the CBD, to develop a Greenfield airport. Currently, the design and construction of Western Sydney Airport are underway, and the government set a goal to inaugurate the new airport in 2026. Figure 5 depicts the location of the existing airports and the proposed new airport.

Figure 5

Airports and Aerodromes in the Sydney Metropolitan Region



Note. Geographical map to display the locations of airports and population centers in the Sydney metropolitan area. Modified by the researcher using the information from "Western Sydney Airport Environmental Impact Study" by Western Sydney Airport Co., 2014, https://www.westernsydneyairport.gov.au/sites/default/files/WSA-EIS-Volume-1-Chapter-7-Airspace-architecture.pdf.

Referring to this example case, a deterministic airport capacity expansion model was developed while considering the four plausible solutions, as shown in Figure 3. Four airports have the potential to develop future airport networks in the Sydney metropolitan area: one existing primary airport, two potential secondary airports, and one potential new airport to serve nine population centers. The design of the airport network was modeled in the form of a mixed-integer non-linear programming (MINLP) problem to determine the optimal solution. This general model served to formulate the costs of expanding the capacity of the future airport network in the Sydney region.

Variables, Scales, and Parameters

A decision variable for this study is an optimal solutions of airport capacity expansion and each airport's ultimate capacity within the metropolitan area. In the MINLP model, a binary variable is used to indicate the operational status of each airport, showing whether it is to be operational or not at the specific time. Table 9 shows the list of variables that were used in the optimization model. In this model, using given constraints and operational conditions on existing airport and population centers as input variables, required cost information was produced as output variables. Two decision variables were the number of airports in the metropolitan area and target capacity of each airport as identified as an optimal solution.

Table 9

Input, Output, and Decision Variables

Variable	Type	Description
Initial Airport Capacity (IAC)	Input	Existing airports' base annual passenger capacity
Maximum Airport Capacity (MAC)	Input	Airport's maximum annual passenger capacity
Distance (DAP)	Input	Distance between airports and population centers
Passenger Demand (PXD)	Input	Annual passenger demand at a specific time
Demand Population Center (PCD)	Input	Annual passenger demand at the population center
Capital Costs (CC)	Output	Costs to expand the airport capacity
Fixed Capital Costs (FCC)	Output	Fixed capital costs to expand the airport capacity
Land Acquisition Costs (LAC)	Output	Fixed capital costs to purchase the required airport land
Access Infrastructure Costs (AIC)	Output	Fixed capital costs to build access infrastructure (Road/Rail)
Utility Development Costs (UDC)	Output	Fixed capital costs to connect utilities (hydraulic/power/comm)
Variation Capital Costs (VCC)	Output	Variable capital costs to expand the airport capacity
Airfield Costs (AFC)	Output	Variable capital costs to build airfield facilities
Terminal and Building Costs (TBC)	Output	Variable capital costs to build terminals and vertical assets
Navigational Aid Costs (NAC)	Output	Variable capital costs to install NAVAIDs facilities
Airport System Costs (ASC)	Output	Variable capital costs to develop airport special systems
Operation Costs (OPC)	Output	Costs to maintain facilities and provide required services
Delay Costs (DG)	Output	Costs occurred from operational delay and congestion
Noise Costs (NC)	Output	Costs to address aircraft noise pollution
Access Costs (AC)	Output	Costs for passengers, visitors, and staff to access airports
Unit Access Cost (UAC)	Output	Individual Unit Cost to access airports
ORAT Costs (ORC)	Output	Costs for operational readiness and airport transfer
Commissioning Cost (CMC)	Output	Costs for commissioning new airports / new facilities
De-commissioning Cost (DCC)	Output	Costs for de-commissioning airport/facilities to be closed
Relocation Cost (RLC)	Output	Costs to relocate resources to new airport/facilities
Training Cost (TRC)	Output	Costs to provide staff with required familiarization training for new airport/facilities
Supplied Airport Capacity (SAC)	Output	The airport's supplied passenger capacity at a specific time
Number of airports	Decision	The number of airports serving a metropolitan area
Target Airport Capacity (TAC)	Decision	Passenger capacity of each airport at the end of the period

Note. These variables were used to develop an MINLP optimization model. The model also generated a separate variable table to develop the Monte Carlo trials. The objective function and deterministic model section of this chapter contain a detailed discussion of these variables.

Parameters:

i = A component airport in a metropolitan area, I={1, 2, …, a}, $i \in I$

j = A component population center in a metropolitan area, J={1, 2, …, p}, $j \in J$

y = Period within the planning horizon, Y={0, 1, 2, …, t}, $y \in Y$

k = Binary variable, whether airport i provide services in period y, k={0 or 1}.

δ^y = Discount coefficient for the year y, $\delta = 1/(1+\text{discount rate})$

Cost Functions

The objective of this MINLP model is to identify an optimal solution to minimize the total cost for airport capacity expansion to meet the target traffic demand. The total cost includes capital costs (CC), operation costs (OPC), delay costs (DC), noise costs (NC), passenger access costs (AC), and ORAT costs (ORC). By the inclusion of the six cost functions, this study can provide an optimization model that can address multiple stakeholders' needs and concerns. For instance, including delay costs and ORAT costs can help to expand the model's interest and benefits to the areas of airlines and airport tenants.

Capital Cost. Capital costs include various costs, as described in chapter two. According to Sun and Schonfeld (2015), it can be generally divided into fixed costs and variable costs. While the fixed costs are incurred once a project is initiated and independent of the capacity increment size, the variable costs depend on the planned capacity increment. The capital costs of Airport i in period y can be written as:

$$CC_{iy} = FCC_{iy} + VCC_{iy} \tag{1}$$

$$FCC_{iy} = LAC_{iy} + AIC_{iy} + UDC_{iy} \tag{1.1}$$

$$VCC_{iy} = AFC_{iy} + TBC_{iy} + NAC_{iy} + ASC_{iy} \quad (1.2)$$

While the fixed capital costs include land acquisition, access infrastructure, and utility installation, variable capital costs are incurred to develop in-site airport infrastructure and facilities, such as airfields, passenger terminals, cargo facilities, navigational aids, and special airport systems. The fixed capital costs are to be considered only for developing a new airport in the metropolitan area.

Operation Cost. Airport operation costs are primarily spent to maintain and operate airport infrastructure and facilities. Therefore, they are highly related to the supplied airport capacity. In this research, in order to avoid unnecessary addition of the capacities to airports compared to the demand requirement, operating costs are considered. According to Sun and Schonfeld (2015), operating costs of component i in period y can be estimated by the unit operating cost (UOPC) multiplied by the supplied capacity (SAC), as shown below:

$$OPC_{iy} = UOPC_{iy} \times SAC_{iy} \quad (2)$$

Delay Cost. Airports experience increasingly larger delays when demands keep growing, but the capacity is fixed, causing high costs to aviation stakeholders, especially when the demand exceeds the capacity limit of the airport. While the delay costs increase in proportion to traffic demand growth, the curve is nonlinear in general. According to Sun and Schonfeld (2014), delay costs are airport traffic demands multiplied by the delay level (DL) as a function of the capacity utilization rate, which can be written as follows:

$$DC_{iy} = DL_{iy} \times PXD_{iy} \tag{3}$$

In different practical settings, the delay function can assume various mathematical forms (Sun & Schonfeld, 2014). In airports, because various facilities have different operating characteristics, either simulation or benchmarking is the dominant method for estimating the delay cost. In this study, a delay function is denoted as the following exponential form:

$$DC_{iy} = D_0 \times \left(\frac{PXDiy}{SACiy}\right) \times PXD_{iy} \tag{4}$$

where:

D_0 is a delay parameter, PXD_{iy} and SAC_{iy} are passenger demand and supplied airport capacity of Airport i in period y.

Noise Cost. By using the hedonic method proposed by Morrell and Lu (2000), the annual total noise social cost of airport *i* in period *y* can be derived using the following formula:

$$NC_i = I_{NDI} \times P_i \times (N_{ai} - N_0) \times H_i \tag{5}$$

Here, I_{NDI} is a Noise Depreciation Index (NDI), and P_i is the annual average house rent adjacent to the airport i. Hence, $I_{NDI} \times P_i$ can present the annual noise social cost per residence per dB(A). The noise level above the ambient level is shown as (N_{ai} - N_0), where N_{ai} is the average noise level for the a^{th} section of the noise contour, and N_0 is the ambient noise level. Then, the outcome is multiplied by H_i, the number of households within the affected noise area.

Due to the unknown factors of the noise-affected zone and contour within each metropolitan area, localized noise studies are necessary to build an optimization model based on the specific noise conditions. In a general term, the costs to provide noise abatement measures to mitigate the negative impact of aircraft noise on the affected households can be denoted below.

$$NC_{iy} = \textit{Average cost to retrofit noise-affected houses (RHC)} \times H_{iy} \tag{6}$$

ORAT Cost. ORAT costs are a one-off cost element that occurs for airport capacity projects while commissioning new airport facilities or expanding existing facilities. The costs for decommissioning existing airport facilities can also be considered as ORAT costs. The costs for shifting resources and staff between the new and existing airports are also included when the capacity of airports is to be increased. ORAT costs can be written as:

$$ORC_{iy} = CMC_{iy} + DCC_{iy} + RLC_{iy} + TRC_{iy} \tag{7}$$

Access Cost. Access costs are directly proportional to the passenger demand between an airport and population centers. Therefore, the access costs between Airport i and Population Center j in period y can be written as below. A parameter R_0 is a meeter/greeter/staff ratio against the number of passengers:

$$AC_{jy} = DAP_{jy} \times PXD_{jy} \times (1+R_0) \times UAC \tag{8}$$

Present Value. Airport capacity planning usually involves a long-term period analysis. Due to the long-term period of planning, the researcher considered the value of all future cash flows over the entire planning period of an investment discounted to the present:

$$PV = C_t/(1+\rho)^t \tag{9}$$

where:

C_t = cost at time *t*.

ρ = discount rate.

t = years over which the future costs are expected to occur.

Data Analysis Approach

Assumptions

The problem of expanding airport capacity and appropriately distributing air traffic is quite complicated. Therefore, other than the five key assumptions in chapter one, some simplifying assumptions were made in modeling to construct the optimization model, as listed below.

(1) As the economic life of airport infrastructure generally exceeds 50 years' planning horizon of this study, replacement or decommissioning costs were considered only for the case of downsizing or closure of an existing airport, which is presented as the Solution 2 in Chapter 3.

(2) Air traffic was not segregated by traffic type such as international vs. domestic or long-haul vs. short-haul. Each airport is expected to be capable to accommodate all types of air traffic demand.

(3) For the general model, the passenger traffic and population of each population center constantly increase at a fixed annual rate throughout the timeframe of the study. This assumption was removed when a stochastic model is developed using a Monte Carlo method.

(4) Delay costs exponentially increase until additional capacity is provided to the airport through capacity expansion.

(5) Operating costs of each airport are assumed to be fixed at the rate per supplied airport capacity, but they can vary depending on the airport type. The operating costs consider both operation and maintenance activities associated with the day-to-day operation of the airport.

(6) This model evaluated a time value of money when calculating capital costs and other non-capital costs. Therefore, cost variables were discounted or inflated due to the time factor.

(7) A noise cost is incurred only after air traffic is increased at an airport.

(8) The passenger access cost is formulated by multiplying (i) the distance between airports and the population centers, (ii) the surface traffic demand from each population center, and (iii) the ground access costs per passenger per mile.

(9) Internal funding sources finance all required costs; thus, it does incur additional financing costs apart from the financial discount rate.

(10) The maximum number of airports in this metropolitan area was not limited.

(11) The maximum fiscal budget for capital costs was not limited.

(12) Whereas it takes multiple years to implement an airport capacity expansion project, in this study, the extra capacity is assumed to be added to the airport without a lead time to complete the capacity expansion project.

(13) In this model, any alternative mode of transportation such as high-speed rail connecting to other cities which may absorb the air transport demand or a new type of aircraft technology such as vertical take-off and landing aircraft were not considered.

Type of Constraints

In this optimization model, there are four major types of constraints.

(1) Airport capacity of the metropolitan area: The ultimate capacity of each airport in metropolitan areas is to be limited to a certain passenger volume per annum.

(2) Demand vs. Capacity: Airports cannot handle passenger traffic demand beyond the supplied capacity of the airports.

(3) Integer nature of variables: Passenger demand and capacity are treated as integer variables.

(4) Airport capacity: While the traffic demand of airports may decrease, airport capacity cannot be reduced.

Model Validity

It is important to validate the input data, the performance of the optimization model, and the efficiency of the proposed algorithms. It is also necessary to validate whether the model outcomes appropriately vary when coupled with the proposed key constraints. First, to validate the integrity of the mathematical computations proposed in the model, the model formula and cost input data were reviewed before executing the model for the optimal solution analysis. Each computation and variable in the model were manually examined to ensure that it produces an expected result when executed.

Second, to validate the proposed optimization model, the researcher took the example of the Sydney metropolitan area to validate the model outcomes. The results were expected to confirm whether the proposed solution for airport capacity expansion can considerably minimize the total cost requirements. Additionally, a computational study was conducted to test the proposed model by adopting different constraint values: maximum budget, target airport capacity, number of airports in the metropolitan area, and elimination of noise and delay costs from the model.

Model Reliability

To ensure the optimization model yields feasible optimal solutions from expanded applications, the researcher developed various experimental models using different values for three independent variables: annual discount rate, operation unit cost, and passenger access unit cost. Because each experiment model used different assumptions, statistical analysis to compare the outputs from the different models was not required.

Data Analysis Process

The MINLP model can be solved using multiple methods. However, due to a large number of variables in this optimization model and the non-linear nature of the air traffic growth pattern, solving it either graphically or algebraically is almost impossible. To handle the complex algorithm and mathematical model, LINGO 18.0 was used to identify the optimal solution.

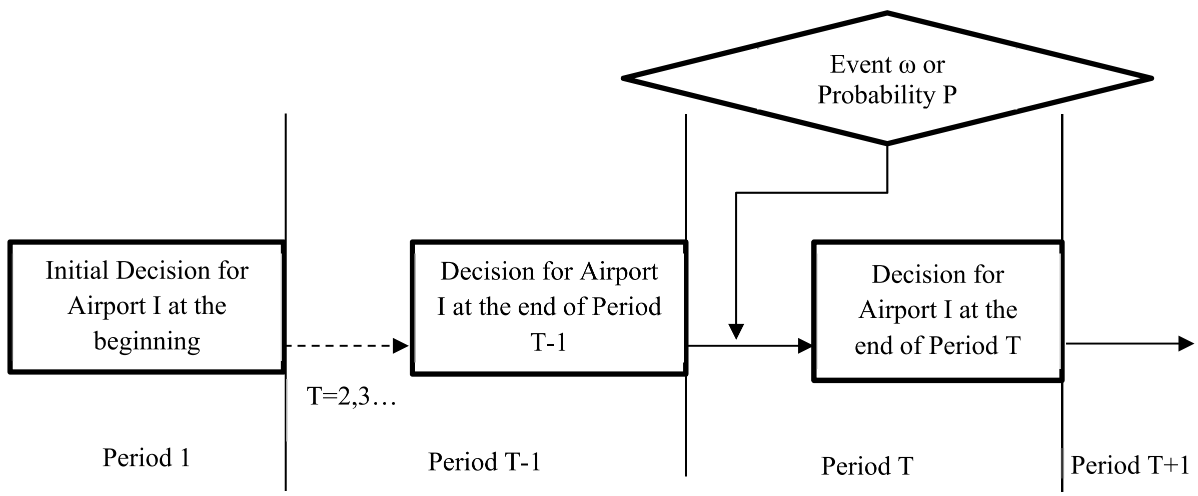
This step found an optimal solution to expand airport capacity at a minimum cost for the metropolitan area. The limitations of the traditional deterministic approach, which may result in the inability to guarantee the optimality of a solution, can be overcome by using simulation methods to solve stochastic optimization problems (Anani et al., 2017). Thus, the researcher attempted to analyze multiple plausible what-if demand patterns focused on future traffic demand due to uncertainties in social, economic, and demographic changes. The input parameters, such as the passenger traffic demand and distribution of catchment, are discrete stochastic variables. The optimization model was therefore simulated as a stochastic discrete event model with stochastic input variables using a Monte Carlo method that characterized the uncertainty inherent in the aviation system.

The what-if model formulated using a Monte Carlo simulation framework randomly selected annual growth rates for the passenger traffic and catchment distribution within the metropolitan area to provide values for the annual traffic demand. Normal probability distributions were used to generate the what-if demand patterns, which addressed the aforementioned uncontrollable input variables and the uncertainty in the future air traffic demand. In this final step, Lingo software's stochastic programming functions were used to analyze the impact of the changes in traffic demand and catchment population (input variable) on the proposed solution (output variable).

In this study, the term what-if modeling refers to multi-stage stochastic modeling, and the term stage means time series, which is an important concept considering the uncertain future traffic demand. Multi-stage decision-making with uncertainty usually involves a complex process to find an optimal solution for a long-time horizon. In a simple form, the multi-stage decision modeling for a T+1 stage can follow an alternating sequence of uncontrollable events and decisions, as illustrated in Figure 6 below. In period 1, the same parameters and input variables were used as the previously defined deterministic model. Then, each decision at the end of each time series leads to an uninterrupted sequence of following a decision sequence until the next uncontrollable event occurs. Then, each random observation is linked to an uninterrupted occurrence of the random event until the next decision point.

Figure 6

Multi-stage What-if Modelling Scheme



In this stochastic model, random variables that have a continuous event probability make it computationally impossible to handle the infinite number of possible outcomes. A Monte Carlo sampling method can approximate the challenging problem by taking a finite scenario approach. In a model with a single stochastic parameter that shows a continuous distribution, infinite event probability can be discretized by producing certain sample points and constructing a finite optimization model (Lindo

System, 2020). Using this approach, the multi-stage stochastic program can be expanded using the simplistic form below with the pre-defined deterministic model.

Minimize:

$$c_{i0}x_{i0} + E_1c_{i1}x_{i1} + E_2c_{i2}x_{i2} \ldots + E_tc_{it}x_{it} \tag{10}$$

where:

E_t = the finite random outcomes from an event at time *t*.

c_{it} = the coefficient at Airport i at time *t*.

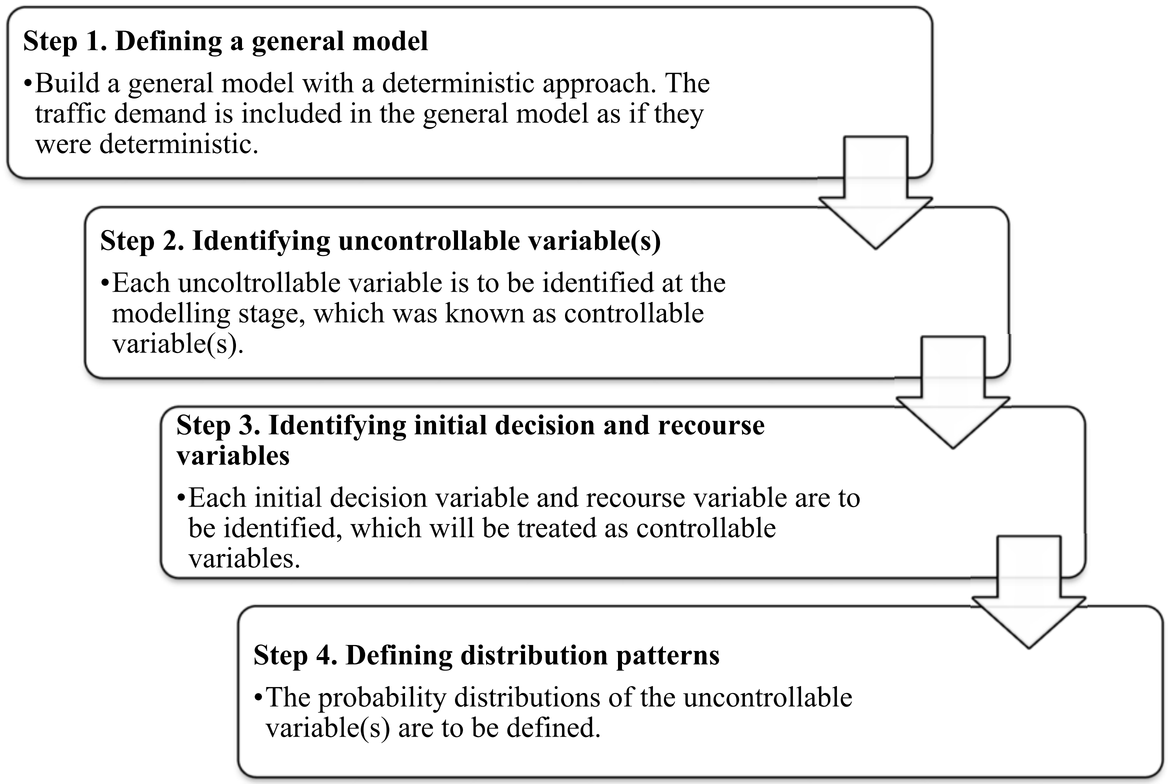
x_{it} = the cost at Airport i at time *t*.

Then, Step 6 of the model procedure which was shown in Figure 4 can be further detailed, as shown in Figure 7.

The models also executed various sensitivity analyses to see how certain constraints on the input variables, such as the available budget, maximum number of airports, and maximum future capacity, affect the pre-defined objective function and optimal solution. Moreover, by changing the objective function from cost minimization to other considerable functions, such as maximizing productivity or passenger benefits, this model was tested to see if it can accommodate other optimization functions.

Figure 7

Stochastic Model Development Steps



Note. Schematic sequence of developing a stochastic model. Adapted from "Setting up SP Models," by Lindo System Inc., 2018, Lingo 18 User Manual, p. 740.

Summary

MINLP and a Monte Carlo analysis are combined to develop an effective decision model with an optimization approach, focusing on solving airport capacity expansion problems at the metropolitan level. This mathematical optimization model aimed to identify an optimal solution for expanding airport capacity under uncertain market conditions. The air traffic and airport capacity of the Sydney region was reviewed to validate the general optimization model.

The optimal solution for metropolitan areas involves four plausible solutions—expanding an existing airport, developing a new airport and closing down the existing airport, developing a new airport and co-operating with the existing airport, and pairing the existing airport and the secondary airport under the MAS operation environment—and can be solved through complete enumeration. The research process began with an analysis of the airport cost functions for expanding airport capacity and operating ground infrastructure. Then, the researcher used data collected from relevant case studies to formulate the required decision variables, modeling parameters, and constraints. A deterministic cost optimization MINLP model was then developed, which allowed the researcher to identify an optimal solution. At the end of the research, the researcher conducted what-if analyses under various demand scenarios to assess the impact of uncertain future traffic demand on the proposed optimal model.

CHAPTER IV

RESULTS

The purpose of the study was to develop an optimization model for airport capacity development in metropolitan areas with a focus on cost minimization under an uncertain air traffic demand pattern. To solve this problem, the optimization method was used to build a base decision model with a deterministic approach. This deterministic model was validated by using the case of the Sydney metropolitan area, and its reliability was tested by changing the values of various input variables. Then, this deterministic optimization model was expanded to a stochastic model using the Monte Carlo simulation method.

This chapter analyzes and compares the results of the various deterministic and stochastic model outcomes. A total of 12 MINLP optimization models were developed to achieve the goal of this study, as shown in Table 10. While the General Model and Stochastic Model present mathematical models that can be used by any airports or metropolitan areas, these two mathematical models cannot present scalable model outcomes without specific model input parameters. Therefore, to overcome this issue, using the case of the Sydney metropolitan area, Sydney Model, Experiment 1-3 Models, and What-if 1-3 Models present scalable model outcomes and compare differences between the deterministic and stochastic models.

Table 10

MINLP Optimization Models Overview

Model	Model ID	Description
Deterministic General Model	General	A mathematical model to build a general model structure with a deterministic approach. Traffic growth rate as a controllable variable.
Deterministic Sydney Model	Sydney	Scalable model to validate the General model by using Sydney Case.
Sydney Experiment Model 1-1 Sydney Experiment Model 1-2	Experiment 1-1 Experiment 1-2	Experimental model to test the reliability of the General Model by differentiating a financial discount rate.
Sydney Experiment Model 2-1 Sydney Experiment Model 2-2	Experiment 2-1 Experiment 2-2	Experimental model to test the reliability of the General Model by differentiating operation costs.
Sydney Experiment Model 3-1 Sydney Experiment Model 3-2	Experiment 3-1 Experiment 3-2	Experimental model to test the reliability of the General Model by differentiating passenger access costs.
Stochastic General Model	Stochastic	A mathematical model to expand a deterministic model to a stochastic model. The traffic growth rate becomes an uncontrollable variable.
Sydney What-if Model 1	What-if 1	What-if scenario model by using random annual growth rates between 0%-5.8%.
Sydney What-if Model 2	What-if 2	What-if scenario model by using annual growth rates with a normal distribution pattern without an upper or lower limit of changes.
Sydney What-if Model 3	What-if 3	What-if scenario model reflecting the recent COVID-19 pandemic effect.

Deterministic MINLP Model

General Model

As discussed in the previous chapters, this cost optimization model has a focus on six cost elements that are highly related to airport capacity problems: capital cost, operation cost, delay cost, noise cost, passenger access cost, and ORAT cost. Using a deterministic approach, an objective function of the optimization model is to minimize overall costs over the timeline of the model and to find the optimal solution for airport capacity expansion. Also, this optimization model has a strong focus to decide a timeline of airport expansion in the region to support a long-term traffic demand. The objective function of the model and the decision variable of the target capacity of each airport can be written as Equation 11.

$$\min \delta^{y} \times \sum_{y}\sum_{i} (k_{iy} \times CC_{iy} + k_{iy} \times OPC_{iy} + k_{iy} \times DC_{iy} + k_{iy} \times NC_{iy} + k_{iy} \times ORC_{iy}) + \delta^{y} \sum_{y}\sum_{i}\sum_{j} (k_{iy} \times AC_{ijy}) \tag{11}$$

where:

y = period within the planning time horizon.

i = existing or potential airports within the metropolitan area.

j = population centers within the metropolitan area.

δ = discount coefficient.

k = Binary variable, whether airport i provide services in period y, k={0 or 1}.

CC = capital costs.

OPC = operation cost.

DC = delay cost.

NC = noise cost.

ORC = ORAT cost.

AC = access cost.

The six cost functions are described in detail in Chapter 3 as Equations 1, 2, 4, 6, 7, and 8, and they are summarized below. δ is the discount rate as described in (9) to calculate a present value (PV) of cost C in the future at time t.

$$CC_{iy} = FCC_{iy} + VCC_{iy} \tag{1}$$

$$FCC_{iy} = LAC_{iy} + AIC_{iy} + UDC_{iy} \tag{1.1}$$

$$VCC_{iy} = AFC_{iy} + TBC_{iy} + NAC_{iy} + ASC_{iy} \tag{1.2}$$

$$OPC_{iy} = UOPC_{iy} \times SAC_{iy} \tag{2}$$

$$DC_{iy} = D_0 \times \left(\frac{PXDiy}{SACiy}\right) \times PXD_{iy} \tag{4}$$

$$NC_{iy} = \text{Average cost to retrofit noise-affected houses (RHC)} \times H_{iy} \tag{6}$$

$$ORC_{iy} = CMC_{iy} + DCC_{iy} + RLC_{iy} + TRC_{iy} \tag{7}$$

$$AC_{jy} = DAP_{jy} \times PXD_{jy} \times (1+R_0) \times UAC \tag{8}$$

where:

FCC = Fixed Capital Cost.

VCC = Variable Capital Cost.

LAC = Land Acquisition Cost.

AIC = Access Infrastructure Development Cost.

UDC = Utility Development Cost.

AFC = Airfield Cost.

TBC = Terminal and Building Cost.

NAC = Navigational Aids System Cost.

ASC = Airport Special System Cost.

UOPC = Unit Operation Cost per Passenger.

SAC = Supplied Airport Capacity.

PXD = Passenger Demand.

H = The number of houses that are affected by the airport operations.

CMC = Commissioning Cost.

DCC = De-commissioning Cost.

RLC = Relocation Cost.

TRC = Training Cost.

DAP = Distance between Airport and Population Center.

UAC = Unit Access Cost.

R_0 = Meeter/Greeter/Staff ratio against Passenger Demand.

This General Model denotes the objective function to minimize six key cost functions for the expansion of airport capacity in the metropolitan areas to support a long-term traffic demand. Also, the outcome of the model can be used as a decision-making support tool to determine when and which candidate airport will be developed or expanded to handle the exceeding traffic beyond the existing airport capacity. From this model formulation, the target capacity of each airport (TAC) that is the decision variable of the optimization model can be written as Equation 12.

$$TAC_i = IAC_i + \sum_{y} SAC_{iy} \tag{12}$$

where:

TAC = Target Airport Capacity.

IAC = Initial Airport Capacity.

SAC = Supplied Airport Capacity.

y = period within the planning time horizon.

i = existing or potential airports within the metropolitan area.

Since demand and capacity have a strong correlation and the number of passenger traffic is finite, we can write the following constraints:

$$SAC \geq PXD \tag{13.1}$$

$$TAC \leq MAC \tag{13.2}$$

$$PXD, IAC, SAC, TAC, MAC \geq 0 \text{ and integer} \tag{13.3}$$

$$k_{iy} = 1 \text{ if Airport } i \text{ is operating in period } y \text{, otherwise } 0 \tag{13.4}$$

Here, SAC and MAC denote supplied airport capacity and maximum airport capacity respectively, and PXD is passenger demand. In this model, DC shows nonlinear patterns as per the proposed formula defined in Chapter 3. A discount rate and passenger traffic demand also add nonlinear attributes to the optimization model. Overall, this optimization model needed to solve airport capacity problems in consideration of both continuous and discrete variables, and nonlinear functions in the objective function and the constraints. Therefore, mixed-integer nonlinear programming (MINLP) was identified to solve this airport capacity problem.

Model Validation: Sydney Model

Model Description. To validate the General Model and to produce scalable research outcomes, a Sydney Model was developed by using a case of the Sydney metropolitan area. The Sydney metropolitan area was selected to validate the General Model because the Sydney region can provide all four possible airport capacity expansion solutions as defined in Table 7: Solution 1. Expand existing commercial airport(s); Solution 2, Develop new airport(s) and close existing airport(s); Solution 3. Develop new airport(s) to handle exceeding traffic beyond the capacity of the existing airport(s); and Solution 4. Transform non-commercial airport(s) into commercial airport(s) to resolve the over-capacity problem in the metropolitan area.

The general situation of the Sydney region's airport capacity problems in 2011 and potential solutions are described in Chapter 2. Specific conditions to develop the deterministic case MINLP model are to be considered as shown in Table 11, Table 12, and Table 13, which have been extracted from two major data sources: Sydney Airport Master Plan 2033 (Sydney Airport Corporation Limited, 2013) and the Joint Study conducted by Australian and NSW Government (2012) to assess the requirement for additional aviation capacity for the Sydney metropolitan region. Both studies show data collected from various research in 2011.

Key Input Parameters. In this study, the Sydney Model used the input parameters based on the information presented in the aforementioned two existing studies, Sydney Airport Master Plan (2013) and the Joint Study (2012), and was compared to the stochastic model which incorporates various demand forecasts scenarios. This comparison provides a meaningful research outcome to understand the impact of the demand uncertainty on the proposed optimization model and highlight the importance of the stochastic model over the deterministic model.

Table 11

Key Parameters for Sydney Model

Timeline	50 years: Year 0 – Year 50
Sydney Region Passenger Demand Forecast[a]	Base year for Year 0: 37.0 MAP Forecast for Year 10: 50.6 MAP Forecast for Year 25: 75.8 MAP Forecast for Year 50: 145.7 MAP Annual passenger traffic growth: - 3.7% (2011-2020), 2.8% (2020-2035), 2.6% (2035-2060) - Average Growth Rate: 2.8% / Standard Deviation: 0.00356
Discount Rate[b]	7% per annum for a discounted rate, 3% per annum for CPI rate increase
Airport Operation Costs (OPC)[c]	OPC(AU$)/Pax Capacity = Type 1: 6, Type 2: 6, Type 3: 8, Type 4: 5
Airline Passenger Delay Costs (DC)	DC per passenger per hour: AU$ 40.06 (Business) / AU$13.67 (Leisure)
Average Noise Abatement Cost[d]	AU$20,000 per affected house in terms of the population within a 20 Australian Noise Exposure Forecast (ANEF) contour
ORAT Costs	ORC(AU$)/Pax Capacity = Brownfield: 6, Alteration: 8, Greenfield: 10
Surface Transport Demand Ratio	Passenger: Employee: Meeter/Greeter = 56%: 24%: 20%
Required Land Size[e]	Type 1 Full-service International Airport: 1,012.6 ha Type 2 Land-constrained International Airport: 944.9 ha Type 3 Limited-service Regular Passenger Transport Airport: 723.3 ha Type 4 Minimum-service Airport Servicing GA / Limited RPT: 366 ha
Constraints	A legislated cap of 80 aircraft movements per hour will be maintained at Sydney (Kingsford-Smith) Airport. Sydney Airport and Bankstown Airport cannot construct additional runway due to land constraints.

Note. All figures presented in this table are extracted from the Joint Study (Australian and NSW Government, 2012). [a]The underlying assumption for the air traffic demand of the Sydney region is that additional airport capacity can be developed to eliminate current capacity constraints that can not be provided by the existing Sydney Airport. [b]The analysis timeframe of this study was over a 50-year time horizon, using a 7% real discount rate based on Commonwealth evaluation guidance. [c]Operating costs were estimated by Airbiz as a part of the Joint Study (2012) based on benchmarking airports in Australia. [d] The number of persons residing within 20 ANEF contours is assumed by WorleyParsons as a part of the Joint Study (2021). [e]Generic airport types 1, 2, 3, and 4 are defined by the Joint Study (2012).

Table 12

Potential Airport Expansion in Sydney Metropolitan Region

Airport	Commercial Operations in 2012			Potential Expansion			
	Airport Type	Site	Available Capacity	Airport Type Conversion	Required Investment (Billion AU$)[a]	Maximum Capacity / ARC Code[b]	Weighted Distance to Centers[c]
Kingsford Smith (SYD)	International + Domestic	907 ha (2241ac)	48MAP	Type 2 → Type 2	72MAP: 5.2	72MAP / Code 4F	22.52km
Bankstown (BWU)	GA	313 ha (770ac)	Nil	Type 4 → Type 3	1MAP: 0.3 5MAP: 1.7 15MAP: 4.7	10MAP / Code 3C	23.34km
Richmond (RCM)	Air Force Base	800 ha (1977ac)	Nil	Type 4 → Type 2	1MAP: 0.15 5MAP: 0.5 10MAP: 3.85 20MAP: 5.4 32MAP: 10.8	32MAP / Code 4E	54.18km
Western Sydney (W_SYD)	Not existing	Nil	Nil	Nil → Type 1	10MAP: 3.27 15MAP: 4.15 37MAP: 9.9 60MAP: 13.7 82MAP: 17.5	82MAP / Code 4F	51.31km

Note. All figures presented in this table are extracted from the Joint Study (Australian and NSW Government, 2012) and the base date of all costs is 1 January 2011. [a]The required investment costs are discounted at 7% per annum to 2011 and no budget limitation is considered in this deterministic model. Based on the defined capital investment program of each airport, linear equation models are produced: CC_{SYD}=216.7×Increased Passenger Capacity, CC_{BWU}=313.5×Increased Passenger Capacity, CC_{RCM}=333.8×Increased Passenger Capacity, CC_{WEST_SYD}=FCC(Land Acquisition) + 210.3×Increased Passenger Capacity. [b]Aerodrome Reference Code (ARC) Codes are defined by ICAO, which is shown in ICAO Annex 14. [c]Weighted average distance to/from population centers is calculated as shown in Table 13 based on the airport passenger demand profile in 2011. (Joint Study, 2012).

Table 13

Major Population Centers in the Sydney Metropolitan Region

Population Centre	Origin/ Destination Demand Ratio[a]	Distance to/from Airports (km)[b]			
		SYD	BWU	RCM	W_SYD
Sydney Inner & East	46.6%	13.6	24.8	64.2	60.3
Sydney North	16.7%	22.8	27.4	53.8	57.5
Sydney West	10.9%	16.1	4.4	56.8	36.5
Hurstville	6.2%	8.7	13.2	63.2	47.9
Parramatta	4.2%	26.4	13.9	35.8	34.8
Penrith	3.6%	59.1	48.1	24.5	18.6
Sutherland	3.3%	18.3	23.9	74.5	59.4
Campbelltown	2.9%	43.6	27.9	62.3	30.7
Blacktown	2.9%	44.3	28.4	26.6	32.8
Liverpool	2.7%	26.2	6.1	49.4	25.4
Weighted Average Distance	100%	22.5	23.3	54.2	51.3

Note. [a]The origin and destination demand of airport users in the Sydney region was sourced from Booz & Company, which was part of a Joint Study by the Australian and NSW Government (2012). The National Visitors Survey 20052009 (NVS) and the International Visitors Survey 2005-2008 (IVS) provide information on the profiles of passengers traveling to and from the Sydney Airport. [b]Distance between airports and each region is measured by the shortest surface access route using Google Map.

The Sydney Model algorithms and input data to solve this MINLP problem are included in Appendix A. This model has a deterministic nature to decide the airport capacity expansion options without consideration of uncertain future air traffic demand. It also aims to provide a projection for the required costs to achieve the proposed objectives.

Model Outcomes. Sydney Model was performed using software from LINDO System Inc called Lingo. The researcher used Extended LINGO/Win64 Release 18.0.44. Figure 8 shows the model output summary status. This MINLP model contains 3,717 variables which include 388 non-linear variables. Out of the total of 7,774 constraints, 1,767 constraints show a non-linear nature. Using a PC with Intel Core i3@ 2.00GHz CPU and 8GB RAM with a Microsoft Windows 10 operating system, it took 69 seconds and 1,737 iterations to solve this deterministic MINLP model.

Figure 8

Sydney Model Output Status Summary

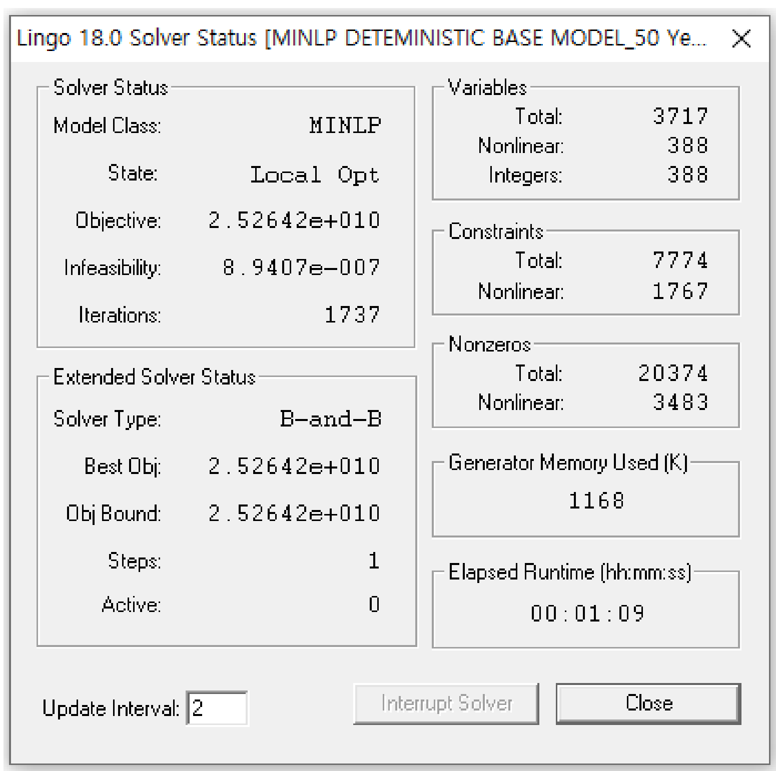


Table 14 presents the projected annual passenger demand for the Sydney region for a 50-year timeline and proposed airport capacity to accommodate the demand. The outcomes from the Sydney Model suggest a dual airport system in Sydney, from the cost minimization perspective: The existing Sydney Airport and new Western Sydney Airport are identified to serve the air transport industry within the Sydney region from Year 23. In the meantime, Bankstown Airport and Richmond Airport are not identified as cost-efficient solutions to service the growing air traffic demand of the Sydney region.

Table 14

Sydney Model: Traffic Demand and Airport Capacity (Passengers in Thousand)

Year	1	6	11	16	21	26	31	36	41	46	50
Demand	36,967	44,011	52,029	59,790	68,710	78,784	89,528	101,739	115,614	131,382	145,532
Capacity											
SYD	48,000	48,000	52,029	59,790	68,710	72,000	72,000	72,000	72,000	72,000	72,000
BWU	0	0	0	0	0	0	0	0	0	0	0
RCM	0	0	0	0	0	0	0	0	0	0	0
W_SYD	0	0	0	0	0	6,784	17,528	29,739	43,614	59,382	73,532
Total	48,000	48,000	52,029	59,790	68,710	78,784	89,528	101,739	115,614	131,382	145,532

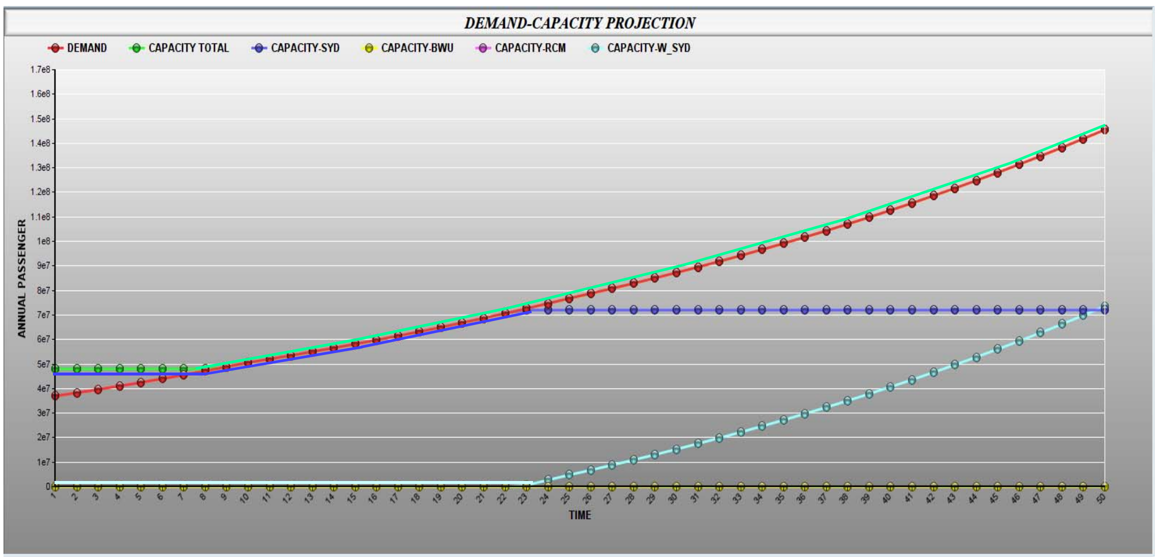
Note. This table shows the optimized airport capacity solution using the traffic forecast date from the Joint Study (2012) conducted by the Australian and NSW governments.

Between Year 1 and Year 23, the existing Sydney Airport will serve as the sole airport in the Sydney region by increasing its capacity from its current capacity of 48 million passengers per year (MAP) to its maximum capacity of 72 MAP. Because the traffic demand is forecasted to outpace the current capacity of Sydney Airport from Year

9, an additional capacity expansion for Sydney Airport needs to be considered in the early stage. Once the traffic demand reaches the maximum capacity of Sydney Airport, Western Sydney Airport will be operational to accommodate the exceeding traffic demand from Year 24. Figure 9 presents the air traffic demand and capacity projection over time.

Figure 9

Sydney Model: Traffic Demand vs. Airport Capacity Projection



Note. This line chart shows the optimized airport capacity expansion solution to accommodate future air traffic demand of the Sydney region which was forecasted by the Joint Study (2012). As shown in this figure, a dual airport solution is recommended to minimize overall cost requirements.

Table 15 projects the cost profile to develop and operate the dual airport system in the Sydney region for a 50-year timeline. Figure 10 presents the capacity expansion costs over time. Whereas the total traffic demand is expected to grow at a steady rate, as shown in Figure 9, the cost graph shows a slow decreasing slope from Year 10 except for Year 22 because of 4% of the annual discount rate applied to each cost element. Year 22 shows a stiff increase in the capital cost due to the investment to inaugurate the new Western Sydney Airport in Year 23. Figure 11 and Figure 12 illustrate the required costs to provide the required airport capacity and operate the airport facilities over time for Sydney Airport and Western Sydney Airport, respectively. A capital cost input is required for Sydney Airport between Year 9 and Year 23 to add the capacity up to its maximum capacity of 72 MAP. In Year 22, significant capital investment is shown for the inauguration of Western Sydney Airport, which requires fixed capital costs to the new airport site. The continuous capital cost will be invested on Western Sydney Airport from Year 23 to accommodate the growing traffic demand.

Table 15

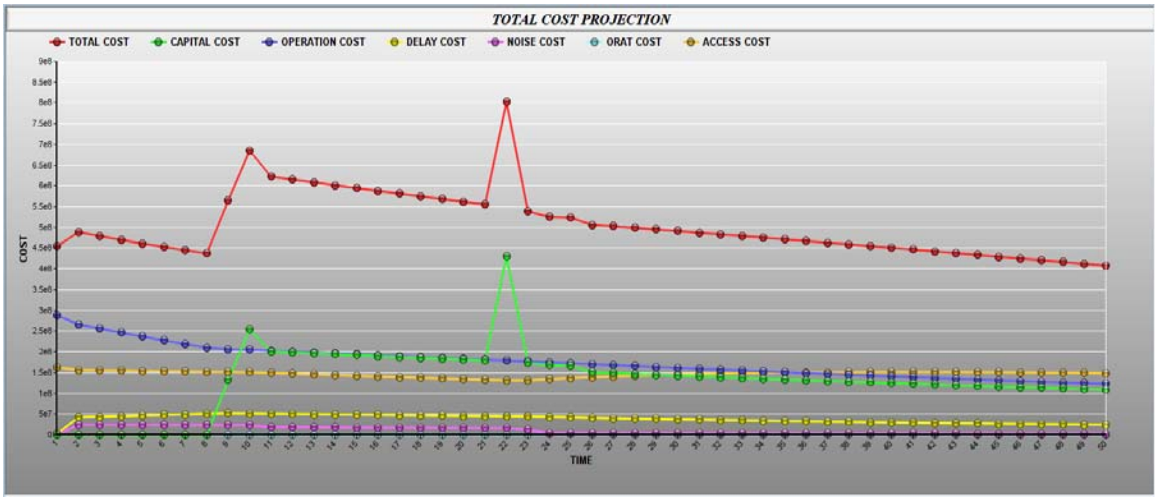
Sydney Model: Airport Capacity Expansion Cost Projection (AUD in Thousand)

Year	1	6	11	16	21	26	31	36	41	46	50
Capital Cost	-	-	201,145	189,990	179,454	150,655	140,716	131,432	122,761	114,661	108,569
Operation Cost	288,000	227,610	202,782	191,536	180,914	170,499	159,250	148,744	138,930	129,764	122,869
Delay Cost	2,847	47,839	50,695	47,884	45,228	41,156	36,694	32,838	29,491	26,576	24,509
Noise Cost	-	23,849	18,538	17,510	16,539	3,587	3,350	3,129	2,922	2,730	2,584
ORAT Cost	-	-	834	787	744	1,363	1,273	1,189	1,110	1,037	982
Access Cost	163,004	153,373	149,025	140,761	132,954	139,093	146,327	150,161	151,340	150,468	148,623
Total	453,851	452,672	623,023	588,471	555,836	506,355	487,612	467,494	446,557	425,238	408,137

Note. This table presents the overall cost information to provide the required airport capacity in the Sydney region based on the traffic forecast date from the Joint Study (2012) conducted by the Australian and NSW Government. A 4% discount rate per annum is applied.

Figure 10

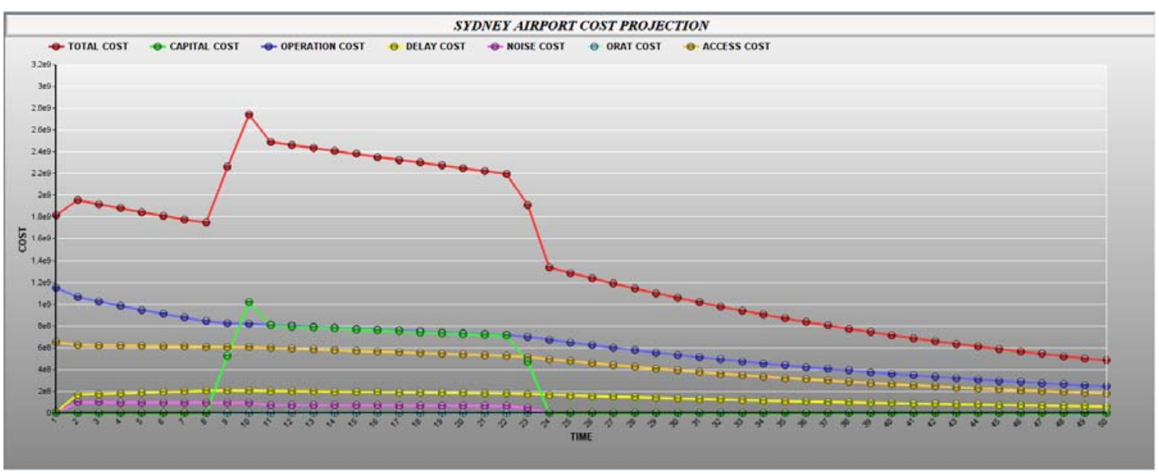
Sydney Model: Capacity Expansion Total Cost Projection (in AUD)



Note. This figure shows the total cost estimate results from Sydney Model to provide the required airport capacity in the Sydney region through a dual airport solution. A peak cost input in 2022 will be required to purchase airport land for Western Sydney airport.

Figure 11

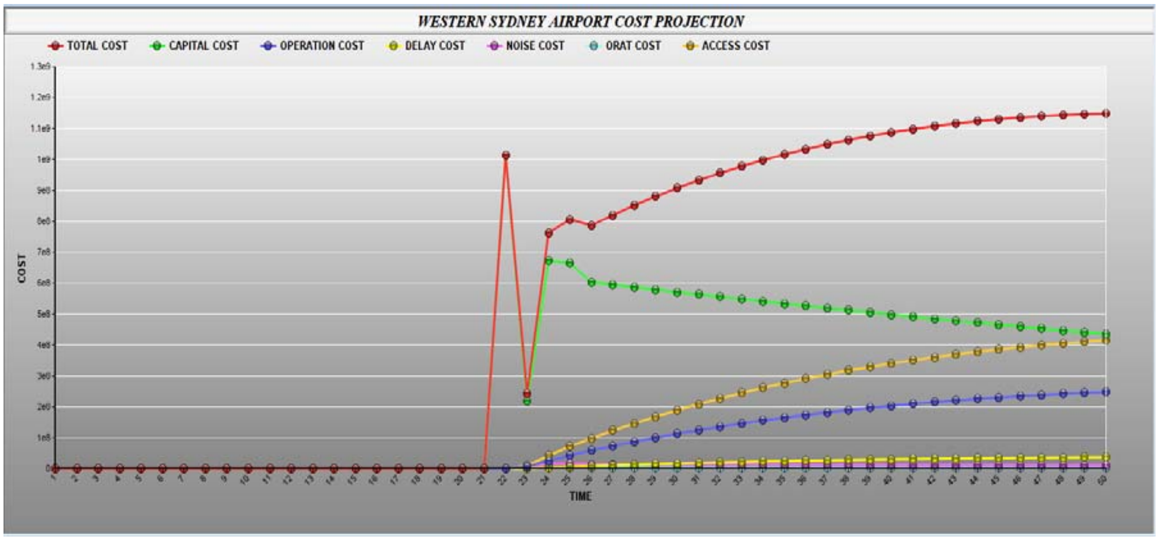
Sydney Model: Sydney Airport Cost Projection (in AUD)



Note. This figure shows the total cost estimate results from Sydney Model to expand the capacity of the existing Sydney Airport.

Figure 12

Sydney Model: Western Sydney Airport Cost Projection (in AUD)



Note. This Figure shows annual cost inputs from Year 22 to develop and operate the new Western Sydney Airport.

Using the case of the Sydney region, the General Model was successfully validated, yielding an optimal solution along with scalable model outcomes over 50 years. Given that the traffic demand growth rate is fixed, four cost functions that are correlated with passenger demand - operation cost, passenger access cost, delay cost, and noise cost - show a steady and continuous growth trend, following the traffic demand pattern. Capital cost and ORAT cost are directly influenced by airport capacity increase and required to be invested in advance to cater for the increasing future traffic demand.

Reliability Test: Six Experiment Models

In optimization models, reproducibility and reliability are key features to ensure the effectiveness of the model and avoid potential model processing issues for future expanded applications. In complex and long-term multi-period MINLP models like this study, challenges can occur when the model does not present solid boundary conditions or the solution is prone to slightly off from the boundary. Also, vanishing eigenvectors are a problem in MINLP models that do not have a pendant in MILP.

Therefore, the primary objective of the model reliability experiment was to compare the performances of the optimization model system under the different operational scenarios using the same model structure, in contrast to the baseline operational scenario. In particular, this experiment engaged different input parameters such as operation costs, access unit costs, and financial discount ratio. The result of the reliability experiment using six Experiment Models is shown in Table 16.

All six Experiment Models which are intended to validate the reliability of the Base Model present effective model outcomes to achieve the cost minimization goal. Like the Sydney Model, Experiment Model 1 and Experiment Model 2, which applied differentiated discount rates and operation unit costs, recommend a dual airport solution from Year 23. The existing Sydney Airport is suggested to accommodate the traffic capacity at the maximum allowable capacity and then a new Western Sydney Airport will be operational to handle the exceeding air traffic demand. Figure 13, Figure 14, Figure 15, and Figure 16 demonstrate different levels of the discount rate and operation unit cost do not affect the optimal solution proposed by the Sydney Model.

In contrast to Experiment Model 1-2 which used a 6% annual discount rate and shows a stiff downward trend of the time-cost graph, as displayed in

Figure **20**, Experiment Model 1-1 presents a gradual upward trend, as shown in Figure 19, due to the lower financial discount rate within the cost optimization model. Both Experiment Model 1 and Experiment Model 2 indicate the discount rate and operation unit cost do not affect the model outcome in terms of the optimal solution of the airport expansion.

Importantly, Experiment Model 3 indicates that the different levels of passenger access cost to/from airports may suggest a different solution. Experiment Model 3-1, which incorporates a lower rate of access unit cost at AU $0.07/km per passenger, presented a similar solution to the Sydney Model, Experiment Model 1, and Experiment Model 2: Western Sydney Airport needs to be operational when Sydney Airport reaches a maximum capacity from Year 23, as shown Figure 17. Lower access costs can be achievable by introducing a more convenient mode of public transportation between population centers and airports, such as train and bus systems. Experiment Model 3-2 considered a higher rate of access unit cost at AU $1.5/km per passenger. It can happen when the airport system does not provide an efficient public transportation system and motivates passengers and airport visitors to use private vehicles or taxis. This model recommends the early introduction of a dual airport system of Sydney Airport and Western Sydney Airport from Year 9 to achieve the cost optimization goal, as shown in Table 17 and Figure 18.

The result from Experiment Model 3 demonstrates the effectiveness of the model. By splitting the catchment of the passenger demand into two distant airports, Sydney and Western Sydney Airports, the dual airport system can contribute to achieving the cost optimization goal by reducing passenger access costs. Table 17 shows a comparison of the six Experimental Models against the Sydney Model in terms of cost proportion among the six cost components. A more detailed review of this difference is discussed in Chapter 5.

Table 16

Sydney Base Model vs. Six Experiment Models: Model Performance

Model ID	Manipulated Input Variable	Parameter		Result	Model Performance	
		Sydney Model	Experiment Model		Runtime	Iteration
Sydney Model	-	-	-	Success	00:01:09	1737
Experiment 1-1 Model	Discount Rate	4%	2%	Success	00:01:32	2041
Experiment 1-2 Model	Discount Rate	4%	6%	Success	00:01:11	1076
Experiment 2-1 Model	Operation Unit Cost	SYD, RCM W_SYD: AU$6, BWU: AU$8	All Airports: AU$5	Success	00:00:41	1064
Experiment 2-2 Model	Operation Unit Cost	SYD, RCM W_SYD: AU$6, BWU: AU$8	All Airports: AU$10	Success	00:00:43	951
Experiment 3-1 Model	Access Unit Cost	AU$0.11/km	AU$0.07/km	Success	00:00:42	878
Experiment 3-2 Model	Access Unit Cost	AU$0.11/km	AU$0.15/km	Success	00:01:43	2,832

Note. This table shows the overall comparison of the six Experiment Models to test the reliability of the General Model, by differentiating input values of the three parameters: discount rate, operation unit cost, and access unit cost. All six models successfully present an optimal solution to minimize the cost to meet the increasing air traffic in the Sydney region.

Table 17

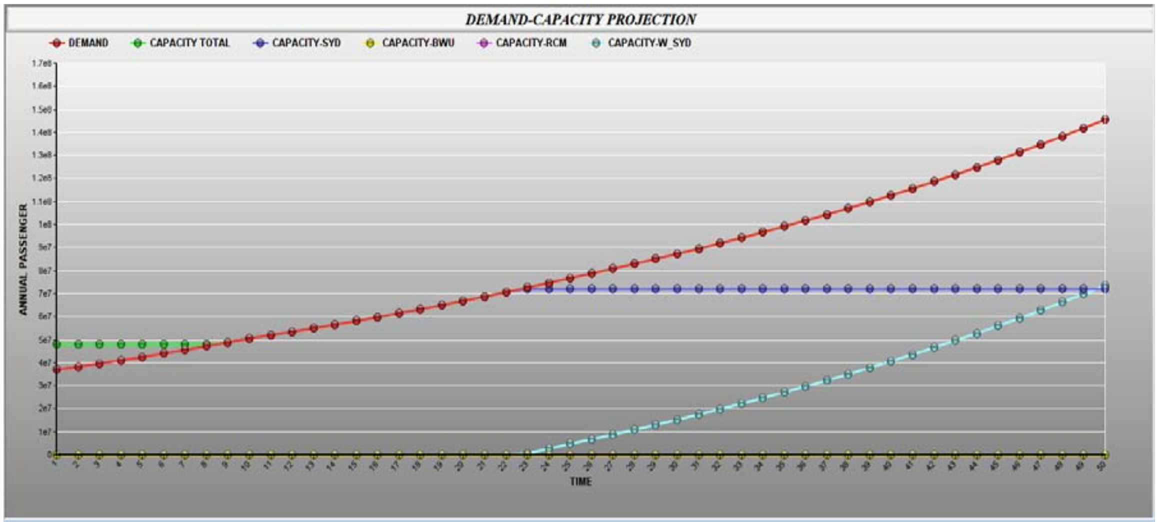
Sydney Base Model vs. Six Experiment Models: Model Outputs Comparison

Model ID	Proposed Solution	Total Costs (Y1-Y50, in AU$000s)	Cost Distribution (%)						Remark
			CC	OPC	DC	NC	ORC	AC	
Sydney Model	Dual Airports SYD: Y1-Y50 W_SYD: Y23-Y50	25,259,885	26.2%	34.9%	7.6%	2.1%	0.2%	29.0%	Figure 9 Figure 10
Experiment 1-1 Model	Dual Airports SYD: Y1-Y50 W_SYD: Y23-Y50	42,105,310	27.3%	33.7%	7.5%	1.7%	0.2%	29.7%	Figure 13 Figure 19
Experiment 1-2 Model	Dual Airports SYD: Y1-Y50 W_SYD: Y23-Y50	17,031,179	27.6%	34.8%	7.5%	2.3%	0.2%	27.6%	Figure 14 Figure **20**
Experiment 2-1 Model	Dual Airports SYD: Y1-Y50 W_SYD: Y23-Y50	23,836,811	27.8%	31.0%	8.1%	2.2%	0.2%	30.7%	Figure 15 Figure **21**
Experiment 2-2 Model	Dual Airports SYD: Y1-Y50 W_SYD: Y23-Y50	30,942,668	21.4%	46.8%	6.2%	1.7%	0.2%	23.7%	Figure 16 Figure 22
Experiment 3-1 Model	Dual Airports SYD: Y1-Y50 W_SYD: Y23-Y50	22.652,467	29.2%	38.9%	8.5%	2.3%	0.2%	20.9%	Figure 17 Figure 23
Experiment 3-2 Model	Dual Airport SYD: Y1-Y50 W_SYD: Y9-Y50	28,297,552	24.0%	31.1%	6.7%	1.8%	0.2%	36.2%	Figure 18 Figure 24

Note. The model output values provide cost profiles from the six Experiment Models.

Figure 13

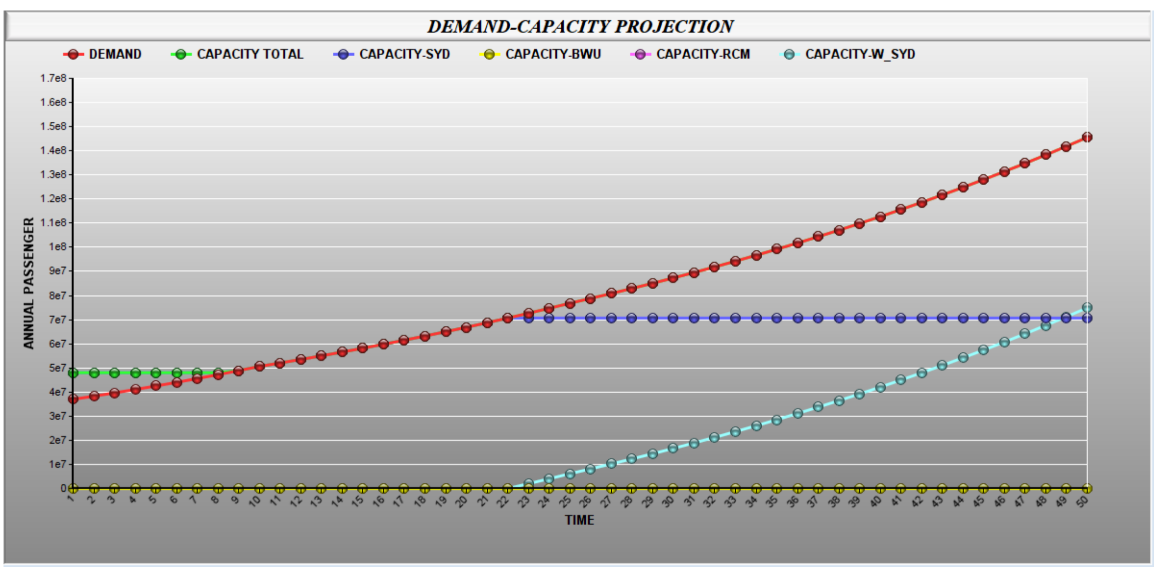
Experiment Model 1-1: Demand vs. Capacity (Discount Rate = 2%)



Note. This figure shows the airport capacity distribution results of Experiment Model 1-1 for 50 years. The proposed capacity expansion solution is identical to the Sydney Model.

Figure 14

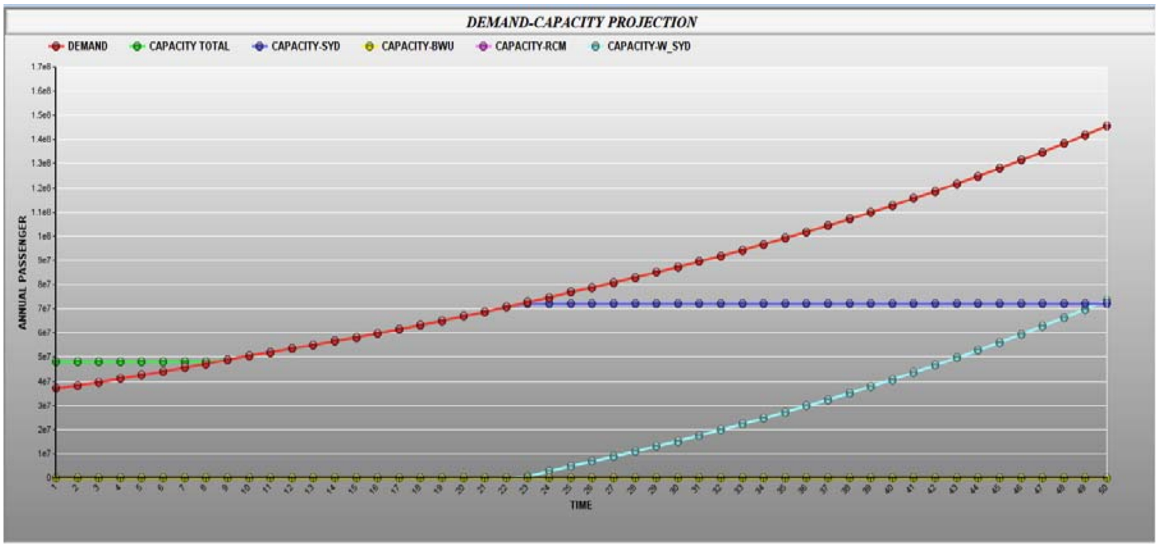
Experiment Model 1-2: Demand vs. Capacity (Discount Rate = 6%)



Note. This figure shows the airport capacity distribution results of Experiment Model 1-2 for 50 years. The proposed capacity expansion solution is identical to the Sydney Model.

Figure 15

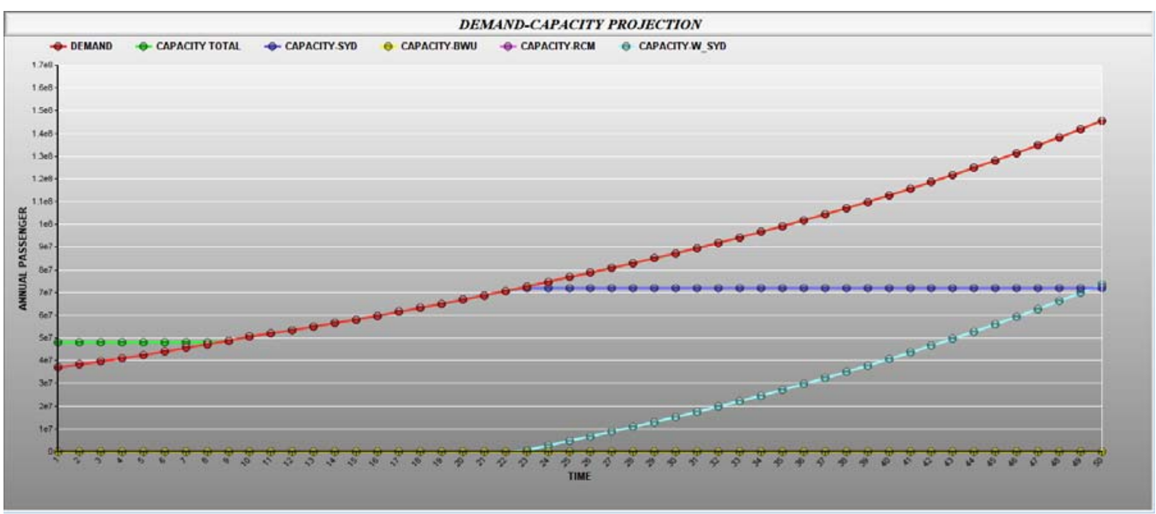
Experiment Model 2-1: Demand vs. Capacity (Operation Unit Cost = AU $5)



Note. This figure shows the airport capacity distribution results of Experiment Model 2-1 for 50 years. The proposed capacity expansion solution is identical to the Sydney Model.

Figure 16

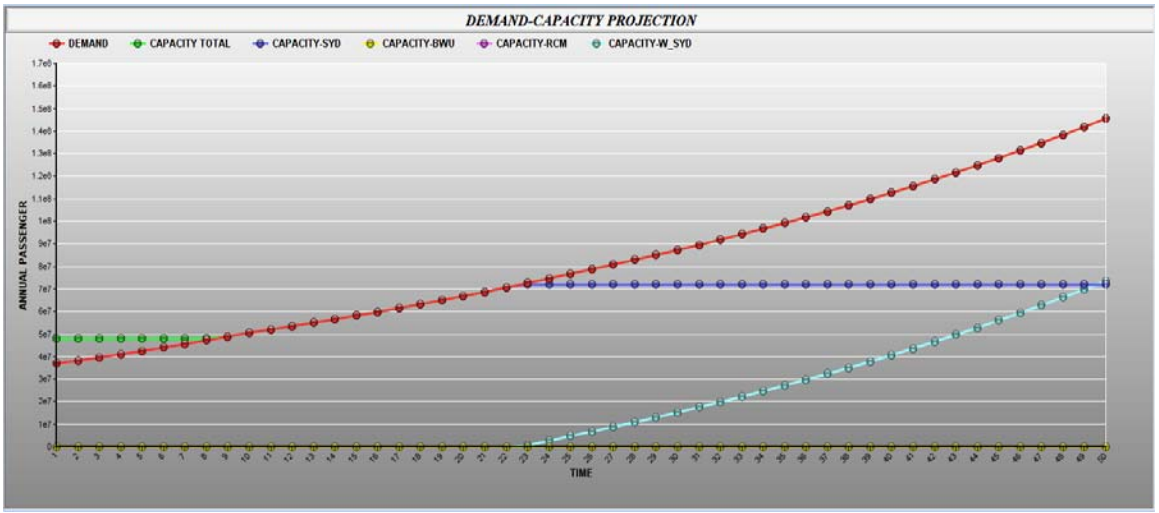
Experiment Model 2-2: Demand vs. Capacity (Operation Unit Cost = AU $10)



Note. This figure shows the airport capacity distribution results of Experiment Model 2-2 for 50 years. The proposed capacity expansion solution is identical to the Sydney Model.

Figure 17

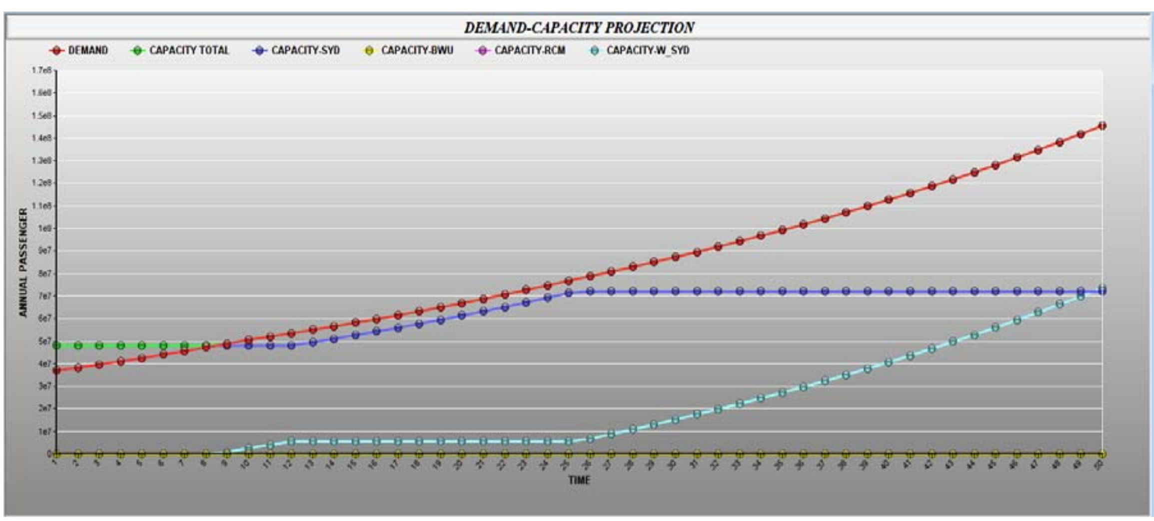
Experiment Model 3-1: Demand vs. Capacity (Access Unit Cost = AU $0.07/km)



Note. This figure shows the airport capacity distribution results of Experiment Model 3-1 for 50 years. The proposed capacity expansion solution is identical to the Sydney Model.

Figure 18

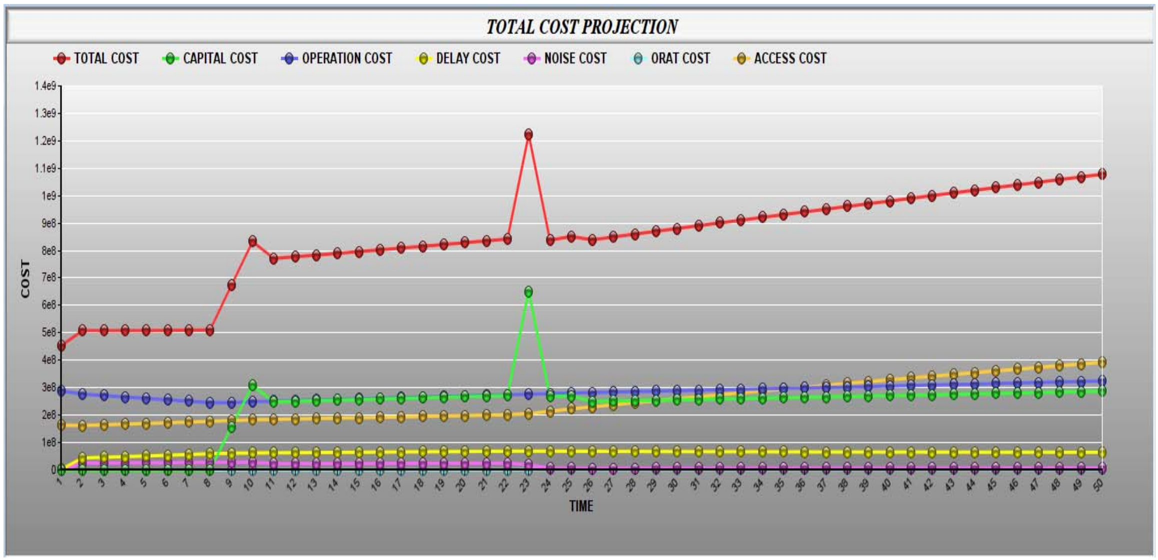
Experiment Model 3-2: Demand vs. Capacity (Access Unit Cost = AU $0.15/km)



Note. This figure shows the airport capacity distribution results of Experiment Model 3-2 for 50 years. This model requires Western Sydney Airport's early entry into the market to reduce passenger access costs across the Sydney region.

Figure 19

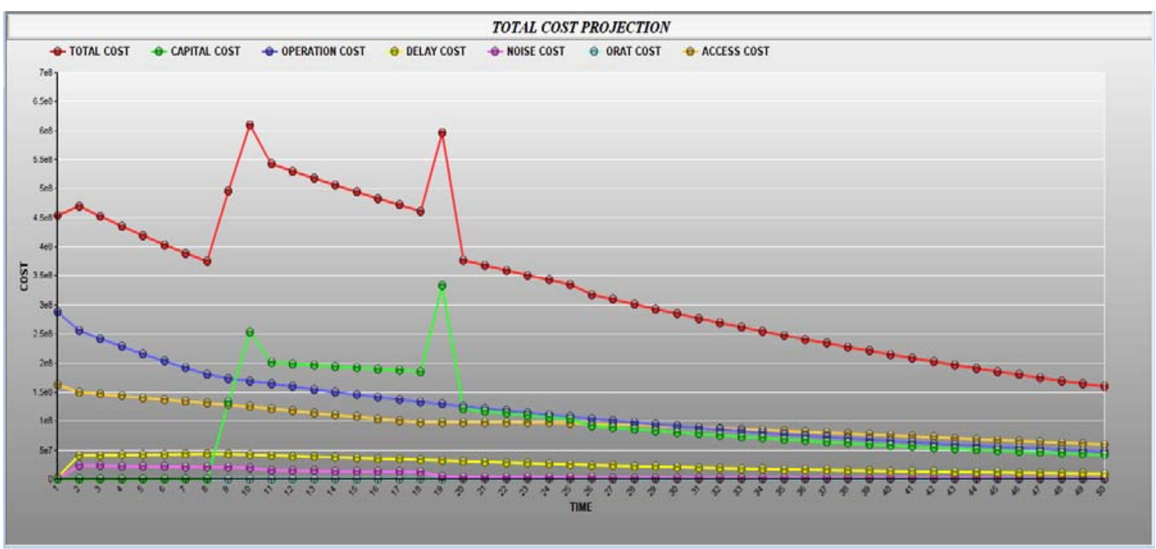
Experiment Model 1-1: Total Cost Projection (Discount Rate = 2%)



Note. This figure shows the overall cost profile presented by Experiment Model 1-1 by using a lower discount rate of 2% compared to the Sydney Model.

Figure 20

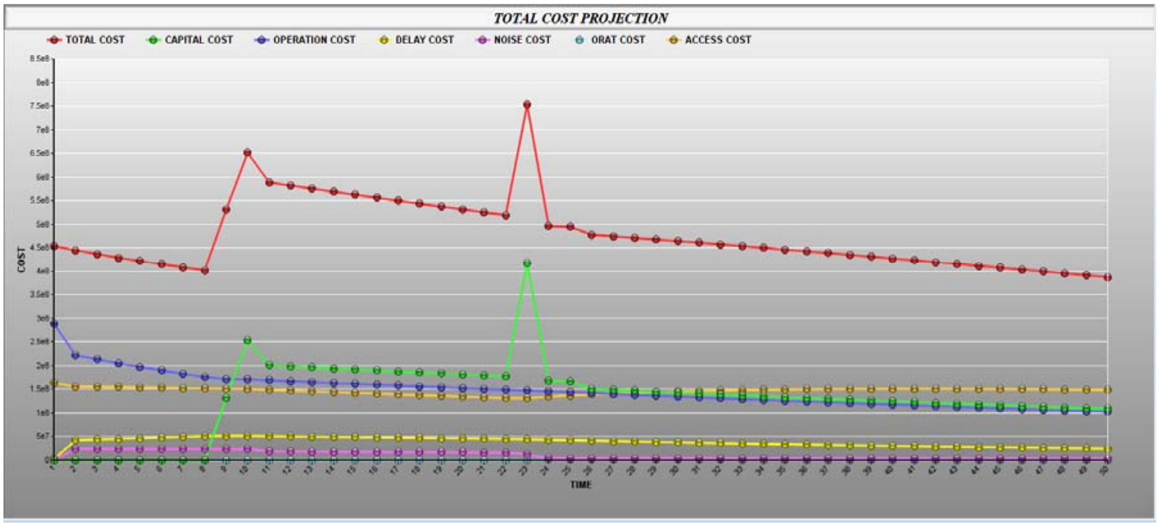
Experiment Model 1-2: Total Cost Projection (Discount Rate = 6%)



Note. This figure shows the overall cost profile presented by Experiment Model 1-2 by using a higher discount rate of 6% compared to the Sydney Base Model.

Figure 21

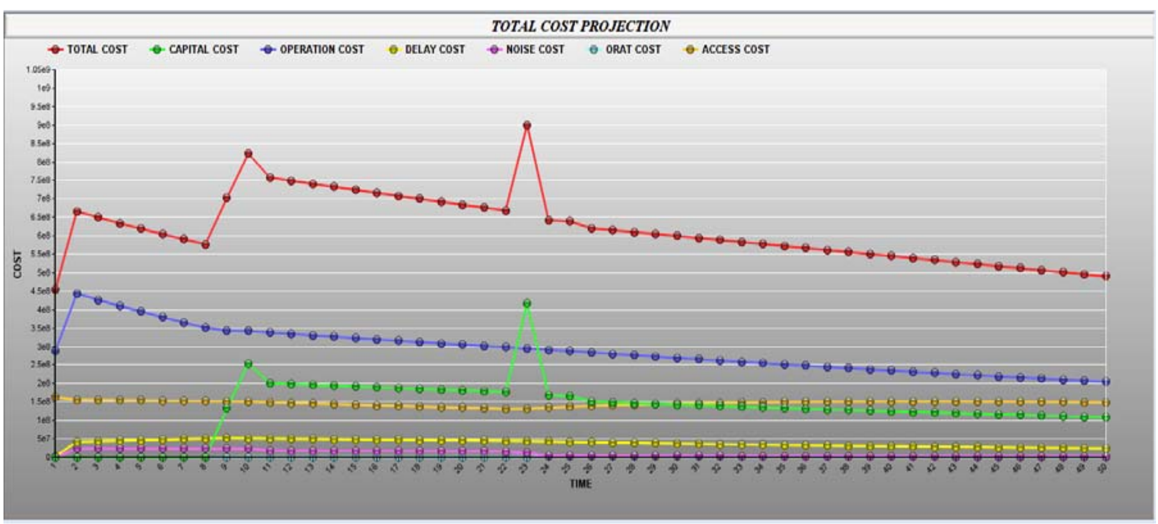
Experiment Model 2-1: Total Cost Projection (Operation Unit Cost = AU $5)



Note. This figure shows the overall cost profile presented by Experiment Model 2-1 by using a lower operation unit cost of AU $5/passenger compared to the Sydney Model.

Figure 22

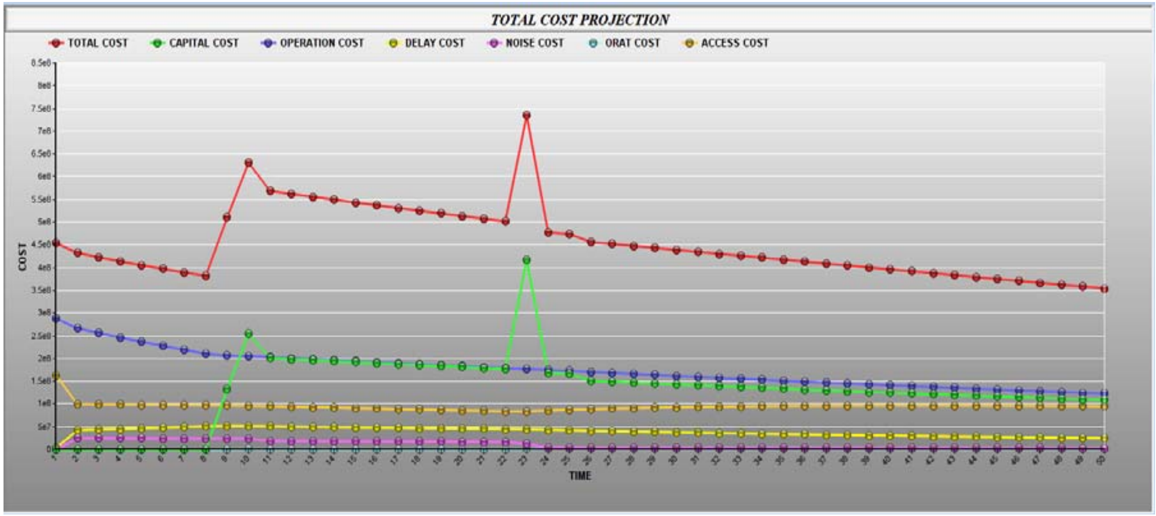
Experiment Model 2-2: Total Cost Projection (Operation Unit Cost = AU $10)



Note. This figure shows the overall cost profile presented by Experiment Model 2-2 by using a higher operation unit cost of AU $10/passenger compared to the Sydney Model.

Figure 23

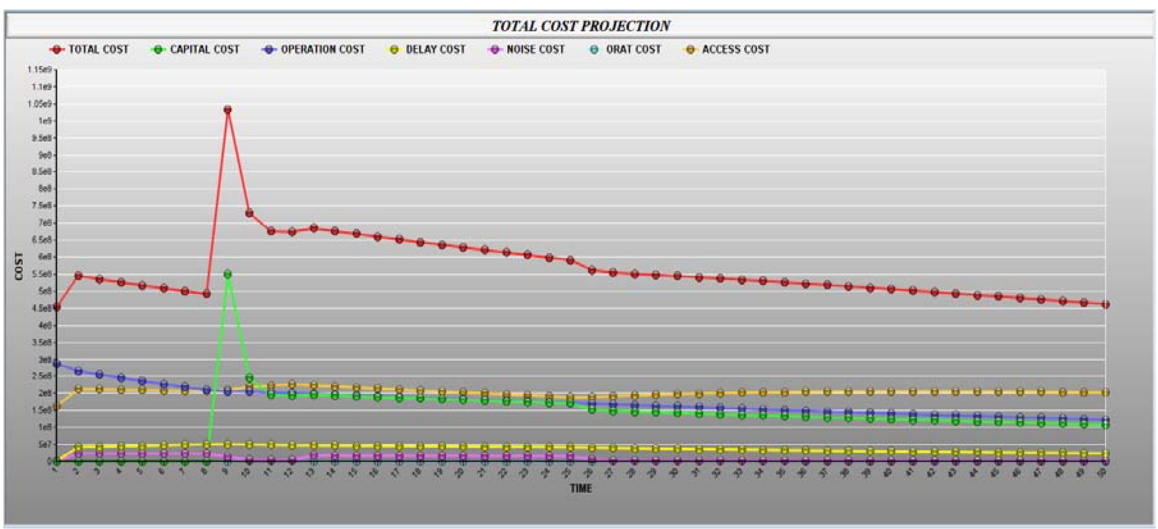
Experiment Model 3-1: Total Cost Projection (Access Unit Cost = AU $0.07/km)



Note. This figure shows the overall cost profile presented by Experiment Model 3-1 by using a lower access unit cost of AU $0.07/passenger-km compared to the Sydney Model.

Figure 24

Experiment Model 3-2: Total Cost Projection (Access Unit Cost = AU $0.15/km)



Note. This figure shows the overall cost profile presented by Experiment Model 3-2 by using a higher access unit cost of AU $0.15/passenger-km compared to the Sydney Model.

Using three experiment models with different input values of discount rate, operation unit cost, and passenger access cost, the reliability of the General Model and the Sydney Model was tested. Experiment Model 1 used different discount rates. While the cost projection curve between Experiment Model 1-1 and Experiment Model 1-2 shows the significant difference over 50 years affected by the differentiated input value, the same optimal solution as the Sydney Model was yielded by the model outcome. Experiment Model 2, which used differentiated operation unit costs, also presented the same optimal solution as the Sydney Model, showing differentiated cost projection with airport operation cost. Meanwhile, different input values of passenger access unit cost yielded different optimal solutions: Experiment Model 3-2, which used a higher rate of passenger access cost, suggested an earlier entry of the new Western Sydney Airport than Experiment Model 3-1 to achieve the cost minimization goal by splitting passenger catchment into two airports.

Generalizability

As discussed in Chapter 3, three measures were considered to ensure the generalizability of the optimization model. First, four case studies were conducted to identify the required cost functions of this model. Each case study can represent one of the four possible solutions to expand airport capacity in metropolitan areas. From each case study, as shown in Table 18, required cost functions for this optimization model were included in the study

Table 18

Case Study: Airport Expansion Key Cost Functions

City	Airport	Solution	Cost Elements
Hong Kong	Hong Kong International Airport	Single airport system, continuously expanding an existing airport	• Airport operations • Operation delay • Noise abatement • Airport facility expansion • Passenger access
Munich	Munich Airport	Single airport system, developing a new airport, and closing the existing airport	• Airport operations • Airport development o Land acquisition o Airport infrastructure o Access infrastructure o Utility connection • ORAT activities • Passenger access • Airport decommissioning
Seoul	Incheon and Gimpo airports	Dual airports system, developing a new airport and pairing with the existing airport	• Airport operations • Operation delay • Noise abatement • ORAT activities • Airport development o Land acquisition o Airport infrastructure o Access infrastructure o Utility connection • Passenger access
New York	JFK, Newark, and La Guardia airports	Multi-airport system, activating or expanding secondary airports to accommodate market growth	• Airport operations • Operation delay • Noise abatement • ORAT activities • Airport conversion, expansion o Land acquisition o Commissioning o Facility modernization and expansion • Passenger access

Second, the case of the Sydney metropolitan area is selected to validate this model because the Sydney region may consider all four possible solutions to deal with the airport capacity expansion problem.

Solution 1. Expansion of existing Sydney airport until it reaches the maximum allowable capacity;

Solution 2, Developing a new Western Sydney Airport and closing an existing Sydney Airport;

Solution 3. Developing a new Western Sydney Airport to set up a dual airport system along with the existing Sydney Airport; and

Solution 4. Conversion either of Bankstown GA Airport or Richmond Airbase into a commercial airport to relieve the airport capacity issue of the Sydney region.

Last, because this optimization model took a quantitative research method and was developed using mathematical functions, any localized input variable can directly affect the output and decision variable of the model. Therefore, any localized cost factors such as statutory costs and taxation were not considered because they can vary by airport, city, or country.

Stochastic MINLP Models

The current deregulated and competitive market environment necessitates airlines to quickly respond to changing market conditions. As a result, airlines may suddenly change fares, flight schedules, and service networks (de Neufville and Barber, 1991). For example, the new entrant of low-cost carriers can generate unprecedented traffic demand for the region and require airports to accommodate the increased demand in a short timeframe in order not to lose the demand growth opportunity. On the other hand, air traffic demand may fall back when major air carriers cease the operations or abandon any major route at the airport, which radically affects the capacity and operation planning of the airport. Therefore, it is critically important for airport operators to develop multiple plausible demand scenarios due to the uncertainties from political, economic, social, technological, and demographic changes. In this chapter, the deterministic general MINLP model was extended into the multi-stage stochastic model by considering various plausible traffic scenarios of the market.

Stochastic Model

The stochastic optimization models are developed using Extended LINGO/Win64 Release 18.0.44. Its stochastic programming solver provides various functions to support the development of an optimization model under uncertainty through a multistage stochastic process. The researcher first selected an input variable that has uncertainty and identified the distribution functions of the specific variables. Then, the stochastic solver optimized the stochastic model by minimizing the overall cost over the 50-year planning horizon.

The stochastic version of the airport capacity expansion optimization model can be formulated by combining the format of the general model and the multi-stage stochastic model, which are pre-defined as Equation 11 and Equation 10, respectively, and can be written as:

$$\begin{aligned} min\ \delta^{y} \times \sum_{y}\sum_{i} (&E_y \times k_{yi} \times CC_{yi} + E_y \times k_{yi} \times OPC_{yi} + E_y \times k_{yi} \times DC_{yi} + E_y \times k_{yi} \times NC_{yi} + \\ &E_y \times k_{yi} \times ORC_{yi}) + \delta^{y} \sum_{y}\sum_{i}\sum_{j} (E_y \times k_{yi} \times AC_{yij}) \end{aligned} \tag{14}$$

where:

E_y = finite random outcomes or probability from an event at time *y*.

k_{yi} = binary variable, 1 = serviceable, 0 = non-serviceable.

CC_{yi} = capital cost at Airport i at time *y*.

OPC_{yi} = operation cost at Airport i at time *y*.

DC_{yi} = delay cost at Airport i at time *y*.

NC_{yi} = noise cost at Airport i at time *y*.

ORC_{yi} = ORAT cost at Airport i at time *y*.

AC_{yi} = access cost between Airport i and Population Center j at time *y*.

δ = discount coefficient.

Three what-if scenarios that take different traffic demand assumptions into considerations were selected to develop the stochastic decision-making models. Detailed model parameters for the three what-if models are shown in Table 18. In the stochastic models, only future traffic demand will be treated as an uncontrollable variable. Other model parameters such as cost functions and airport profiles will remain the same as the model parameters that are used in the Sydney Base Model.

Table 19

Traffic Demand Parameters for Three What-if Models

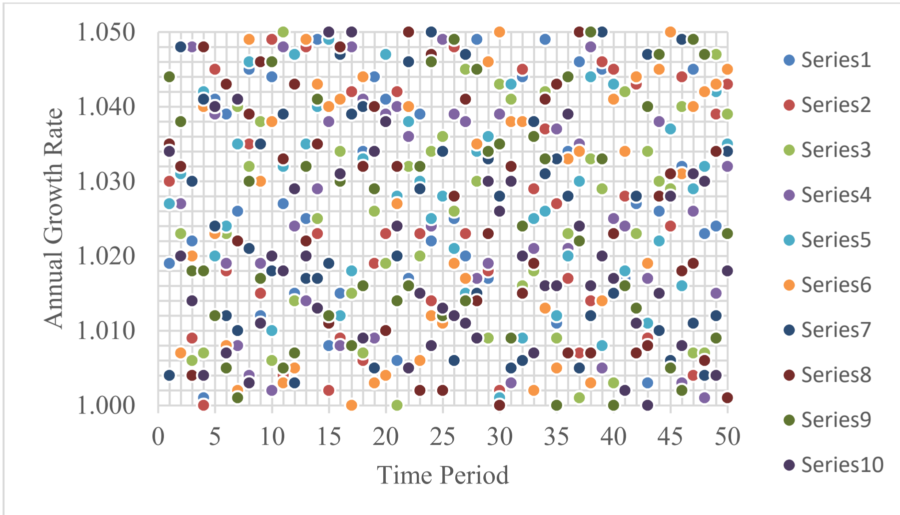
Model	What-if Model 1	What-if Model 2	What-if Model 3
Traffic Growth Scenario	Random growth of air traffic demand between 0 – 5% (low and upper limit)	Normal distribution of annual traffic growth rates based on Sydney's previous 25 years' records (no low or upper limit)	Reflection of the pandemic COVID-19 impact on air traffic demand (no low or upper limit)
Traffic Growth Rate			
- Mean	2.87	3.25	2.70
- Median	2.85	2.42	2.73
- Highest	4.09	18.81	93.15
- Lowest	1.01	-11.98	-65.07
- Standard Deviation	0.62	7.31	19.39
Traffic Forecast			
- Year 0	37.0 MAP	37.0 MAP	37.0 MAP
- Year 10	46.0 MAP	45.9 MAP	32.2 MAP
- Year 25	67.0 MAP	59.9 MAP	51.1 MAP
- Year 50	146.9 MAP	156.9 MAP	121.9 MAP

What-if Model 1: Random Growth of Air Traffic Demand

Annual growth rates of passenger traffic demand are randomly selected for annual traffic growth between 0% - 5.7%. In this What-if Model, traffic volume does not consistently increase. Also, the traffic volume is not expected to decrease. Figure 25 shows 500 randomly chosen numbers, which consist of 10 observed numbers per time series. Using these randomly distributed growth rate values, Table 20 shows detailed air traffic parameters that were used to develop this What-if Scenario.

Figure 25

What-if Model 1: Scatter Chart of 500 Random Values (1.00 - 1.057)



Note. 10 random values were generated per each time series between 0% and 5.7%, and the averaged value per period was used to define the annual traffic demand growth rate of each time series.

Table 20

What-if Model 1: Traffic Demand Parameters

Timeline	50 years: Year 0 – Year 50	
Sydney Region	Year 0:	37.0 MAP
Passenger Demand	Year 10:	46.0 MAP
Forecast	Year 25:	67.0 MAP
	Year 50:	146.9 MAP
Annual Traffic	Mean:	2.87
Growth (%)	Median:	2.85
	Highest:	4.09
	Lowest:	1.01
	Standard Deviation:	0.62

Note. This what-if scenario assumes that traffic demand in the Sydney region would not decrease over a 50-year time horizon and will have both upper and lower limit of annual traffic demand changes.

Table 21 presents the projected annual passenger demand for the Sydney region for a 50-year timeline and proposed airport capacity to cater to the demand. The MINLP model suggests a dual airport system in Sydney from the cost minimization perspective. The existing Sydney Airport and Western Sydney Airport are required to serve the air transport industry within the Sydney region. In the meantime, Bankstown Airport and Richmond Airport are not recommended as cost-efficient solutions to service the growing air traffic demand of the Sydney region.

Table 21

What-if Model 1: Traffic Demand and Airport Capacity (in thousand passengers)

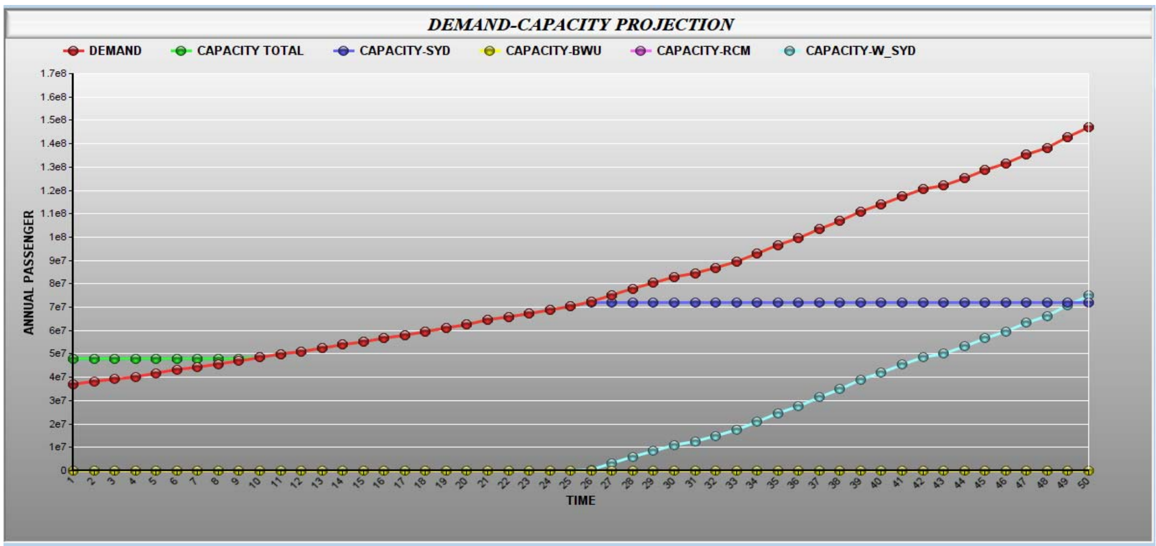
Year	1	6	11	16	21	26	31	36	41	46	50
Demand	36,967	43,300	49,964	56,760	64,648	72,404	84,525	99,551	117,346	131,575	146,977
Capacity											
SYD	48,000	48,000	49,964	56,760	64,648	72,000	72,000	72,000	72,000	72,000	72,000
BWU	-	-	-	-	-	-	-	-	-	-	-
RCM	-	-	-	-	-	-	-	-	-	-	-
W_SYD	-	-	-	-	-	404	12,525	27,551	45,346	59,575	74,977
Total	48,000	48,000	49,964	56,760	64,648	72,404	84,525	99,551	117,346	131,575	146,977

Note. This table shows the optimized airport capacity solution from the stochastic MINLP model. A dual airport solution is suggested.

Between Year 1 and Year 25, the existing Sydney Airport will serve as the sole airport in the Sydney region by increasing its capacity from its current capacity of 48 MAP to its maximum capacity of 72 MAP. Because the traffic demand is forecasted to outpace the current capacity of Sydney Airport from Year 10, additional capacity is required for Sydney Airport to accommodate the exceeding passenger volume. Once the traffic demand reaches the maximum capacity of Sydney Airport in Year 26, Western Sydney Airport will be operational to handle the exceeding traffic demand. Figure 26 depicts this information graphically.

Figure 26

What-if Model 1: Demand vs. Airport Capacity Projection (in Annual Passenger)



Note. This line chart shows the optimized airport capacity expansion solution to accommodate uncertain future air traffic demand of the Sydney region. The total capacity curve follows the demand curve from Year 10.

Table 22 shows the required total and each component costs to develop and operate the dual airport system in the Sydney region for a 50-year timeline. Figure 27 depicts this information graphically. Whereas the total traffic demand is expected to grow at a steady rate, as shown in Figure 26, the cost graph shows strong fluctuations from Year 10 when Sydney Airport reaches the maximum capacity. From Year 11, different levels of capital costs are required, depending on the random growth of the air traffic.

Table 22

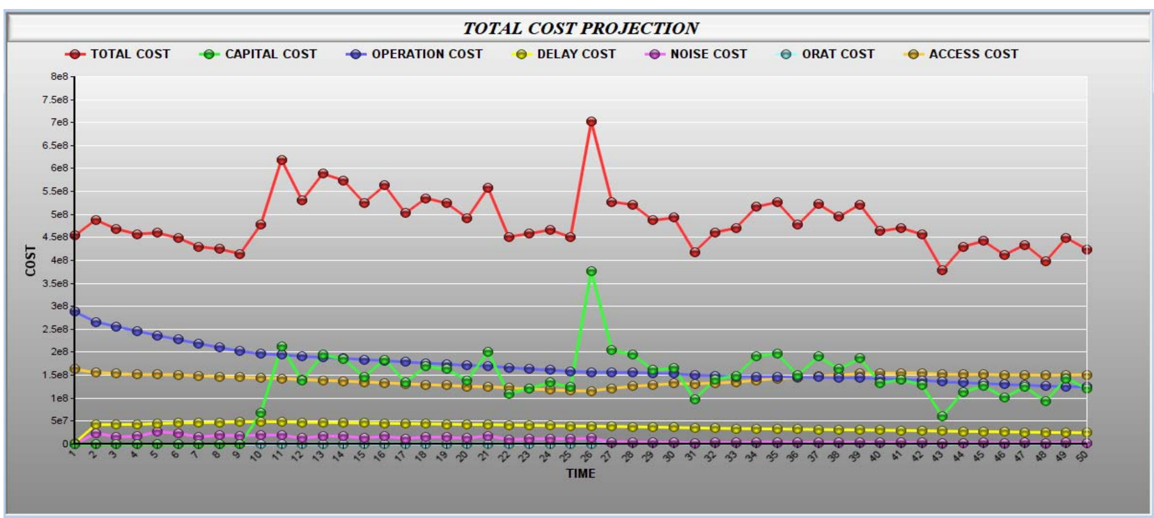
What-if Model 1: Airport Capacity Expansion Cost Projection (in thousand AU$)

Year	1	6	11	16	21	26	31	36	41	46	50
Capital Cost	-	-	212,096	184,278	200,934	376,978	98,068	149,812	140,584	101,261	120,472
Operation Cost	288,000	227,610	194,734	181,829	170,220	156,692	150,351	145,546	141,011	129,954	124,089
Delay Cost	2,847	46,306	48,683	45,457	42,555	39,085	35,359	32,358	29,803	26,604	24,692
Noise Cost	-	23,859	19,548	16,984	18,519	12,705	2,334	3,566	3,347	2,410	2,868
ORAT Cost	-	-	879	764	833	815	887	1,355	1,271	916	1,089
Access Cost	163,004	150,895	143,110	133,627	125,095	115,975	131,426	144,807	154,825	150,786	150,666
Total	453,851	448,672	619,053	562,940	558,157	702,253	418,427	477,446	470,844	411,934	423,878

Note. This table presents the overall cost information to provide the required airport capacity in the Sydney region based on the results of the base deterministic MINLP model. A 4% discount rate per annum is applied.

Figure 27

What-if Model 1: Capacity Expansion Total Cost Projection (in AUD)

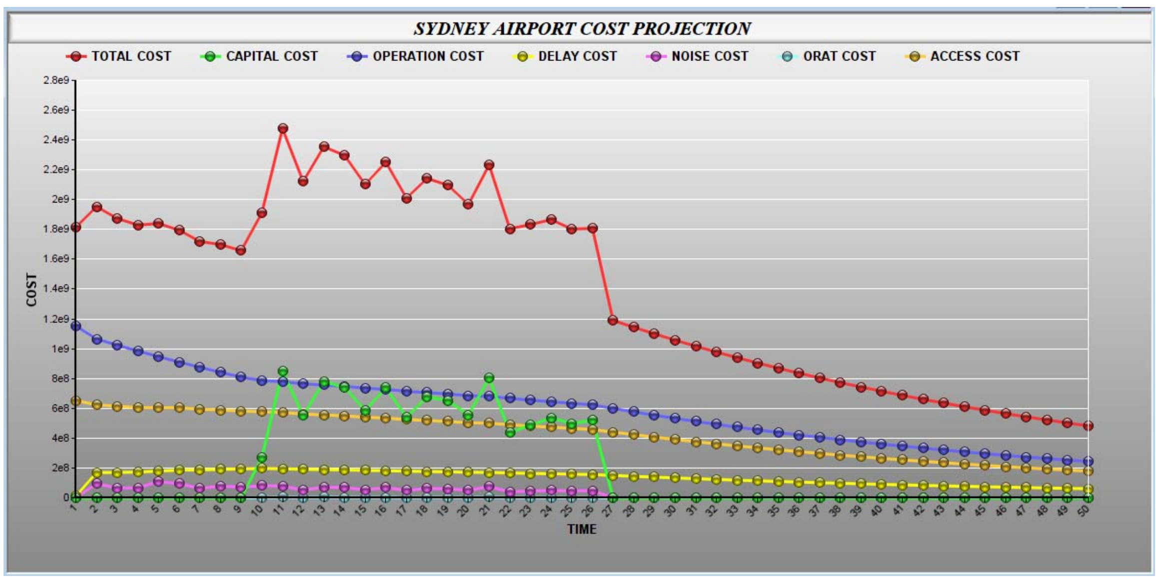


Note. This figure shows the total cost estimate results from the What-if Model 1 to provide the required airport capacity in the Sydney region through a dual airport solution. A peak cost inputs indicate the required capital cost to add additional airport capacity.

Figure 28 and Figure 29 illustrate the required costs to provide the required airport capacity and operate the airport facilities for Sydney Airport and Western Sydney Airport, respectively. The cost requirements per year vary due to the random rate of traffic increase and associated cost inputs to the airport infrastructure expansion. In Year 26, significant capital investment is shown for the inauguration of Western Sydney Airport, which requires fixed capital costs for land acquisition, access infrastructure, and utility connection to the new airport site.

Figure 28

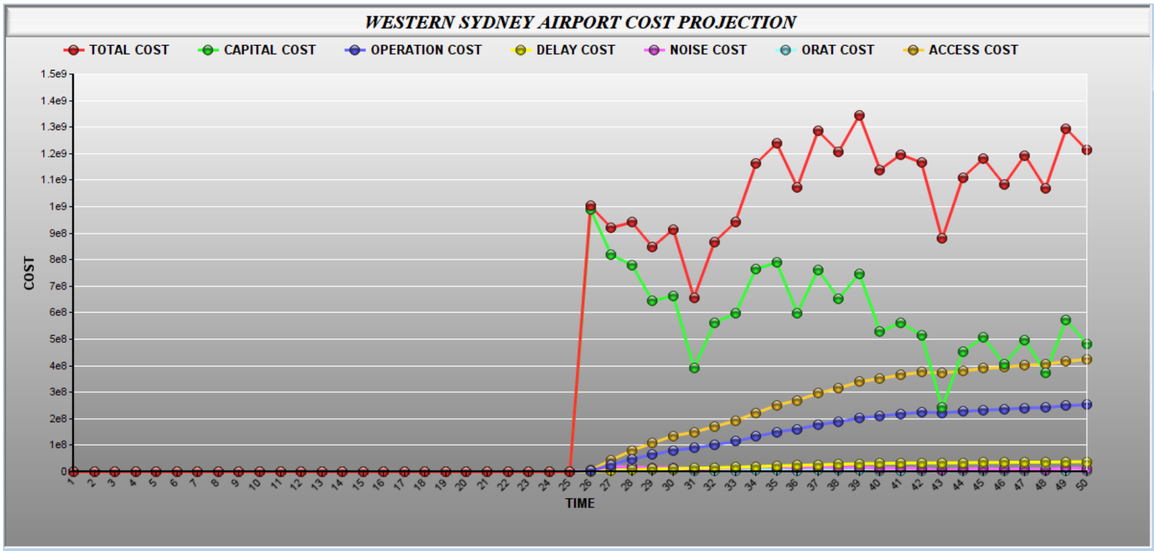
What-if Model 1: Sydney Airport Cost Projection (in AUD)



Note. This figure shows the total cost estimate results from the What-if Model 1 to expand the capacity of the existing Sydney airport. A capital cost input is required between Year 9 and Year 23 to increase the capacity up to its maximum allowance of 72 MAP.

Figure 29

What-if Model 1: Western Sydney Airport Cost Projection (in AUD)



Note. This Figure shows annual cost inputs from Year 22 to develop and operate Western Sydney airport.

What-if Model 2: Normal Distribution of Traffic Growth Rates

This model uses a normal distribution pattern for annual traffic growth with 10,000 observations. From the historical air traffic trend between 1985 and 2019 and future traffic forecast from the Joint Study (Australian and NSW Government, 2012), Mean Value = 2.8% and Standard Deviation = 8.08 are suggested for this What-if Scenario 2. The input parameters of passenger demand used for this what-if scenario were produced by a Monte Carlo simulation model using randomly selected numbers to account for uncertain future market environments. In this scenario, traffic demand may have sudden positive or negative impacts caused by changes in airline hub strategy or unforeseen external events which were not considered in the Sydney Model and What-if Model 1.

Testing of the traffic demand uncertainty used various numbers of observations ranging from 50 up to 100,000 to ensure the number of observations was adequate to expect consistent model outcomes from the simulation. Noticeable aberrations with the mean and standard deviation data were found when fewer than 500 observations were used. The results were identical from the observation numbers more than 500, as shown in Table 23. The researcher conducted 10,000 trials, and the normal distribution histogram from the analysis is presented in Figure 30. Table 24 provides air traffic demand input parameters that were used for this What-if scenario model.

Table 23

What-if Model 2: Observed Mean and Standard Deviation per Seed Values

Observations	Mean	Standard Deviation
50	2.57	8.53
100	2.47	8.18
250	2.48	8.08
500	2.50	8.10
750	2.50	8.08
1000	2.50	8.08
5000	2.50	8.08
10000	2.50	8.08
100000	2.50	8.08

Note. With more than 500 observations, the mean values from this testing present the same value of 2.50.

Figure 30

What-If Model 2: Annual Traffic Change Normal Distribution

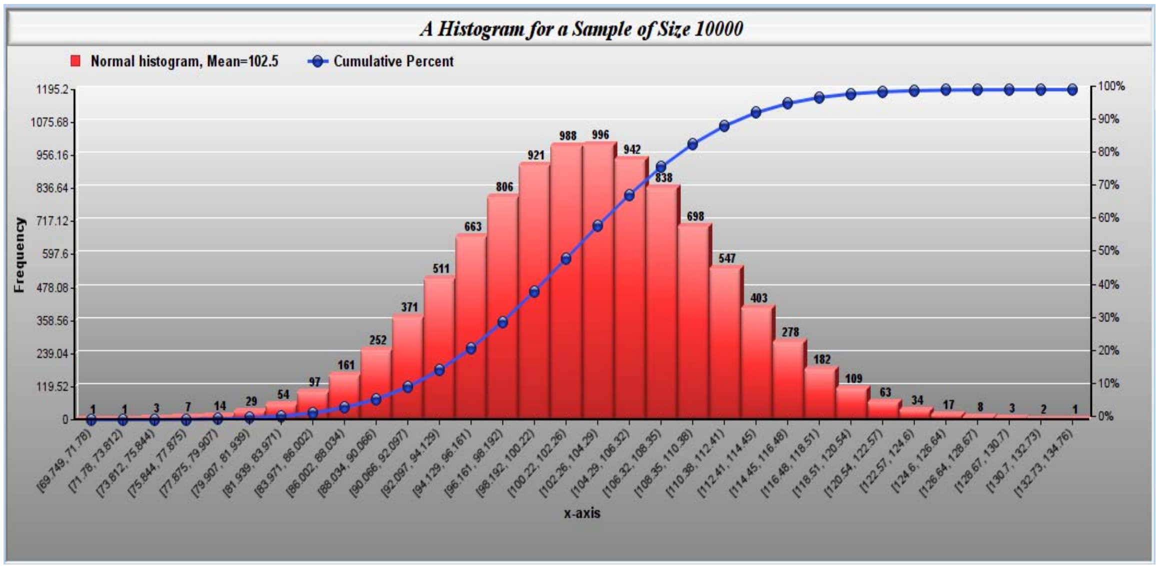


Table 24

What-If Model 2: Traffic Demand Parameters

Timeline	50 years: Year 0 – Year 50	
Sydney Region Passenger Demand Forecast[a]	Year 0:	37.0 MAP
	Year 10:	45.9 MAP
	Year 25:	59.9 MAP
	Year 50:	156.9 MAP
Annual Traffic Growth (%)	Mean:	3.25
	Median:	2.42
	Highest:	18.81
	Lowest:	-11.98
	Standard Deviation:	7.31

Note. The underlying assumption of this model is that the air traffic demand changes within the Sydney region will follow previous historic traffic demand patterns and have no upper or lower limit of annual traffic demand changes. The analysis timeframe for the economic impact of the project is over a 50-year time horizon.

Using the normal distribution function of Lingo Ver. 18, What-is Model 2 was developed, as shown in Table 25 and Figure 31, which presents the projected annual passenger demand for the Sydney region for a 50-year timeline. This What-if model proposes a three-airport system in the Sydney region, utilizing the existing Sydney Airport, Western Sydney Airport, and Bankstown Airport to serve the future demand.

Between Year 1 and Year 29, with the slow growth of the traffic demand, the existing Sydney Airport will serve as the sole airport in the Sydney region while it increases its capacity up to the maximum level. From Year 30, additional capacity is handled by Western Sydney Airport, which will reach the maximum capacity of 82 MAP in Year 39. Bankstown Airport will need to be transformed into a commercial airport from Year 49 to form a part of Sydney's multi-airport system with a 3.6 MAP airport capacity.

Table 25

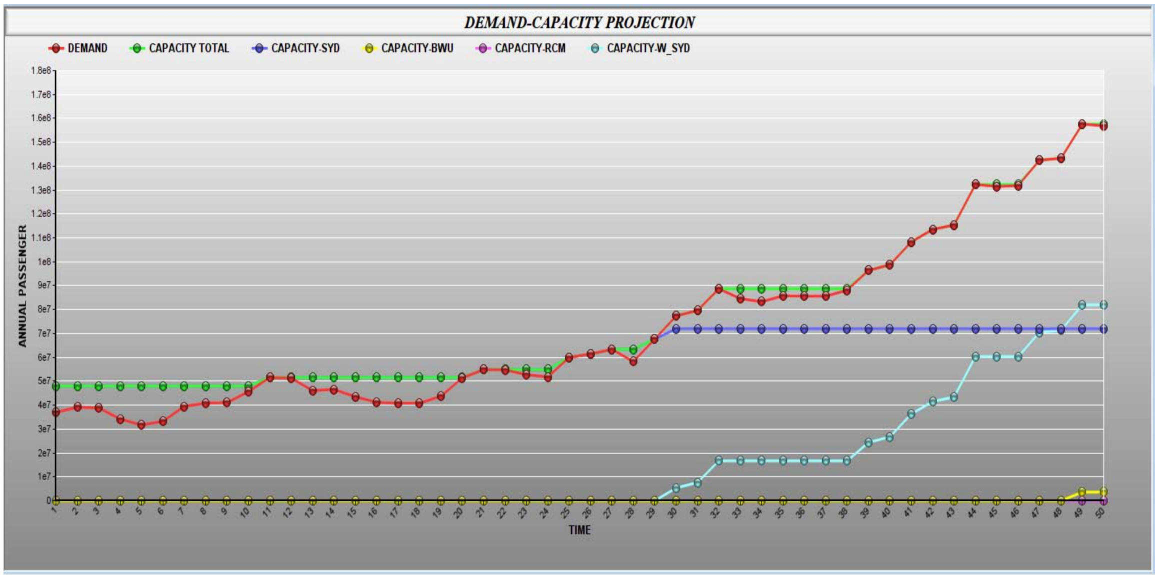
What-if Model 2: Traffic Demand and Airport Capacity (in Thousand Passengers)

Year	1	6	11	16	21	26	31	36	41	46	50
Demand	36,967	33,230	51,550	41,155	54,885	61,438	79,628	85,571	108,305	131,890	156,897
Capacity											
SYD	48,000	48,000	51,550	51,550	54,885	61,438	72,000	72,000	72,000	72,000	72,000
BWU	-	-	-	-	-	-	-	-	-	-	3,602
RCM	-	-	-	-	-	-	-	-	-	-	-
W_SYD	-	-	-	-	-	-	7,628	16,672	36,305	60,345	82,000
Total	48,000	48,000	51,550	51,550	54,885	61,438	79,628	88,672	108,305	132,345	157,602

Note. This table shows the optimized airport capacity solution from the What-if Model 2. A multi-airport system utilizing three airports is suggested.

Figure 31

What-if Model 2: Demand vs. Airport Capacity Projection (in Annual Passenger)



Note. This line chart shows the optimized airport capacity expansion solution to accommodate future air traffic demand of the Sydney region. As shown in this figure, a dual airport solution is recommended to minimize overall cost requirements.

Table 26 shows the required total and each component cost to develop and operate the multi-airport system in the Sydney region for a 50-year timeline. Figure 32 depicts this same information graphically. The cost graph shows strong variances in Year 11, between Year 20 and Year 33, and between Year 38 and Year 49, when major capacity expansion projects will be undertaken to maximize the capacity of Sydney Airport and inaugurate Western Sydney Airport. Between Year 49 and Year 50, a significant investment of capital costs will be injected to inaugurate Bankstown Airport with a 3.6 MAP capacity.

Table 26

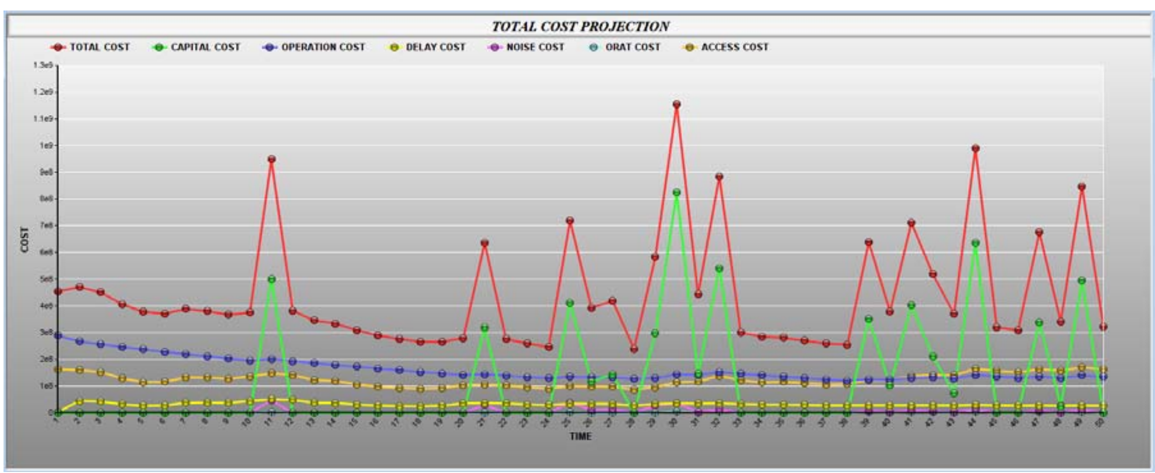
What-if Model 2: Airport Capacity Expansion Cost Projection (in Thousand AU$)

Year	1	6	11	16	21	26	31	36	41	46	50
Capital Cost	-	-	500,346	-	317,665	117,452	144,703	-	402,808	-	-
Operation Cost	288,000	227,610	200,913	165,136	144,513	132,959	141,639	129,639	130,146	130,714	134,072
Delay Cost	2,847	27,270	50,228	26,313	36,128	33,239	34,053	28,738	28,174	26,584	26,062
Noise Cost	-	-	46,114	-	29,277	10,825	3,445	-	9,590	-	-
ORAT Cost	-	-	2,075	-	1,317	487	1,309	-	3,644	-	-
Access Cost	163,004	115,799	147,652	96,887	106,203	97,712	116,840	110,582	136,633	151,306	161,913
Total	453,851	370,680	947,330	288,337	635,106	392,676	441,990	268,960	710,997	308,605	322,048

Note. This table presents the overall cost information to provide the required airport capacity in the Sydney region based on the results of the base deterministic MINLP model. A 4% discount rate per annum is applied.

Figure 32

What-if Model 2: Capacity Expansion Total Cost Projection (in AUD)

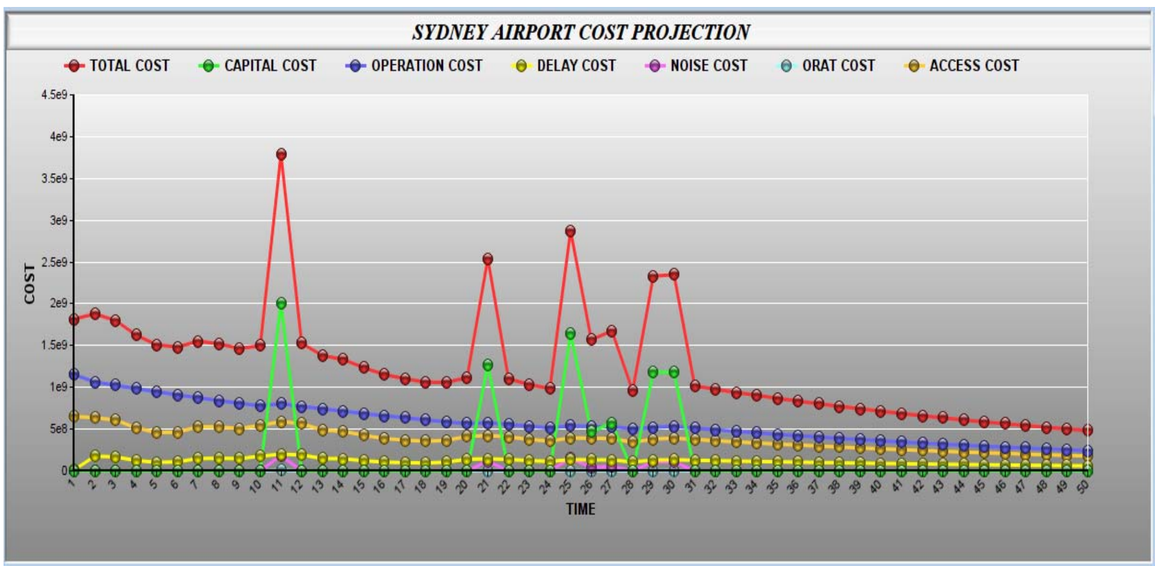


Note. This figure shows the total cost estimate results from the What-if Model 2 to provide the required airport capacity in the Sydney region through a three-airport solution. A peak cost input indicates the required capital cost to add additional airport capacity.

Figure 33 and Figure 34 illustrate the required annual costs to expand airport capacity and operate the airport facilities for the existing Sydney Airport and Western Sydney Airport, respectively. The cost requirements per year vary due to the associated capital cost inputs to the airport infrastructure. In Year 29, significant capital investment is shown for the major expansion of Western Sydney Airport, which requires fixed capital costs to double the size.

Figure 33

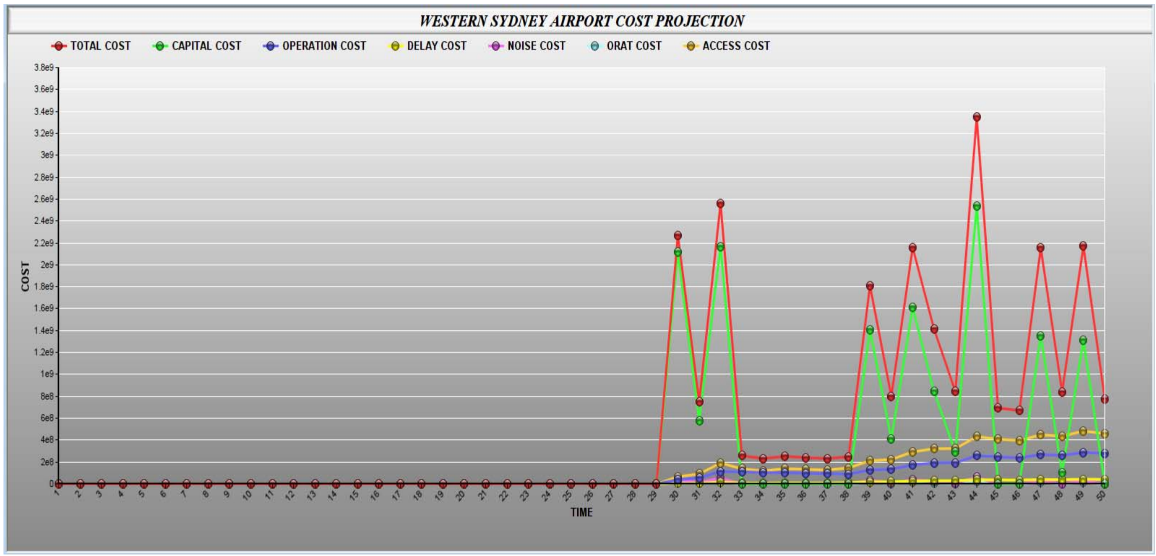
What-if Model 2: Sydney Airport Cost Projection (in AUD)



Note. This figure shows the total cost estimate results from the What-if Model 2 to expand the capacity of the existing Sydney airport. A capital cost input is required in Year 11, Year 21, and between Year 25 and Year 30 to add the capacity up to its maximum allowance of 72 MAP.

Figure 34

What-if Model 2: Western Sydney Airport Cost Projection (in AUD)



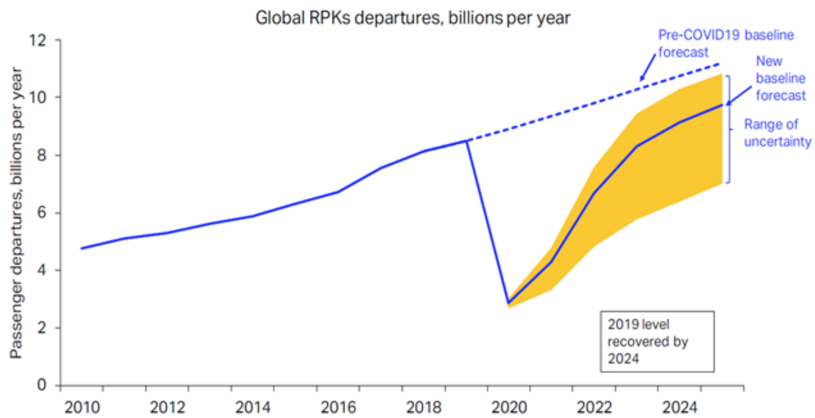
Note. This figure shows annual cost inputs from Year 30 to develop and operate Western Sydney Airport.

What-if Model 3: Reflection of Pandemic COVID-19 Impact

The COVID-19 pandemic has caused a striking downturn in passenger traffic demand, but demand is expected to eventually show resilience; this is considered a temporal but significant decrease of the traffic demand for a short-term period. IATA published a post-COVID traffic forecast in 2020, which projects that 2019 level traffic would be recovered by 2024, as illustrated in Figure 35 (IATA, 2020), which is one of the critical assumptions of this what-if stochastic modeling. In the meantime, the actual air passenger traffic volumes of the Sydney region between 2010 (Year 1) and 2020 (Year 11) are reflected in this model to make the What-if scenario most realistic. Also, in this model, air traffic volume can be either increase or decrease like What-if Model 2. Table 27 shows detailed parameters for this What-if Model.

Figure 35

Outlook for Air Transport Passenger Traffic Demand



Note. Adapted from "Outlook for Air Transport and the Airline Industry" by IATA, 2020, https://www.iata.org/en/iata-repository/pressroom/presentations/outlook/

Table 27

What-if Model 3: Traffic Demand Parameters

Timeline	50 years: Year 0 – Year 50	
Sydney Region Passenger Demand Forecast[a]	Year 0:	37.0 MAP
	Year 10[a]:	32.2 MAP
	Year 12[b]:	7.8 MAP
	Year 16[c]:	44.3 MAP
	Year 25:	51.1 MAP
	Year 50:	121.9 MAP
Annual Traffic Growth (%)	Mean:	2.70
	Median:	2.73
	Highest:	93.15
	Lowest:	-65.07
	Standard Deviation:	19.39

Note. This model used the actual passenger traffic data between 2010 and 2020 published by Sydney International Airport Corporation at https://www.sydneyairport.com.au/investor/company-information/asx-newsroom. [a] The pandemic COVID-19 started to have an impact on air traffic demand in the Sydney region from Year 10. [b] Air traffic demand is expected to drop at the lowest point in Year 12. [c] It is forecasted for the Sydney region to recover its pre-COVID-19 air traffic volume of 2019 by Year 16.

Table 28 presents the annual passenger demand for the Sydney region affected by the pandemic COVID-19 event and the optimized airport capacity to cater to the modified demand. While this What-if MINLP model still suggests a dual airport system in Sydney from the cost minimization perspective, Western Sydney Airport is required to serve the air transport industry within the Sydney region once the affected traffic is recovered from the COVID-19 downturn and reaches the current Sydney Airport's capacity of 48 MAP. Bankstown Airport and Richmond Airport are not identified as cost-efficient solutions to service the growing air traffic demand of the Sydney region, even under this What-if scenario.

Table 28

What-if Model 3: Traffic Demand and Airport Capacity (in Thousand Passengers)

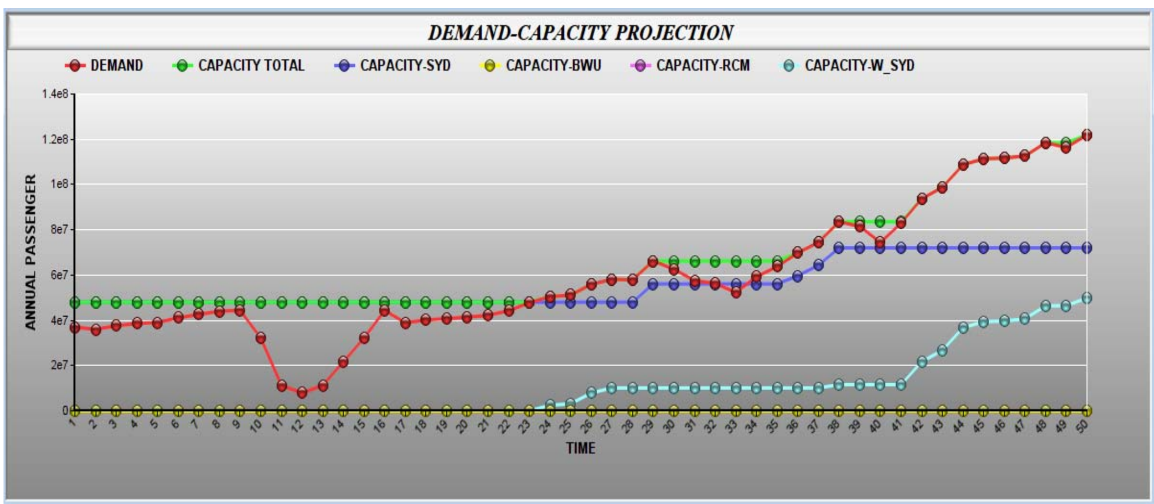
Year	1	6	11	16	21	26	31	36	41	46	50
Demand	36,967	41,105	11,245	44,375	42,171	55,877	57,535	69,783	82,928	111,710	121,866
Capacity											
SYD	48,000	48,000	48,000	48,000	48,000	48,000	56,093	59,667	72,000	72,000	72,000
BWU	-	-	-	-	-	-	-	-	-	-	-
RCM	-	-	-	-	-	-	-	-	-	-	-
W_SYD	-	-	-	-	-	7,877	10,115	10,115	11,569	39,710	49,866
Total	48,000	48,000	48,000	48,000	48,000	55,877	66,209	69,783	83,569	111,710	121,866

Note. This table shows the optimized airport capacity solution from the stochastic MINLP model. A dual airport solution is suggested.

Between Year 1 and Year 23, the existing Sydney Airport will serve as a sole airport in the Sydney region by utilizing its current capacity of 48 MAP without adding infrastructure, due to the plunge of the traffic impacted by the COVID-19 pandemic during Year 11 and Year 15. After the full recovery of air traffic by Year 16, additional airport capacity required for the Sydney region will be accommodated by Western Sydney Airport until it reaches its phase 1 capacity of 10 MAP until Year 28. From Year 29 to Year 38, Sydney Airport will increase the capacity up to 72 MAP. From Year 38, Western Sydney Airport will handle the growing demand and increase the capacity by 50 MAP in Year 50. Figure 36 depicts this information graphically.

Figure 36

What-if Model 3: Demand vs. Airport Capacity Projection (in Annual Passenger)



Note. This line chart shows the optimized airport capacity expansion solution to accommodate future air traffic demand of the Sydney region. As shown in this figure, a dual airport solution is recommended to minimize overall cost requirements.

Table 29 shows the required total and each component cost to develop and operate the dual airport system in the Sydney region for a 50-year timeline. Whereas the total traffic demand is forecasted to dramatically deviate from its trend line, as depicted in Figure 36, the already secured capacity cannot be reduced and remains as redundancy. The gap between traffic volume and airport capacity means unnecessary operation costs because it is associated with the supplied airport capacity, which is illustrated in Figure 37. From Year 24, different levels of the capital cost investment are required, depending on the random growth of the air traffic.

Table 29

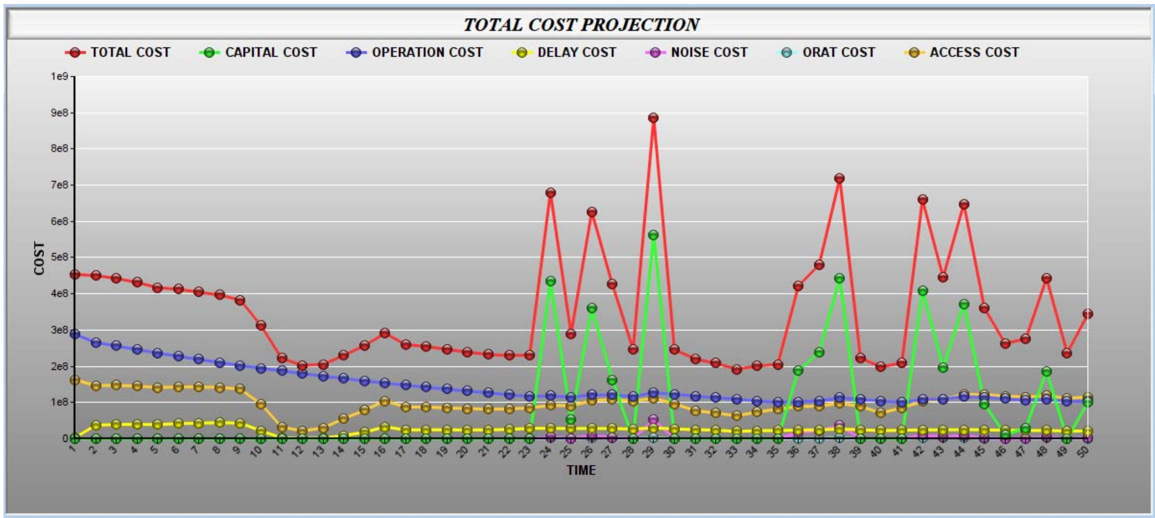
What-if Model 3: Airport Capacity Expansion Cost Projection (in Thousand AU$)

Year	1	6	11	16	21	26	31	36	41	46	50
Capital Cost	-	-	-	-	-	360,272	-	188,996	-	10,877	100,824
Operation Cost	288,000	227,610	187,079	153,765	126,384	120,926	117,770	102,024	100,423	110,334	102,888
Delay Cost	2,847	41,729	2,566	32,855	24,388	28,526	24,999	24,027	23,490	23,661	21,512
Noise Cost	-	-	-	-	-	8,577	-	17,419	-	258	2,400
ORAT Cost	-	-	-	-	-	3,259	-	783	-	98	912
Access Cost	163,004	143,245	32,208	104,470	81,601	104,885	77,621	88,872	85,572	117,934	115,167
Total	453,851	412,585	221,854	291,091	232,373	626,448	220,390	422,123	209,486	263,165	343,706

Note. This table presents the overall cost information to provide the required airport capacity in the Sydney region based on the results of the base deterministic MINLP model. A 4% discount rate per annum is applied.

Figure 37

What-if Model 3: Capacity Expansion Total Cost Projection (in AUD)

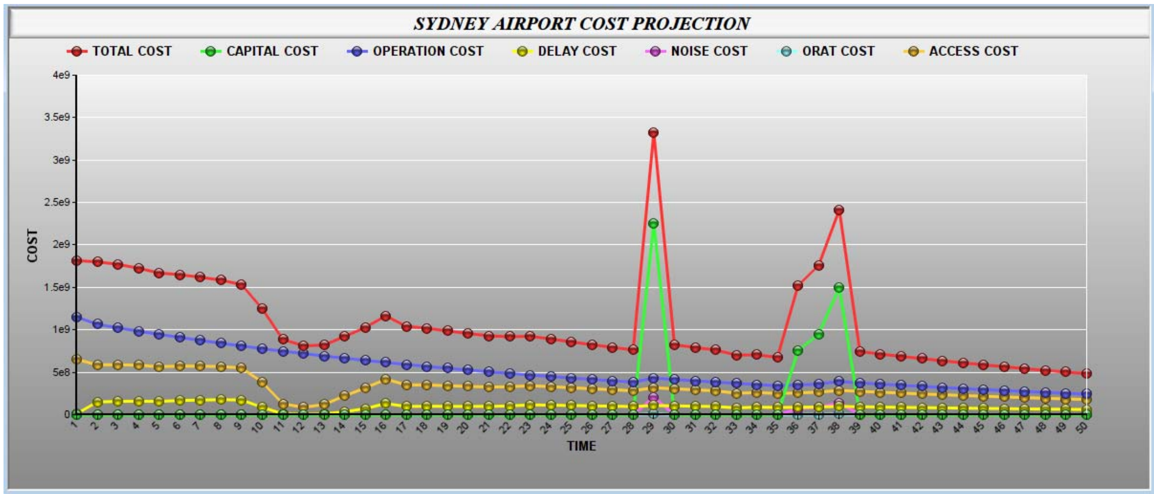


Note. This figure shows the total cost estimate results from the What-if Scenario-3 model to provide the required airport capacity in the Sydney region through a dual airport solution. A peak cost input indicates the required capital cost to add additional airport capacity.

Figure 38 and Figure 39 illustrate the necessary costs to add the required airport capacity for Sydney Airport and Western Sydney Airport, respectively. The cost requirements per year vary due to the random rate of traffic increases and decreases with the airport infrastructure expansion. From Year 24, Sydney Airport and Western Sydney Airport will form a dual airport system to support increasing air traffic demand in the Sydney region.

Figure 38

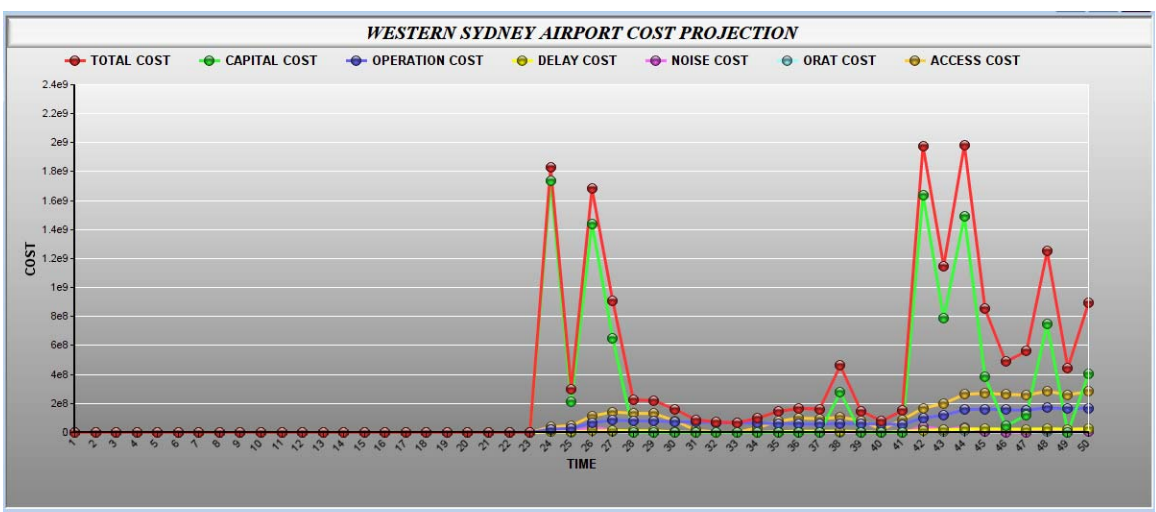
What-if Model 3: Sydney Airport Cost Projection (in AUD)



Note. This figure shows the total cost estimate results from the What-if Scenario-3 model to expand the capacity of the existing Sydney airport. A capital cost input is required between Year 28 and Year 30 and between Year 35 and Year 39 to add the capacity up to its maximum allowance of 72 MAP.

Figure 39

What-if Model 3: Western Sydney Airport Cost Projection (in AUD)



Note. This Figure shows annual cost inputs from Year 36 to develop and operate Western Sydney airport.

Comparison of Deterministic vs. Stochastic Models

Table 30 presents the overall comparison of the model outcomes between the deterministic Sydney Model and the three What-if Models, which were developed using a stochastic approach. Even with the significant difference of the presented future traffic demand among the four scenarios, the optimization model successfully yielded the model outcomes with optimal capacity expansion solutions to minimize the overall costs.

Whilst the Sydney Model, What-if Model 1, and What-if Model 3 suggest a dual airport solution by utilizing Sydney Airport and Western Sydney Airport to handle the future traffic demand, What-if Model 2 proposes a three-airport solution and recommends Western Sydney Airport's maximum capacity utilization. This result indicates that the optimal solution of airport capacity expansion can vary depending on the future traffic demand profile.

Figure 40 illustrates the traffic demand comparison between the Sydney Base Model and three What-if scenario models. Whilst the Sydney Model and What-if Model 1 show a gradual increase of the traffic demand at a steady rate, What-if Model 2 and Model 3 present strong fluctuation of the future demand change, which would cause unnecessary cost expenditure due to the gap between supplied capacity and actual demand. Careful consideration of airport capacity expansion strategy and decision-making will be required to minimize the overall costs.

Table 30

Sydney Model vs. What-if Model Outputs Comparison

Model ID	Proposed Solution	Annual Traffic Growth (%)	Total Costs (Y1-Y50, in AU$000s)	Target Capacity (Year 50, in thousand passengers)				Remark
				Total	SYD	W_SYD	BWU	
Sydney Model (fixed growth)	Dual Airports: •SYD: Y1-50 •W_SYD: Y23-50	Mean: 2.85 Median: 2.60 Highest: 3.50 Lowest: 2.60 S. Dev: 0.35	25,259,885	145,532	72,000	73,532	-	Table 14 Table 15
What-if Model 1: Random Rate (0-5.7%)	Dual Airports: •SYD: Y1-50 •W_SYD: Y27-50	Mean: 2.87 Median: 2.85 Highest: 4.09 Lowest: 1.01 S. Dev: 0.62	24,263,080	146,977	72,000	74,977	-	Table 21 Table 22
What-if Model 2: Normal Distribution	Multi-Airports: •SYD: Y1-50 •W_SYD: Y30-50 •BWU: Y49-50	Mean: 3.25 Median: 2.42 Highest: 18.81 Lowest: -11.98 S. Dev: 7.31	22,041,104	157,601	72,000	82,000	3,601	Table 25 Table 26
What-if Model 3: COVID-19	Dual Airports: •SYD: Y1-50 •W_SYD: Y24-50	Mean: 2.70 Median: 2.73 Highest: 93.15 Lowest: -65.07 S. Dev: 19.39	17,563,488	121,866	72,000	49,866	-	Table 28 Table 29

Figure 41 depicts the annual cost comparison between Sydney Model and three What-if Models. The cost graph has a strong relationship with the traffic demand pattern: Sydney Model and What-if Model 1 show less fluctuation compared to What-if Model 2 and Model 3. While What-if Model 2 will require the larger target airport capacity in the Sydney region than Sydney Model and What-if Model 1, the required total cost over time for the What-if Model 2 is less than that of the other two models. This scenario considers a low growth rate of the traffic demand at the beginning of the model timeline, which does not require airport capacity expansion projects until Year 20. The model considers a financial perspective of the investment, so delaying the capital investment until the additional capacity is required by the market demand helps to achieve the cost minimization goal.

What-if Model 3 projects the smallest investment over time due to the COVID-19 pandemic impact between Year 10 and Year 15. The plunge of the air traffic demand does not necessitate airport capacity expansion projects until Year 23. The gap of air traffic demand between What-if Model 3 and the other three models makes a significant difference in the required costs over time.

Figure 40

Traffic Demand Comparison

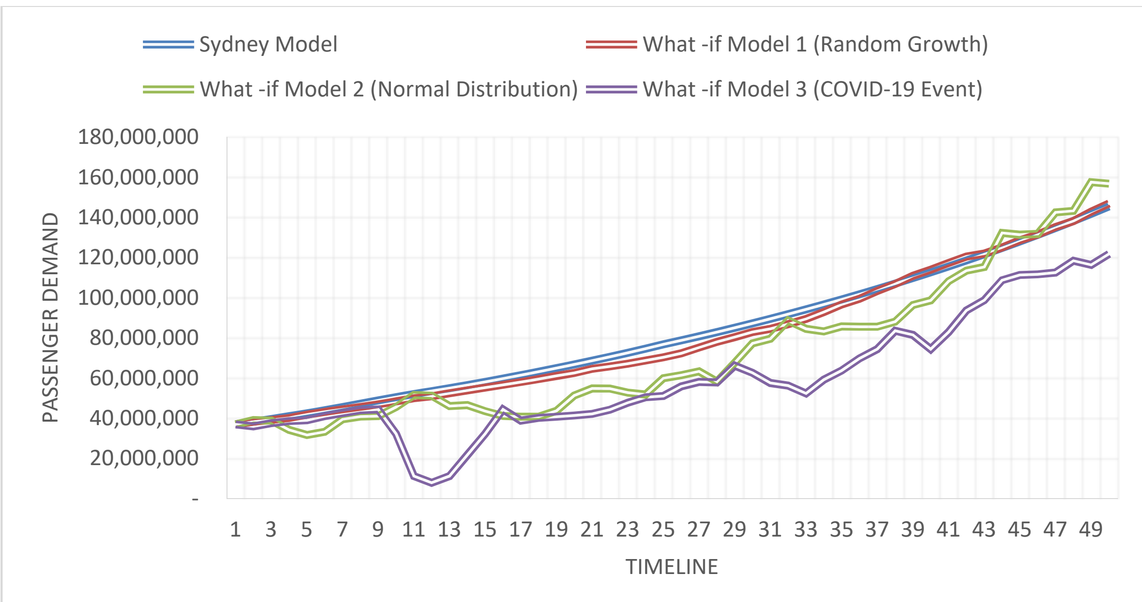
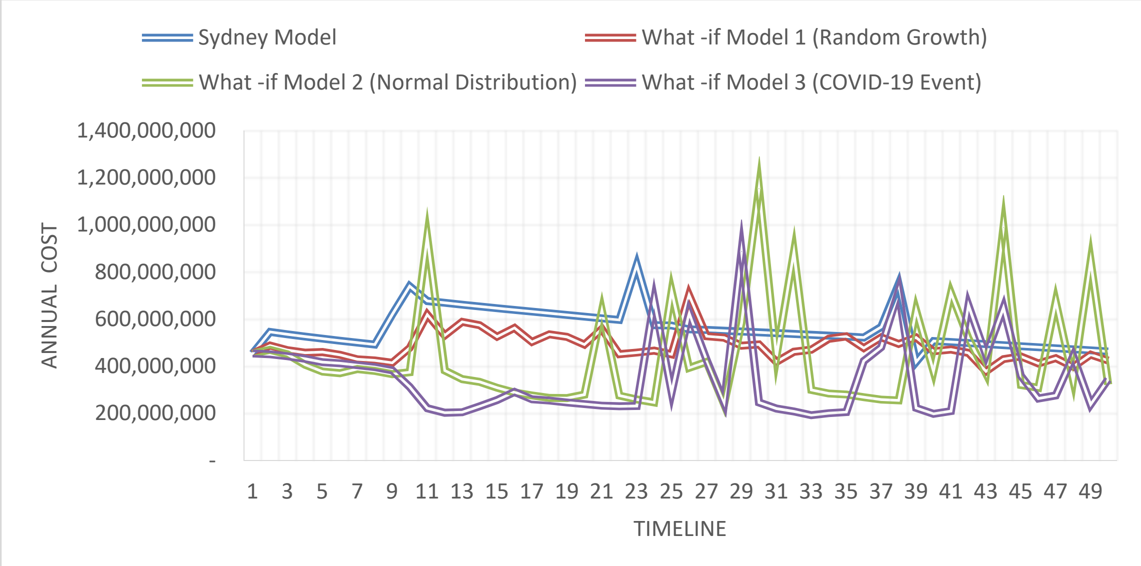


Figure 41

Annual Cost Comparison



Summary

The proposed MINLP model was validated using the example case of the Sydney region, which presented an optimal solution of a dual airport system in the Sydney region for the 50-year timeline. Its model reliability was also tested through six Experiment Models by introducing different input values for three independent variables: discount rates, operational unit costs, and passenger access unit cost. All six models ran successfully and yielded meaningful model outcomes. Sydney Model and the six Experiment Models consistently yielded similar results as an optimal capacity expansion solution: a dual airport system in the Sydney region is needed by introducing a new Western Sydney Airport into the market to cater to the exceeding air traffic demand beyond the maximum capacity of the Sydney Airport.

The deterministic MINLP model was expanded to a stochastic model to address concerns with the uncertainty of traffic demand. Three What-if scenario models were developed by differentiating the approach with the traffic demand uncertainty: random annual growth rates between 0% and 5%, normal distribution of annual growth rates based on Sydney aviation market's previous traffic history, and devastating air transport market situation reflecting the COVID-19 pandemic event. The introduced stochastic model successfully responded to the three different demand scenarios and yielded optimal solutions to minimize the required costs for the next 50-year timeline.

The results of the stochastic MINLP model demonstrated the adequacy and usefulness of the proposed optimization model to support decision-making for airport capacity expansion problems under the future traffic demand uncertainty.

CHAPTER V

DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

This chapter focus on discussing the results produced from Chapter IV and answering the three research questions presented in Chapter I. It also describes the overall achievement of the optimization model, outcomes produced by the various optimization models, and conclusions of the present study. The limitations of this study are discussed to provide recommendations for future research.

The main purpose of this research was to develop an optimization model to identify an optimal solution for airport capacity expansion in metropolitan areas. As a first step, a deterministic MINLP model was developed with the inclusion of six cost functions: capital cost, operation cost, delay cost, noise cost, ORAT cost, and passenger access cost, all of which are highly related to airport capacity problems. This deterministic MINLP model was validated using an example case of the Sydney metropolitan area for a 50-year timeline. The Sydney Model was augmented into six additional experimental models by differentiating input values of three independent variables to test the reliability of the model.

This deterministic model was then extended to a stochastic MINLP model to address concerns with the uncertainty of future traffic demand. Whereas future traffic demands were treated as controllable input variables within the deterministic MINLP model, it became an uncontrollable input variable when a stochastic model was developed. Three what-if scenarios were used to compare the model outcomes with the deterministic Sydney Model: random growth of traffic demand, normal distribution of traffic demand changes based on the historical traffic record, and reflection of the current

COVID-19 pandemic situation. To deploy a stochastic approach into the deterministic model, the researcher used a Monte Carlo simulation method for the treatment of uncontrollable future traffic demand. The Sydney Model and three what-if models successfully produced objective outcomes and identified optimal solutions to expand airport capacity while minimizing overall costs.

Discussion

This study presents both deterministic and stochastic models to optimize the overall costs for airport capacity expansion over time in the presence of demand uncertainty. The impact of demand uncertainties on airport capacity problems was reviewed by comparing deterministic and stochastic optimization models.

Deterministic MINLP Model

As described in Chapter 3, a deterministic mathematical model was first built based on the literature review and four case studies that represent each type of airport capacity expansion solutions. This model was named General Model and used to develop both scalable deterministic and stochastic models. In the deterministic model, the traffic growth rate was treated as a controllable variable. Because this General Model presents only a mathematical form as an outcome, it was necessary to use an actual case to confirm the validity and effectiveness of the model. To overcome this challenge, this General Model was validated by the case of the Sydney region based on the various assumptions which were presented by the Australian and NWS government in 2011. Then, six experiment models were developed to confirm the reliability of the model using the Sydney Model with a variation of the values for three input variables: discount rate, operation unit cost, and passenger access unit cost.

The air traffic demand, total airport capacity, and costs of each experiment model against the Sydney Model are presented in Figure 42, Figure 43, and Figure 44. Whereas traffic demand and airport capacity follow steady growth curves at a fixed rate increase, change of the values with the three input variables yielded significant cost gaps between Sydney Model and the experiment models. The six experiment models successfully demonstrate the reliability of the General Model by generating the same optimal solution of a dual airport system and target airport capacity.

Figure 42

Demand-Capacity-Cost Comparison: Sydney Model vs. Experimental Model 1

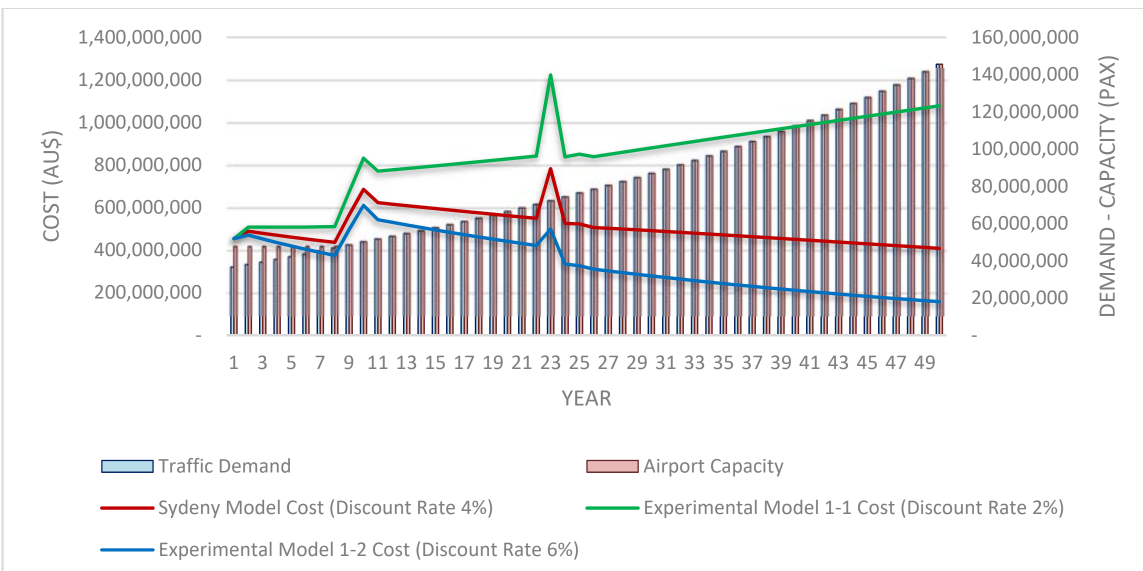


Figure 43

Demand-Capacity-Cost Comparison: Sydney Model vs. Experimental Model 2

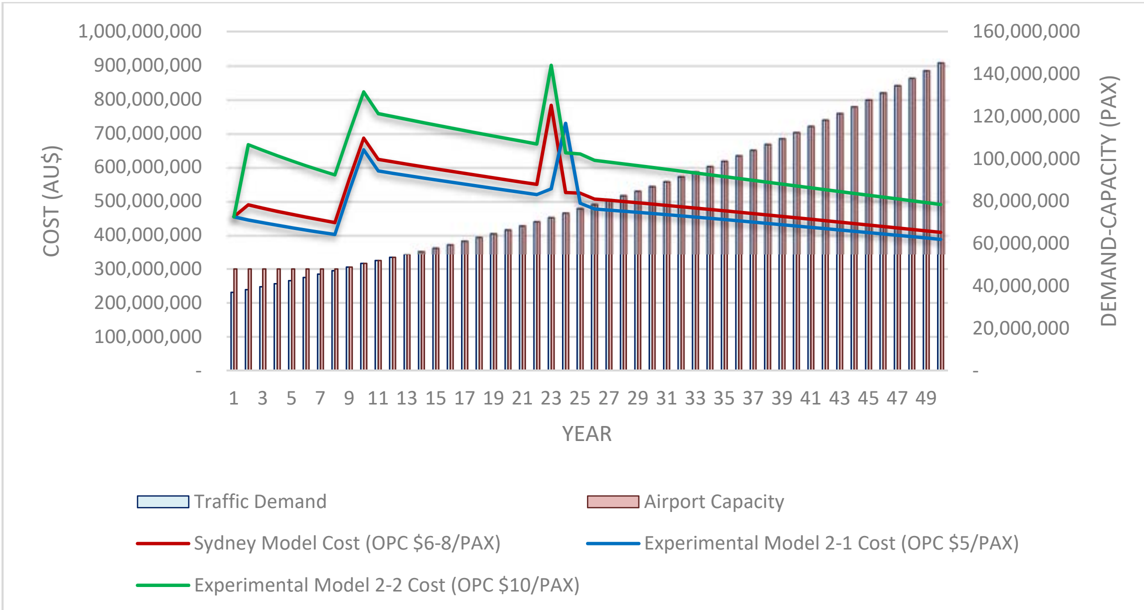
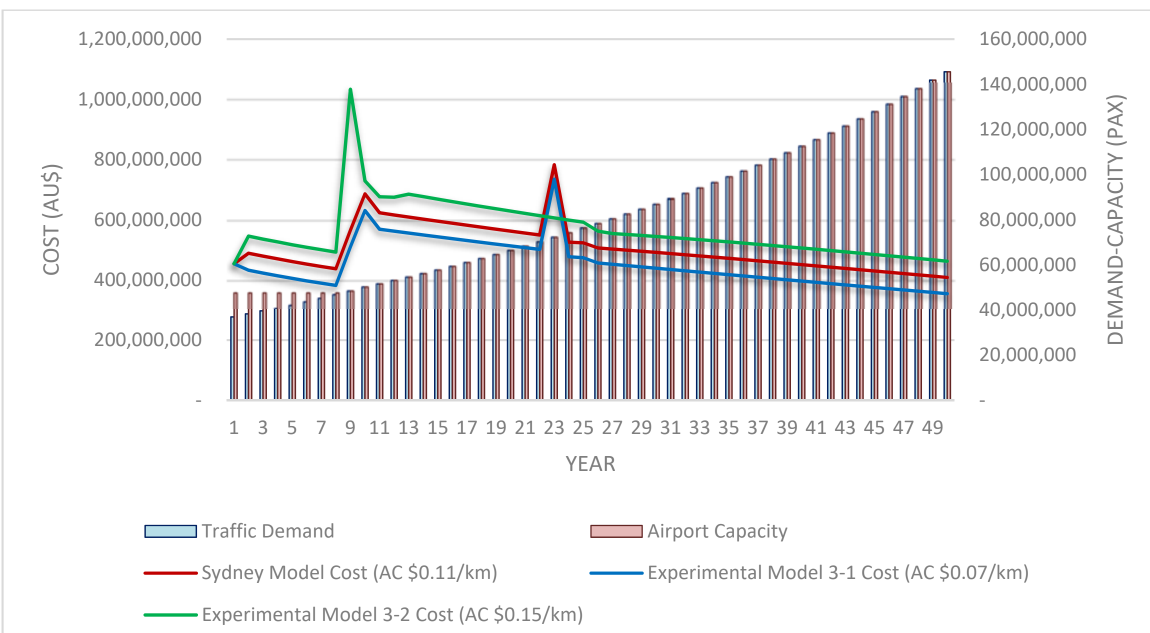


Figure 44

Demand-Capacity-Cost Comparison: Sydney Model vs. Experimental Model 3



From this deterministic optimization model development, the MINLP formulations for the airport capacity problem in metropolitan areas can be characterized by the three aspects below:

1) In the General Model, several variables were defined as integer variables such as passenger demand and airport capacity. Integer variables, due to the combinatorial nature of the optimization problem, helped to simplify the computing process to find an optimal solution;

2) A majority of the variables in this model have a nature of continuous variables such as six cost variables and distance between airports and population centers. The researcher notes that continuous variables were often bounded based on operational constraints and assumptions; and

3) Nonlinearities in the objective and constraints were essentially required to reflect real-world operational conditions on this optimization model. In this model, financial discount rate, passenger demand, and delay costs are populated as non-linear variables or constraints. Noting that nonlinearities can come from products of continuous as well as discrete variables, they are expected to affect modeling outcomes and solution processes.

Stochastic MINLP Model

One of the principal assumptions of deterministic optimization models is that all input data or variables are known with certainty. However, in real-world situations, certain data or variables are highly changeable and sometimes unpredictable. In the General Model, future traffic demand cannot be taken as a deterministic factor due to an externality of the air transport industry. For instance, when an airline changes its market strategy for the coming seasons or the global economy experiences a large-scale recession, the demand for air traffic would be significantly affected. The main reason why the long-period optimization model is difficult and complex is primarily due to the uncertainty about the market demand and future state of the industry. Some action or decision must be taken based on the best assumptions of the possible future, but its consequence can become massive.

If air traffic demand for a city or region is forecasted to be strong and immediate action is required to increase its airport capacity radically, then developing a brand-new airport at a large scale would be regarded as a wise decision. On the other hand, if the expected market demand disappears in the region and the airport cannot accommodate the expected traffic, the regional municipality or airport operator shall bear the costs to maintain the infrastructure until the traffic is recovered. However, if the distribution probabilities for the future air traffic demand are known, the stochastic optimization modeling technique can tackle the challenges with the uncertainty problem in the deterministic optimization model.

After validation and reliability test of the deterministic General Model were successfully implemented, the General Model was transformed into the stochastic optimization model by using the Monte Carlo simulation method. Then, three What-if Models were developed using the Sydney Model with the variation of future traffic demand growth scenarios: What-if Model 1, Model 2, and Model 3 consider a random traffic growth between 0 – 5.7%, random traffic growth based on the normal distribution of the 25-year record of the Sydney region, and reflection of COVID-19 pandemic effect respectively.

The total costs, air traffic demand, and airport capacity of three What-if Models are presented in Figure 45, Figure 46, and Figure 47. What-if Model 2 and What-if Model 3 used a more realistic approach than What-if Model 1 by using actual traffic data of the Sydney region. The sudden increases in the cost curve shown in the three model outcomes can be explained by initial capital investment for the required capacity expansion of airports and ORAT activities. In the meantime, cost decreases primarily result from a reduced traffic demand associated with passenger access cost, noise cost, and congestion cost. Capital cost, operation cost, and ORAT cost are correlated to airport capacity in this model.

The three what-if models helped to demonstrate the effectiveness of the Stochastic Model by yielding differentiated model outcomes responding to each traffic demand scenario. While What-if Model 1 and Model 3 proposed a dual airport system by utilizing the existing Sydney Airport and new Western Sydney Airport, What-if Model 2 suggested a three-airport system by converting Bankstown Airport into a commercial airport. The Stochastic Model was able to develop an optimal solution to expand airport capacity in metropolitan areas under the uncertainty of the future traffic demand.

Figure 45

Demand-Capacity-Cost Comparison: What-if Model 1

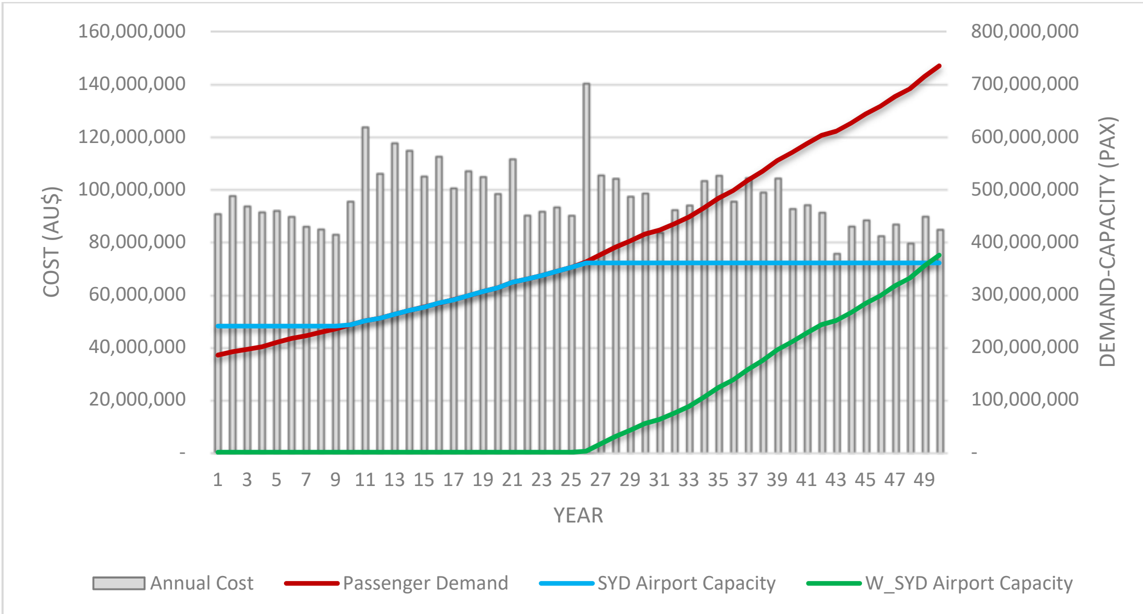


Figure 46

Demand-Capacity-Cost Comparison: What-if Model 2

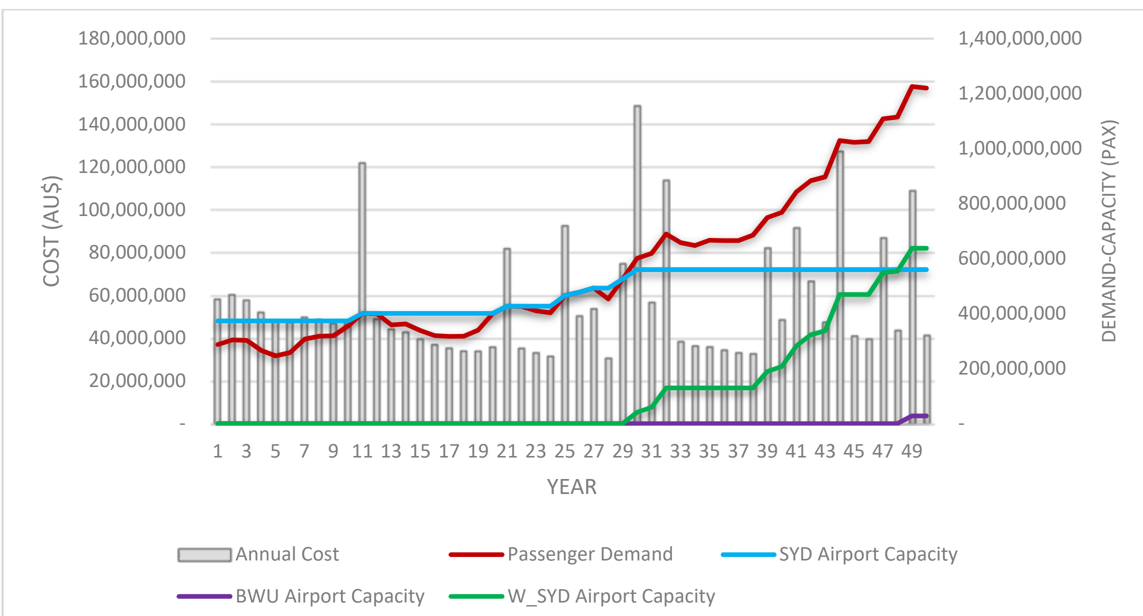
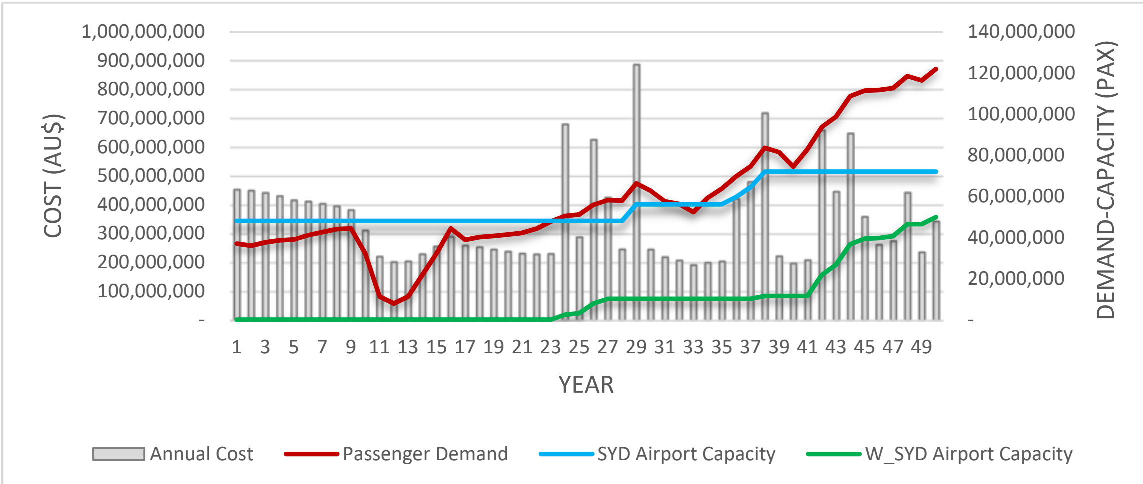


Figure 47

Demand-Capacity-Cost Comparison: What-if Model 3



As defined in Chapter 3, the decision variables of this study are the number of airports in the metropolitan area and the target airport capacity of each airport. Also, this research aimed to identify the optimized timeline for any new or existing non-commercial airport to initiate commercial operations. Table 31 shows the target airport capacity and operation timeline of the four existing and potential airports in the Sydney region both from the deterministic and stochastic optimization model outcomes.

Table 31

Optimization Model Results (Passengers in Thousand)

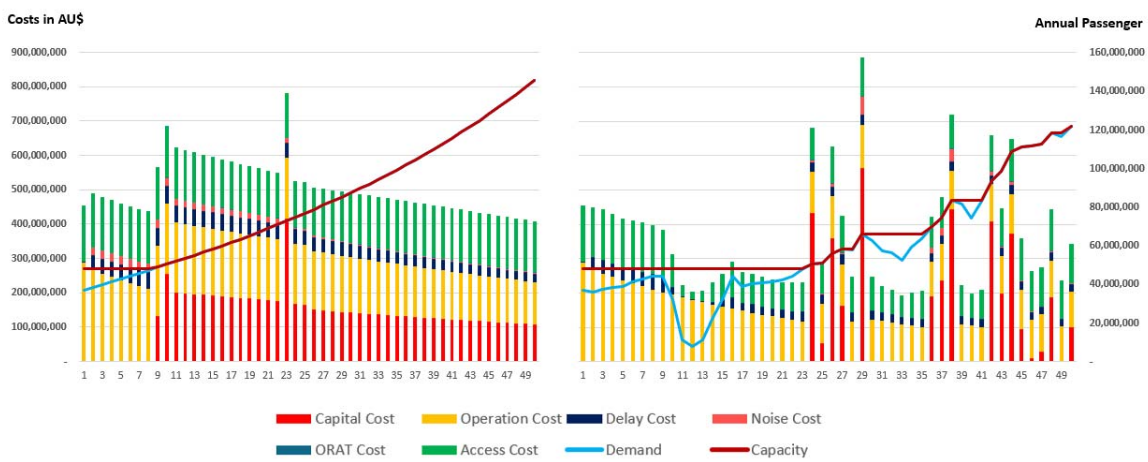
Model	Passenger Demand (in Y50)	Target Capacity (in Y50) / Operation Timeline			
		SYD	BWU	RCM	W_SYD
Sydney Model	145,532	72,000 / Y1-Y50	0	0	73,532 / Y23-Y50
Sydney What-if Model 1	146,977	72,000 / Y1-Y50	0	0	74,977 / Y26-Y50
Sydney What-if Model 2	156,896	72,000 / Y1-Y50	3,600 / Y49-Y50	0	82,000 / Y30-Y50
Sydney What-if Model 3	121,866	72,000 / Y1-Y50	0	0	49,866 / Y24-Y50

Sydney Model, What-if Model 1, and What-if Model 3 identified a dual airport system utilizing the existing Sydney Airport and new Western Sydney Airport as an optimal solution to minimize the cost over a 50-year timeline. Meanwhile, What-if Model 2 requires a three-airport system in the Sydney region by converting Bankstown Airport into a commercial airport. The three-airport system is required because the forecasted market demand exceeds the combined maximum capacity of Sydney Airport and Western Sydney Airport from Year 49. The time to introduce the new Western Sydney Airport to the market varies between Year 23 and Year 30 because of the difference in market demand and the capacity expansion plan of the existing Sydney Airport. Even though air traffic demand has recently plummeted due to the impact of the COVID-19 pandemic, the needs for the Western Sydney Airport are not largely affected, which indicates the introduction of Wester Sydney Airport can be an effective solution to accommodate increasing air traffic demand in the Sydney region from the cost optimization perspective.

Figure 48 exemplify the significant difference in future demand and cost profiles between the deterministic model and stochastic model by comparing General Model and What-if Model 3. This figure illustrates the impact of changes in traffic demand and airport capacity on six cost functions. While passenger access costs directly correlate with the passenger demand, operations costs and noise costs are influenced by the increase of airport capacity. Capital costs and ORAT costs occur when passenger demand exceeds the existing airport capacity, which requires the addition of airport capacity. Delay costs, as discussed in Chapter 3, have a complex cost function in a proportion to the ratio of the square of passenger demand to an airport capacity.

Figure 48

Demand-Capacity-Cost Comparison: Sydney Model and What-if Model 3



Answers to Research Questions

The conclusions for each of the three research questions follow next.

Q1. What are the cost functions related to airport capacity expansion, and how are they related to traffic demand change over time?

From four case studies and the literature review, six cost functions were identified as key components for the airport capacity expansion problem: capital cost, operation cost, delay cost, noise cost, ORAT cost, and passenger access cost. Financial discount rates, passenger demand, and delay costs were populated as non-linear variables or constraints, which gave a nonlinear nature to all six cost functions over time. This study also found tradeoffs among the six cost functions over time. Traffic demand growth necessitates the capacity expansion of airports, which requires an investment in capital costs and ORAT costs. While the increased airport capacity results in additional costs for airport operations and noise abatement, the increased airport capacity can reduce delay costs by alleviating airport congestion. Meanwhile, passenger access cost is directly proportional to the level of passenger traffic demand.

Q2. How can an optimum solution for the airport capacity expansion be determined by the proposed cost functions in terms of minimizing related costs?

The objective function of this optimization model is the net present value of total cost, which includes the aforementioned six cost functions. The correlation of the six cost functions with traffic demand changes over time and future cost discounted enabled the optimization model to identify the optimal solution in terms of cost minimization. The consideration of capital cost, operation costs, and ORAT costs can help to avoid the early addition of airport capacities unwarranted by traffic demand. Also, the inclusion of the delay costs will prevent delay of airport capacity projects which can help to reduce stakeholders' unnecessary costs from airport congestion. The inclusion of noise costs and passenger access costs explored identifying optimal airport locations in terms of minimizing the cost imposed on airport users and communities.

Q3. How can the optimum solution be decided in consideration of various factors that may impact future traffic demand?

Deregulated and competitive market conditions have created substantial demand uncertainty for the airport industry. Airlines can select their hub locations and routing strategy depending on the market environment. Also, the impact of pandemic diseases or global financial crisis can largely impact air travel demand. In the presence of the air traffic demand uncertainty, the researcher considered three what-if demand scenarios, both airline-driven demand changes and the pandemic impact on the aviation market. The demand uncertainties were found to interact with the cost functions of the optimization model. The stochastic approach and use of the Monte Carlo simulation method demonstrated the effectiveness of identifying an optimal solution in the face of uncertainties of future demand.

Conclusions

Theoretical Implications

The present research provides important contributions to the body of knowledge, particularly to the literature on airport capacity problems. Firstly, while each cost function serves as an independent component of the optimization model to identify an optimal solution, at the same time it interacts with other cost functions and demand changes over time. The research formulated six cost functions in the optimization model to address the specific needs of various airport stakeholders. No previous airport capacity optimization model was found that introduced a wide range of cost functions. Also, a trade-off effect between the costs for airport capacity increases and airport congestion was considered.

Secondly, the results of the research are not only the cost optimization model for airport expansion but also an integrative optimization model to solve airport choice problems in metropolitan areas. To achieve this goal, airport access and noise problems are incorporated into the optimization model as part of the mathematical form. The different levels of airport access and noise costs imply the impact on the communities, passengers, and employees, which can be regarded as such a critical subject when deciding on airport location.

Thirdly, in the presence of air traffic demand uncertainty in a competitive market environment, the findings demonstrated the effectiveness and benefits of a combination between the mixed-integer non-linear programming (MINLP) and the Monte Carlo simulation method. To the best of the knowledge of the researcher, the present study is the first to use the combination of the two research methods to identify an optimal solution for airport capacity expansion over time in metropolitan areas.

Lastly and importantly, the research also contributes to the body of knowledge by introducing an optimization model to solve airport capacity problems in metropolitan areas. Airports in metropolitan areas are highly dependent on the urban economy and social dynamics, so the integrated development of airports within the metropolitan region is critical. Hence, the consideration of connectivity between airports and population centers and aircraft noise issues within the optimization model will support decision-makers taking a more strategic approach for the planning and decision process.

Practical Implications

This research has been motivated by real-world problems with airport capacity issues which can be observed in many metropolitan areas. Because this problem can engage various types of stakeholders, such as airport operators, airlines, tenants, employees, communities, and passengers, the cost functions need to address their concerns. For instance, the cheapest solution would be to develop a new airport in a remote area from population centers to reduce land acquisition costs. However, this approach would require more costs over time for passengers to access the airport. Similarly, developing a new airport next to a large residential area would incur excessive noise costs to the communities, even though it would help passengers reduce access costs.

Additionally, three What-if Models under the stochastic approach can help the airport industry to better understand the potential impact of air traffic uncertainty on the future costs for airport development and operations. For instance, the model outcomes from What-if Model 3 can support airport authorities and operators to re-establish the future expansion strategy and modify the current investment plan in consideration of the COVID-19 pandemic impact.

Limitations

Chapter 1 of this dissertation describes several limitations and delimitations for the present study. Also, Chapter 3 presents many assumptions to formulate the optimization algorithm of the model. Because this optimization model had a strong focus on minimizing overall costs to expand airport capacity, other sources of optimization such as maximizing profits or throughputs were not considered. If the objective function changes, the optimization model may suggest different solutions.

Another limitation of this research is related to the large scale of the model to solve the airport capacity problem in metropolitan areas. Having a macro view on the problems, several practical factors such as the economies of scale and each component of airports such as runway and cargo terminal were not considered. This study also did not consider a seasonal factor of the airport peak-time operations, which can be further reviewed and incorporated into this optimization model. In contrast to most previous studies which focused on one specific component of the airport system, the present study provides a global planning model, considering multi-airport systems in metropolitan areas.

Last, it needs to be noted that this study did not take into account the impact of political events or socio-economic factors such as change of government or job creations associated with airport expansion, which may lead to a radical decision about airport capacity projects. The present research intentionally excluded the political or socio-economic factors to have a pure focus on the cost function and demand uncertainties of the industry.

Recommendations

The results of the present study indicated that future traffic demand uncertainty may have an impact on the optimal solution to expand airport capacity in metropolitan areas. Therefore, regulators, airport authorities, and airport planners should carefully consider the uncertainty factors that would influence the future demand profile. Because the number of demand scenarios that can be considered is finite, a careful approach to select the meaningful demand scenarios can be one of the major concerns with the future study. Also, by careful examination of the latest actual traffic data from reliable data sources, researchers can produce more feasible demand scenarios.

When developing an optimization model, it is important to understand that the model can become complex in proportion to the number of input variables such as the number of airports and population centers and the planning period. As reviewed in the discussion section of this chapter, optimization models can become quite large if the number of input variables cannot be controlled, which is particularly true for multi-period optimization models. Therefore, a careful selection of input variables and constraints during the modeling process is a key for the successful development of the optimization model. Pre-processing with a simplified model structure can help to reduce the potential problem when a full-scale optimization model is processed. Also, the use of integer variables can be an effective measure to reduce the complexity of the model.

Future Research Opportunities

This section proposes opportunities for future research to augment the presented optimization model and to improve the accuracy of the model performance. Three areas, as below, are identified to expand the benefits of this optimization model. First, different sources of uncontrollable variables can be considered to augment the stochastic optimization model. Additional uncertainty factors, such as competition with high-speed trains, financial crisis, political events, airline competition and consequent airfare changes, technological innovation, and demographic changes might also be populated as uncertain and uncontrollable variables.

Second, future studies could consider additional constraints in consideration of real-world problems associated with financing and resource capacity: availability of land, maximum allowable fiscal budget, and the maximum number of airports in consideration of the size of the metropolitan area. By modifying the mathematical model algorithm, any other constraints can be added to the optimization model. However, because the nature of different constraints may clash with each other during the modeling process, careful treatment is required to consider additional constraints. For instance, if the maximum budget allowance cannot pay for the required capital cost, the model needs to be structured for a capacity expansion project to be implemented under the budget constraints and over the multiple-year timeline.

Last, while this optimization model was developed to identify an optimal solution for airport capacity issues in metropolitan areas in terms of minimizing required costs, it can also be used to optimize other interested objective functions. For instance, this model can be used to find an optimal solution to maximize social benefits, passenger throughput, and commercial revenues. Different types of decision-making research methods such as Markov process model, dynamic programming, and goal programming can be considered, tailored to the objective functions.

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APPENDIX A

Sydney Model Algorithms and Input Data

```
MODEL:

SETS:

AIRPORT:

  IAC, ! INITIAL AIRPORT CAPACITY;

  MAC, ! MAXIMUM POTENTIAL AIRPORT CAPACITY;

  TAC; ! Airport capacity at the end of the program;

PERIOD: DTOTAL, SAC_TOTAL, SAC_SYD, SAC_BWU, SAC_RCM, SAC_W_SYD, COST_TOTAL, CC_TOTAL, OPC_TOTAL, DC_TOTAL,
NC_TOTAL, ORC_TOTAL, AC_TOTAL,

COST_SYD, CC_SYD, OPC_SYD, DC_SYD, NC_SYD, ORC_SYD, AC_SYD, COST_W_SYD, CC_W_SYD, OPC_W_SYD, DC_W_SYD,
NC_W_SYD, ORC_W_SYD, AC_W_SYD;

AIRPORTP (AIRPORT, PERIOD): DAIRPORT, SAC, CC, OPC, DC, NC, ORC, AC, TC;

ENDSETS

DATA:

AIRPORT, IAC, MAC =

  SYD       48000000 72000000

  BWU              0  5000000

  RCM              0 32000000

  W_SYD            0 82000000;

PERIOD = 1..50;

! Import the data from Excel;

DTOTAL=

@OLE('C:\Woojin Work\ERAU_PhD in Aviation\Dissertation\MINLP MODEL\DATA_SAMPLE.XLSX', 'DTOTAL');

! Export the solution back to Excel;

@OLE('C:\Woojin Work\ERAU_PhD in Aviation\Dissertation\MINLP MODEL\DATA_SAMPLE.XLSX') = SAC;

@OLE('C:\Woojin Work\ERAU_PhD in Aviation\Dissertation\MINLP MODEL\DATA_SAMPLE.XLSX') = TC;

@OLE('C:\Woojin Work\ERAU_PhD in Aviation\Dissertation\MINLP MODEL\DATA_SAMPLE.XLSX') = CC;

@OLE('C:\Woojin Work\ERAU_PhD in Aviation\Dissertation\MINLP MODEL\DATA_SAMPLE.XLSX') = OPC;

@OLE('C:\Woojin Work\ERAU_PhD in Aviation\Dissertation\MINLP MODEL\DATA_SAMPLE.XLSX') = DC;

@OLE('C:\Woojin Work\ERAU_PhD in Aviation\Dissertation\MINLP MODEL\DATA_SAMPLE.XLSX') = NC;

@OLE('C:\Woojin Work\ERAU_PhD in Aviation\Dissertation\MINLP MODEL\DATA_SAMPLE.XLSX') = ORC;

@OLE('C:\Woojin Work\ERAU_PhD in Aviation\Dissertation\MINLP MODEL\DATA_SAMPLE.XLSX') = AC;

ENDDATA
```

```
SUBMODEL COST_MODEL:

! OBJECTIVE FUCNTIONS;

MIN = @SUM(AIRPORTP(I, T): TC(I, T));

! COST FUNCTIONS;

@FOR(AIRPORTP(I, T):

TC(I, T) = CC(I, T) + OPC(I, T) + DC(I, T) + NC(I, T) + ORC (I, T) + AC (I, T));

@FOR(AIRPORTP(I, T) | T #GT# 1:

CC(1, T) = 216.67 * (SAC(1, T)-SAC(1, T-1)) * (1/(1.04))^T;

CC(2, T) = 342.86 * (SAC(2, T)-SAC(2, T-1)) * (1/(1.04))^T;

CC(3, T) = 333.81 * (SAC(3, T)-SAC(3, T-1)) * (1/(1.04))^T;

CC(4, T) = 210.27 * (SAC(4, T)-SAC(4, T-1)) * (1/(1.04))^T;

NC(1, T) = 20000 * (DAIRPORT(1, T) - DAIRPORT(1, T-1)) / 1000 * (1/(1.04))^T;

NC(2, T) = 20000 * (DAIRPORT(2, T) - DAIRPORT(2, T-1)) / 2000 * (1/(1.04))^T;

NC(3, T) = 20000 * (DAIRPORT(3, T) - DAIRPORT(3, T-1)) / 3000 * (1/(1.04))^T;

NC(4, T) = 20000 * (DAIRPORT(4, T) - DAIRPORT(4, T-1)) / 4000 * (1/(1.04))^T;

ORC(1, T) = 0.6 * @ABS((SAC(1, T) - SAC(1, T-1))) * (1/(1.04))^T;

ORC(2, T) = 0.8 * @ABS((SAC(2, T) - SAC(2, T-1))) * (1/(1.04))^T;

ORC(3, T) = 1.0 * @ABS((SAC(3, T) - SAC(3, T-1))) * (1/(1.04))^T;

ORC(4, T) = 1.2 * @ABS((SAC(4, T) - SAC(4, T-1))) * (1/(1.04))^T;

OPC(1, T) = 6 * SAC(1, T) * (1/(1.04))^T;

OPC(2, T) = 8 * SAC(2, T) * (1/(1.04))^T;

OPC(3, T) = 6 * SAC(3, T) * (1/(1.04))^T;

OPC(4, T) = 6 * SAC(4, T) * (1/(1.04))^T;

DC(1, T) = 1.5 * DAIRPORT(1, T) ^ 2 / SAC(1, T) * (1/(1.04))^T;

DC(2, T) = 1.3 * DAIRPORT(2, T) ^ 2 / SAC(2, T) * (1/(1.04))^T;

DC(3, T) = 1.1 * DAIRPORT(3, T) ^ 2 / SAC(3, T) * (1/(1.04))^T;

DC(4, T) = 0.9 * DAIRPORT(4, T) ^ 2 / SAC(4, T) * (1/(1.04))^T;

AC(1, T) = 22.52 * DAIRPORT(1, T) * 1.78 * 0.11 * (1/(1.04))^T;

AC(2, T) = 23.34 * DAIRPORT(2, T) * 1.78 * 0.11 * (1/(1.04))^T;

AC(3, T) = 54.18 * DAIRPORT(3, T) * 1.78 * 0.11 * (1/(1.04))^T;

AC(4, T) = 51.31 * DAIRPORT(4, T) * 1.78 * 0.11 * (1/(1.04))^T;

);

! COST FUNCTION FOR THE FIRST YEAR;

@FOR(AIRPORTP(I, T) | T #EQ# 1:

CC(I, T) = 0;

NC(I, T) = 0;

ORC(I, T) = 0;

DC(I, T) = 0.1 * DAIRPORT(I, T) ^ 2 / SAC(1, T);

OPC(I, T) = 6 * SAC(I, T);

AC(I, T) = 22.52 * DAIRPORT(I, T) * 1.78 * 0.11;
```

```
! Demand constraints;
@FOR(PERIOD(T):
  @SUM(AIRPORTP(I, T): DAIRPORT(I, T)) = DTOTAL(T));
@FOR(AIRPORTP(I, T): SAC(I,T) >= DAIRPORT(I, T));
@FOR(AIRPORTP(I, T) | T #LE# 8: DAIRPORT(1, T) = DTOTAL(T));
! Capacity constraints;
@FOR(AIRPORTP(I,T): SAC(I,1) = IAC(I));
@FOR(AIRPORTP(I,T): SAC(I,50) = TAC(I));
@FOR(AIRPORTP(I,T): SAC(I,T) <= MAC(I));
@FOR(PERIOD(T):
   SAC_TOTAL(T) = @SUM(AIRPORTP(I, T): SAC(I, T)); !TOTAL AIRPORT CAPACITY;
   SAC_SYD(T) = SAC(1, T); !SYD AIRPORT CAPACITY;
   SAC_BWU(T) = SAC(2, T); !BWU AIRPORT CAPACITY;
   SAC_RCM(T) = SAC(3, T); !RCM AIRPORT CAPACITY;
   SAC_W_SYD(T) = SAC(4, T); !W_SYD AIRPORT CAPACITY;

   @SUM(AIRPORTP(I, T): SAC(I, T)) >= DTOTAL(T);
);
! Integer Value Only;
@FOR(AIRPORTP(I, T): @GIN(DAIRPORT(I,T)));
@FOR(AIRPORTP(I, T): @GIN(SAC(I,T)));
```

```
!Total Cost Calculation;

@FOR(PERIOD(T):

COST_TOTAL(T) = @SUM(AIRPORTP(I, T): TC(I, T)); !TOTAL COST;

CC_TOTAL(T) = @SUM(AIRPORTP(I, T): CC(I, T)); !TOTAL CAPITAL COST;

OPC_TOTAL(T) =  @SUM(AIRPORTP(I, T): OPC(I, T)); !TOTAL OPERATION COST;

DC_TOTAL(T) = @SUM(AIRPORTP(I, T): DC(I, T)); !TOTAL DELAY COST;

NC_TOTAL(T) = @SUM(AIRPORTP(I, T): NC(I, T)); !TOTAL NOISE COST;

ORC_TOTAL(T) =  @SUM(AIRPORTP(I, T): ORC(I, T)); !TOTAL ORAT COST;

AC_TOTAL(T) = @SUM(AIRPORTP(I, T): AC(I, T)); !TOTAL ACCESS COST;

!SYD Airport Cost Calculation;

COST_SYD(T) = @SUM(AIRPORTP(I, T): TC(1, T)); !SYD COST;

CC_SYD(T) = @SUM(AIRPORTP(I, T): CC(1, T)); !SYD CAPITAL COST;

OPC_SYD(T) =  @SUM(AIRPORTP(I, T): OPC(1, T)); !SYD OPERATION COST;

DC_SYD(T) = @SUM(AIRPORTP(I, T): DC(1, T)); !SYD DELAY COST;

NC_SYD(T) = @SUM(AIRPORTP(I, T): NC(1, T)); !SYD NOISE COST;

ORC_SYD(T) =  @SUM(AIRPORTP(I, T): ORC(1, T)); !SYD ORAT COST;

AC_SYD(T) = @SUM(AIRPORTP(I, T): AC(1, T)); !SYD ACCESS COST;

!W_SYD Airport Cost Calculation;

COST_W_SYD(T) = @SUM(AIRPORTP(I, T): TC(4, T)); !W_SYD TOTAL COST;

CC_W_SYD(T) = @SUM(AIRPORTP(I, T): CC(4, T)); !W_SYD  CAPITAL COST;

OPC_W_SYD(T) =  @SUM(AIRPORTP(I, T): OPC(4, T)); !W_SYD  OPERATION COST;

DC_W_SYD(T) = @SUM(AIRPORTP(I, T): DC(4, T)); !W_SYD  DELAY COST;

NC_W_SYD(T) = @SUM(AIRPORTP(I, T): NC(4, T)); !W_SYD  NOISE COST;

ORC_W_SYD(T) =  @SUM(AIRPORTP(I, T): ORC(4, T)); !W_SYD  ORAT COST;

AC_W_SYD(T) = @SUM(AIRPORTP(I, T): AC(4, T)); !W_SYD  ACCESS COST;

);

ENDSUBMODEL
```

```
CALC:

@SOLVE(COST_MODEL);

!LINE CHART OF TOTAL COST PROJECTION;

@CHARTLINE(

'TOTAL COST PROJECTION', !CHART TITLE;

'TIME', !X-AXIS LABLE;

'COST', !Y-AXIS LABLE;

'TOTAL COST', COST_TOTAL, 'CAPITAL COST', CC_TOTAL, 'OPERATION COST', OPC_TOTAL, 'DELAY COST', DC_TOTAL, 'NOISE
COST',NC_TOTAL, 'ORAT COST', ORC_TOTAL, 'ACCESS COST', AC_TOTAL !ATTRIBUTE;

);

!LINE CHART OF SYD COST PROJECTION;

@CHARTLINE(

'SYDNEY AIRPORT COST PROJECTION', !CHART TITLE;

'TIME', !X-AXIS LABLE;

'COST', !Y-AXIS LABLE;

'TOTAL COST', COST_SYD, 'CAPITAL COST', CC_SYD, 'OPERATION COST', OPC_SYD, 'DELAY COST', DC_SYD, 'NOISE COST',NC_SYD,
'ORAT COST', ORC_SYD, 'ACCESS COST', AC_SYD !ATTRIBUTE;

);

!LINE CHART OF W_SYD COST PROJECTION;

@CHARTLINE(

'WESTERN SYDNEY AIRPORT COST PROJECTION', !CHART TITLE;

'TIME', !X-AXIS LABLE;

'COST', !Y-AXIS LABLE;

'TOTAL COST', COST_W_SYD, 'CAPITAL COST', CC_W_SYD, 'OPERATION COST', OPC_W_SYD, 'DELAY COST', DC_W_SYD, 'NOISE
COST',NC_W_SYD, 'ORAT COST', ORC_W_SYD, 'ACCESS COST', AC_W_SYD !ATTRIBUTE;

);

!LINE CHART OF DEMAND VS. CAPACITY;

@CHARTLINE(

'DEMAND-CAPACITY PROJECTION', !CHART TITLE;

'TIME', !X-AXIS LABLE;

'ANNUAL PASSENGER',!Y-AXIS LABLE;

'DEMAND', DTOTAL, 'CAPACITY TOTAL', SAC_TOTAL, 'CAPACITY-SYD', SAC_SYD, 'CAPACITY-BWU', SAC_BWU, 'CAPACITY-RCM',
SAC_RCM, 'CAPACITY-W_SYD', SAC_W_SYD !ATTRIBUTE;

);

ENDCALC

END
```

APPENDIX B

Demand Comparison: Sydney Model, What-if Model 1, 2, and 3

Year	Sydney Model		What-if Model 1		What-if Model 2		What-if Model 3	
	Passenger Demand	Demand Growth	Passenger Demand	Demand Growth	Passenger Demand	Demand Growth	Passenger Demand	Demand Growth
1	36,967,350		36,967,350		36,967,350		36,967,350	
2	38,279,690	1.035	38,250,486	1.035	39,111,417	1.058	35,986,799	0.973
3	39,638,618	1.035	39,169,645	1.024	38,858,892	0.994	37,602,505	1.045
4	41,045,788	1.035	40,148,102	1.025	34,204,389	0.880	38,629,304	1.027
5	42,502,913	1.035	41,791,363	1.041	31,670,552	0.926	39,022,004	1.010
6	44,011,766	1.035	43,300,867	1.036	33,229,605	1.049	41,105,429	1.053
7	45,574,183	1.035	44,338,788	1.024	39,478,526	1.188	42,614,222	1.037
8	47,192,066	1.035	45,670,725	1.030	40,809,068	1.034	44,034,832	1.033
9	48,867,384	1.035	46,967,773	1.028	41,035,354	1.006	44,375,769	1.008
10	50,602,176	1.035	48,459,469	1.032	45,631,200	1.112	32,194,925	0.726
11	52,029,157	1.028	49,964,135	1.031	51,549,587	1.130	11,245,000	0.349
12	53,496,379	1.028	50,981,904	1.020	51,296,195	0.995	7,871,500	0.700
13	55,004,976	1.028	52,475,163	1.029	46,120,477	0.899	11,245,000	1.429
14	56,556,116	1.028	53,954,437	1.028	46,589,648	1.010	21,719,962	1.932
15	58,150,998	1.028	55,170,030	1.023	43,517,448	0.934	32,194,925	0.986
16	59,790,856	1.028	56,760,581	1.029	41,154,945	0.946	44,375,769	0.876
17	61,476,958	1.028	57,974,689	1.021	40,760,129	0.990	38,864,819	1.034
18	63,210,608	1.028	59,553,339	1.027	40,825,678	1.002	40,181,446	1.014
19	64,993,147	1.028	61,136,862	1.027	43,698,754	1.070	40,738,559	1.017
20	66,825,953	1.028	62,538,730	1.023	51,367,843	1.175	41,411,421	1.018
21	68,710,444	1.028	64,648,786	1.034	54,885,466	1.068	42,171,306	1.049
22	70,648,078	1.028	65,846,728	1.019	54,759,358	0.998	44,256,994	1.078
23	72,640,353	1.028	67,228,850	1.021	52,750,133	0.963	47,722,916	1.057
24	74,688,810	1.028	68,810,072	1.024	51,799,102	0.982	50,445,096	1.013
25	76,795,034	1.028	70,339,719	1.022	59,937,215	1.157	51,121,030	1.093
26	78,784,025	1.026	72,404,189	1.029	61,437,827	1.025	55,877,434	1.040
27	80,824,531	1.026	75,212,023	1.039	63,342,324	1.031	58,115,629	0.996
28	82,917,886	1.026	77,995,619	1.037	58,244,346	0.920	57,901,473	1.143
29	85,065,459	1.026	80,388,524	1.031	67,597,212	1.161	66,209,061	0.946
30	87,268,654	1.026	82,950,506	1.032	77,304,128	1.144	62,628,724	0.919
31	89,528,912	1.026	84,525,736	1.019	79,628,430	1.030	57,535,662	0.979
32	91,847,710	1.026	86,872,170	1.028	88,671,987	1.114	56,298,703	0.930
33	94,226,565	1.026	89,465,304	1.030	84,589,256	0.954	52,339,604	1.132
34	96,667,033	1.026	92,915,980	1.039	83,266,092	0.984	59,254,264	1.076
35	99,170,709	1.026	96,624,256	1.040	85,744,381	1.030	63,742,051	1.095
36	101,739,230	1.026	99,551,970	1.030	85,571,335	0.998	69,783,388	1.067
37	104,374,276	1.026	103,421,555	1.039	85,616,018	1.001	74,458,249	1.122
38	107,077,569	1.026	106,873,766	1.033	88,110,135	1.029	83,569,937	0.975
39	109,850,878	1.026	110,980,924	1.038	96,391,362	1.094	81,497,719	0.913
40	112,696,015	1.026	114,004,044	1.027	98,727,862	1.024	74,404,766	1.115
41	115,614,841	1.026	117,346,642	1.029	108,305,220	1.097	82,928,406	1.130
42	118,609,265	1.026	120,532,603	1.027	113,530,071	1.048	93,702,374	1.054
43	121,681,244	1.026	122,088,678	1.013	115,391,868	1.016	98,768,114	1.101
44	124,832,788	1.026	125,120,139	1.025	132,344,664	1.147	108,734,959	1.024
45	128,065,957	1.026	128,646,024	1.028	131,496,422	0.994	111,395,821	1.003
46	131,382,865	1.026	131,575,293	1.023	131,889,859	1.003	111,710,480	1.008
47	134,785,681	1.026	135,318,610	1.028	142,525,087	1.081	112,617,720	1.052
48	138,276,630	1.026	138,245,551	1.022	143,316,536	1.006	118,454,452	0.983
49	141,857,994	1.026	142,900,278	1.034	157,601,513	1.100	116,382,403	1.047
50	145,532,116	1.026	146,977,222	1.029	156,896,513	0.996	121,866,505	0.915
Mean		**1.028**		**1.029**		**1.032**		**1.027**
Median		**1.026**		**1.028**		**1.024**		**1.027**
St. Dev.		**0.00357**		**0.00626**		**0.07308**		**0.19392**