A study of optimization of air traffic network and flight schedules

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2019

Sailauov, T. (2019). A study of optimization of air traffic network and flight schedules.
Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/104791>

<https://doi.org/10.32657/10220/48614>

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A Study of Optimization of Air Traffic Network and Flight Schedules

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School of Mechanical and Aerospace Engineering

2019

A Study of Optimization of Air Traffic Network and Flight Schedules

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School of Mechanical and Aerospace Engineering

A thesis submitted to the Nanyang Technological
University in fulfilment of the requirement for the degree
of
Doctor of Philosophy

2019

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

6 June 2019

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I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

6 June 2019

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Date

A handwritten signature in blue ink, appearing to read 'Zhong Zhaowei', written over a dotted line.

.....

[Assoc Prof Zhong Zhaowei]

Authorship Attribution Statement

This thesis contains material from 2 papers published in the following peer-reviewed journals and from 3 papers accepted at conferences in which I am listed as an author.

Chapter 4 is partially published as Sailauov T. and Z. W. Zhong (2017), "Air traffic forecasting using optimization for econometric models." International Journal of Technology and Engineering Studies, vol. 3, no. 5, pp. 197-203 and Sailauov T. and Z. W. Zhong (2016), "Air traffic forecasting using optimization for econometric models", International Conference on Engineering & Technology, Computer, basic & Applied Sciences (ECBA-2016) Singapore, September 26-27.

The contributions of the co-authors are as follows:

- Assoc Prof Zhong Zhaowei provided the initial project direction.
- I prepared the manuscript drafts. The manuscript was revised by Assoc Prof Zhong Zhaowei.

Chapter 5 is partially published as Sailauov T. and Z. W. Zhong (2016), "An Optimization Model for Large Scale Airspace," International Journal of Modeling and Optimization vol. 6, no. 2, pp. 86-90 and Sailauov T. and Z. W. Zhong (2016), "An Optimization Model for Large Scale Airspace", 1st Journal Conference on Modeling and Optimization vol. 6, no. 2, pp. 86-90.

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- Assoc Prof Zhong Zhaowei provided the initial project direction.
- I prepared the manuscript drafts. The manuscript was revised by Assoc Prof Zhong Zhaowei.

Chapter 6 is partially published as Sailauov T. and Z. W. Zhong (2017), "Determining optimal air traffic waypoint location using A star search", International Conference on Engineering & Technology, Computer, basic & Applied Sciences (ECBA-2017) Singapore, August 07-08.

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- Assoc Prof Zhong Zhaowei provided the initial project direction.

- I prepared the manuscript drafts. The manuscript was revised by Assoc Prof Zhong Zhaowei.

6 June 2019

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Tolebi Sailauov

Abstract

South-East Asia is considered one of the fastest air traffic growing regions in the world. Congested air traffic and weather conditions have thus become major factors in air traffic management. Models have been proposed to manage air traffic flow efficiently and to solve congested airspace problems. In order to manage air traffic flow efficiently, this thesis focused on forecasting air traffic, rescheduling of flights and restructuring an air network.

In this research the model for air traffic forecasting was able to forecast the country, city-pair and airport-pair air traffic. Results show that the passenger forecasting for Singapore has dependence not only on that country but on neighbouring countries as well. The research predicts that the passenger movements in Changi airport will increase up to 81.65 million people by year 2023, which is 31.23 % more than that in 2017. Also, the number of passenger aircraft between Singapore and Jakarta city-pair will increase up to 34702 by year 2023, which is 26.6 % more than that in 2017. In addition, the number of passenger aircraft between Changi airport and KLIA airport-pair will be between 31698 and 40311 by year 2023.

The model to reschedule flights focuses on solving reduced capacity problems and on reducing delays efficiently. Rescheduling of flights was done operationalizing and satisfying the constraints of delay costs, airport departure and arrival capacities, waypoints' capacities, routes capacity and rerouting options. Results show that in the flights between KLIA and Changi airport, ground delays were reduced by 4.98 min and 3.05 min on average. More importantly, the airborne delays were reduced by 2.70 min and 3.95 min on average. The model made sure none of the flights got delayed longer than a specific time and ensured fairness to all flights.

Also, a model was developed to reconstruct the air network. A case study was implemented involving 8 airports. The total route distance and the objective function were reduced by 1.53% and 1.48 % respectively. The results show that restructuring the air network can reduce flights' distances using proper merging methods.

Acknowledgements

First and foremost, I would like to express my sincere gratitude and appreciation to my supervisor Professor Zhong Zhaowei for his utmost patience, invaluable instructions and encouragement in the past four years. Without his support, my research would not reach this stage.

I would also like to thank my colleagues in ATMRI, especially Shafirah Aneeka and Lee Yu Xuan.

Finally, but most importantly, I wish to take this opportunity to thank my mother and sister, who love me, encourage me and support me all the time, all the way.

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List of Abbreviations

ASEAN	Association of Southeast Asian Nations
ATC	Air Traffic Control
FIR	Flight Information Regions
DEA	Data Environment Analysis
MILP	Mixed-Integer Linear Programming
GA	Genetic Algorithms
N/A	Not Applicable
RBV	Resource - Based View
FHA	Functional Hazard Assessment
PATS	Personal Air Transport System
PPlane	Personal Plane
AENA	Aeropuertos Españoles y Navegación Aérea
DHMI	Devlet Hava Meydanları İşletmesi
GDP	Gross Domestic Product
ICAO	International Civil Aviation Organization
LCC	Low-Cost Carrier
FSC	Full-Service Carrier
IAG	International Airlines Group
RMS	Root Mean Square
GMCPi	Global Malmquist Carbon Emission Performance Index
SAAM	System for traffic Assignment and Analysis at a Macroscopic level
NM	Nautical Mile

List of Symbols

$\mathcal{R}$	Set of airports
$\mathcal{P}$	Set of fixes
$\mathcal{P}^f \in \mathcal{P}$	Set of fixes that can be flown by flight f , including the departure and arrival airports of flight f
F	Set of all existing flights
$\mathbb{T}$	Set of time intervals
$\mathcal{L}_i^f$	Set of fixes that follow fix i
$\mathcal{P}_j^f$	Set of fixes that precede fix j
$\text{Dep}_k(t)$	Departure capacity of airport k at time t
$\text{Ar}_k(t)$	Arrival capacity of airport k at time t
$S_j(t)$	Capacity of fix j at time t
dep_f	Anticipated take off time of flight f
ar_f	anticipated landing time of flight f
t_f	Turnaround time of an aeroplane after flight f
$l_{fjj'}$	Minimum number of time units that flight f must spend between j and j'
end_f	Maximum allowed duration of flight f
$T_j^f = [\underline{T}_j^f, \overline{T}_j^f]$	Set of feasible time intervals for flight f to land to fix j
$\underline{T}_j^f$	First time interval in set T_j^f
$\overline{T}_j^f$	Last time interval in set T_j^f

CHAPTER 1

Introduction

1.1 Background

Air traffic control (ATC) is a service provided by ground controllers to secure the road of aircraft in some controlled airspace or during ground movements [1]. Air traffic controllers' main purpose is to prevent collisions, organize traffic movements and give ground support to pilots. Controllers use traffic collisions avoidance schemes such as traffic separation rules and radar information to ensure that a minimum separation between flights in all directions is constantly maintained. In addition, aircraft have been equipped with collision avoidance systems, which further enhance safety by warning pilots when separation rules have been breached [2].

As time passes, new technologies come, which enable better safety control of airspace. Despite these technologies, air traffic congestion continues to occur to a certain degree. To deal with congestion more effectively, there is a need for an automatized system, which can assist air traffic management staff in finding optimal solutions in a reasonable time [3].

Reliable air traffic forecasting plays an important role in planning for future projects and makes countries ready for coming difficulties or challenges. There have been three fundamental ways of forecasting: quantitative, qualitative, and decision analysis, which is a mix of the first two methods [4]. Quantitative methods can be divided into time series analysis and causal methods, and an econometric analysis is part of causal methods. Recently, researchers started using optimization methods to increase the efficiency of the airspace. Li used a co-evolution based method to optimize crossing waypoints locations and adjacency relation in the air route network [5]. Similarly, Chen

and Du used the Multi-Objective Crossing Waypoints Location Optimization in Air Route Network to minimize flight cost by adjusting crossing waypoints [6]. This thesis aims to find a better solution, compared to existing methods, to accurately forecast the air traffic. This thesis proposes a new model for forecasting air traffic which uses an optimization approach for econometric models.

Flight Information Regions (FIR) have been implemented since 1947 [7]. Current waypoints have been located few decades ago, based on the traffic of that time and limitations of the landscape. However, the volume of air traffic changes as time passes. Therefore, there is a need for the air network to be restructured. This thesis proposes a model to reconstruct air route network using the optimization approach in merging of the waypoints.

Currently, free route airspace is getting more popular globally. Some of the European countries have already implemented this concept on their airspace. In free route airspace, pilots have the freedom to choose a route to reach their destinations. However, even in free route airspace, pilots need to go through at least 1 waypoint in each airspace, assigned by controllers [8, 9]. If the location of the waypoint is not optimal, pilots will be forced to use non-optimal flight trajectory. This thesis suggests a way how to handle air traffic congestion in hazardous weather. If some waypoints happen to be under weather hazards, flights passing this waypoint cannot go through. As a result, most flights would be postponed or have their trajectories replaced with other flight paths. However, those flight paths are usually not optimal flight trajectories. This thesis helps to find optimal paths for flights.

This thesis presents models, which are able to increase efficiency of the air traffic flow by accurately forecasting air traffic, rescheduling of flights and restructuring an air network. The model to reschedule flights was designed to provide operational and

mathematical control of multiple constraints including route capacities, airport capacities and waypoint capacities. The model might thus find technological application to airspaces such as ASEAN, which is expected to lead the air traffic by 2035, according to Airbus forecast [10].

1.2 Research objectives

As cities grow and become more interconnected, air traffic flow is increasing gradually. As a result, there is a need for efficient use of airspace. It can be achieved by using new technologies and making analysis for the current situation in airspace. For example, determining growth rate of the air traffic and identifying non-efficient air routes can help to overcome future congestion problems.

In order to have better control on the airspace, FIRs are divided into sectors [11]. Each sector is controlled by 2 controllers. For example, Singapore FIR consists of 8 sectors (currently 7 but unofficially 8), and these sectors have certain airspace load. As air traffic flow increases, the controller's task increases as well. At some point, controllers will not be able to cope with that load. That is why this thesis investigates which Singapore sector is more flight dense than other sectors and tries to find potentially troublesome sectors so that some actions can be taken to prevent potential disasters in the future. There are many ways of improving airspace efficiency: having better radar systems, a better navigation system, proper sectorization of the airspace, etc. However, this study focuses on:

- Proposing of a model which uses optimization to forecast air traffic.
- Rescheduling of flights satisfying the constraints of delay cost, airport departure and arrival capacities, waypoint's capacities, route capacities and rerouting options.

- Reconstructing an air route network to suit the current air traffic flow.

1.3 Research scope

The research scope of this project is to address a few points in air traffic management. Firstly, this thesis concentrates on proposing a model which aims to accurately forecast the air traffic. A mathematical model has been developed in order to forecast air traffic of any country. The simulation has been done using the optimization tool CPLEX and historical and forecasted GDP data from World Bank.

Secondly, a mathematical model has been developed to reschedule air traffic. The model considers multiple constraints like airspace, airport and air traffic controller's constraints. Simulation has been done on flights between Singapore and Kuala-Lumpur.

Next, a model has been developed to reconstruct an air route network. Case studies were done on the airspace where Prohibited, Restricted and Dangerous (PRD) areas were present. The efficiency of the proposed algorithm has been studied. The effect on different flight groups has been studied.

1.4 Organization of the thesis

This thesis is organized into 7 chapters. Chapter 2 gives a broad description of past research and challenges in air traffic. Chapter 2 gives a brief explanation of the past research related to air traffic management. It includes air traffic network optimization, efficiency evaluation of airports, pollution through air traffic, various models for air traffic optimization. Also, it gives a general overview of the air traffic and current stance on the air traffic development. Also, this chapter shows results of the investigation on the correlation between GDP and air traffic. In Chapter 3, methodologies of the proposed models are presented. It consists of 3 parts: forecasting air traffic, rescheduling

of flights, and restructuring an air network. Chapter 4 includes results and discussions of the model for forecasting country, city-pair and airport-pair air traffic. The developed models use the correlation between GDP and air traffic as a base. Each model has its own advantages and disadvantages. Chapter 5 includes results and discussions of the model which focuses on solving reduced capacity problems and on reducing delays efficiently by rescheduling of the flights. Also, comparison with other existing models is presented. Chapter 6 includes results and discussions of the model for reconstructing the air network. A case study has been implemented on the air route network between 8 cities. The last chapter summarizes the main conclusions reached in this work and highlights the overall direction of the future work for this research.

CHAPTER 2

Literature review

2.1 General background

Traffic in Asia-Pacific region continues to grow. Tsui et al. [12] investigated the effectiveness of 21 airports located in Asia. His study shows that, during the period 2002-2011, several airports in Asia have been the world's top 30 busiest airports. His investigation is theoretically and methodologically based on Data Environment Analysis (DEA) [13], a recognized method for airports efficiency evaluation [14]. DEA calculates the efficiency index $B_0 = \max_{u_r, v_i} \frac{\sum_{r=1}^m u_r y_{r0}}{\sum_{i=1}^n v_i x_{i0}}$, where x_{i0} are inputs and y_{r0} are outputs of the airport, and u_r, v_i are weights of aggregation (virtual multipliers bigger than zero) used to maximize the value of B_0 . Results show that Kuala-Lumpur and Singapore are the least efficient airports within the examined samples. This might be related to factors of underutilization or over investment. These results, however, are questionable because this study does not adequately consider that the airports, as it happens in many cases worldwide, might entrust operational services with third parties to save operating costs. This is one of the occurrences that have not been sufficiently studied yet because of lack of available financial data.

Research has widely shown that the airline sector is publicly perceived as producing high environmental and ecological costs [15]. For example, 12% of passengers think that flying less is one of the top 3 best ways to prevent global warming, despite research showing otherwise [16].

Mayer et al. [17] analyzed differences in perception and actual performances of airlines on eco-positioning. Whenever one flight deviates from its schedule, it affects

other flights as well. Approximately 24% of flights in Europe and about 18% of the flights in the US have been out of the schedule for more than 15 min [18].

Another paper has examined five proposals using Monte Carlo simulation to estimate future airport capacity in South-East England and London. Previously, it has been used for runway capacity and has proven to be usable for precision modelling as well [19]. Traffic data has been extracted from Airport Coordination Ltd [20] and Heathrow Airport [21].

Another paper [22] described an effort to define a future Personal Air Transport System (PATs) and studied different aspects with the aim to help with the introduction of PATs. Their research provided details on the Functional Hazard Assessment (FHA) done for the PPlane (Personal Plane) System and summarized the recommendations for future PATs. PPlane vehicles were operated from small airports close to urban areas. Users/passengers on the board were only able to perform high-level tasks such as the decision to change destination. The operations of PPlane vehicles were supported by a ground infrastructure (ground segment) that includes remote pilot stations (RPS), air traffic control (ATC) and a PPlane System Operation Management Centre. In the case of an emergency situation (failure, health problems on the board, etc.), a pilot at a ground pilot station takes over the control and brings the PPlane vehicle to the nearest airport. The ground pilot can also be contacted by the users/passengers on the board. In normal situations, the ground pilot supervises multiple aircraft, and he takes over in emergency situations only. Even in an emergency situation, the ground pilot can only change the aircraft's trajectory and has general control over aircraft systems. Thus, direct handling and control of the aircraft is not foreseen.

There is another paper, written by Zhang and Wang [23], which introduces one of the ways how to calculate the efficiency of the airspace using new term utilization

rate. Utilization rate in this paper is a ratio of the airspace that has been used for flights to the airspace which is possible to be used for flights. The formula for utilization rate is $U = \sum_{i=1}^m P_i U_i = \sum_{i=1}^m P_i \frac{\sum_{k=1}^{n_t} t_{ik}}{C_i C_{oi} T_i} * 100\%$. As different aircraft have different separation times, it should be considered by calculating P_i , which is the probability of each aircraft type flying throughout region. U_i is a utilization rate of an i^{th} flight level. $\sum_{k=1}^{n_t} t_{ik}$ is an actual airspace load, where t_{ik} is a flying time of k th aircraft on i^{th} flight level. $C_i C_{oi} T_i$ is an airspace load. Average efficiency scores of the airports are shown in Figure 2.1.

Figure 2.1 Average efficiency scores in Turkish and Spanish airports [23]

Similarly, Adler et al. [24] showed a significant negative effect of airport belonging to an airport group and provided some reasons like no flexibility on minimizing cost due to cross-subsidizing. In addition, the motivation to establish additional revenues at group level seemed to be low in comparison with individual airports [25].

There is an efficiency comparison done by Ulku on Spanish and Turkish airports [26]. In Spain, there are 46 airports and 2 heliports under AENA (Aeropuertos Espanoles y Navegacion Aerea). In Turkey, there are 52 airports under Devlet Hava Meydanlari İşletmesi (DHMI). That is why it was said that airport density in terms of per square meter and in terms of per capita is higher in Spain than in Turkey because Spain has the population of 47 million and area of 500 thousand square meters and Turkey has the population of 76 million and area of 780 thousand of square meters.

Tobaruela et al. [27] introduced a framework to characterize the error of the trajectory predictions, subsequently used to perform certain function across European airspace. The framework consists of different components like data generation, error calculation, and new concepts testing. Sources for the data generation section have been taken from Enhanced Tactical Flow Management System or track data (actual data). In the error calculation section, trajectory prediction is defined as predicted entry time. For both cases prediction is taken from ETFMS Flight data (EFD) and actual data is taken from track data and varies by time of the day. The framework has been proposed to track prediction performance of the airspace volume, the entry time to an airspace, and the traffic occupancy [27].

Low et al. [28] proposed a Resource - Based View model to investigate airline competitiveness. An empirical study was conducted on 114 major airlines and 6 LCCs for the period between 1987 and 2010. Some interesting managerial insights on the effects of internal resources via their endowment, resource efficiency and resource effectiveness on airline performances are obtained.

Resource endowment: The value of manual labour in human resource diminishes over the years as technology advancement allows greater automation and raises the productivity of labour [28]. With the prevalence of use of the internet, the conversions

of ticketing and sales to online sales to reach out to its market provide opportunities for reducing the number of employees. In view of the ever more demanding consumers, a larger aircraft fleet is necessary to promise seat availability and higher flight frequencies. Whilst the importance of aviation safety in airline's intangible resource cannot be understated, there is a growing consumer acceptance of new airlines. This represents good news for new entrants, but it also means that traditional airlines could no longer be complacent and rely on their establishment years for continued profitability and market share.

Resource efficiency: As airlines basically operate in a service industry, a certain level of personal intensity is important [28]. A more uniform aircraft fleet with a high proportion of long-haul aircraft lowers maintenance costs and improves the cost efficiency in operations. Due to lower drag and more payload per unit of weight, larger flights are found to incur a lower cost per seat kilometre. The longer the sector distance (or stage length) is, the more this enhances the utilization of flight personnel and aircraft, since they spend more time flying. The longer horizontal distance travelled relative to the ascent and descent allows for lower fuel consumption (which is one of the single most important items in airlines' operating costs). At the same time, airlines save money on maintenance checks, spare parts and airport charges by eliminating en-route stops (even though en-route charges apply).

Resource effectiveness: Other than cost considerations, a larger aircraft fleet with long-haul flights is essential as airlines expand their network to serve routes of longer distances. Airlines that registered longer available passenger-kilometres enjoy higher operating profit in the contemporary times [28].

There has been a research on ASEAN Single Aviation Market policy using examples of the joint venture Low-Cost Carriers (LCCs) [29]. Foreign carriers will get

the opportunity to widen their network if joint ventures are established. It is a unique system where joint ventures are not subsidiaries of Full-Service Carriers (FSCs), as is the case in the US and EU.

Similarly, Takebayashi [30] studied the policy impact on Manila airport, where new LCCs are entering from three hub airports. The results of their study show that the preference of LCCs is on low fare and high-frequency flights. Because LCCs are flexible, most of the passengers enjoy a reduction in the cost of airfare and do not mind losing some of the utilities. At last, LCCs lead reduction in FSCs profit and reduction in transit passengers in hub airports. Runway occupation time has been assigned to all aircraft in the simulation. Time starts when the first arrival reaches runway threshold. It is assumed that next aircraft will reach runway right at the minimum separation time

Quite recently, Irvine et al. [31] used Monte-Carlo approach to investigate effects on runway capacities in London's airports. Departures have been simulated considering separation time, runway occupancy and aircraft categories. Simulation has been run repeatedly over 1 hour. Their paper concluded that any future decision on UK airport must take into account environmental implications as well as socio-economic implications on the global and local scales. Despite having many assumptions, the paper showed how the comparison between the most popular proposals has been made, in terms of peak hours. They found out that new unrestricted runways in London can increase peak-hour movement capacity by 21%.

Yang et al. [32] used a two-level nested logit model to analyze the combined choice of airport and route for a direct flight between Taiwan and Shanghai. They conducted the survey with what they termed a "stated preference" design to investigate the potential demand for new routes and the trade-off between airport and flight attributes. The empirical study focused on three operating routes and one new route

involving two departures Taoyuan International Airport (TPE) and Songshan International Airport (TSA) and two destinations Pudong International Airport (PVG) and Hongqiao International Airport (SHA). The choice dimension of the departure airport is in the upper nest while the flight route is in the lower nest. They found that only the TPE nest, comprising the TPE-SHA and TPE-PVG routes, is reasonable and significant. Thus, introducing the new route will take a larger market share from the TPE-PVG route. In contrast, the other two flight routes departing from TSA would face less competition from the new route. They also used strategy map pricing analysis, which suggests that the two flight routes departing from TPE (the leading route of the three operating flights and the flight yet to operate) should aggressively adopt a discount strategy to increase the irrespective market shares from each other. Since the departure and destination airports of the TSA – SHA route were located in the cities of Taipei and Shanghai, with the advantage of fast access to the capital city, this route did not have to engage in active price wars but just follow the competitors' pricing policies. They suggest that following the competitors' pricing policy would keep the total revenues at a maximum even if there is a loss in market share. The results of the policy simulation suggested that with the opening of the Taoyuan MRT, the leading TPE-PVG flight route would have to adopt aggressive price discounting strategies to resist intensive competition from the new route. Finally, they observed that most travellers preferred to arrive at a metropolitan airport than an international airport but there was no significant difference in departure airport [32].

In Asia, more than 50% of flights were taken by LCC [33], and their percentage is constantly increasing. Pearson et al. [33] investigated the capability of Asian network airlines to compete with LCCs. They used the formula:

$$S_a = I_a - D_a \quad (2.1)$$

where S_a is the strategic capability, I_a is the average deviance for level of importance or in other words, importance of responses to compete with LCCs. D_a is the average deviance for level of difficulty or difficulty in implementing responses to compete with LCCs.

$$D_a = \frac{1}{n} \sum_{j=1}^n (x_{aj} - X_j) \text{ [34] and } I_a = \frac{1}{n} \sum_{i=1}^n (y_{ai} - Y_i) \quad (2.2)$$

where a is the specific airline, n is the number of competitive responses, x_{aj} is the ranking of specific airline on j^{th} question, X_j is the ranking of benchmark airline on j^{th} question, y_{ai} is the ranking of specific airline on i^{th} question and Y_i is the ranking of benchmark airline on i^{th} question. The result of this paper says that Vietnam Airlines, Malaysia Airlines and Garuda Indonesia are capable of competing strongly. However, Air India, Thai Airways, Philippine Airlines and SilkAir have low compatibility, and are more exposed to the entrance of LCCs [33].

Also, Taumoepeau et al. [35] showed that in the Asia Pacific region it is necessary to have LCCs. This is because there are many isolated places with less population to be connected. It is believed that by having small airfare and having more frequency than FCC, it can help Pacific regions to grow economically.

On 15th of April, the Eyjafjallajökull volcano erupted ash into the atmosphere [36]. As a result, the wind brought ashes to Europe and caused a shutdown in commercial aviation and cost the European economy US\$ 5 billion [36]. To prevent this kind of things happening in fast-growing Asia, good technologies must be brought to detect, forecast and mitigate the hazard. Prata and Rose [36] investigated the volcanic ash hazards to aviation. When aircraft encounter volcanic clouds, ash enters jet engines. The gas pyroclasts inside the engine might melt because ashes have high temperatures. Ashes depending on their sizes can stay in the atmosphere up to several months. Figure

2.2 shows a comparison of sizes of ash with other common things like hair and sand particle.

Figure 2.2 Electron micrograph of volcanic ash size with other common materials [36]

When ash particles enter the engine, they melt at temperatures of 1200-1500 °C. However, when the engine is powered off, the glasses in ashes start to become brittle and can damage metals there. The Eyjafjallajökull incident closure of European airspace from April to May of 2010 was considered to be an overreaction, caused by limited information and investigation on volcanic ashes[36].

Zhang et al. [37] used a non-additive multiple criteria analysis method for evaluation of airline service quality. Passengers' demand for high-quality service keeps rising and the quality of the service is becoming a deciding factor for the airline they choose. Therefore, it was required to evaluate service qualities and needs of passengers. Zhang et al. developed λ_k fuzzy measure and its corresponding Choquet integral to

analyze quality of airline services like delays, baggage losses, etc. The procedure consists of 7 steps:

Step 1: Build the evaluation criteria system for airlines' service alternatives.

Step 2: Value each criterion for each airline's service alternative.

Step 3: Determine the contributions of criteria.

Step 4: Calculate the λ_k fuzzy measures.

Step 5: Normalize the values of criteria.

Step 6: Value airlines' service alternatives using the Choquet integral based on normalized values and the λ_k fuzzy measures of criteria.

Step 7: Rank the airlines' service alternatives according to their performance values.

The results of their research proposed that when there is an interaction between criteria it is better to work with multiple-criteria decision making (MCDM) issues. Here in Figure 2.3, results of non-additive method criteria are compared to Bowen and Headley results. Their paper only considered two criteria, but in reality, there might be multiple criteria that interact with each other [37].

Figure 2.3 The ranking of service quality of some US airlines in 2012 using 2 methods [37]

Spence et al. [38] studied international standardization compliance in aviation using ANOVA tests. There are currently 191 member states in ICAO, but only 177 of the member states were analyzed. The results of their study showed that as the effective implementation of ICAO increases, the fatality rate decreases. Similarly, when the GDP of a country increased, implementation of ICAO rules increased as well. As stated by the ICAO Safety Report (2012), “the growth in volume in commercial scheduled flights seen in 2010 continued in 2011 at a rate of 3.5 percent. This increase coincides with a 3.7 percent increase in the global real Gross Domestic Product (GDP)”. Based on the study by Spence et al., the more a particular state complies with international standards, the less commercial airline fatalities occur [38]. This holds true despite the size of a state, the wealth of a state, the number of commercial operations, and the number of total fatalities in a given period of time.

Schossor and Wittmer [39] investigated cost and revenue synergies in airline mergers by considering geographical differences. In last few decades, there has been a lot of changes in the airline industry: deregulation, privatization, increasing price pressure, etc. In response, some airlines created alliances like Star Alliance, Oneworld, and SkyTeam to make cost and revenue synergies. Similarly, in Europe, we have three large airlines: Air France-KLM, the International Airlines Group (IAG) and the Lufthansa Group. Their paper addressed questions on how cost and revenue synergy estimates differ between mergers and how estimated synergies have been established and developed. Table 2.1 presents the initial synergy estimates for five mergers.

Table 2.1. Comparison of initial synergy estimates [39].

	Air France-KLM	IAG	Delta / Northwest	United / Continental	LATAM	Avianca-TACA
Estimated yearly synergies (million US\$)	550	520	1100	1100	400	220
In % of revenues	2.5	2.7%	3.5%	3.8%	4.4%	8.2%
Thereof cost synergies	60%	63%	33%	23%	30%	NR
Thereof revenue synergies	40%	37%	67%	77%	70%	NR
Cost synergies in % of total costs	1.5%	1.7%	1.2%	0.9%	1.4%	NR
Revenue synergies in % of total revenues	1.0%	1.0%	2.4%	2.9%	3.1%	NR
Years for full synergy extraction	5	5	4	4	4	3
Planned non-recurring integration costs (million US\$)	NR	350	1000	1000	500	NR

NR – Not required

Table 2.1 shows that IAG and Air France-KLM have similar synergy levels, equivalent to United/Continental with Delta/Northwest in absolute magnitudes as well as on relative percentages. It proves that there is a geographical divergence in synergy estimates. Schosser and Wittmer concluded that Latin American airlines should expect 6.3% of total synergies, whereas North America should expect 3.7% and European airlines should expect only 2.6% [39].

Similarly, Profillidis and Botzoris [40] analyzed the correlation among economic activities and air passenger transportation in the world. The results can be seen from Figure 2.4 and Figure 2.5. Figure 2.4 illustrates the relationship between GDP per capita and the number of air trips per inhabitant of 53 countries for 2013.

Figure 2.4. The relationship between GDP per capita and the number of air trips per 1000 inhabitants in 2013 [40]

From Figure 2.5 we can see an increase in air trips worldwide from 145 to 424 just in 33 years. Also, it was forecasted that it will reach to 560 in 2020 and to 812 in 2030.

Figure 2.5 Relationship of GDP per capita and air trips for 1980, 1990, 2000, 2010, 2013, and estimated for 2020 and 2030 [40]

The airline industry is one of the few sectors where energy consumption has increased at a rate of more than 6% over the past 10 years [41]. However, energy production has lagged behind, increasing at less than 6% over the same period [41]. The gap between the energy supply and demand is becoming more and more pronounced. A Virtual Frontier Benevolent DEA Cross Efficiency model (VFB-DEA) was proposed and applied to evaluate the energy efficiencies of 11 airlines from 2008 to 2012 [41]. A number of employees, capital stock and tons of aviation kerosene were chosen as the inputs. The results verify the rationality of the new model. Revenue Ton-Kilometers, Revenue Passenger Kilometers, total business income and carbon dioxide emission volume were selected as the outputs. Table 2.2 shows that the average energy efficiency of Delta Air Lines over the period from 2008 to 2012 is the highest.

Table 2.2. Energy efficiency of airlines from 2008 to 2012 [41]

Results of the VFB-DEA model.

Airlines	2008	2009	2010	2011	2012	Average	Order
China Eastern Airlines	0.660	0.569	0.803	0.802	0.894	0.746	4
China Southern Airlines	0.613	0.514	0.663	0.668	0.768	0.645	10
Korean Air	0.594	0.516	0.792	0.789	0.803	0.699	7
Qantas Airways	0.707	0.510	0.812	0.805	0.826	0.732	5
Air France-KLM	0.779	0.586	0.907	0.906	0.816	0.799	3
Lufthansa Airlines	0.640	0.563	0.785	0.788	0.803	0.716	6
Scandinavian Airlines	0.856	0.854	0.852	0.874	0.835	0.854	2
Delta Air Lines	0.913	0.841	0.893	0.891	0.884	0.884	1
Alaska Airlines	0.580	0.486	0.754	0.753	0.763	0.667	9
Air China	0.694	0.485	0.685	0.692	0.785	0.668	8
Hainan Airlines	0.651	0.536	0.561	0.563	0.773	0.617	11

The average energy efficiency of Chinese airlines (China Eastern Airlines, China Southern Airlines, Air China and Hainan Airlines) was 0.669 and it was less than the average level of the 11 airlines (0.730) [41].

Gravio et al. [42] analyzed overall safety performance of the air traffic management system. They use Analytic Hierarchy Process (AHP) to get AHP weights and calculate safety index using formulas:

$$Event_i APF \text{ Safety Index} = \frac{Event_i \text{ annual count}}{TOTAL \text{ traffic count}} Event_i AHP \text{ weight} \quad (2.3)$$

$$APF \text{ Safety Index}_j = \sum_i^n Event_i APF \text{ Safety Index} \quad (2.4)$$

Using these formulas Figure 2.6 was obtained. Figure 2.6 shows the critical value of June 2009 which requires further investigation on the causes of this case and all the factors influencing safety indexes [42].

Figure 2.6 Safety index for en-route related accidents, incidents, issues and in total [42]

There is a research conducted in the United States that shows that in general airline sector has a poor environmental image compared to other industries [15]. One of the ways to reduce congestion in the airline industry is to introduce high-speed rails between high demanded cities. Xia and Zhang [43] examined the effects of introducing high-speed rails. They suggested that merging high-speed rail and airports can reduce travel time in between in order to enhance social welfare.

There has been research to determine the cause of ground delays. Aydemir et al. [44] proposed that the bigger the market share of the airline, the smaller the delay becomes. They stated that dominant airlines have priorities over nondominant airlines. The research was conducted by considering variables like airport market share, airport market concentration, hub size, and slot coordination level, along with other demand and logistical factors. Robust regression technique has been used rather than ordinary least squares estimator.

2.2 Literature review on forecasting air traffic

In the forecasting area, many different models have been proposed. Some researchers used a neural network approach as in [45], and some researchers used support vector machines [46] to determine air traffic. Paper [47] proposes a model which forecasts air traffic movements taking into account airport capacity. The model consists of 5 steps. However, it has a lot of assumptions in each step. Paper [48] uses time series to forecast safety performance of the air traffic. It is done by estimating the number of occurrences of each event. However, it is very difficult to have an accurate database for it.

In the past, many researchers and organizations proved that there is a correlation between GDP and air traffic [49]. ICAO has been using worldwide GDP to estimate world traffic in [4] on page I-31. They have been using model:

$$Y = aX_1^b X_2^c \quad (2.5)$$

where Y is world air traffic, X_1 is world GDP and X_2 is a yield. However, this model would not be able to represent some specific airspace or country air traffic accurately. That is why this thesis proposes an econometric model combined with optimization to increase accuracy of the air traffic forecasting. As we can see, forecasting area is very big. That is why this thesis focuses on econometric models using GDP values.

Meanwhile, Jenatabadi and Ismail [50] conducted the research on the impact of economic situations on airline performance. It was done using a triangular model, and by considering internal operations. They addressed the three most common gaps in estimating performance, by using a latent variable instead of the measurement variable. Their research concluded that the economic status of the country plays an important role in planning, decision and strategy making.

2.3 Literature review on rescheduling of the flights

Air traffic is increasing rapidly. Meanwhile, technologies and techniques to solve congestion are not increasing at the same rate. Whenever one flight deviates from its schedule, it affects other flights as well. About 24% of all flights in Europe and about 18% of flights in the US were delayed for more than 15 min [51]. The following are the solutions proposed so far to solve this problem.

A solution has been proposed by Choi et al. [52]. They compare 3 methods: mixed-integer linear programming (MILP), MILP with first come first serve (FCFS) based heuristics and MILP with heuristics of genetic algorithms (GA). Duration of the computation and average delays of the eight flights are calculated in seconds. MILP can find the optimal solution, but it is computationally highly costly. The model might not be applicable in dealing with high amount of air traffic. On the other hand, MILP with GA has faster computational time and still maintains the accuracy. MILP with FCFS is somewhere in between MILP and MILP with GA. The sum of total travel time has been chosen as an objective function for their paper. Also, their paper considers uncertainty in departure time (linear, quadratic) during flights and adds buffers. However, this model has limitations. Firstly, the objective function seems to need some improvements. It does not consider cost, safety, and fairness to the aircraft. Secondly, for all four cases during simulations, all possible routes have been considered for each flight, which is very inefficient and that is probably why it cannot calculate for a lot of flights. Thirdly, by considering uncertainty and adding buffers, the result becomes much more astray from the optimal solution and loses the purpose of finding the optimal solution.

Kammoun et al. [53] proposed a model to solve ground holding problem using control theory. In their study, Timed Petri Nets and Discrete Time Reachability Graph were employed. However, continued flights, cancellation cost, and opportunity cost

have not been considered, which limits possibility of finding optimal rescheduling solution.

Vaaben and Larsen [54] suggested their own model in order to fast cope with congested air traffic system. The model was designed both graphically and mathematically. In this model, airports are placed row by row. The objective function was formulated as shown below:

$$\sum_{f \in F} \sum_{k \in CC_f} cc_f^k a_m^k + \sum_{f \in F} cc_f b_f + \sum_{pm \in PM} \widetilde{cc}_{pm} n_{pm} \tau_{pm} \quad (2.6)$$

The objective function consists of 3 parts. The first part is a flight plan cost where cost parameter cc_f^k is a summation of the aircraft swap cost, flight delay cost, and incremental fuel cost. The second part is a cancellation cost. The third part is a passenger misconnection cost, where $\widetilde{cc}_{pm}$ is an approximate re-accommodation cost for the passengers. This model has limitations as well. It does not consider flights trajectories. In their model, indeed, the flight is represented as a connection from one airport to another, whereas the uniqueness of routes is ignored. Second, it does not consider routes changes and assumes delay costs and fuel costs are constants, notably expressed by the single value cc_f^k . However, fuel costs and flight delay costs may vary depending on several factors, which include chosen route, weather conditions, and cause and duration of the delay. Safety, airspace and runway capacity limitations are also neglected.

Alonso-Ayuso et al. [55] used a mixed-integer nonlinear optimization to solve congestion problem by manoeuvring aircraft both horizontally and vertically. However, it is unrealistic to solve conflict detection and resolution using three manoeuvres for more than 10 aircraft in conflict due to computing time.

Bertsimas et al. [56] proposed a model to reschedule the flights. Their model used 1 matrix variable to find optimal rescheduling solution for the airspace. However,

the objective function was approximate value of the delay cost. As a consequence, the model identifies approximate rescheduling of the flights.

Another paper proposes integer programming (IP) model. Whereas:

$$w_{j,t}^f = \begin{cases} 1, & \text{if a flight } f \text{ reaches sector } j \text{ by time } t \\ 0, & \text{in other cases} \end{cases} \quad (2.7)$$

The objective function was formulated as shown below [4]:

$$\text{Min} \sum_{f \in F} (\sum_{t \in T_{dest_f}^f} c_{td}^f(t) (w_{dest_f,t}^f - w_{dest_f,t-1}^f) - \sum_{t \in T_{orig_f}^f} c_g^f(t) (w_{orig_f,t}^f - w_{orig_f,t-1}^f)) \quad (2.8)$$

The objective function is constructed in such a way that it first takes into account cost of the total delay then subtracts the reduction of the cost done by ground holding.

Constraints [57]:

$$\sum_{f \in F: \text{orig}_f=k} (w_{k,t}^f - w_{k,t-1}^f) \leq \text{Dep}_k(t) \quad \forall k \in \mathcal{R}, t \in \mathbb{T} \quad (2.9)$$

$$\sum_{f \in F: \text{dest}_f=k} (w_{k,t}^f - w_{k,t-1}^f) \leq \text{Ar}_k(t) \quad \forall k \in \mathcal{R}, t \in \mathbb{T} \quad (2.10)$$

$$\sum_{f \in F: j \in \mathcal{P}^f} (\max\{0, w_{j,t}^f - \sum_{j' \in \mathcal{L}_j^f} w_{j',t}^f\}) \leq \text{Sec}_j(t) \quad \forall j \in \mathcal{P}, t \in \mathbb{T} \quad (2.11)$$

$$w_{j,t}^f \leq \sum_{j' \in \mathcal{P}_j^f} w_{j',t-1}^f \quad \forall f \in F, t \in T_j^f, j \in \mathcal{P}^f: j \neq \text{orig}_f \quad (2.12)$$

$$w_{j,T_j}^f \leq \sum_{j' \in \mathcal{L}_j^f} w_{j',T_{j'}}^f \quad \forall f \in F, j \in \mathcal{P}^f: j \neq \text{dest}_f \quad (2.13)$$

$$\sum_{j' \in \mathcal{L}_j^f} w_{j',T_{j'}}^f \leq 1 \quad \forall f \in F, j \in \mathcal{P}^f: j \neq \text{dest}_f \quad (2.14)$$

$$w_{\text{orig}_f,t}^f - w_{\text{dest}_{f'},t-s_f}^{f'} \leq 0 \quad \forall f, f' \in F, t \in T_{\text{orig}_f}^f: t - s_f \in T_{\text{orig}_{f'}}^{f'} \quad (2.15)$$

$$w_{\text{orig}_f,t}^f - w_{\text{dest}_f,t+\text{end}_f}^f \leq 0 \quad \forall f \in F, t \in T_{\text{orig}_f}^f: t + \text{end}_f \in T_{\text{dest}_f}^f \quad (2.16)$$

$$w_{j,t-1}^f - w_{j,t}^f \leq 0 \quad \forall f \in F, t \in T_j^f, j \in \mathcal{P}^f \quad (2.17)$$

$$w_{j,t}^f \in \{0,1\} \quad \forall f \in F, t \in T_j^f, j \in \mathcal{P}^f \quad (2.18)$$

Constraint (2.9) ensures that a number of flights departing at time t in airport k will not exceed departure capacity of the airport k at time t . Constraint (2.10) ensures that a number of flights arriving at time t to airport k will not exceed arrival capacity of

the airport k at time t . Constraint (2.11) ensures that a number of flights in sector j at time t will not exceed the capacity of the sector j at the time. Constraint (2.12) ensures that any flight f must spend at least $l_{fj'j}$ units of time in preceding sector j' before reaching sector j . Constraint (2.13) ensures that flight f must reach one of the subsequent sectors by latest time interval. Constraint (2.14) ensures that any flight will take only 1 path to flight. Constraint (2.15) ensures that if a flight has a stop at some airport then it must spend minimum required time s_f at that stop. Constraint (2.16) ensures that any flight duration will not exceed maximum flight duration of that flight. It will ensure that none of the aircraft will get delayed for a very long time. Finally, Constraints (2.17) ensure connectivity in time.

Limitations

- There is no consideration of rerouting options inside sectors.
- Model does not consider controllers workload.
- Cost for ground and airborne holding may differ in different sectors and airports.

2.4 Literature review on restructuring an air network

Research in air traffic network optimization has been started quite recently but already gives very promising results. Yang et al. [58] demonstrated how air traffic robustness can be measured using Laplacian energy. The air traffic network was represented as a graph. Laplacian energy of matrix created by this network was taken as a measure of robustness. However, it is a long way to be used in real life situations. In their research, the connections between airports have been made using straight-line connections, and it does not consider flight paths, local geographic limitations, waypoints in the airspace and an aerospace structure.

The technology and procedures used for managing air traffic have evolved gradually over 60 years to deal with increased traffic load and complexity. However, incremental changes to technology and procedures are no longer sufficient to keep up with the growth in traffic. Therefore, new ATM system should be implemented to make dynamic, integrated management of air traffic and airspace. Neal et al. [59] proposed a general hierarchy of means (Figure 2.7) as a first step to solve these problems.

Figure 2.7. Analysis of air traffic management system using abstraction hierarchy [59]

In another paper, an optimization-based approach was developed for ATFM that explicitly promotes equity and airline collaboration [60]. Specifically, in stage 1 of their approach, models were introduced for the ATFM problem that encourage equity by controlling reversals and overtaking. Given a schedule from this stage, in stage 2, they proposed an optimization model for slot reallocation to mimic the current substitution-

cancellation process in a GDP setting. Also, they reported empirical results of the proposed models and datasets to quantify the price of fairness and benefits of collaboration.

The purpose of this thesis is to propose a model which will help establish efficient Air Traffic Flow Management (ATFM). The main purpose of ATFM is to have effective and efficient air traffic management [61]. It includes safety, cost-effectiveness, efficiency and management of the environmental impact of the air traffic management system. ATFM needs to solve several problems, and one of them is to mitigate the effects of unexpected events or situations of reduced capacity efficiently.

CHAPTER 3

METHODOLOGY

3.1 Introduction

A lot of air traffic accidents happen because of miscommunication between air traffic controllers and pilots. Miscommunication between pilots and air traffic controllers has contributed to the death of more than 2000 people since the mid-1970s [62]. In order to prevent that, current research emphasizes on creating an automated pilot or ground controlling system [22]. However, there is a risk of losing contact between ground station and aircraft. In such emergency cases, if there are no pilots in aircraft for backing up, then aircraft control is lost. It might lead to great catastrophe. Another possible solution is to have an automated system, which could fully or partially substitute air traffic controllers' work.

Satellites give promising results on communication between aircraft and air traffic controllers. Pouzet and Fistas [63] studied possible effects of using satellite components and proposed to use them in combination with terrestrial components. Their research suggested that new standards have to be implemented for new satellite systems.

Based on literature review, there is no automated system which could significantly assist air traffic controllers in handling airspace during peak hours or during unexpected weather hazards. As we all know a human has limited capacity, and when dealing with congested airspace during peak hours, controllers might not have time to find optimal solution in dealing with congested airspace. Furthermore, the complexity of the problem might be very high.

3.2. Proposed research

The major objective of this study is to establish a system which can automate air traffic controllers job and improve the accuracy of air traffic forecasting. The proposed research consists of three parts: forecasting air traffic, air traffic optimization by manoeuvring flights and network optimization. These are explained in following sections.

3.2.1 Forecasting air traffic

The first part of the system is forecasting of the air traffic, which is an essential part of any project planning. The project success heavily depends on the accuracy of the forecasting. That is why an accurate air traffic forecasting is needed for the aviation industry.

In general, air traffic forecasting models are divided into 2 categories: macroscopic models and microscopic models [64]. Macroscopic models aim to forecast air traffic in a whole region or country or a city. On the other hand, microscopic models aim to forecast air traffic between city pairs or regions only. Also, depending on explanatory variables used, forecasting models can be divided into geo-economic factors and service-related factors. Geo-econometric factors can be location-based factors and economic factors like GDP. Usually, these factors are out of airline control. Service-related factors are airline dependant factors, like the quality of service and airfare price. In this thesis, a macroscopic model with geo-economic factors has been implemented which uses the microscopic method of forecasting as a base. The model shows the relationship between city-pair air traffic and country air traffic.

In order to accurately forecast air traffic, historical data have been obtained, and investigation of the past forecasting models has been done. As we can see from literature

review, there have been different models proposed in the past starting from linear models till using GDP data to forecast air traffic. However, based on the studied literature review, an optimization has not been used for air traffic forecasting, especially in Singapore. Optimization helps to find a specific model for the specific country to forecast air traffic accurately.

One of the ways to examine airport congestion is to determine the number of aircraft movements or passenger movements in the airport. Similarly, to examine airspace congestion is to determine the number of aircraft movements in the airspace. The mathematical model was developed in order to calculate it. General formulas of this model are:

$$NAM_j = \sum_{k \in \text{other countries}} NAM_{jk} \quad (3.1)$$

$$NAM_{jk} = \frac{NPF_{jk}}{(LF)(AS)} + CF_{jk} \quad (3.2)$$

$$NPF_{jk} = A * GDP_j^x * GDP_k^y + l * year + m \quad (3.3)$$

$$CF_{jk} = B * e_j^{z_1} * e_k^{z_2} + r \quad (3.4)$$

NAM_j is a number of aircraft movements in airport j . NAM_{jk} is a number of aircraft movements between j and k . NPF_{jk} is a number of passengers flying between j and k . LF is a load factor [4], which is a ratio of passenger-kilometres travelled to seat-kilometres available. AS is an aircraft size, which is a ratio of total seats offered to total number of aircraft. CF_{jk} is a number of cargo flights between j and k . e_j and e_k are the export of goods (millions of USD) of country j and k respectively. A, B, C, D, r, l, m, z_1 and z_2 are constants to be found by optimization program. Formula (3.1) calculates the number of aircraft movements in airport j . It can be seen that the number of aircraft movements in airport j is equal to the sum of the number of aircraft movements between j and k (other countries). Formula (3.2) gives the formula of how to calculate a number

of aircraft movements between 2 countries. They are equal to a number of passengers flying between those 2 countries divided by load factor and aircraft size [4], plus cargo flights in between. As it is shown in [4], air traffic depends on GDP of the countries. Formula (3.3) shows how a number of passengers flying between 2 countries are calculated. This formula is proposed based on fact that traffic between 2 countries is related to GDP of these countries. That is why general formula dependent on GDP has been proposed, where coefficients have to be found by optimization program.

Similarly, when $j = k$, number of domestic flights can be calculated from Formula (3.2). Formula (3.2) shows that a number of domestic aircraft movements in j is equal to the number of passengers in domestic flights divided by load factor and aircraft size plus cargo flights in country j . The model proposes to find cargo flight movements between j and k to be found by Formula (3.4). When $j = k$, Formula (3.4) can be used for calculation of internal cargo flights.

The traffic on specific air routes can be found with help of these formulas. Assuming airport j has w numbers of air routes from 1 to w . Let the number of aircraft movements in airport j using air route a to be NAM_{aj} . Then $\sum_{a=1}^w NAM_{aj} = NAM_j$.

If we assume that the ratio of NAM_j to NAM_{aj} to be: $\frac{NAM_j}{NAM_{aj}} = p_1 + p_2 * t$, where p_1 and p_2 are constants, then the number of flights on the air route a of airport j can be found by formula:

$$NAM_{aj} = \frac{NAM_j}{p_1 + p_2 t} \quad (3.5)$$

NAM_j can be found by Formula (3.1). p_1 and p_2 can be found from historical data. These general formulas can be applied to any country. Using formula (3.3), number of passengers' movements to airport j can be found:

$$NAM_j = GDP_j^x \left(\sum_{i \in \text{other countries}} B_i GDP_i^y \right) + m \quad (3.6)$$

Due to the limitation of available data, formula (3.1) can be simplified. Instead of using all other countries GDP data, some flight movements can be simplified as:

$$NAM_j \approx GDP_j^x \left(\sum_{i \in \text{some countries}} B_i GDP_i^y \right) + l \text{ year} + m \quad (3.7)$$

In order to apply this model to Changi airport, the number of countries whose GDP was used for the model is restricted to be 8. They are Singapore, Indonesia, Malaysia, Philippines, Australia, China, Thailand, and India. These countries were chosen because they are the top countries which have highest air traffic flow with Singapore, based on Innovata data (Table 3.1).

Table 3.1 Number of flights between Singapore and other countries in 2018

Country	Number of flights
Malaysia	56,751
Indonesia	54,903
China	38,278
Thailand	35,781
India	27,641
Australia	24,720
Philippines	16,321
Vietnam	16,006
Japan	13,593
South Korea	5,799
Myanmar	5,495
Cambodia	4,721
New Zealand	2,380
Laos	336

Singapore does not have domestic flights, which is why domestic flights have not been considered. Formula (3.8) shows how number of passenger movements in Changi airport can be calculated.

$$NAM_{SG} = GDP_{SG}^x \left(B_{CN} GDP_{CN}^y + B_{TH} GDP_{TH}^y + B_{IN} GDP_{IN}^y + B_{ID} GDP_{ID}^y + B_{AU} GDP_{AU}^y + B_{PH} * GDP_{PH}^y + B_{MY} * GDP_{MY}^y \right) + l (\text{year} - 1997) + m \quad (3.8)$$

Here x, y, B, l and m are design variables which will be found through optimization program in such a way that model minimizes sum of squared errors (objective function). x and y are coefficients in range $[a, b]$ (constraint) with iteration rate r . B, l and m are coefficients to be found using linear regression. Then, computational complexity will be $\frac{b-a}{r}$ (*linear regression*) $= \frac{b-a}{r} O(C^2N)$, where C is a number of variables and N is a number of training samples. This method is chosen for calculation because its computational complexity is lower than Brute-force optimization.

Optimization program used for this calculation is IBM ILOG CPLEX Optimizer. The IBM ILOG CPLEX Optimizer solves integer programming problems, very large linear programming problems using either primal or dual variants of the simplex method or the barrier interior point method, convex and non-convex quadratic programming problems, and convex quadratically constrained problems [65]. GDP values of Singapore and its neighbour countries are given in Table 3.1. These values will be used for formulas (3.1) – (3.8).

Table 3.2. GDP of countries from 1998 to 2017 in billions of USD [66]

Year	Singapore	Indonesia	Malaysia	Philippines	Australia	China	Thailand	India
1998	85.71	115.323	77.508	72.207	380.530	1032.573	113.676	428.767
1999	86.29	169.158	84.996	82.995	410.865	1097.138	126.669	466.841
2000	95.84	179.482	100.719	81.023	398.933	1214.915	126.392	476.636
2001	89.29	174.507	99.639	76.262	376.539	1344.077	120.297	493.934
2002	91.94	212.807	108.296	81.358	424.182	1477.501	134.301	523.768
2003	97	255.428	118.344	83.908	539.430	1671.065	152.281	618.369
2004	114.19	279.556	133.966	91.371	655.612	1966.244	172.895	721.589
2005	127.42	310.815	148.245	103.074	733.746	2308.800	189.318	834.218
2006	147.79	396.293	168.084	122.211	780.351	2774.293	221.759	949.118
2007	179.98	470.144	199.960	149.360	946.481	3571.451	262.943	1238.700
2008	192.23	558.582	238.645	173.603	1,054.240	4604.285	291.383	1224.096
2009	192.41	577.539	208.914	168.485	997.261	5121.681	281.710	1365.373
2010	236.42	755.256	255.024	199.591	1249.523	6066.351	341.105	1708.460
2011	275.972	892.590	297.961	224.143	1511.427	7522.103	370.818	1823.052
2012	290.679	919.002	314.443	250.092	1566.533	8570.348	397.558	1827.637
2013	304.454	916.646	323.276	271.836	1515.767	9635.025	420.334	1856.721
2014	311.552	891.051	338.066	284.585	1454.957	10534.526	407.339	2039.127
2015	304.092	860.741	296.434	292.774	1232.918	11226.186	401.384	2102.392
2016	309.754	932.445	296.536	304.906	1264.944	11221.836	411.847	2273.556
2017	323.902	1015.411	314.497	313.419	1379.548	12014.610	455.378	2611.012

Then testing on 2010-2014 data has been done, followed by the forecasting of the Singapore air traffic from 2018 to 2023. In addition, data on aircraft movements, air freight movements and aircraft movements in Singapore are given in Table 3.2. All these values were used for formulas above.

Table 3.3. Operational statistics [67]

Year	Passenger movements (millions)	Airfreight movements (millions of tonnes)	Aircraft movements
1998	23.80	1.28	165242
1999	26.06	1.50	165961
2000	28.62	1.68	173947
2001	28.09	1.51	179359
2002	28.98	1.64	174820
2003	24.66	1.61	154346
2004	30.35	1.78	184932
2005	32.43	1.83	204138
2006	35.03	1.93	214000
2007	36.70	1.92	221000
2008	37.69	1.88	232000
2009	37.20	1.63	240360
2010	42.04	1.81	263593
2011	46.50	1.87	301700
2012	51.18	1.81	324722
2013	53.73	1.85	343800
2014	54.09	1.84	341386
2015	55.45	1.85	346334
2016	58.70	1.97	360490
2017	62.22	2.16	373201

3.2.2 Reduction of delay cost by rescheduling of flights

The second part of the model is to optimize flights in an airspace, by efficiently managing aircraft movements. The model needs to consider airspace capacities, airport capacities [68], and controllers limitations. If there is sufficient airport capacities [68], airspace capacities, and if controllers can manage all incoming or leaving flights then there is no ground holding and airborne holding required for any flight. However, when traffic is congested or when there are bad weather conditions in some areas of airspace there is a need for delaying or cancelling some of the flights. That is why air traffic optimization was implemented by adjusting airborne and ground holding delays for each flight. Also, optimization has to be done by considering controllers' workload, airspace

capacities, and airports' capacities. The model has been proposed where objective is to minimize sum of total costs of flights. However, it is done in such a way that it satisfies all constraints given to the model. Each constraint is given separately so that it gives flexibility in changing inputs to the system. The model structure is shown in Figure 3.1.

Firstly, all flight details, the capacity of waypoints and airports are given to the program. After that, the program starts iteration. It checks if possible solution satisfies constraints in (3.12) – (3.22) and if it minimizes the cost. If the possible solution satisfies constraints, then the scenario is saved until new scenario comes which satisfies all constraints and further minimizes the cost. After finding the least cost solution which satisfies constraints in (3.12) – (3.22), the program stops iteration.

Figure 3.1. The model structure for traffic optimization

Mixed-Integer Linear Programming was used for calculation, where design variables will be $w_{j,t}^f$.

$$w_{j,t}^f = \begin{cases} 1, & \text{if flight } f \text{ arrives at fix } j \text{ by time } t \\ 0, & \text{otherwise} \end{cases} \quad (3.9)$$

Then the original objective function will be:

$$\begin{aligned} \text{Min } & \sum_{f \in F} (\sum_{t \in T_{\text{orig}_f}^f} f_{\text{GH}}^{\text{orig}_f}(t - \text{dep}_f)(w_{\text{orig}_f,t}^f - w_{\text{orig}_f,t-1}^f) + P + O + \\ & \sum_{j^* \in \mathcal{P}^f} \sum_{j \in \mathcal{P}^f} \sum_{t \in T_j^f} f_{\text{AH}}^j(t - \text{ar}_{f,j} + \text{ar}_{f,j^*} - t_1)(w_{j,t}^f - w_{j,t-1}^f)(w_{j^*,t_1}^f - w_{j^*,t_1-1}^f)) \end{aligned} \quad (3.10)$$

where j^* is a set of waypoints that precede fix j , $\mathcal{P}^f$ is a set of waypoints that flight f can fly, $\text{ar}_{f,j}$ is a scheduled arrival time to waypoint j of the flight f . $f_{\text{GH}}^{\text{orig}_f}(t)$ and $f_{\text{AH}}^j(t)$ are ground holding and airborne holding cost function for particular airport orig_f and waypoint j , P is a passenger cost for cancelling flights and O is an opportunity cost of the airline [69]. P and O are considered when some of the flights can be cancelled. For the case study in chapter 5 solution can be achieved without cancellation of flights. Therefore, P and O were not considered in the case study.

The simplified objective function will be:

$$\begin{aligned} \text{Min } & \sum_{f \in F} (\sum_{t \in T_{\text{orig}_f}^f} f_{\text{GH}}^{\text{orig}_f}(t - \text{dep}_f)(w_{\text{orig}_f,t}^f - w_{\text{orig}_f,t-1}^f) + \sum_{j \in \mathcal{P}^f} \sum_{t \in T_j^f} f_{\text{AH}}^j(t - \\ & \text{ar}_{f,j})(w_{j,t}^f - w_{j,t-1}^f)) \end{aligned} \quad (3.11)$$

Constraints:

$$\sum_{f \in F} (w_{j,t}^f - w_{j,t-1}^f) \leq k_{j,t} \quad \forall j \in \mathcal{P} \quad (3.12)$$

$$\sum_{f \in F: \text{orig}_f=a} (w_{k,t}^f - w_{k,t-1}^f) \leq \text{Dep}_k(t) \quad \forall a \in \mathcal{R}, t \in \mathbb{T} \quad (3.13)$$

$$\sum_{f \in F: \text{dest}_f=a} (w_{a,t}^f - w_{a,t-1}^f) \leq \text{Ar}_a(t) \quad \forall a \in \mathcal{R}, t \in \mathbb{T} \quad (3.14)$$

$$\sum_{f \in F: j \in \mathcal{P}^f} (\max\{0, w_{j,t}^f - \sum_{j' \in \mathcal{L}_j^f} w_{j',t}^f\}) \leq S_j(t) \quad \forall j \in \mathcal{P}, t \in \mathbb{T} \quad (3.15)$$

$$w_{j,t}^f \leq \sum_{j' \in \mathcal{P}^f: j' \in \mathcal{L}_j^f} w_{j',t-1}^f \quad \forall f \in F, t \in T_j^f, j \in \mathcal{P}^f: j \neq \text{orig}_f \quad (3.16)$$

$$w_{j,T_j^f}^f \leq \sum_{j' \in \mathcal{L}_j^f} w_{j',T_{j'}^f}^f \quad \forall f \in F, j \in \mathcal{P}^f: j \neq \text{dest}_f \quad (3.17)$$

$$\sum_{j' \in \mathcal{L}_j^f} w_{j',T_{j'}^f}^f \leq 1 \text{ for } \forall f \in F, j \in \mathcal{P}^f: j \neq \text{dest}_f \quad (3.18)$$

$$w_{\text{orig}_f, t}^f - w_{\text{dest}_{f'}, t-t_f}^{f'} \leq 0 \text{ for } \forall f, f' \in F \text{ that are continued flights,}$$

$$t \in T_{\text{orig}_f}^f : t - t_f \in T_{\text{orig}_{f'}}^{f'} \quad (3.19)$$

$$w_{\text{orig}_f, t}^f - w_{\text{dest}_f, t+\text{end}_f}^f \leq 0 \text{ for } \forall f \in F, t \in T_{\text{orig}_f}^f, t + \text{end}_f \in T_{\text{dest}_f}^f \quad (3.20)$$

$$w_{j, t-1}^f - w_{j, t}^f \leq 0 \text{ for } \forall f \in F, t \in T_j^f, j \in \mathcal{P}^f \quad (3.21)$$

$$w_{j, t}^f \in \{0, 1\} \text{ for } \forall f \in F, t \in T_j^f, j \in \mathcal{P}^f \quad (3.22)$$

Constraint (3.12) makes sure that the total number of aircraft will not exceed the capacity of that waypoint. Controllers can handle a particular amount of aircraft per time interval at waypoint j . Controllers workload ($k_{j,t}$) can be estimated, as it is shown in [70]. Constraint (3.13) makes sure that the number of flights departing at time t in airport a will not exceed the takeoff capacity of airport k . Constraint (3.14) ensures that the number of flights arriving at time t to airport a will not exceed landing capacity of airport a . Constraint (3.15) ensures that the total number of flights that may fly between fix j and following fix j' at time t will not exceed the capacity of the segment between j and j' at time t . It ensures the capacity limitation of that segment and safety of flights. Capacity of the segment usually is affected by weather conditions.

Constraint (3.16) ensures that any flight f cannot reach fix j on its path until it has spent at least $l_{f,j'j}$ time units traveling from one of the previous fixes on its way. Constraint (3.17) ensures that flight f must reach one of the previous fixes before reaching fix j . Constraint (3.18) ensures that any flight can only choose 1 path to flight. Constraint (3.19) ensures that if a flight has a stop at some airport then it must spend

minimum required time s_f at that stop. Constraint (3.20) ensures that any flight duration will not exceed maximum flight duration of that flight. It also ensures “fairness” of the delays so that none of the flights gets delayed for very long time. Finally, constraints (3.21) and (3.22) come from the definition of w .

Ground holding cost for any airport can be computed as follows:

$$f_{GH}^{orig_f}(t) = 2t, \quad (3.23)$$

where t is a ground holding time, and $f_{GH}^{orig_f}(t)$ is a ground holding cost function of an airport $orig_f$.

Similarly, airborne holding cost for any airport can be computed as follows:

$$f_{AH}^f(t) = 4t, \quad (3.24)$$

where t is an airborne holding time. $f_{AH}^f(t)$ is an airborne holding cost function of flight f .

Limitation of the model is that it requires accurate estimation of all airports capacity, airspace capacity, and controllers’ capacity, which is difficult to obtain.

3.2.3 Restructuring an air network

The third and final part of the research is to develop a model for restructuring air network efficiently. The model proposes to use free route airspace. The model structure is shown in Figure 3.2. Firstly, all airspace entry (or exit) points, military airspace and hazardous weather locations have to be inserted into the program. It can be done just by clicking on the map. The map is created when the simulation starts running. Then for each route (or a pair of points on the map) new, the shortest path will be found. It is created in such a way that it avoids prohibited areas and satisfies turn angle limitations.

Figure 3.2. The structure for finding shortest path avoiding prohibited areas

3.3 Research significance

It is believed that the above research will have significant contribution in the following 4 aspects.

- Forecasting air traffic
- Autonomous rescheduling of flights
- Reducing flight delays and cancelling flights
- Restructuring an air network using merging method to reduce costs associated with flights

CHAPTER 4

FORECASTING OF THE AIR TRAFFIC

4.1 Introduction

The future of air traffic is unknown, but it is essential to have an idea of air traffic in order to plan current projects. Efficient ATFM relies on accurate air traffic forecasting [71]. Also, Akça shows that by analyzing future passenger demand, air traffic network performance and accessibility of the waypoints can be evaluated [72]. Air traffic forecasting has been an important topic since 1970 [73]. Initially, air traffic forecasting was done using linear or quadratic models, but they were not able to predict accurately. Lately, correlation between GDP and air traffic has been discovered. Using this finding, researchers developed econometric models, which use GDP as the biggest parameter to estimate air traffic [74]. Past researches have shown that there is a need for liberalization of air traffic and adopting an open sky concept [75]. These methods might help to increase competitiveness and increase the efficiency of airspace. In addition, Hazledine suggests that forecasting air traffic of passenger flights on city-pair routes depends on many factors [76].

There have been many ways of forecasting air traffic [77, 78]. There has been researching on air traffic forecasting based on Time Series Models with Aggregated and Disaggregated Approaches in Spain [79]. Hazledine [76] used a gravity model of trade to forecast air traffic [76]. However, treating passengers as “trade” between countries did not produce promising results. Some researchers proposed forecasting “air traffic congestion status” instead of normal forecasting to evaluate air traffic situation [80]. It was done by using fuzzy C-means and support vector machine. Similarly, Athina states that Madrid-Barajas planners forecasted air traffic in Madrid-Barajas airport using Spain

GDP only [81]. However, it might be insufficient and can lead to unnecessary deviation. These were points which motivated the development of the proposed model. Also, there is a probabilistic method proposed by researchers in NASA [82]. This method estimates probability distribution function of aircraft passing a particular point. However, probability distribution function was estimated based on each individual aircraft probability of passing that point. If large number of aircraft is considered, the resulting cumulative error can be large too.

4.2 Modelling

First of all, there is a need to determine if the proposed methodology can produce valid results. In order to do that, air traffic data from 1999 to 2019 have been used to forecast air traffic, and data from 2010 to 2015 have been used to validate. There are 8 models proposed which consider different number of inputs. The first model uses formula (3.8), where the GDPs of Singapore, Malaysia, Indonesia, Philippines, Australia, China, Thailand, and India have been used to find a number of passenger movements in Singapore. The second model is a simplified version of the first model, where the least impactful country has been eliminated from the model. Similarly, other models are simplified versions of the previous models, where the least significant impact giving country has been eliminated. The least significant impact giving country for air traffic forecasting of Singapore has been determined by looking at the coefficients of each contributor (B values), as shown in Table 4.1. The smaller the value of the contributor, the less significant it is.

Figure 4.1 shows the structure of the forecasting model proposed in this chapter. Firstly, all the countries with high traffic flow need to be determined. The number of countries can be from 5 to 10. For example, if the country that is going to be forecasted

is Singapore, then the top busiest route countries, based on Innovata data, are Malaysia, Indonesia, Thailand, Philippines, China, Australia and India (Table 3.1). After that, past traffic data and GDP data have to be collected. Collection of data was done by collecting data from OAG, International Monetary Fund, Statista.

Figure 4.1. The structure of the forecasting model

Secondly, the model coefficients are determined by iterating x and y with iteration rate of 0.01, and other coefficients are found using linear regression.

Each country in each model has its own “B” coefficient. Using these coefficients, the optimal model is determined. After that, future air traffic is forecasted using forecasted GDP values. These values can be extracted from different sources, for example, from World Bank website or International Monetary Fund website. More details are given in the results and discussion section.

4.3 Results and discussion

4.3.1 Case study 1: Forecasting passenger movements in Changi airport

Firstly, the simulation has been done using data from 1999 to 2009. Average error, maximum error, and RMS (root mean square) error of forecasting for years 2010 to 2015 have been found to be 2.84%, 7.82%, and 3.79% respectively. These errors (below 10 %) are considered to be acceptable for forecasting. Hence, proposed methodology was applied to the prediction of passenger movements in Singapore.

Passenger movements in Changi airport has been forecasted using 10 different models. First 7 out of 8 models are proposed by the thesis, which are shown in Table 4.1. Table 4.1 shows the results of the optimization software for 8 models, where numbers of variables have been decreased 1 by 1. It was done by eliminating the least important variables. “-” indicates where it is not applicable. In Table 4.1, model 1 is a model with all GDP data, model 2 is a model with all GDP data excluding GDP of China, model 3 is a model with all GDP data excluding GDP of China and India. Model 4 is a model with all GDP data excluding GDP of China, India and Indonesia. Model 5 is a model with all GDP data excluding GDP of China, India, Indonesia and Australia.

Model 6 is a model with GDP data from Singapore, Malaysia, Thailand and linear model. Model 7 is a model with GDP data from Singapore, Thailand and linear model. Model 8 is a linear model. Model 9 is a multiple linear regression model using all countries data [83]. Model 10 is a Log-Log model using all countries data [84].

The coefficients (B values, x, y, l, m) of the model as shown in Table 4.1, are computed using CPLEX. These coefficients have been calculated in such a way that CPLEX minimizes objective function:

$$\text{Min } \sum_{year=1998}^{2017} (year - 1997) (error(year))^2 \quad (4.1)$$

where $error(year)$ is an *actual traffic – model prediction*.

Historical data of older years usually have less importance compared to recent years. Therefore, the objective function uses the prioritized least sum of square errors, instead of the least sum of square errors.

After running simulation using all data, we can see that B_{Chi} has the smallest absolute value among all B values. Therefore, GDP of China has been dropped for the second simulation. In the third simulation, GDP of India has been dropped because B_{India} has the smallest absolute value among B values in the second simulation. Similarly, GDP of the country with the lowest B value is dropped in each of the following simulation until the model becomes linear.

Table 4.1. The coefficient values obtained from the optimization model using CPLEX software (B values are in 10^{-7})

Model	x	y	B_{AUS}	B_{China}	B_{India}	B_{ID}	B_{MY}	B_{PH}	B_{TH}	L	M
1	2.21	0.8	6.76	-0.62	1.5	-9.45	-24.31	32.66	3.40	0.59	-1148.5
2	2.24	0.87	3.35	-	0.44	-3.86	-12.85	10.23	1.36	0.86	-1687.5
3	2.18	0.85	2.69	-	-	-2.58	-13.40	10.37	4.33	0.87	-1719.8
4	2.19	0.85	0.94	-	-	-	-6.63	5.32	2.21	0.89	-1752.2
5	1.8	0.7	-	-	-	-	-122.34	82.80	135	0.66	-1286.1
6	2.64	0.22	-	-	-	-	-57.26	-	66.56	0.81	-1598.8
7	2.81	0.65	-	-	-	-	-	-	0.29	1.07	-2112.9
8	-	-	-	-	-	-	-	-	-	2.31	-4591.1

Each B value in Table 4.1 represents the level of significance of a particular country. The smallest absolute B value for model 1 is B_{China} . It means that GDP value of China does not affect Singapore air traffic as much as GDP values of other countries considered in the case study.

After that, real values of passenger movements in Changi airport and model values have been compared for years 1998 to 2017. Table 4.2 shows passenger movement values for Changi airport from 1998 to 2017 using 10 models. Similarly, Figure 4.2 shows graphical representation of passenger movement values for Changi airport from 1998 to 2017 using models from 1 to 3 and from 8 to 10.

Table 4.2. Passenger movements values for 1998 to 2017 using 10 different models
(millions of people).

Year	Actual Passenger movements	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9 [83]	Model 10 [84]
1998	23.80	26.05	25.16	24.98	24.89	25.60	25.03	23.79	16.90	27.63	28.05
1999	26.06	26.61	25.95	25.87	25.83	26.36	25.87	24.87	19.21	28.10	26.05
2000	28.62	27.07	26.61	26.64	26.70	27.07	26.75	26.00	21.52	26.99	29.00
2001	28.09	27.31	27.28	27.37	27.50	27.54	27.44	27.02	23.82	26.31	27.70
2002	28.98	27.90	28.12	28.27	28.44	28.31	28.32	28.12	26.13	26.71	27.11
2003	24.66	28.73	29.19	29.30	29.44	29.14	29.25	29.25	28.43	27.64	25.93
2004	30.35	30.18	30.65	30.61	30.62	30.29	30.45	30.54	30.74	29.40	28.53
2005	32.43	31.65	32.09	31.90	31.81	31.43	31.63	31.83	33.05	31.02	30.17
2006	35.03	32.98	33.20	33.28	33.28	33.14	33.26	33.40	35.35	32.91	34.21
2007	36.70	37.08	36.37	35.90	35.55	35.75	35.72	35.63	37.66	36.86	38.27
2008	37.69	37.13	36.69	36.96	36.98	37.23	37.04	37.38	39.97	37.98	38.74
2009	37.20	37.91	38.36	38.34	38.27	38.25	38.27	38.39	42.27	39.75	39.92
2010	42.04	42.71	42.14	42.29	42.47	42.87	42.84	42.54	44.58	43.63	44.16
2011	46.50	46.38	46.59	46.66	47.15	47.02	47.34	47.45	46.88	46.68	46.69
2012	51.18	50.90	51.01	50.78	50.55	50.28	50.39	50.61	49.19	50.11	49.06
2013	53.73	53.88	53.84	54.15	53.59	53.71	53.74	53.86	51.50	53.30	53.27
2014	54.09	54.18	54.15	54.02	54.24	54.29	54.19	55.57	53.80	54.07	54.28
2015	55.45	55.49	55.95	55.99	55.71	55.98	55.79	55.53	56.11	57.14	58.11
2016	58.70	58.74	58.22	58.33	58.40	58.20	58.00	57.58	58.42	58.36	57.74
2017	62.22	62.05	62.22	62.08	62.29	62.24	62.43	61.74	60.72	60.98	59.27

Figure 4.2 Passenger movements values for 1998 to 2017 using 10 different models (millions of people).

The models show the trend of the passenger movements in Changi airport, but with different accuracy. Table 4.3 shows the error percentage of 10 models for number of passenger movements in Changi airport from 1998 to 2017. Similarly, Figure 4.3 shows graphical representation of the error percentage for number of passenger movements in Changi airport of 10 models from 1998 to 2017. It can be observed that error percentage of each model has decreasing trend from year 1998 to 2017. Error percentages in 1998 for model 1 to model 7 are up to 9.45 %, whereas in 2017 error percentages for model 1 to model 7 are up to 0.77 %. However, for year 2003, error percentages for 10 models are from 5.15% to 19.39%, which is the largest error percentage compared to other years. This might be due to decrease of passengers travelling to Singapore caused by the outbreak of Severe Acute Respiratory Syndrome (SARS). 238 people have been infected and 33 of them died [85].

Also, model 8 shows better performance than other models (except model 1) in year 2006. Linear model has intersection points with actual passenger movements, and one of them happen to be in year 2006. Intersection can be seen from Figure 4.4, which shows curve fitting of linear model to actual passenger movements.

Table 4.3. The error percentages of 10 models for 1998 to 2017 (in %)

Year	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9 [83]	Model 10 [84]
1998	9.45	5.71	4.97	4.58	7.56	5.17	0.06	28.98	16.09	17.87
1999	2.11	0.42	0.74	0.88	1.13	0.72	4.56	26.29	7.82	0.02
2000	5.41	7.02	6.91	6.69	5.43	6.52	9.14	24.82	5.68	1.32
2001	2.79	2.88	2.58	2.10	1.95	2.32	3.80	15.20	6.33	1.40
2002	3.72	2.96	2.44	1.86	2.30	2.29	2.95	9.84	7.82	6.44
2003	16.52	18.38	18.83	19.39	18.18	18.62	18.63	15.31	12.07	5.15
2004	0.56	0.98	0.85	0.87	0.20	0.33	0.61	1.29	3.14	5.98
2005	2.41	1.04	1.62	1.91	3.08	2.48	1.85	1.90	4.36	6.98
2006	5.85	5.22	5.00	5.01	5.39	5.07	4.66	0.92	6.05	2.35
2007	1.05	0.90	2.17	3.14	2.59	2.68	2.92	2.61	0.45	4.28
2008	1.47	2.65	1.93	1.89	1.21	1.73	0.82	6.04	0.78	2.78
2009	1.91	3.12	3.07	2.89	2.82	2.87	3.20	13.64	6.86	7.33
2010	1.60	0.24	0.59	1.02	1.97	1.91	1.19	6.04	3.79	5.04
2011	0.26	0.20	0.34	1.40	1.13	1.80	2.05	0.83	0.38	0.40
2012	0.55	0.34	0.78	1.23	1.75	1.55	1.11	3.89	2.09	4.15
2013	0.29	0.20	0.78	0.26	0.04	0.02	0.24	4.16	0.80	0.86
2014	0.17	0.11	0.12	0.28	0.37	0.18	2.74	0.53	0.03	0.35
2015	0.07	0.90	0.97	0.46	0.96	0.61	0.15	1.19	3.05	4.80
2016	0.07	0.82	0.62	0.52	0.86	1.20	1.91	0.48	0.58	1.63
2017	0.27	0	0.23	0.11	0.03	0.34	0.77	2.41	1.99	4.75

Table 4.4 shows average, maximum, RMS values of the errors and the values of the prioritized objective function for all models mentioned above. Maximum error for each model does not consider year 2003, due to SARS outbreak. Also, Table 4.4 shows that models from 1 to 7 are outperforming models from 7 to 10 in all aspects.

Furthermore, models from 4 to 7 have a smaller number of variables than models 9 and 10. Model 1 has the smallest value of objective function. It shows that for accurate prediction of the air traffic, there is a need for more GDP data as an input to the model. However, from model 3 to model 1, error percentages of passenger movements do not decrease significantly. RMS errors from model 1 to model 7 increase up to 5.19 %, which is still 2.37 times less than RMS error for linear model.

Figure 4.3 The error percentages of 10 models for 1998 to 2017 (in %)

Figure 4.4 Intersection of linear model to actual passenger movements

Also, model 3 shows that it can forecast passenger movements in Changi airport with similar accuracy as model 1 and model 2, where the RMS error is less than 5% and the average error is less than 3%.

In order to forecast passenger movements in Changi airport, there is a need for GDP data of 8 countries. The GDP prediction from World bank has been used for air traffic forecasting. Table 4.5 shows the GDP prediction of World Bank from 2018 to 2023 for Singapore, Indonesia, Malaysia, Philippines, Australia, China, Thailand, and India.

Table 4.4. Average, maximum and RMS errors for 10 models

Model number	Model name	Number of parameters	Average error (%)	Maximum error (%)	RMS of error (%)	Prioritized objective function
1	With all GDP data	11	2.82	9.45	4.84	182.84
2	With all GDP data except China	10	2.70	7.02	4.93	213.30
3	With all GDP data except China and India	9	2.78	6.92	4.95	219.83
4	With all GDP data except China, India and Indonesia	8	2.83	6.71	5.03	234.39
5	With all GDP data except China, India, Indonesia and Australia	7	2.95	7.56	4.96	234.90
6	With GDP data from Singapore, Malaysia, Thailand and linear model	6	2.92	6.53	4.94	244.11
7	With GDP data from Singapore, India and linear model	5	3.17	9.15	5.19	301.99
8	Linear model	2	8.32	28.99	12.29	1152.38
9	Multiple linear regression model [83]	9	4.51	16.09	6.11	402.64
10	Log-Log model (multiplicative) [84]	9	4.19	17.87	5.71	692.13

Table 4.5. GDP forecasting from International monetary fund [86]

Country	Unit	2018	2019	2020	2021	2022	2023
Australia	Billions of USD	1500.26	1581.89	1666.74	1754.99	1852.06	1958.17
China	Billions of USD	14092.51	15543.71	16952.01	18401.84	19925.40	21573.91
India	Billions of USD	2848.23	3155.23	3477.05	3832.91	4226.69	4663.02
Indonesia	Billions of USD	1074.97	1152.89	1247.65	1340.77	1440.89	1548.50
Malaysia	Billions of USD	364.92	402.61	439.06	478.22	521.22	568.02
Philippines	Billions of USD	332.45	355.74	392.21	430.79	474.67	523.01
Singapore	Billions of USD	349.66	367.78	385.24	401.86	419.19	437.82
Thailand	Billions of USD	483.74	520.07	550.33	581.51	614.41	649.92

Using Table 4.1 and Table 4.5, passenger movements forecasting has been done using models from 1 to 3. Numerical and graphical representation of forecasting the passenger movements in Changi airport from 2018 to 2023 are shown in Table 4.6 and Figure 4.5 respectively. Models from 1 to 3 show that passenger movements in Changi airport will increase up to 81.65 million people by year 2023, which is 31.23 % more than that in 2017. The project proposes that model 1 to model 3 can be used to forecast passenger movements in Changi airport accurately.

Table 4.6. Forecasting passenger movements (millions of people) for Changi airport

	Model name	2018	2019	2020	2021	2022	2023
1	With all GDP data	59.83	59.46	62.99	67.39	73.64	81.65
2	With all GDP data except China	63.11	63.82	66.53	69.57	73.44	78.23
3	With all GDP data except China and India	63.95	66.02	69.38	72.78	76.71	81.27
4	With all GDP data except China, India and Indonesia	65.92	69.79	74.86	80.16	86.26	93.39
5	With all GDP data except China, India, Indonesia and Australia	66.09	70.36	75.06	79.89	85.24	91.32
6	With GDP data from Singapore, Malaysia, Thailand and linear model	66.55	70.79	74.85	78.83	83.03	87.71
7	With GDP data from Singapore, Thailand and linear model	67.97	73.82	79.93	86.48	93.94	102.69
8	Linear model	63.03	65.34	67.64	69.95	72.25	74.56
9	Multiple linear regression model [83]	63.24	65.82	69.10	72.47	76.17	80.24
10	Log-Log model (multiplicative) [84]	61.59	63.39	64.00	64.41	64.68	65.01

Figure 4.6 shows a graphical representation of the ASEAN traffic on 25th October 2013 (Innovata data). The simulation was done using SAAM software. Airspace border of each ASEAN country is highlighted in black. Each flight can deviate from original path based on Required Navigation Performance (RNP). Therefore, boxes have been used to capture flights with small deviation. Box colours represent number of flights passing that box.

Figure 4.5 Forecasting passenger movements from 2018 to 2023

3D traffic densities are shown in colourful boxes. The colour tone from green to red represents the density from low to high. The light green boxes represent airways with 5 or fewer aircraft passing in 1 day. Similarly, yellow-green boxes represent airways with 6-10 aircraft, yellow boxes represent airways with 11-20 aircraft, dark yellow boxes represent airways with 21-50 aircraft, orange boxes represent airways with 51-100 aircraft and red boxes represent airways with 101-200 aircraft. Most of the airspace is shown in green and yellow (no congestion), and only a few areas are shown in red and orange boxes (congestion).

Figure 4.7 shows a graphical representation of the ASEAN air traffic in 2021 using same percentage increase as in Table 4.6 (model 1). Comparing Figure 4.7 with Figure 4.6, a significant increase in the numbers of red boxes can be observed (from 69 to 281), suggesting that congested areas are expected to increase between Singapore, Kuala-Lumpur, Bangkok and Jakarta. Also, the number of flights between Singapore and China is expected to grow significantly.

Figure 4.6. ASEAN traffic on 25th October 2013

Figure 4. 7. Forecasted ASEAN traffic for 2021

The proposed model is applied to forecast city-pair air traffic. Here the model is used to forecast a number of non-stop passenger aircraft between Singapore - Kuala-Lumpur and Singapore – Jakarta city-pairs. Formula (3.7) with GDP data of Singapore, China, Australia, India, Indonesia, Malaysia, Philippines and Thailand is used for forecasting numbers of passenger aircraft in the city-pair. The coefficients are calculated in such a way that it minimizes the objective function:

$$\text{Min } \sum_{year=2004}^{2017} (year - 2003) (error[year])^2 \quad (4.2)$$

In order to give more importance in minimizing latest year's errors rather than older year's error, the objective function uses prioritized least sum of square errors, instead of the least sum of square errors.

4.3.2 Case study 2: Forecasting the number of passenger aircraft between Singapore–Jakarta city-pair

Numbers of passenger aircraft between Changi airport and Jakarta International airport are forecasted using 8 different models. Table 4.7 shows the results of the optimized coefficients for 8 models. Models have number of variables ranging from 11 to 2. “-” indicates where it is not applicable. The country with the lowest B value is dropped in each of the following simulation until the model becomes linear. For example, model 1 is a model with all GDP data. Since, the smallest absolute value among these 7 coefficients is B_{China} , GDP of China is not considered in model 2. Model 2 is a model with all GDP data excluding GDP of China. In model 3, India has been dropped because B_{India} has the smallest absolute value among B values in model 2. Model 3 is a model with all GDP data excluding GDP of China and India. Model 4 is a model with all GDP data except China, India and Indonesia. Model 5 is a model with all GDP data excluding GDP of China, India, Indonesia and Australia. Model 6 is a

model with GDP data of Singapore, Malaysia, Thailand and linear model. Model 7 is a model with GDP data of Singapore, Thailand and linear model. Model 8 is a linear model. Model 9 is a multiple linear regression model using all countries data [83]. Model 10 is a Log-Log model using all countries data [84].

Table 4.7. The optimized coefficient values obtained using CPLEX for the number of passenger aircraft between Changi airport and Jakarta International airport

Model	x	y	B_{AUS}	B_{China}	B_{India}	B_{IDN}	B_{MY}	B_{PH}	B_{TH}	L	M (10 ⁶)
1	1.63	-0.36	30.42	-11.17	12.89	-32.05	12.76	-15.06	25.95	-1144.7	2.30
2	1.8	-0.49	21.66	-	11.59	-20.81	6.88	-8.32	16.11	-987.83	1.99
3	1.79	-0.44	29.88	-	11.78	-24.62	-	-4.40	12.51	-1016.1	2.05
4	2.05	-0.68	25.86	-	12.11	-16.61	-	-	6.22	-868.86	1.75
5	1.77	-0.44	43.12	-	16.79	-24.65	-	-	-	-1117.6	2.25
6	1.55	-0.3	80.14	-	-	-32.47	-	-	-	-1502.2	3.02
7	1.63	-0.38	41.13	-	-	-	-	-	-	-973.46	1.96
8	-	-	-	-	-	-	-	-	-	1007.2	-2

Number of passenger aircraft between Changi airport and Jakarta International Airport for 10 models are compared with actual values (from Innovata) from 2004 to 2017. Numbers of passenger aircraft between Changi airport and Jakarta International airport from 2004 to 2017 using 10 models are shown in Table 4.8 and Figure 4.7.

Table 4.8 The number of passenger aircraft from 2004 to 2017 between Changi airport
and Jakarta International airport

Year	Passenger aircraft (Innovata)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9 [83]	Model 10 [84]
2004	17375	16477	16371	16435	16329	16301	16205	15832	16521	15077	14893
2005	16137	16264	16248	16177	16161	16004	15913	16009	17528	15655	15900
2006	17469	17353	17390	17470	17478	17519	17380	17245	18535	17349	17215
2007	18445	18756	18813	18653	18686	18834	19316	19438	19542	18882	19456
2008	18479	19186	19208	19368	19295	19459	19303	19455	20549	18970	18752
2009	19140	18981	18950	18886	18927	18779	18574	18834	21557	19656	19814
2010	23037	22199	22182	22214	22224	22316	22589	22341	22564	22368	22310
2011	25254	25670	25661	25693	25734	25525	25687	25358	23571	25647	25589
2012	26199	26500	26501	26429	26409	26347	26184	26168	24578	26351	26441
2013	27837	27537	27543	27534	27563	27829	27543	27589	25585	27551	27544
2014	28048	27768	27779	27824	27790	27627	27796	28166	26592	27768	27631
2015	27614	27896	27851	27844	27879	27933	27930	27903	27600	28000	28140
2016	28233	28069	28102	28079	28009	27878	27702	27559	28607	28058	27959
2017	27411	27541	27541	27555	27588	27693	27862	27858	29614	27417	27294

Numerical and graphical representation of the error percentages of 10 models for the number of passenger aircraft between Changi airport and Jakarta International airport from 2004 to 2017 are shown in Table 4.9 and Figure 4.9. It can be observed that the error percentage of each model has decreasing trend from year 2004 to 2017. Error percentages in 2004 for model 1 to model 8 are up to 8.88 %, whereas in 2017 error percentages from model 1 to model 7 are up to 1.64 %.

Figure 4.8 The number of passenger aircraft between Changi airport and Jakarta International airport

Table 4.9 The error percentages of the number of passenger aircraft between Changi airport and Jakarta International airport using 10 models

Year	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9 [83]	Model 10 [84]
2004	5.17	5.78	5.41	6.02	6.18	6.74	8.88	4.92	13.22	14.29
2005	0.79	0.69	0.25	0.15	0.83	1.39	0.80	8.62	2.99	1.47
2006	0.67	0.45	0.00	0.05	0.29	0.51	1.28	6.10	0.68	1.45
2007	1.68	2.00	1.13	1.31	2.11	4.72	5.38	5.95	2.37	5.48
2008	3.83	3.94	4.81	4.41	5.31	4.46	5.28	11.20	2.66	1.48
2009	0.83	0.99	1.33	1.11	1.89	2.96	1.60	12.63	2.7	3.52
2010	3.64	3.71	3.57	3.53	3.13	1.94	3.02	2.05	2.9	3.16
2011	1.65	1.61	1.74	1.90	1.07	1.71	0.41	6.66	1.55	1.33
2012	1.15	1.15	0.88	0.80	0.56	0.06	0.12	6.19	0.58	0.92
2013	1.08	1.06	1.09	0.99	0.03	1.06	0.89	8.09	1.03	1.05
2014	1.00	0.96	0.80	0.92	1.50	0.90	0.42	5.19	1	1.49
2015	1.02	0.86	0.83	0.96	1.15	1.15	1.05	0.05	1.4	1.91
2016	0.58	0.46	0.55	0.79	1.26	1.88	2.39	1.32	0.62	0.97
2017	0.48	0.47	0.53	0.65	1.03	1.64	1.63	8.04	0.02	0.43

Figure 4.9 The error percentages of the number of passenger aircraft between Changi airport and Jakarta International airport

Table 4.10 shows average, maximum, RMS values of the errors and the value of the objective function for all models mentioned above. Model 1 has the smallest value of the objective function, whereas model 8 has the highest value of the objective function. It shows that for accurate prediction of the air traffic, there is a need for more GDP data as an input to the model. However, from model 4 to model 1, error percentages of passenger aircraft do not decrease significantly, indicating that they have similar level of accuracy. Also, model 4 shows that it can forecast the number of passenger aircraft between Changi airport and Jakarta International airport with similar accuracy as from model 1 to model 3, where the RMS error is less than 2.40% and the average error is less than 1.70%. RMS errors from model 1 to model 7 increase up to 2.36 %, which is still 3 times less than the RMS error for the linear model.

Table 4.10. Average, maximum and RMS errors for different models

Model number	Model name	Number of parameters	Average error (%)	Maximum error (%)	RMS of error (%)	Prioritized objective function (million)
1	With all GDP data	11	1.68	5.17	2.19	14.34
2	With all GDP data excluding GDP of China	10	1.72	5.78	2.32	14.53
3	With all GDP data excluding GDP of China and Malaysia	9	1.64	5.41	2.32	14.86
4	With all GDP data excluding GDP of China, Malaysia and Philippines	8	1.69	6.02	2.38	15.22
5	With all GDP data excluding GDP of China, Malaysia, Philippines and Thailand	7	1.88	6.18	2.57	17.73
6	With GDP data of Singapore, Australia, Indonesia and linear model	6	2.22	6.74	2.86	22.04
7	With GDP data for Singapore, Australia and linear model	5	3.17	8.88	2.36	25.79
8	Linear model	2	6.22	12.63	7.08	260.94
9	Multiple linear regression model [83]	9	2.41	13.22	3.32	17.80
10	Log-Log model (multiplicative) [84]	9	2.78	14.29	3.70	26.05

Using Table 4.5 and Table 4.9, forecasting of the number of passenger aircraft is done using 10 models. Table 4.11 and Figure 4.9 show numerical and graphical representation of forecasting the number of passenger aircraft between Changi airport and Jakarta International airport from 2018 to 2023. Table 4.11 shows that the number of passenger aircraft will increase up to 34702 using model 1 by year 2023, which is 26.6 % more than that in 2017. The project proposes that model 1 to model 4 can be used to forecast the number of passenger aircraft accurately.

Table 4.11. Forecasting of the number of passenger aircraft between Changi airport and Jakarta International airport using 10 models

Model	2018	2019	2020	2021	2022	2023
1	28896	29594	30937	32053	33288	34702
2	28824	29462	30730	31764	32905	34208
3	29279	30327	31882	33196	34617	36215
4	29365	30343	31551	32495	33481	34604
5	29421	30593	31853	32849	33891	35089
6	29959	31432	32914	34184	35539	37106
7	30055	31378	32584	33642	34763	36050
8	30621	31628	32635	33643	34650	35657
9 [83]	28198	27871	27332	26371	25141	23716
10 [84]	27612	27040	26506	25843	25181	24587

Figure 4.10. Forecasting of the number of passenger aircraft between Changi airport and Jakarta International airport using 8 models

4.3.3 Case study 3: Forecasting the number of passenger aircraft between Changi airport and KLIA airport-pair

Numbers of passenger aircraft between Changi airport and Kuala Lumpur International Airport (KLIA) are forecasted using 4 different models. Table 4.12 shows the coefficient values obtained from the optimization model using CPLEX for the number of passenger aircraft between Changi airport and KLIA, where numbers of variables have been decreased 1 by 1. “-” indicates where it is not applicable. Model 1 is a model with GDP data of Singapore, Malaysia, Indonesia, China and linear model. Model 2 is a model with GDP data of Singapore, Indonesia, China and linear model. Model 3 is a model with GDP data of Singapore, China and linear model. Model 4 is a linear model. Model 5 is a multiple linear regression model using Singapore, Malaysia, Indonesia, China data [83]. Model 6 is a Log-Log model using Singapore, Malaysia, Indonesia, China data [84].

Table 4.12. The coefficient values for number of passenger aircraft between Changi airport and KLIA

Model	x	y	B_{China}	$B_{Indonesia}$	$B_{Malaysia}$	L	M
1	-0.17	0.2	78868	56022	-90000	-1262	$24.06 \cdot 10^5$
2	-0.17	0.2	62676	39811	-	-499.14	$8.25 \cdot 10^5$
3	-0.13	0.2	47469	-	-	-539.83	$9.73 \cdot 10^5$
4	-	-	-	-	-	1695.2	$-3.39 \cdot 10^6$

Numbers of passenger aircraft between Changi airport and KLIA for 6 models are compared with actual values (from Innovata) for years 2004 to 2017. The numbers of passenger aircraft between Changi airport and KLIA from 2004 to 2017 using 6 models are shown in Table 4.13 and Figure 4.10.

Figure 4.11 The number of passenger aircraft between Changi airport and KLIA

Table 4.13 The number of passenger aircraft from 2004 to 2017 between Changi airport and KLIA using 6 models

Year	Passenger aircraft	Model 1	Model 2	Model 3	Model 4	Model 5 [83]	Model 6 [84]
2004	9889	7285	6818	7766	10691	10329	9125
2005	11280	8228	8193	9333	12386	11152	9805
2006	11290	10694	10493	10887	14082	12963	11686
2007	10766	12180	12279	13400	15777	15101	12609
2008	14135	16927	18487	18215	17472	15379	16560
2009	21866	22827	21325	20446	19167	17876	19882
2010	22045	22372	21754	20845	20862	21458	21495
2011	24726	24182	24060	23391	22557	24699	23866
2012	26561	25608	25885	25513	24252	25899	25393
2013	28154	26783	27181	27411	25948	27180	26226
2014	26499	26806	28203	28987	27643	27110	26394
2015	30998	30914	30097	30742	29338	29232	29321
2016	30563	30420	29860	29842	31033	30573	31073
2017	30031	30671	30849	30447	32728	32141	33366

Numerical and graphical representations of the error percentages for number of passenger aircraft between Changi airport and KLIA from 2004 to 2017 are shown in Table 4.14 and Figure 4.11. The error percentages of models from 1 to 3 have decreasing trend from year 2004 to 2017, except year 2008. In 2008, traffic between KLIA and SG was reduced, which might be due to escape of Mas Selamat Kastari, leader of the Jemaah Islamiah (JI), the same organisation who tried to take down Yishun MRT Station and several foreign embassies. There were rumours of him plotting bomb targets in Singapore and Malaysia [87]. Error percentages in 2004 for model 1 to model 4 are up to 31.05%, whereas in 2017 error percentages are up to 8.98 %.

Table 4.14 Error percentages of the number of passenger aircraft between Changi airport and KLIA using 6 models

Year	Model 1	Model 2	Model 3	Model 4	Model 5 [83]	Model 6 [84]
2004	26.33	31.05	21.47	8.11	4.45	7.72
2005	27.05	27.37	17.26	9.81	1.14	13.08
2006	5.28	7.06	3.57	24.73	14.82	3.51
2007	13.14	14.06	24.46	46.54	40.26	17.11
2008	19.75	30.79	28.86	23.61	8.8	17.15
2009	4.39	2.47	6.49	12.34	18.25	9.07
2010	1.48	1.32	5.44	5.37	2.66	2.5
2011	2.2	2.69	5.40	8.77	0.11	3.48
2012	3.59	2.54	3.95	8.69	2.49	4.4
2013	4.87	3.46	2.64	7.84	3.46	6.85
2014	1.16	6.43	9.39	4.32	2.3	0.39
2015	0.27	2.91	0.83	5.35	5.7	5.41
2016	0.47	2.30	2.36	1.54	0.03	1.67
2017	2.13	2.72	1.39	8.98	7.03	11.11

Figure 4.12 Error percentages of the number of passenger aircraft between Changi airport and KLIA

Table 4.15 shows average, maximum, RMS values of the errors and value of the objective function for all models mentioned above.

Table 4.15. Average, maximum and RMS error for different models

Model number	Number of parameters	Average error (%)	Maximum error (%)	RMS of error (%)	Prioritized objective function (million)
1	7	8.01	27.05	12.20	116.18
2	6	9.80	31.05	14.65	211.20
3	5	9.53	28.86	13.15	253.43
4	2	12.57	46.54	16.95	522.53
5 [83]	5	7.97	40.26	10.92	306.79
6 [84]	5	7.39	17.15	7.59	322.46

Using Table 4.5 and Table 4.1, forecasting of the number of passenger aircraft is done using model 1. Table 4.16 and Figure 4.13 show numerical and graphical representation of forecasting the number of passenger aircraft between Changi airport

and KLIA from 2018 to 2023. Model 1 has the smallest value of the objective function, which is at least 1.82 times lower than the objective functions of other models. Therefore, only model 1 was used to forecast passenger movements between Changi airport and KLIA. According to model 1, the number of passenger aircraft will be 31698 by year 2023.

Table 4.16. Forecasting of the number of passenger aircraft

	Model name	2018	2019	2020	2021	2022	2023
1	With GDP data of Singapore, Malaysia, Indonesia, China and linear model	31164	31332	31592	31708	31717	31698
2	With GDP data of Singapore, China, Indonesia and linear model	33183	34739	36219	37637	38991	40311
3	With GDP data of Singapore, China and linear model	33161	34586	35774	36920	38005	39080
4	Linear model	34424	36119	37814	39509	41204	42899
5	Multiple linear regression [83]	33161	34158	35351	36302	37197	38129
6	Log-log model [84]	35116	37339	40057	42738	45481	48309

Figure 4.13. Forecasting of the number of passenger aircraft

4.4 Advantages and limitations of the model

1. Compared to the model proposed by Viktor Surian [88], the model described here takes into account important factors such as the economic well-being of surrounding countries. Also, Viktor Surian [88] considers only 4 variables in his model, but this research considers 11 variables initially.
2. The model can be used to forecast air traffic of any airport. A specific model can be obtained for a specific airport using optimization toolbox. An optimization toolbox finds values of coefficients of general formula using data provided.
3. The model provides flexibility for the user to trade-off between accuracy of forecasting to the complexity of the model. There are multiple models that can be obtained for a specific airport depending on a number of variables. The user can choose which model suits best to his requirements.

4. By using optimization to find coefficients of the model, the best fit model to the historical data has been found. In that way, it gives the least possible error of fitting. By having optimal coefficients, it gives a model with more accurate forecasting.
5. The accuracy of the forecasted GDP values of countries is unknown. Air traffic forecasting of any country is directly related to GDP of that country. That is why air traffic forecasting accuracy depends on the accuracy of forecasting of GDP values of that country and countries nearby. In case study, forecasted GDP values are taken from World Bank website.
6. Forecasting cannot be certain. Unexpected events could happen in the future, like a global crisis, some virus outbreak or war. It is very difficult to estimate effects of such unexpected events on the air traffic, which is why they are not discussed in this thesis.
7. The proposed model has short computational time with computational complexity $\frac{b-a}{r} O(C^2N)$. C is a number of variables (up to 11). N is a number of training samples (up to 11). b and a are upper and lower limits of iteration (10 and -10 respectively). r is an iteration rate (0.05). Therefore, computational times are up to few seconds.

CHAPTER 5

TRAFFIC OPTIMIZATION

5.1 Introduction

In general, an airport is the first place where tourists get their first impression of the country. Receiving poor service or facing long delays from flight attendants may give a bad first impression of the country [89]. Also, delays result in extra carbon dioxide emission due to extra fuel usage, which causes negative environmental impact. Thus, Chao et al. [90] developed a model to analyze the environmental performance of airports. 16 potential factors have been considered in his work, and the most significant 3 causes are ‘energy-saving control,’ ‘easy airport access by public transport,’ and ‘aircraft carbon management’. Also, Brueckner et al. [91] introduced determining factors on fuel usage and carbon dioxide emissions. Their research showed that the delays are the major contributor of high fuel consumption. The results suggest that either increasing peak-hour congestion penalties on the airlines or managing flights efficiently will reduce delays. For example, if average delay gets reduced by 3% then it can save \$48 million per year spent for fuel. Also, their research suggests imposing optimal emission charges on airlines.

In addition to reducing carbon emission, reducing computational time of the model is important too [92]. With the increase of the air traffic density, there is a need for accurate rescheduling based on up to date weather information [93]. Hence, Cao and Sun [94] proposed a model using the Lagrangian method and parallel programming methods to reduce the computational time of the model. Programs can be run in the cloud so that it can eliminate hardware limitations. Therefore, this thesis aims to reduce delays to improve efficiency of the air traffic management. Corver and Grote [95]

studied sources of uncertainty in en route air traffic control and strategies air traffic controllers use to cope with it.

Currently, global airlines consume more than 5 million barrels of oil per day, and it is going to increase further if no actions are taken [96]. However, a study was conducted on China airlines and it was found that global Malmquist carbon emission performance index (GMCPI) was decreased by 11.92% from 2007 to 2013 [97]. The reason is due to technological progress and due to traffic optimization. Therefore, traffic optimization in order to reduce delay cost was chosen to be one of the research areas in this thesis.

The purpose of this chapter is to propose a model which will help establish efficient Air Traffic Flow Management (ATFM). The main purpose of ATFM is to have effective and efficient air traffic management [61]. It includes safety, cost-effectiveness, efficiency and manage environmental impact of the air traffic management system. ATFM needs to solve several problems, and some of them are mitigation of the effects of unexpected events or situations of reduced capacity efficiently [61] and reduction of the air traffic delay [98]. Also, in order to maintain safe and efficient air traffic flow, efficient air traffic scheduling has to be made [99]. Therefore, chapter 5 focuses on solving reduced capacity problems and on reducing delays efficiently by rescheduling of the flights.

5.2 Modelling

In the past, Bruno proposed an integer linear model to optimize air traffic, with consideration of detailed airport capacity, like runway capacity, taxiway capacity and ground capacity [100]. However, this model optimizes departures to benefit one airport

only. Moreover, other factors such as other airports capacity and flights cost have also not been considered.

In this chapter, the model optimizes delay cost by manoeuvring aircraft to benefit airlines, and to mitigate negative environmental impact. The model structure has been explained in section 3.2.2. The objective of the model is to minimize the total sum of the delay cost of the flights. The cost of the flights is determined by airborne and ground holding delays. Also, minimization is done by considering the factors like airports capacity and waypoints capacity. The model makes sure none of the flights gets delayed longer than a specific time, to ensure fairness to all flights. The model structure is shown in Figure 3.1.

5.3 Results and discussion

The traffic between Changi airport and Kuala-Lumpur airport is considered to be the 4th busiest international air route in the world by passenger volume [101]. Therefore, this route was examined in the case study.

There are few air routes between Changi Airport and Kuala-Lumpur International Airport. Figure 5.1 shows the main air route between Changi and Kuala-Lumpur from flightdatabase.com, which passes through 1 waypoint, GUPTA.

Similarly, Figure 5.2 shows one of the alternative air routes, passing through waypoints: BATAR, OGAKO, TOPOR and ARAMA.

In the case study, there are 88 aircraft flying in a day, in which 44 flights are from Singapore to Kuala-Lumpur, and another 44 flights are from Kuala-Lumpur to Singapore. The inputs to the case study are shown in Table 5.1.

Table 5.1. Values of input parameters

Input parameters	Values	Units
Number of flights from Kuala-Lumpur to Singapore	44	Number of flights per day
Number of flights from Singapore to Kuala-Lumpur	44	Number of flights per day
Number of waypoints in the trajectory	1 and 4	
Maximum airborne holding delay time	8	Min
Maximum ground holding delay time	26	Min
Total capacity of the Kuala-Lumpur airport for the city-pair	10	Flights per hour
Total capacity of the Changi airport for the city-pair	12	Flights per hour
Capacity of the waypoint	12	Per hour
Cost ratio of airborne delay to ground delay	2	-

Let us suppose that there are only 2 routes, and flights from Singapore have to pass GUPTA, and flights from Kuala-Lumpur have to pass BATAR, OGAKO, TOPOR and ARAMA. Both routes are unidirectional. Maximum airborne and ground holding delay times are set to be 8 min and 26 min respectively. Maximum airborne and ground holding delay times are needed to make sure that none of the flights gets delayed for a very long time. The objective function has been used as in formula (3.11) to calculate delay cost. Airport capacities in this case study were sufficient not to consider P and O.

The model considers all constraints from (3.12) to (3.22). Also, ground holding cost and airborne holding cost for all airports are calculated using formulas (3.23) and (3.24) respectively.

Several assumptions are made in the case study. It is assumed that capacities of the waypoints and airports for the city-pair are constant throughout the day, which means that the effects from other city-pairs on the capacities of the waypoints and airports are constant. Also, the speeds of the aircraft and taxiway holding times of the flights do not change from the original schedule.

The cost ratio of airborne delay to ground delay is set to be 2 [104]. The capacities of 5 waypoints: GUPTA BATAR, OGAKO, TOPOR and ARAMA are set to be 12 flights per hour, meaning 5 min separation time [105]. The capacities of airports and waypoints are shown regarding how many aircraft can pass through that location per hour. The capacity of KLIA for the city-pair is 10 flights per hour, which is a 6 min separation time between departing or arriving aircraft. Similarly, capacity of Changi airport for the city-pair is set to be 12 flights per hour, which is a 5 min separation time between departing or arriving aircraft.

Flight plan has been extracted for KLIA-Changi pair from Flight Aware for the 2nd of August 2018 [106]. Flight schedule for 44 flights from Changi airport to KLIA is shown in Table 5.2. Similarly, flight schedule for 44 flights from KLIA to Changi airport is shown in Table 5.3. However, actual departure and arrival times differ from the flight schedules in both directions. Table 5.4 shows actual rescheduled 44 flights from Changi airport to KLIA. Maximum ground delay is up to 81 min and maximum airborne delay is up to 16 min. Also, flight 16 is cancelled. Similarly, Table 5.5 shows the actual rescheduled 44 flights from KLIA to Changi airport. Maximum ground delay is up to 50 min and maximum airborne delay is up to 25 min. Also, flight 10 is cancelled.

Using the model described in this chapter, rescheduling has been done in order to satisfy constraints (3.12) – (3.22) (safety) and minimize objective function (total delay cost) in (3.10). Table 5.6 shows the rescheduled 44 flights from Changi airport to KLIA using the model. The table shows that none of the flights from Changi airport to KLIA is cancelled. Maximum ground delay is up to 14 min and maximum airborne delay is up to 6 min. Similarly, Table 5.7 shows rescheduled 44 flights from KLIA to Changi airport. None of the flights from Changi airport to KLIA is cancelled.

CPLEX branch-and-bound method is used to compute optimal solution. Computational time is 40h 54min 28sec on a PC with Intel Core i7-7700HQ, 2.80GHz, 8GB RAM with Windows 10 OS.

Table 5.2. Schedule of the flights from Changi airport to KLIA [106]

Flight	Callsign	Aircraft type	Departure time	Arrival time
1	SLK320	A319	06:00AM	06:55AM
2	MAS602	B738	06:40AM	07:40AM
3	JSA683	A320	07:05AM	08:10AM
4	SLK322	B738	07:10AM	08:05AM
5	AXM700	A320	07:45AM	08:45AM
6	SIA106	A333	08:30AM	09:30AM
7	MAU646	A332	09:00AM	10:00AM
8	AXM702	A320	09:10AM	10:10AM
9	SLK324	B738	09:20AM	10:20AM
10	TGW452	A319	09:55AM	10:55AM
11	SLK326	B38M	10:25AM	11:15AM
12	AXM704	A320	10:30AM	11:35AM
13	MXD802	B738	10:45AM	11:45AM
14	MAS614	B738	11:05AM	12:05PM
15	AXM706	A320	11:40AM	12:40PM
16	MAS628	B738	12:15PM	01:15PM
17	MXD804	B739	12:20PM	01:25PM
18	SLK328	B738	12:45PM	01:45PM
19	JSA685	A320	12:50PM	01:55PM
20	AXM710	A320	01:30PM	02:35PM
21	MAS606	B738	01:40PM	02:40PM
22	AXM712	A320	02:10PM	03:15PM
23	SLK330	B738	03:25PM	04:25PM
24	MAS624	B738	03:35PM	04:21PM
25	ETH638	B788	03:50PM	05:10PM
26	SLK340	A319	04:10PM	05:10PM
27	AXM714	A320	04:10PM	05:10PM
28	MAS620	B738	04:35PM	05:38PM
29	SIA116	A333	04:45PM	05:45PM
30	MXD808	B738	05:00PM	06:05PM
31	TGW468	A320	05:45PM	06:45PM
32	JSA669	A320	05:55PM	07:05PM
33	MAS608	B738	06:10PM	08:21PM
34	SIA118	A359	06:45PM	07:45PM
35	AXM716	A320	07:10PM	08:10PM
36	MAS616	B738	07:15PM	08:24PM
37	TGW466	A320	07:25PM	08:25PM
38	JSA687	A320	07:35PM	08:40PM
39	SLK342	A319	08:00PM	08:55PM
40	AXM718	A320	08:45PM	09:45PM
41	MAS610	B738	09:15PM	10:15PM
42	AXM720	A320	09:20PM	10:20PM
43	MXD806	B738	09:30PM	10:35PM
44	AXM722	A320	11:00PM	11:59PM

Table 5.3. Schedule of the flights from KLIA to Changi airport [107]

Flight	Callsign	Aircraft type	Departure time	Arrival time
1	AXM701	A320	06:10AM	07:15AM
2	AXM703	A320	07:30AM	08:40AM
3	SLK319	A319	07:35AM	08:35AM
4	AXM705	A320	08:40AM	09:50AM
5	JSA684	A320	08:50AM	10:00AM
6	SLK321	B738	08:55AM	09:50AM
7	MXD801	B738	09:00AM	10:05AM
8	MAS611	B738	09:10AM	10:15AM
9	AXM707	A320	09:55AM	11:10AM
10	MAS627	B738	10:15AM	11:25AM
11	SIA107	A333	10:25AM	11:35AM
12	MXD803	B739	10:30AM	11:30AM
13	SLK323	B738	11:10AM	12:10PM
14	TGW453	A319	11:35AM	12:50PM
15	AXM711	A320	11:45AM	01:00PM
16	MAS603	B738	11:45AM	12:55PM
17	SLK325	B38M	12:00PM	01:00PM
18	AXM713	A320	12:30PM	01:40PM
19	MAS623	B738	01:25PM	02:45PM
20	MAU647	A332	01:35PM	02:35PM
21	MAS619	B738	02:25PM	03:40PM
22	SLK327	B738	02:30PM	03:30PM
23	AXM715	A320	02:30PM	03:40PM
24	JSA686	-	02:45PM	03:31PM
25	MXD807	B738	03:05PM	04:10PM
26	MAS605	B738	04:25PM	06:08PM
27	SLK329	B738	05:10PM	06:10PM
28	AXM717	A320	05:15PM	06:30PM
29	MAS613	B738	05:20PM	06:32PM
30	SLK339	A319	06:05PM	07:05PM
31	SIA117	A333	06:40PM	07:50PM
32	AXM719	A320	06:50PM	08:00PM
33	MAS607	B738	07:25PM	08:25PM
34	TGW469	A320	07:30PM	08:45PM
35	AXM721	A320	07:35PM	08:50PM
36	MXD805	B738	07:40PM	08:40PM
37	JSA670	A320	07:50PM	08:55PM
38	SIA119	A359	08:40PM	09:50PM
39	TGW467	A320	09:05PM	10:20PM
40	AXM723	A320	09:15PM	10:30PM
41	JSA688	A320	09:20PM	10:30PM
42	SLK341	A319	09:45PM	10:40PM
43	MAS609	B738	11:05PM	12:10AM
44	ETH639	B788	11:15PM	12:35AM

Table 5.4. Actual rescheduled flights from Changi airport to KLIA [106]

Flight	Ground delay	Airborne delay	Rescheduled departure time	Rescheduled arrival time
1	0	1	5:53AM	6:49AM
2	0	0	6:39AM	07:34AM
3	0	0	06:59AM	07:52AM
4	0	6	07:08AM	08:09AM
5	23	1	08:08AM	09:09AM
6	0	0	08:28AM	09:26AM
7	54	0	09:54AM	10:28AM
8	0	2	09:05AM	10:07AM
9	0	0	09:17AM	10:14AM
10	0	0	09:40AM	10:37AM
11	15	14	10:40AM	11:44AM
12	16	5	10:46AM	11:56AM
13	5	16	10:50AM	12:06PM
14	19	9	11:24AM	12:33PM
15	0	2	11:37AM	12:39PM
16	CANCELLED			
17	0	0	12:16PM	01:20PM
18	0	4	12:44PM	01:48PM
19	4	0	12:54PM	01:55PM
20	0	0	01:25PM	02:30PM
21	0	0	01:38PM	02:25PM
22	10	11	02:20PM	03:36PM
23	0	10	03:19PM	04:29PM
24	6	0	03:41PM	04:21PM
25	0	0	03:49PM	04:43PM
26	0	0	04:04PM	05:01PM
27	0	16	04:03PM	05:19PM
28	13	0	04:48PM	05:38PM
29	0	10	04:35PM	05:45PM
30	0	8	05:00PM	06:13PM
31	0	0	05:45PM	06:41PM
32	0	0	05:52PM	06:59PM
33	81	0	07:31PM	08:10PM
34	5	3	06:50PM	07:53PM
35	30	0	07:40PM	08:36PM
36	19	0	07:34PM	08:15PM
37	0	0	07:25PM	08:10PM
38	0	0	07:33PM	08:30PM
39	6	5	08:06PM	09:06PM
40	0	7	08:38PM	09:45PM
41	19	0	09:34PM	10:24PM
42	0	0	09:12PM	10:08PM
43	7	0	09:37PM	10:42PM
44	0	2	10:59PM	12:00AM

Table 5.5. Actual rescheduled flights from KLIA to Changi airport [106]

Flight	Ground delay	Airborne delay	Rescheduled departure time	Rescheduled arrival time
1	24	0	06:34AM	07:34AM
2	0	0	07:27AM	08:27AM
3	0	13	07:26AM	08:39AM
4	2	0	08:42AM	09:46AM
5	0	5	08:42AM	09:57AM
6	1	13	08:56AM	10:04AM
7	0	6	08:55AM	10:06AM
8	0	10	09:10AM	10:25AM
9	0	0	09:48AM	11:01AM
10	CANCELLED			
11	0	10	10:11AM	11:31AM
12	0	6	10:27AM	11:33AM
13	0	9	11:00AM	12:09PM
14	6	0	11:41AM	12:17PM
15	0	0	11:35AM	12:42PM
16	0	1	11:45AM	12:56PM
17	23	9	12:23PM	01:32PM
18	16	0	12:46PM	01:52PM
19	0	0	01:20PM	02:21PM
20	18	0	01:53PM	02:46PM
21	25	0	02:50PM	03:40PM
22	5	24	02:35PM	03:59PM
23	0	0	02:27PM	03:33PM
24	0	0	02:45PM	03:31PM
25	0	0	02:58PM	03:56PM
26	50	0	05:15PM	06:08PM
27	1	7	05:11PM	06:18PM
28	37	5	05:52PM	07:12PM
29	20	0	05:40PM	06:32PM
30	0	19	06:02PM	07:21PM
31	0	0	06:40PM	07:49PM
32	0	1	06:49PM	08:00PM
33	34	0	07:59PM	08:47PM
34	11	0	07:41PM	08:22PM
35	0	0	07:28PM	08:41PM
36	4	10	07:44PM	08:54PM
37	0	0	07:49PM	08:52PM
38	0	25	08:39PM	10:14PM
39	11	0	09:16PM	10:19PM
40	0	0	09:14PM	10:29PM
41	3	0	09:23PM	10:29PM
42	0	14	09:41PM	10:50PM
43	4	4	11:09PM	12:18AM
44	9	8	11:24PM	12:52AM

Table 5.6. Rescheduled flights from Changi airport to KLIA using the model

Flight	Ground delay in Changi airport	Airborne delay	Rescheduled departure time	Rescheduled arrival time
1	0	0	06:00AM	06:55AM
2	2	0	06:42AM	07:42AM
3	0	1	07:05AM	08:11AM
4	0	0	07:10AM	08:05AM
5	1	0	07:46AM	08:46AM
6	0	0	08:30AM	09:30AM
7	1	0	09:01AM	10:01AM
8	0	0	09:10AM	10:10AM
9	2	0	09:22AM	10:22AM
10	5	0	10:00AM	11:00AM
11	1	0	10:26AM	11:16AM
12	6	0	10:36AM	11:41AM
13	14	0	10:59AM	11:59AM
14	0	6	11:05AM	12:11PM
15	4	0	11:44AM	12:44PM
16	0	0	12:15PM	01:15PM
17	6	0	12:26PM	01:31PM
18	0	0	12:45PM	01:45PM
19	5	0	12:55PM	02:00PM
20	2	0	01:32PM	02:37PM
21	9	0	01:49PM	02:49PM
22	0	0	02:10PM	03:15PM
23	1	2	03:26PM	04:28PM
24	1	0	03:36PM	04:22PM
25	6	0	03:56PM	05:16PM
26	0	0	04:10PM	05:10PM
27	12	0	04:22PM	05:22PM
28	2	0	04:37PM	05:40PM
29	7	0	04:52PM	05:52PM
30	6	0	05:06PM	06:11PM
31	1	0	05:46PM	06:46PM
32	0	0	05:55PM	07:05PM
33	0	0	06:10PM	08:21PM
34	0	4	06:45PM	07:49PM
35	0	0	07:10PM	08:10PM
36	0	0	07:15PM	08:24PM
37	5	0	07:30PM	08:30PM
38	0	0	07:35PM	08:40PM
39	0	0	08:00PM	08:55PM
40	13	0	08:58PM	09:58PM
41	0	0	09:15PM	10:15PM
42	1	0	09:21PM	10:21PM
43	0	0	09:30PM	10:35PM
44	0	0	11:00PM	11:59PM

Table 5.7. Rescheduled flights from KLIA to Changi airport using the model

Flight	Ground delay in KLIA	Airborne delay	Rescheduled departure time	Rescheduled arrival time
1	0	0	06:10AM	07:15AM
2	0	1	07:30AM	08:41AM
3	1	0	07:36AM	08:36AM
4	0	0	08:40AM	09:50AM
5	2	3	08:52AM	10:05AM
6	3	2	08:58AM	09:55AM
7	4	1	09:04AM	10:10AM
8	0	0	09:10AM	10:15AM
9	0	0	09:55AM	11:10AM
10	1	0	10:16AM	11:26AM
11	3	1	10:28AM	11:39AM
12	4	0	10:34AM	11:34AM
13	0	0	11:10AM	12:10PM
14	0	0	11:35AM	12:50PM
15	8	0	11:53AM	01:08PM
16	2	3	11:47AM	01:00PM
17	5	0	12:05PM	01:05PM
18	0	0	12:30PM	01:40PM
19	0	0	01:25PM	02:45PM
20	2	0	01:37PM	02:37PM
21	0	1	02:25PM	03:41PM
22	1	0	02:31PM	03:31PM
23	13	8	02:43PM	03:51PM
24	15	0	03:00PM	03:46PM
25	4	1	03:09PM	04:15PM
26	9	0	04:34PM	06:17PM
27	18	0	05:28PM	06:28PM
28	19	1	05:34PM	06:50PM
29	26	0	05:46PM	06:58PM
30	0	0	06:05PM	07:05PM
31	0	0	06:40PM	07:50PM
32	5	0	06:55PM	08:05PM
33	0	0	07:25PM	08:25PM
34	1	2	07:31PM	08:48PM
35	2	1	07:37PM	08:53PM
36	3	0	07:43PM	08:43PM
37	8	0	07:58PM	09:03PM
38	6	0	08:46PM	09:56PM
39	0	0	09:05PM	10:20PM
40	0	0	09:15PM	10:30PM
41	5	0	09:25PM	10:35PM
42	0	0	09:45PM	10:40PM
43	0	0	11:05PM	12:10AM
44	0	0	11:15PM	12:35AM

Table 5.8 shows summary of comparison between actual rescheduling and rescheduling using the model. The value of the standard deviation of the delays shows the “fairness” of the rescheduling method, with low values indicating more “fairness”. Standard deviations of the rescheduling using the model are less than standard deviations of the actual rescheduling. Therefore, rescheduling using the model is fairer than actual rescheduling.

Table 5.8 The comparison of delays between actual rescheduling and rescheduling using the model (in min)

	Actual rescheduling from WSSS to WMKK	Rescheduling using the model from WSSS to WMKK	Actual rescheduling from WMKK to WSSS	Rescheduling using the model from WMKK to WSSS
Average ground delay	7.55	2.57	6.91	3.86
Standard deviation of ground delay	15.52	3.71	11.83	5.86
Maximum ground delay	81	14	50	26
Average airborne delay	3	0.30	4.52	0.57
Standard deviation of airborne delay	4.68	1.10	6.63	1.37
Maximum airborne delay	16	6	25	8

Ground delays are reduced by 4.98 min and 3.05 min on average. Standard deviations of the ground delays are reduced by 11.81 min and 5.97 min. More importantly, airborne delays are reduced by 2.70 min and 3.95 min on average. Also, standard deviations of the airborne delays are reduced by 3.58 min and 5.26 min.

5.4 Comparison of the models

Compared to the previous studies discussed in the literature review, this chapter proposes a model which is more practical in use. The model identifies optimal routes by operationalizing and controlling many constraints such as delay cost, airport departure and arrival capacities, waypoints capacity, routes capacity, rerouting options, and “fairness” to aircraft.

This thesis uses a more accurate model to calculate objective function compared to [92]. The objective function used in [92] approximates calculation of airborne holding cost, whereas objective function proposed in this chapter uses exact value of airborne holding cost, which is more complex. Airborne holding cost in [92] is $\sum_{f \in F} \sum_{j \in \mathcal{P}^f} \sum_{t \in T_j^f} f_{AH}^j (t - ar_{f,j}) (w_{j,t}^f - w_{j,t-1}^f)$ whereas airborne holding cost in this chapter is $\sum_{f \in F} \sum_{j^* \in \mathcal{P}_j^f} \sum_{j \in \mathcal{P}^f} \sum_{t \in T_j^f} f_{AH}^j (t - ar_{f,j} + ar_{f,j^*} - t_1) (w_{j,t}^f - w_{j,t-1}^f) (w_{j^*,t_1}^f - w_{j^*,t_1-1}^f)$. The objective function has been improved to show the true cost of the flights. In addition, number of flights in the case study has been increased from 2 to 88 [92].

Compared to the model in [108], the model described in this chapter considers continued flights. In another research, Cao proposes the parallel computing model using a link transmission model in order to improve the computational time [109]. On top of that, he used the dual-decomposition method, to break a big problem into many smaller problems and solve them parallel. The model was able to solve congestion in 6min, whereas for similar models it takes about 2 hours. However, major factors like cancellation cost, airborne holding cost, opportunity cost and weather changes have not been considered in his model. In the real world, it is inevitable to consider these constraints, and by not considering these constraints computational time is reduced. Similar results to Cao’s model was obtained by Ivanov’s model, which optimizes flights

by giving optimal slot allocation [110].

A new en-route optimization model has been proposed by Chen in 2017 [111]. The model considers en-route limitations and considers some uncertainties. However, the model was able to run for 148 flights only. The objective function was to minimize total delay time. Summary of comparison with other models is shown in Table 5.9.

A probabilistic model has been introduced to handle the propagation of the uncertainty from the trajectories to the sectors [112]. The prerequisites of this model are the marginal of the initial arrival in the airspace, the policy of the flight management system when trying to stick to the target schedule, and the potential external disruptions. Thereafter, the probability for a flight to be in a sector has been computed. From there on, the closed-form equation to compute the probability of congestion has been derived. Then, some general formulations for the expected cost of delays and the expected cost of congestion were given. The multi-objective algorithm NSGA-II was proposed to solve the bi-objective problem of minimizing both the congestion and the cumulated delays of the flights, i.e., to approximate the non-dominated solutions of the Pareto front. These solutions were proposed as alternatives for the decision maker, namely here the multisector planner. Furthermore, in order to illustrate how the theoretical model can be useful in practice, he presented some results on two instances. Their results were analyzed to discover the consequences of some previous assumptions and to assess of the computation time of the inference mechanism.

Our proposed model has some advantages and disadvantages compared to currently proposed models. However, it can definitely compete with them in terms of practical usability and computational time. Important limitations have been considered.

Similarly, there are other optimization models which consider air traffic controllers workload in detail [113]. This paper explores methods to include aspects of

controller task load into conflict-resolution programs through a parametric approach. They desire to create conflict-resolution decision support tools that operate within a human-in-the-loop control architecture by actively accounting for, and moderating, controller task load. Specifically, they introduce two conflict-resolution programs with the objective of managing controller conflict-resolution task load, i.e., the number of manoeuvres used to separate air traffic.

Table 5.9 The comparison with other models

	Proposed model	Cao's model [109]	Chen's model [111]	Marceau's model [112]
Airborne holding cost	Yes	No	Yes	Yes
Ground holding cost	Yes	Yes	Yes	Yes
Opportunity cost	Yes	No	No	No
Weather changes	Yes	No	No	Yes
Parallel computing	No	Yes	No	No
Climbing and cruising consideration	No	No	Yes	No

Managing conflict-resolution task load is accomplished by penalizing aircraft manoeuvres through their L1 norm in the cost function or constraining the number of manoeuvres directly. Analysis of the programs reveals that both approaches are successful at managing controller conflict-resolution task load and minimizing fuel burn. Directly constraining conflict-resolution task load is more successful at minimizing the variation in the number of aircraft manoeuvres issued and returning the aircraft to their desired exit point. Penalizing manoeuvres through L1 norm costs is more successful at reducing controller conflict-resolution task load at lower traffic volumes. Their results demonstrate that the inclusion of such parametric models can successfully regulate controller conflict-resolution task load.

CHAPTER 6

RESTRUCTURING AN AIR NETWORK

6.1 Introduction

As discussed in previous studies, FIR has been studied for the past 50 years. In 1995, it was first proposed by Radio Technical Commission for Aeronautics to describe airspace load quantitatively [110]. With time, air traffic has been growing gradually. Airspace characteristics have been studied, and it has been shown that at some time in near future air traffic demand will be higher than air traffic capacity due to the limited management of air traffic [114]. There was no need for optimization of the network locations in the past due to a small number of flights. However, air traffic has increased significantly in the past decades [115].

Wang and Gong [116] proposed a model which optimizes air route network nodes by avoiding restricted areas and adopting cellular automaton method for safe flights. In addition, Lim and Zhong [117] improved this model, by considering dynamic weather. Due to high velocity of aircraft, they have turn angle limitations. In this thesis, a model which considers turn angle limitations of the aircraft has been proposed. In the model turn angle limitation and the number of cells are variables which can be set by the user.

Babić and Kalić [118] showed that selection of the right network makes a significant impact on airlines and passengers in terms of cost and travel time of the flights. Moreover, Hazel [119] showed that having efficient air traffic network leads to increase in airline revenue. Air traffic management without proper regulations might lead to a big increase in flight delays and capacity limitations in airports [120]. In 2003, Alipio et al. [121] introduced a new concept of air high-density highways, by getting

inspired by ground highways. Similarly, in Europe, The Single European Sky (SES) concept has been introduced. With these new ideas, there is a need for more research study on the efficiency of the air traffic network. Cattaneo et al. [122] showed that due to these changes, flight travel duration has decreased by 5.7 minutes on average in the last decade alone. Similar changes can be adopted in ASEAN airspace.

Most of the time, these models can work to find optimal flight trajectories. However, the problem usually arises when there is a hazardous weather in one of the air traffic routes. Therefore, air traffic management needs to consider changes in demand and weather condition.

6.2 Implementing free route airspace

Air transport has been increasingly important as means of transportation in both developed and undeveloped countries. Although associated to relatively high costs, air transport is generally safer and faster in comparison to other means of transportation particularly to connect isolated rural areas and islands with urbanized areas, or to connect mutually distant locations such as cities in different continents. Similar to other modes of transport, aircraft follow pre-defined air routes according to regulations of the aerial space of a given country. Altogether, pairs of cities (or airports) form a complex network of flights in which nodes represent the locations and links represent the fact that at least one flight occurred between the two locations during some interval of time.

However, free route airspace has been implemented in some sectors of Europe, and by 2021 more than 70% of Europe airspace is going to become free route airspace [123]. In the following sections benefits of implementing free route airspace with the obstacle avoidance model in Singapore have been discussed.

6.2.1 Benefits of using free route airspace in Singapore

Figure 6.1 shows Singapore FIR with the air traffic in 2014 for one day. Each segment has a number assigned to it, which shows how many flights have passed that segment on that particular day. No overflights have been considered. All flights (except overflights) passing Singapore airspace are supposed to fly through segments and waypoints indicated on this map.

If airspace is used efficiently, airspace capacity can be significantly increased. One of the solutions is to implement free route airspace in ASEAN region. Free route airspace is a space where pilots can freely plan their routes from the entry point to exit point without the necessity to follow network routes [8]. This concept gives an opportunity for pilots to shorten flight distance and in consequence, save fuel.

Figure 6.1. Representation of the air traffic in Singapore using SAAM

Singapore airspace is shown in grey, and flight trajectories are shown in yellow.
Black dots indicate waypoints, and their names are written on next to them.

A simulation as in Figure 6.2, has been conducted implementing free route airspace. All flight trajectories are shown in red lines. Airspace is shown in light green. Waypoint and airport names are shown in black. Figure 6.2 has more straight flights compared to flights in Figure 6.1. Also, flights were distributed across different trajectories.

Table 6.1 shows a summary of flight distance comparisons in Singapore airspace. Flights have been categorized by flight distances. Also, flight distances have been calculated. From Table 6.1 the biggest impact will be on flights which have a distance above 1200NM, the flight distances has been shortened by 2.59%. In total flight distance was shortened by 2.39%. Shorter flights usually lead to a less fuel consumption. It means that fuel consumption and carbon dioxide emission can be reduced. This model affects all types of flights: long-distance flights as well as short distance flights.

There are 158 flights involved in the simulation with travelling distance less than 150 NM. Their travelling distance has been reduced by 1.29% on average. Also, 67 flights involved in simulation, with flight distance between 150-300 NM. Their travelling distance was reduced by 1.71% on average. Flights with flight distance between 300-500 NM were reduced by 1.09%. Flights with flight distance between 500-800 NM were reduced by 2.43%. Flights with flight distance between 800-1200 NM were reduced by 1.51%.

Table 6.1. Comparison between flight distances in 2014 and after implementation of
free route airspace (1 NM = 1.852 km)

Distance ranges (NM)	Number of flights	Sum of route distances (NM)	Sum of distances after implementation (NM)	Differences in distances
0-150	158	12847.75	12683.77	1.29%
150-300	67	14753.19	14505.35	1.71%
300-500	260	107195.99	106041.39	1.09%
500-800	299	191728.14	187180.72	2.43%
800-1200	221	205159.93	202104.94	1.51%
1200-more	728	1725611.23	1682021.22	2.59%
Total	1733	2257296.24	2204537.38	2.39%

6.2.2 Finding shortest paths avoiding prohibited areas in free route airspace

There can be some deviations between flight trajectories and flight plans. The possible reasons might be due to unforeseen air traffic congestion, weather problems or other sources. For instance, Figure 6.3 a, b, and c show some of the flight trajectories between Changi airport and Kuala Lumpur International airport (KLIA) on 13th June 2018.

Figure 6.3a Actual flight path of AirAsia 703 [107]

Figure 6.3b Actual flight path of SilkAir 5702 [124]

Figure 6.3c Actual flight path of AirAsia 706 [106]

Algorithm describing the model is shown in Algorithm 1. Algorithm 1 shows a modified version of A* method, developed from [125], to determine the shortest paths while avoiding prohibited areas. If we compare A* algorithm with Dijkstra's algorithm, A* algorithm tries to look for a better path by using a heuristic function which gives priority to nodes that are supposed to be better than others. However, Dijkstra's algorithm explores all possible paths, which might give more computational time [126]. Also, if we compare A* search algorithm with a greedy best-first search algorithm, a greedy best-first search algorithm does not consider the cost to reach the node. Xie and Zhong compared Particle Swarm Optimization (PSO) with A* search algorithm for finding shortest paths for aircraft [127]. The results show that PSO gives smoother path, however, takes more iteration and time to compute optimal path. Similarly, ant colony optimization is a probabilistic technique which finds paths over a discrete search space [128], which makes an exhaustive search compared to A* search algorithm. In addition,

genetic algorithm uses population of solutions and tries to find better population using crossover and mutation, which takes more computational time than A* search [129].

First of all, for each pair of entry points, the program creates an “open list” and “closed list”. “Open list” is a list of all available un-expanded nodes. It is usually implemented as a priority queue. In other words, “open list” is a list of nodes which were discovered but not evaluated yet. “Closed list” is an optional record of all expanded nodes. It is used to prevent repeated search and infinite loops. The “closed list” will contain all nodes which have been evaluated. “Heuristic_cost_estimate” is an estimate of the distance from a node n to the goal node [125]. Function $\text{angle}(A, B, C)$ calculates angle between points A, B, and C. Firstly, starting node is discovered, so starting node is placed in “open list”. In the beginning “cameFrom” is empty. The “cameFrom” is a “parent node”, which stores the node that gives the most efficient route to come to target point. The “gScore” is an array which stores the travel cost from each node to starting node. The “gScore[start]” initially is equal to 0 because cost from start to start is 0. The “fScore” is an array, where “fScore[i]” stores cost of the flight in flying from “start” to “goal” passing by node “i”. “fScore[i]” can store heuristic values. The function will run until “open set” is not empty. “*openSet.Remove(current)*” removes a current node from “open set”. “*closedSet.Add(current)*” adds current node to “closed set”. Then the program checks if neighbours of that node are already in “closed list” or not. If they are already in “closed list”, then the node is skipped. The same rule applies if turning angle is less or equal to “limitation angle”. If it is not in the “closed set” and if it is not in the “open set”, then it is added to the “open set”.

Algorithm 1: Modified A* search [125]

Input: entry points, obstacles, start, heuristic_{costestimate}

Output: shortest paths, intersections

Begin

Forall *pairs*:

function *A*(start, goal)*

closedSet := {obstacles}

openSet := {start}

cameFrom := an empty map

gScore := map with default value of Infinity

gScore[start] := 0

fScore := map with default value of Infinity

fScore[start] := heuristic_cost_estimate(start, goal)

while *openSet* is not empty

current := the node in *openSet* having the lowest *fScore*[] value

if *current* = goal

return reconstruct_path(*cameFrom*, *current*)

openSet.Remove(current)

closedSet.Add(current)

for each neighbor of *current*

if neighbor in *closedSet*

continue

if angle(*parent.current*, *current*, neighbor) ≤ limitation angle

continue

if neighbor not in *openSet* // Discover a new node

openSet.Add(neighbor)

 The distance from start to a neighbor

tentative_gScore := *gScore*[*current*] + dist_between(*current*, neighbor)

if *tentative_gScore* ≥ *gScore*[neighbor]

continue

cameFrom[neighbor] := *current*

gScore[neighbor] := *tentative_gScore*

fScore[neighbor] := *gScore*[neighbor] +

 heuristic_cost_estimate(neighbor, goal)

return failure

function reconstruct_path(*cameFrom*, *current*)

total_path := [*current*]

while *current* in *cameFrom.Keys*:

current := *cameFrom*[*current*]

total_path.append(current)

return *total_path*

map.put(total_path)

return failure

The “*tentative_gScore*” stores distance from start to neighbour of the node.

After that, the most efficient path is stored in “*cameFrom*”, “*gScore*” and “*fScore*”.

After that, the path is reconstructed using the function “*function reconstruct_path*”.

Then all paths are merged into one map using function “*map.put*”.

After inserting all the inputs, program starts creating paths as it is shown in Figure 6.4. Figure 6.4 shows results of the model to find 4 paths which start at cell “0”. Prohibited areas are assigned with number “-1”. For each cell in the map, the model assigns a number which shows the shortest “distance” to the starting cell, avoiding prohibited areas and satisfying turn angle limitations.

Figure 6.4 Paths finding using modified A* method (case 1)

The number assigned to each cell is changed if starting cell location is changed.

Figure 6.5 shows paths finding where starting cell location is changed. If we compare

Figure 6.4 and Figure 6.5, we can see that numbers on cells have changed. It shows the distance to the new starting cell. In this way, 4 new paths have been found.

Figure 6.5. Paths finding using modified A* method (case 2)

Figure 6.6 shows implementation of the A* search method in finding shortest paths using MATLAB. The objective of the model was to determine the shortest paths between waypoints. All the lines represent shortest paths for the flights. The simulation uses the algorithm 1 to find all shortest paths. Turn angle limitation is set to be 90 degrees so that no path will have turning angles less than 90 degrees.

Figure 6.6. Paths finding using modified A* method in MATLAB

Another case study on flights between Singapore and Bangkok was implemented. The common route from Singapore to Bangkok is shown in Figure 6.7, which passes through waypoints: PU090, PADLI, PK, VKB, GOLUD, TIKAL, MUBAN, KUMTO, EMELA, IDAGA and REGOS [130]. Length of the route is 774 NM or 1433km [130].

Figure 6.7 Route between Changi airport and Bangkok International airport [130]

However, if there is a convective weather as shown in red colour, the route in black colour cannot be used anymore. Convective clouds present a serious hazard to aviation [131].

Modified A* search finds the shortest path which avoids convective weather, as shown in Figure 6.8. Figure 6.8 shows currently used route and the route determined by

modified A* indicated by black and green colour lines respectively. The route in black colour avoids convective weather and passes through waypoints: GEMAS, VBA, SUKAT, TEPUS, VPG and DUBAX. The route length is 841 NM or 1558 km [132]. However, length of the route determined by modified A* search is 1509km, which is 3.15% shorter than the route in black colour.

Figure 6.8 Flight route which avoids prohibited area [132]

6.3 Optimization of waypoint locations

6.3.1 Merging method

There is a network optimization model proposed in [133], which reduces the number of waypoints and finds optimal locations in the network. The case study was performed on the China airspace. Similar models can be applied in Singapore airspace.

Merging intersection points can reduce the number of waypoints. As a result, this eases controllers' mental workload and improves airspace safety [133].

Total cost of the travel consists of fuel cost, time cost and fixed cost [134]. In order to minimize total cost there is a need to minimize fuel cost plus time cost. If we assume that aircraft is flying under optimal cost index, minimizing total cost is equal to minimizing $c * d$, where c is a cost per nautical mile and d is a length of route in nautical mile.

Objective function to minimize total cost of flights:

$$\min T_c = \sum_{i=1}^n c_i f_i d_i, \quad (6.1)$$

where c_i is an average cost per nautical mile for flights in route i . f_i is a number of flights on route i . d_i is a length of route i . n is a number of the routes.

The objective function used in [133] is:

$$\min T_c = \sum_{i=1}^n f_i d_i, \quad (6.2)$$

Merging method in paper [133] depends on cell size. It uses weighted average of the merging points and moves it to nearby cells to check value of objective function. However, Figure 6.9 shows merging method of 2 intersection points proposed in this thesis which uses convex optimization to merge points.

Figure 6.9 Merging intersection points

In the figure, d is a segment distance between 2 merging points, α_i is an angle between d_i and d , d'_i is a new segment distance for route i . Then objective functions (6.1) and (6.2) will be in form:

$$\begin{aligned} \min T_c = \min \sum_{i=1}^{n+m} (c_i) f_i d'_i &= \min \sum_{i=1}^n c_i f_i \sqrt{d_i^2 + x^2 - 2d_i x \cos \alpha_i} + \\ \sum_{i=n+1}^{n+m} c_i f_i \sqrt{d_i^2 + (d-x)^2 - 2d_i (d-x) \cos \alpha_i} \end{aligned} \quad (6.3)$$

where x is a design variable. x and $d-x$ are distances from new merging point to initial 2 merging points. Constraints:

- 1) $0 \leq x \leq d$
- 2) Number of intersection points is equal to the number of intersection points in current network (which is equal to 6).

In order to prove that (6.3) is convex function, there is a need to prove that

$f(x) = \sqrt{x^2 + b^2}$ is a convex function. In order to do that there is a need to prove:

$$\sqrt{(\alpha x_1 + (1-\alpha)x_2)^2 + b^2} \leq \alpha \sqrt{x_1^2 + b^2} + (1-\alpha) \sqrt{x_2^2 + b^2} \text{ where } \alpha \in [0,1],$$

$$(\alpha x_1 + (1-\alpha)x_2)^2 + b^2 \leq \alpha^2(x_1^2 + b^2) + (1-\alpha)^2(x_2^2 + b^2) + 2\alpha(1-\alpha)\sqrt{x_1^2 + b^2}\sqrt{x_2^2 + b^2},$$

$$2\alpha(1-\alpha)(x_1x_2+b) \leq 2\alpha(1-\alpha)\sqrt{x_1^2+b^2}\sqrt{x_2^2+b^2},$$

$$(x_1x_2+b)^2 \leq (x_1^2+b^2)(x_2^2+b^2),$$

$$0 \leq b^2(x_1-x_2)^2,$$

meaning $f(x)$ is a convex function. From the properties of a convex function, $f(x \pm a)$ is also a convex function, where a is a constant number. Each term in T_c can be written in form of $bf(x \pm a)$, where a, b are constants. It means that each term in T_c is a convex function. From other properties of a convex function, sum of convex functions is a convex function. It means that T_c is a convex function for both objective functions.

If derivative of T_c is negative in range $[0, d]$, then $\min T_c$ will be achieved when $x = d$.

If derivative of T_c is positive in range $[0, d]$, then $\min T_c$ will be achieved when $x = 0$.

Otherwise, by comparing the objective function values for $x = 0$, $x = d$ and for x value where derivative of the function is equal to 0, minimal objective function will be obtained. Due to the fact that this is a continuous function, derivative of the function:

$$\sum_{i=1}^n(c_i)f_i(x-d_i\cos\alpha_i)(d_i^2+x^2-2d_ix\cos\alpha_i)^{-0.5}+\sum_{i=n+1}^{n+m}(c_i)f_i(d-x+d_i\cos\alpha_i)(d_i^2+x^2-2d_ix\cos\alpha_i)^{-0.5}=0, \text{ where } 0 \leq x \leq d \quad (6.4)$$

By solving equation (6.4), values of x are found. Otherwise, the solution can be obtained by using convex optimization methods like Gradient descent, Interior Point, Barrier methods and Nelder-Mead simplex algorithm.

Alternatively,

$$\min \sum_{i=1}^{n+m}(c_i)f_id'_i \approx \sum_{i=1}^{n+m}(c_i)f_id_i'^2 = \min \sum_{i=1}^n(c_i)f_i(d_i^2+x^2-2d_ix\cos\alpha_i) + \sum_{i=n+1}^{n+m}(c_i)f_i(d_i^2+(d-x)^2-2d_i(d-x)\cos\alpha_i) \quad (6.5)$$

Derivative of the function is

$$\sum_{i=1}^n 2(c_i)f_i(x-d_i\cos\alpha_i) + \sum_{i=n+1}^{n+m} 2(c_i)f_i(x-d+d_i\cos\alpha_i) = 0 \quad (6.6)$$

$$x = \frac{\sum_{i=1}^n(c_i)f_id_i\cos\alpha_i + \sum_{i=n+1}^{n+m}(c_i)f_i(d-d_i\cos\alpha_i)}{\sum_{i=1}^{n+m}f_i} \quad (6.7)$$

6.3.2 The case study

The case study was implemented involving 8 airports. Objective function (6.2) was used due to difficulty in obtaining data for c_i values for different routes. If c_i values are equal for different routes then minimizing (6.2) will be the same as minimizing (6.1). They are Changi airport (WSSS), Kuala Lumpur International airport (WMKK), Medan airport (WIMM), Bangkok International airport (VTBS), Phnom Penh airport (VDPP), Ho Chi Minh City airport (VVTG), Brunei airport (WBSB) and Manila airport (RPLL). Currently used routes between these airports are shown in Table 6.2. The routes are described as set of waypoints which an aircraft passes through.

In order to implement the model, 28 routes avoiding PRDs (Prohibited, Restricted and Danger areas) have to be firstly constructed using A* search. Part of the route using A* search method is shown in green in Figure 6.10, where the grid size is 53.65km. However, by reducing the grid size, 28 routes between 8 airports can be constructed as shown in Figure 6.11. As a result, there are 45 intersection points of these routes. PRDs are shown in red colour.

Figure 6.10 Constructing routes using A* search

Table 6.2 Current routes between 8 cities

	Route	Current route
1	WSSS to WMKK	WSSS GUPTA WMKK
2	WSSS to VTBS	WSSS PU090 PADLI APAKI GUNBO LASOB GUGIT VKB GOLUD TIKAL MUBAN KUMTO EMELA IDAGA REGOS VTBS
3	WSSS to VVTS	WSSS ROBMO EGOLO VEPLI ENREP ESPOB CS LATHA VVTS
4	WSSS to RPLL	WSSS LENDA LIPRO LEBIN LUSMO LAGOT LAXOR LULBU LEGED ABLBG RPLL
5	WSSS to WIMM	WSSS REKOP SALAX AMVIL WIMM
6	WSSS to VDPP	WSSS ROBMO EGOLO VEPLI ENREP IPRIX BITOD BAVEN VDPP
7	WSSS to WBSB	WSSS TOMAN OBLLOT ESPIT SABIP KAMIN DARMU SAKMA WBSB
8	WMKK to VTBS	WMKK VBA DAKUS VIH KARMI HTY RELIP UPNEP DIRAX REGOS VTBS
9	WMKK to VVTS	WMKK PIBOS MATSU GUNBO VKT IKUKO IGARI BITOD BIBAN BITIS VVTS
10	WMKK to RPLL	WMKK ISTAN APAKI IDSEL URIGO VISAT MABAL ELGOR LUSMO LAGOT LAXOR LULBU LEGED ABLBG RPLL
11	WMKK to WIMM	WMKK PUGER WIMM
12	WMKK to VDPP	WMKK PIBOS MATSU GUNBO VKT IKUKO IGARI BITOD BAVEN VDPP
13	WMKK to WBSB	WMKK ISTAN APAKI IDSEL URIGO VISAT MABAL ELGOR LUSMO TERIX OLKIT LEDAM BRU WBSB
14	VTBS to VVTS	VTBS GOMES BOKAK PHN POPET VVTS
15	VTBS to RPLL	VTBS BATOK MENAM VIBUN SOURN ANINA PK PCA VEPAM DAMEL MESOX ARESI GUKUM IBOBI DOSUS RPLL
16	VTBS to WIMM	VTBS REGOS DIRAX UPNEP RELIP HTY TAMOS VAS VPG GUNIP WIMM
17	VTBS to VDPP	VTBS GOMES BOKAK PNH VDPP
18	VTBS to WBSB	VTBS GOMES BOKAK PNH POPET SAPEN TSN LOSON ELSAS DAGAG MOXON AKMON LAGOT TODAM ASISU DOGOG WBSB
19	VVTS to RPLL	VVTS PHT DAMVO MIMUX AGSAM PANDI NOBEN REKEL EXORA RPLL
20	VVTS to WIMM	VVTS to WMKK, WMKK to WIMM
21	VVTS to VDPP	VVTS POPET VDPP
22	VVTS to WBSB	VVTS ELSAS DAGAG MOXON AKMON LAGOT TODAM ASISU DOGOG WBSB
23	RPLL to WIMM	RPLL to WMKK, WMKK to WIMM
24	RPLL to VDPP	RPLL EXORA REKEL NOBEN PANDI AGSAM MIMUX DAMVO PHT TSN SAPEN VDPP
25	RPLL to WBSB	RPLL OLRAX TOKON GAMAN TELMO PR OSANU VJN WBSB
26	WIMM to VDPP	WIMM to WMKK, WMKK to VDPP
27	WIMM to WBSB	WIMM to WMKK, WMKK to WBSB
28	VDPP to WBSB	WBSB DOGOG ASISU TODAM LAGOT AKMON MOXON DAGAG ELSAS LOSON TSN SAPEN VDPP

Figure 6.11. Straight routes avoiding PRDs between 8 airports

There are no direct flights between Medan and Phnom Penh, Ho Chi Minh and Manila. Therefore, direct routes from Medan to Phnom Penh, Ho Chi Minh and Manila are eliminated. Also, intersection points in green circles are merged to Phnom Penh airport and Ho Chi Minh airport accordingly. As a result, Figure 6.12 is obtained, where the number of waypoints is reduced from 45 to 12. After that, the intersection points in green circles are merged using the merging method described in section 6.3.1.

Figure 6.13 shows an example of merging 2 points. Where:

$$\min T_c = \min \sum_{i=1}^6 f_i d'_i, 0 \leq x \leq d,$$

$$f_1 = f_4 = 1188, f_6 = f_2 = 5942, \quad f_5 = f_3 = 11315$$

$$d_1 = 471.21km, d_2 = 1388.91km, d_3 = 1331.51km, d = 137.91km,$$

$$d_4 = 511.43km, d_5 = 941.24km, d_6 = 1101.94km$$

Figure 6.12. The air traffic network with 12 waypoints

Figure 6.13. An example of merging 2 points

The value of the objective function depends on the location of the merging point. For example,

$$\text{if } x = 0, \sum_{i=1}^6 f_i d'_i = 42043194.1 \text{ km}$$

Using Nelder-Mead simplex algorithm in python:

$$x = 552.65 \text{ km}$$

However, $x \leq d$, where $d = 137.91 \text{ km}$. Hence, $x = 137.91 \text{ km}$.

The value of the objective function is:

$$\sum_{i=1}^6 f_i d'_i = 41848010.35 \text{ km}$$

Here the plot of the objective function:

Figure 6.14 Plot of the Objective function vs d

Calculations show that the value of the objective function using merging method is smaller than the value of the objective function where $x = 0$. The value of the objective function depends on the location of the merging point.

Table 6.3 shows reduction percentages in the route distances between current routes and routes obtained after merging. The table shows reduction percentage for each of the 28 routes, and total reduction percentage. The reduction percentages are up to 7.02%, and the total reduction percentage is 1.53%. The number of waypoints is reduced from 12 to 6.

Table 6.3 Reduction percentages in the route distances

	Currently route flight distance (km) [135]	Great-circle distance (km) [136]	Optimized route distance (km)	Percentage reduction (%)
1	316	296.29	296.29	6.24
2	1433	1417.46	1417.46	1.08
3	1130	1091.92	1095	3.10
4	2403	2373.94	2401	0.08
5	643	621.32	621.32	3.37
6	1143	1136.85	1141	0.17
7	1290	1277.75	1288.49	0.12
8	1240	1222.97	1225	1.21
9	1065	1051.93	1054	1.03
10	2560	2490.85	2505	2.15
11	354	329.15	329.15	7.02
12	1065	1039.82	1050	1.41
13	1500	1487.90	1498	0.13
14	719	716.95	718.3	0.10
15	2195	2186.76	2186.76	0.38
16	1197	1136.45	1136.45	5.06
17	506	503.89	503.89	0.42
18	1841	1833.32	1838.65	0.13
19	1631	1610.45	1610.45	1.26
20	1419	1171.39	1383.15	2.53
21	213	213	213	0
22	1122	1120.55	1120.55	0.13
23	2914	2710.67	2834.15	2.74
24	1845	1781.96	1781.96	3.42
25	1269	1255.15	1255.15	1.09
26	1419	1097.89	1379.15	2.81
27	1854	1785.12	1827.15	1.45
28	1335	1330.41	1333.55	0.11
Total	37621	36292.11	37044.02	1.53

Table 6.4 shows reduction percentages in the objective function described in (30). The objective function has been reduced by 1.48 % using the model described in

[133]. It means that the model can improve the air network between these 8 cities and reduce flight cost. Total length of the routes for the model is 2.07 % longer than total length of the great-circle distances in order to avoid prohibited areas.

Table 6.4 Reduction percentages in the objective function

Route	Number of flights in 2017 (from Innovata)	Current objective function (km)	Optimized objective function (km)	Reduction percentage (%)
1	30250	9559000	8962772.5	6.24
2	15984	22905072	22656680.64	1.08
3	10728	12122640	11747160	3.10
4	11315	27189945	27167315	0.08
5	3148	2024164	1955915.36	3.37
6	3137	3585591	3579317	0.17
7	1978	2551620	2548633.22	0.12
8	7113	8820120	8713425	1.21
9	9068	9657420	9557672	1.03
10	5942	15211520	14884710	2.15
11	7120	2520480	2343548	7.02
12	3194	3401610	3353700	1.41
13	3060	4590000	4583880	0.13
14	6557	4714483	4709893.1	0.10
15	4337	9519715	9483978.12	0.38
16	0	0	0	0
17	6308	3191848	3178538.12	0.42
18	632	1163512	1162026.8	0.13
19	1799	2934169	2897199.55	1.26
20	0	0	0	0
21	3608	768504	768504	0
22	556	623832	623025.8	0.13
23	0	0	0	0
24	1	1845	1781.96	3.42
25	1226	1555794	1538813.9	1.09
26	0	0	0	0
27	0	0	0	0
28	0	0	0	0
Total	137061	148612884	146418490.1	1.48

Wind direction and speed have effect on optimal path. Figure 6.15 shows wind direction and speed in ASEAN region in 10000 feet altitude [137]. Direction and speed

of wind change within few days. Therefore, minor deviations from general optimal path should be made depending on wind direction and speed.

Figure 6.15 Wind direction and speed from 20 May to 22 May 2019 [137]

Also, shifting waypoints from one country's airspace to another country's airspace might raise political issues. However, there are the practises of delegation of air traffic services [138] which could solve that problem.

Nelder-Mead simplex algorithm in SciPy package (Python) is used to compute merging distances. Due to convexity of the objective function, computational time is up to few seconds for each merging.

The locations of 6 waypoints as per current air network: 1) LAGOT, 2) the waypoint between IDSEL and URIGO, 3) LUSMO, 4) BITOD, 5) VPK (APAKI), 6) GUNBO are shown in brown in Figure 6.16. Figure 6.16 shows the optimized air route network between the 8 airports using merging method in section 6.3.1.

Figure 6.16 Optimized waypoint locations

This chapter shows that efficient air traffic flow can be obtained either using free route airspace or through optimizing air route waypoint locations. Incorporating the current model to avoid convective weather into the free route airspace concept can help find the shorter routes. Similarly, the model for optimizing air route network shows that by considering current air traffic demand, it can find optimal waypoint locations in order

to reduce flights cost, which will result in fuel saving and emitting of less carbon dioxide into the air.

CHAPTER 7

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

Usually, airports are the first place where tourists get their first impression of the country and facing long delays may give bad impression on the country [89]. More importantly, delays result in extra carbon dioxide emission due to extra fuel usage, which causes negative environmental impact. Also, people can make mistakes, and air traffic controllers are not an exception. Currently, global airlines consume more than 5 million barrels of oil per day, and it is going to increase further if no actions are taken [96].

In order to overcome these limitations, the models have been developed. The models have been proposed to manage air traffic flow efficiently and to solve congested airspace problems. In order to manage air traffic flow efficiently, this thesis focused on forecasting of the air traffic, rescheduling of the flights and restructuring the air network. These 3 aspects are summarized below.

7.1 Forecasting the air traffic

In this research the model for air traffic forecasting has been developed. The case studies were performed, and the model was validated based on low average errors and RMS errors. The model was able to forecast the country, city-pair and airport-pair air traffic. Results show that passenger forecasting for Singapore has dependence not only on that country but on neighbouring countries as well. The research predicts that the passenger movements in Changi airport will increase up to 81.65 million people by year 2023, which is 31.23 % more than that in 2017. Also, the number of passenger aircraft

between Singapore and Jakarta city-pair will increase up to 34702 by year 2023, which is 26.6 % more than that in 2017. In addition, the number of passenger aircraft between Changi airport and KLIA airport-pair will be between 31698 and 40311 by year 2023. It can be concluded that the accuracy of the forecasting improves with the increase of a number of neighbouring countries involved.

7.2 Rescheduling of the flights

The model was proposed which helps to establish efficient ATFM. The model focuses on solving reduced capacity problems and on reducing delays efficiently by rescheduling of the flights. Rescheduling of the flights was done operationalizing and satisfying the constraints of delay cost, airport departure and arrival capacities, waypoints' capacities, routes capacity and rerouting options.

In the flights between KLIA and Changi airport, ground delays were reduced by 4.98 min and 3.05 min on average. Standard deviations of the ground delays were reduced by 11.81 min and 5.97 min. More importantly, airborne delays were reduced by 2.70 min and 3.95 min on average. Also, standard deviations of the airborne delays were reduced by 3.58 min and 5.26 min. It can be concluded that the model made sure none of the flights got delayed longer than a specific time and ensured fairness to all flights.

7.3 Restructuring the air network

The algorithm has been developed to determine the shortest paths while avoiding prohibited areas. The length of the route determined by modified A* search was 1509km, which is 3.15% shorter than the current route used to avoid convective weather.

Also, the model was developed to reconstruct the air network. The case study was implemented involving the 8 airports. The total route distance and the objective

function were reduced by 1.53% and 1.48 % respectively. It can be concluded that restructuring the air network can reduce flights distances using proper merging method. Hence, it can reduce fuel cost and negative environmental impact.

7.4 Recommendations for future work

Air traffic depends on many factors, not only on GDP of target country and GDP of surrounding countries. Other factors can be considered for forecasting of the air traffic, like population, cost of living, etc.

Modified A* search allows horizontal manoeuvring of avoiding hazardous areas, but in reality, vertical manoeuvring can be implemented as well, like climbing and descending of the aircraft. In the future climbing and descending of aircraft can be considered, using 3D trajectories instead of 2D.

By applying these models, air traffic management can be significantly improved. The models can be used as a tool in decision making to guide aircraft in bad weather conditions or in heavy traffic, and to give the possibility to automate air traffic management. Pilots will be able to choose most efficient routes, which will lead to saving fuel and flight time. Saving fuel will result in saving money for the airline and less pollution to the environment.

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