ABSTRACT

COLLABORATIVE RESCHEDULING OF FLIGHTS IN A SINGLE MEGA-HUB NETWORK

by
Sufian Ikhmeis

Traditionally, airlines have configured flight operations into a Hub and Spoke network design. Using connecting arrival departure waves at multiple hubs these networks achieve efficient passenger flows. Recently, there has been much growth in the development of global single mega-hub (SMH) flight networks that have a significantly different operating cost structure and schedule design. These are located primarily in the Middle East and are commonly referred to as the ME3. The traditionalist view is that SMH networks are money losers and subsidized by sovereign funds. This research studies and analyzes SMH networks in an attempt to better understand their flight efficiency drivers. Key characteristics of SMH airports are identified as: (i) There are no peak periods, and flight activity is balanced with coordinated waves (ii) No priority is assigned to arrival/departure times at destinations (selfish strategy) only hub connectivity is considered (iii) There is less than 5% OD traffic at SMH (iv) The airline operates only non-stop flights (v) Passengers accept longer travel times in exchange for economic benefits (vi) Airline and airport owners work together to achieve collaborative flight schedules.

This research focuses on the network structure of SMH airports to identify and optimize the operational characteristics that are the source of their advantages. A key feature of SMH airports is that the airline and airport are closely aligned in a partnership. To model this relationship, the Mega-Hub Collaborative Flight Rescheduling (MCFR)

Problem is introduced. The MCFR starts with an initial flight schedule developed by the airline, then formulates a cooperative objective which is optimized iteratively by a series of reschedules. Specifically, in a network of $i \in M$ cities, the decision variables are i^* the flight to be rescheduled, D_{i^*} the new departure time of flight to city i^* and H_{i^*} the new hold time at the destination city i^*. The daily passenger traffic is given by $\mathrm{N_{i,j}}$ and normally distributed with parameters $\mu \mathrm{N_{i,j}}$ and $\sigma \mathrm{N_{i,j}}$.

A three-term MCFR objective function is developed to represent the intersecting scheduling decision space between airlines and airports: (i) Passenger Waiting Time (ii) Passenger Volume in Terminal, and (iii) Ground Activity Wave Imbalance. The function is non-linear in nature and the associated constraints and definitions are also non-linear. An EXCEL/VBA based simulator is developed to simulate the passenger traffic flows and generate the expected cost objective for a given flight network. This simulator is able to handle up to an M=250 flight network tracking 6250 passenger arcs.

A simulation optimization approach is used to solve the MCFR. A Wave Gain Loss (WGL) strategy estimates the impact Z_i of flight shift Δ_i on the objective. The WGL iteratively reschedules flights and is formulated as a non-linear program. It includes functions to capture the traffic affinity driven solution dependency between flights, the relationship between passengers in terminal gradients and flight shifts, and the relationship between ground traffic activity gradients and flight shifts. Each iteration generates a Z_i ranked list of flights. The WGL is integrated with the EXCEL/VBA simulator and shown to generate significant costs reduction in an efficient time. Extensive testing is done on a set of 5 flight network problems, each with 3 different passengers flow networks characterized by low, medium and high traffic concentrations.

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by
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This dissertation is dedicated to my beloved parents,

My wife, Nisreen; my son Jafar; and my daughter, Guynah

“Thank You.”

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CHAPTER 1

INTRODUCTION

The 1978 Airline Deregulation Act (USA) provided airlines with the freedom to serve and schedule flights throughout the U.S. domestic market. Progressively this deregulation act spread far beyond the USA to most of the industrialized world and further to the newly developing countries in Asia and the Middle East. As a consequence of the Deregulation Act, leading airlines reconfigured their flight operations into a Hub and Spoke network design. This allowed them to serve many Origin and Destination (O-D) markets with fewer resources. Using connecting arrival departure waves at the hub station, they were able to achieve efficient passengers flow patterns. Today, most traditional global airlines have operated through similar multi-hub network systems. There is a vast research and development literature which document models and methods used by these airlines to design their networks. Optimization models for the design of their flights networks will typically focus on schedule convenience, fleet utilization, and local operating constraints. Historically, much of the literature has been developed in the U.S with a specific focus on domestic flight operations.

Radnoti (2002) notes that, the major advantages of multi-hub and spoke network are higher passenger revenues, lower number of aircrafts with higher utilization. Likewise, the disadvantages are the peak and valley structure leading to airport congestions and delays, and the uneven use of human resources at the hub leading to higher personnel and operational costs. Despite, these disadvantages, the hub and spoke system remains very popular with medium and large sized airlines and is still in practice.

1.1 The ME3 Global Mega-Hubs

Recently, there has been much growth in the development of single mega-hub networks with a significantly different operating cost structure and objective compared to the traditional airlines. These are located primarily in the Middle East and are commonly referred to as the ME3 (Emirates Airlines, Qatar, and Etihad). The corresponding mega hubs are Dubai, Doha and Abu Dhabi. These operate more of a continuous flow model as opposed to a peak and valley schedule, further origin and destination (OD) traffic at the mega hub is less than 5%. We describe these as selfish hubs in that they are less influenced by the limits of OD nodes and more by the overall network efficiency. The ME3 carriers have witnessed phenomenal growth and Figure 1.1 provides growth data for these airlines relative to other global airlines. Just in 2014 the ME3 have boosted the number of U.S. flights by 47%, and now serve 11 cities. They are drawing complaints of unfair competition from their stateside rivals, and more growth is coming. Emirates can deliver more people each week from New York's Kennedy Airport to Dubai than American Airlines carry from JFK to London (one of the most lucrative international flight routes) or Delta Air Lines can carry between Atlanta and JFK.

Here we present a descriptive model to capture the cost behavior of these networks. We assume that an initial flight schedule is available, which is then used to derive the cost function for the capacity constrained mega hub. Specific objectives modeled include:

(i) passenger wait times (ii) hourly passenger levels at the hub and (iii) hourly ground flight activity. Ideally, a mega hub would operate at an hourly balanced level for each objective.

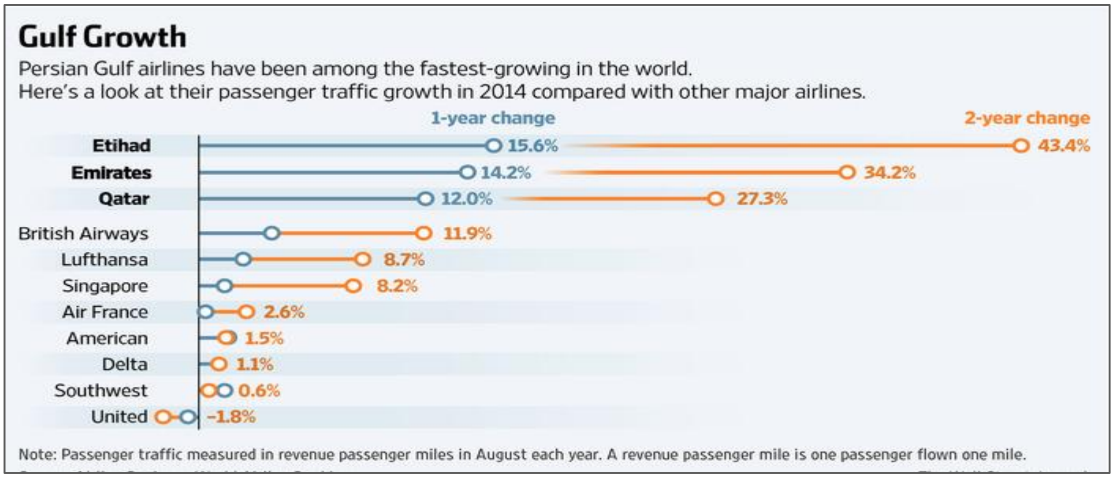


Figure 1.1 Growth in ME3 passengers flows through their mega- hubs.
Source: Airline Business World Airline Rankings.

We define a Mega-Hub as follows:

Mega-Hub: An airport operating a broad network of direct flights to a large number of destination cities in a continuous departure/arrival wave pattern with an efficient and attractive transit process for passengers. Key characteristics of a Mega-Hub are as follows:

- There are no peak periods for flights, it operates 24/7 and attempts to balance the flight activity throughout the day with coordinated arrival/departure waves.

- Flights schedules do not assign any priority to arrival/departure times at destination cities (selfish strategy), times are selected primarily for network connectivity.

- Negligible (less than 5%) Origin-Destination (OD) traffic at the Mega-Hub with all passengers transiting through the airport.

- Operates only non-stop flights to multiple destinations. (Extensive long haul flights a key attribute).

- There is only one hub in the network. Passengers are willing to accept longer travel times in exchange for economic benefits. (Example: Beijing to New York is 13 hours non-stop, while Beijing → Dubai → New York is 25 hours but a significant number of passengers are flying this route).

- Airline and airport owners are closely aligned in tight partnership and are working together to achieve collaborative objectives.

- Typically one airline accounts for 80+% of traffic.

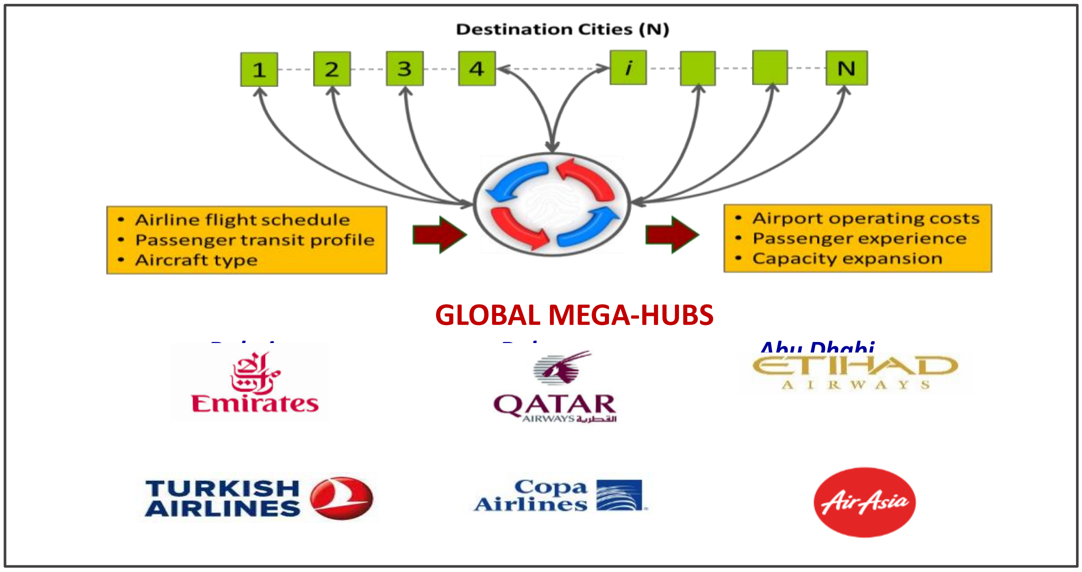


Figure 1.2 Current Examples of Global Mega-Hubs.

Figure 1.2, shows some examples of mega-hubs that are already operating in different parts of the globe. These airlines are all relatively young, and it is now well recognized that their network structure and behavior is quite different compared to other legacy airlines. The operating efficiencies of these airlines are very high and the competition is stiff, in many cases the competition has already "thrown in the towel" (e.g., Qantas in Australia). Today, Emirates flies to 142 destinations in 78 countries, across six continents from its hub in Dubai, the largest international airport in the world. Currently there are economic and political battles brewing both in Europe and the U.S. against the ME3 carriers.

Our focus in this dissertation, is specifically on the network structure and behavior of these mega-hub airports, to identify the operational characteristics that are the source of their advantages. Our research indicates that, one of the key characteristics identified above, is the (Airline and airport owners are closely aligned in tight partnership and working together to achieve collaborative objectives), is a key differentiator of the mega-hub.

1.2 The Airline-Airport Partnership

In the U.S., airports are typically built and managed by a state or municipal entity. Airports and airlines have developed complex contractual arrangements (so-called use and lease agreements) to govern their ongoing business relationships. These agreements are legally binding contracts that specify the terms and conditions of the airlines' use of and payment for airfield and terminal facilities. Such agreements are often grouped into three broad categories: compensatory, residual, and hybrid. Many of the business practices in effect today at U.S. airports were adopted decades ago for specific economic, financial, and political reasons. In general the airport is not involved either directly or collaboratively with the flight schedule design of airlines.

In contrast, we find that Mega-Hubs exist primarily to serve transit passengers so the focus of the airport is to work with the airline to enhance the transit experience. Further the two are collaboratively building the flights schedule so that the airport operating efficiencies can be improved. This research investigates specifically this aspect of the mega-hub. We create a quantitative model to represent this relationship, identifying both objective functions, controllable decision variables, and equations to model the analytical relationships.

1.3 Research Objectives and Accomplishments

This research, is organized into the four research objectives described below. For each objective the accomplishments described in the subsequent chapters is briefly summarized.

1. Define and build an objective function that represents the collaborative airport operational goals of both the airline and the airport owner/operator. This function will capture the primary airport operating costs that are dependent on the flight schedule and the associated passenger traffic.

   Accomplishments: Investigative research on the key dependencies between the operating costs of a mega-hub airport and the airline flight schedule and the associated passenger traffic. The specific focus was on how airlines and airports can collaboratively improve the passenger transfer economics while at the same time reduce any negatives resulting from the longer flight and travel times through the mega hub. Three objective cost components were modeled and formulated: (i) Passenger Waiting Times (ii) Passenger Count in Terminal and (iii) Hourly Ground Traffic Activity. This novel airline-airport objective, which integrates all three components, allows researchers for the first time to performing a detailed analysis of flight schedules in a collaborative manner.

2. Characterize and build a descriptive model to represent the operating behavior of the flight and passenger flows through the mega hub. Specifically this model would capture (i) the waiting time profile of passengers and (ii) the passenger count profile from the given flight schedules. These profiles then provide estimates of the collaborative objective function, for a given stochastic passenger traffic in the flight network.

   Accomplishments: Investigative research on the key dependencies between the operating costs of a mega-hub airport and the airline flight schedule and the associated passenger traffic. An Excel + VBA based model which accurately models (i) passenger transits between city pairs (ii) accumulated in-terminal passenger volumes at any time instant (iii) aircraft schedule feasibility and

(iv) normalized generation of daily passenger volumes. Integrated module for generation of a feasible passenger traffic matrix that also allows for network concentration control, providing a platform for extensive simulation optimization and experimentation. Due to the data intensive nature of the network it is difficult if not impossible to create flow type simulation model using commercial simulation package. Consider a 100-city network, then the simulation model tracks 10,000-passenger types. The Excel + VBA simulation model imports flight schedule data and generates the daily airport operating cost as related to the flight schedule.

3. Using the initial flight schedule as starting point develop an optimization procedure that iteratively reschedules flights to solve the Mega-Hub Collaborative Flight Rescheduling (MCFR) Problem. The procedure should be time efficient and identify specific flights to be rescheduled, a positive or negative shift, and the magnitude of shift.

   Accomplishments: The Wave Gain Loss (WGL) heuristic for optimizing the airline-airport collaborative objective function was developed and tested. Based on the non-linear nature of the collaborative objective our strategy has been to use a heuristic approach to iteratively improve the initial flight schedule. Specifically, we investigated different optimization strategies, which would work. The WGL heuristic exploits the inherent wave structure of the flight schedules to identify cost reduction opportunities. A key component of the WGL heuristic, is an intelligent and intuitive objective function, which looks at the effect of a flight schedule shift on all three components of the objective function. At each iterative step, the following two decision are made: (i) the flight that is currently being rescheduled and (ii) the best flight departure time shift for the selected flight.

4. Simulation based experimentation analysis of the WGL Heuristics as a solution to the MCFR problem. The experiments will statistically confirm the ability of the WGL

Heuristic to provide a significant solution to the MCFR. The experimental space will represent a range of flight networks.

Accomplishments: Five baseline experimental problems were developed with the number of cities being 50, 80, 100, 149 and 184. For each problem, three different levels of route concentration intensity were set, this done by controlling the passenger's traffic on each differently, these were identified as low, medium and high. Statistical significance levels for the experimental runs were derived and appropriate hypothesis tests were conducted.

1.4 Research Significance

Compare to others' work, some significant research targets within different levels have been set up at the beginning or during process.

CHAPTER 2

LITERATURE REVIEW

This chapter presents a literature review of the latest proposals for scheduling design of airlines operating a hub and spoke network. The focus of this dissertation, is on the airport side, and emphasize in developing a strategic partnership between the airports + airline involved on the aviation industry. We start with a review on airline scheduling for a hub and spoke model, their advantages and disadvantages and the subsequent development in the network operation, followed by a review in the field of airports and airlines operating cost in terms of passengers, we look at the network developments in the Middle East in terms of passengers growth, and in the development of single mega-hub networks. A review of the current developments of existing analytical tools that are needed in our approach is also conduced. Finally, we conclude the chapter by looking at some major measurement indices applied to the hub and spokes network models.

2.1 Introduction to Airline Scheduling and Airport Operation

In this section, a brief introduction to airline schedule planning process is summarized, airline scheduling planning is a structured planning process engage in a complex decision-making requiring participation of all departments of the airline, The complexity of such planning process make it impossible to optimize the entire airline scheduling problem at one stage solution, this lead researcher into approaching the problem sequentially, that is dividing it into core problems (i) schedule design, (ii) fleet assignment, (iii) aircraft maintenance routing, and (iv) crew scheduling. The sequencing of the core problem is shown in Figure 2.1. Recently, researchers involve combining two core problems to improve optimization solutions. For detailed impact and challenges on airline schedule planning, see Barnhart, C and Cohn, A, (2004), and Lohatepanont, M. and Barnhart, C, (2004).

The schedule development usually starts as early as a year ahead of actual departure time, scheduling is the most important factor for airline profitability, the airlines tend to optimize its resources for operation in order to maximize profit. At this stage, there are four interrelated steps as defined by Belobaba, P., (2009); (i) frequency planning, (ii) timetable development, (iii) fleet assignment, and (iv) aircraft rotation planning. Management tries to set a satisfactory requirement to the above in order to compete and generate a profit.

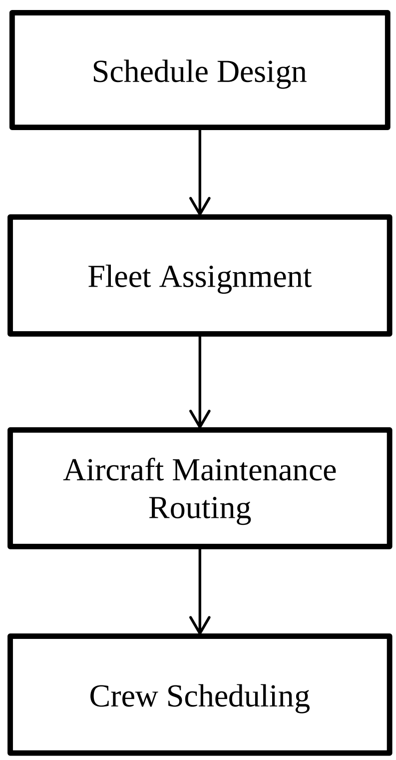


Figure 2.1 Schedule planning core problem, Bootsma, 1997.

2.2 Hub – and – Spoke Network

A hub and Spoke network enables airlines to transfer passengers from different spoke cities characterized by small passenger densities via connecting their flights through the hub to their final destination (another spoke city).

2.2.1 Operating Characteristics

In the era after liberalization and deregulation act of US in 1978, airlines increases their efforts through engagement on bilateral agreements to open skies policies to utilizing the freedoms of the air, That had led airlines to shift from operating a point to point network into a hub and spoke network operation. A hub and spoke networks, allows airlines to moving passengers from outside (spokes) airports to a central airport (hub) to maximize the number of city pairs that can be served with the airline available resources (aircrafts, crew, ground equipment's) Figure 2.2, present HS network. The cost savings and market gain from operating hub and spoke network have been highlighted in the literature of airline operations and scheduling. The presence of economies of traffic density, and economies of scope, allows airlines to increase production efficiency, for more details in the topic see, Brueckner and Spiller, (1994).

Several definition were used in describing the hub and spoke network, for instance the federal aviation administration (FAA) defined the hub in terms of passengers boarding percentage, it classifies hub as small, medium and large in term of how many passengers were boarding. Defines hub airport in term of volume or how large it is as a bases for airline. Clearly these definitions lack theoretical support behind it. To this point, new tools and methods for scheduling operations have emerged into operating such network configurations, passengers and their baggage must be connected within acceptable time.

The minimum acceptable time is required for increasing connectivity for passengers as well as to prepare the aircraft for next flight to meet minimum turnaround time of aircraft. A random scheduling is not accepted for airlines to operate and compete in the market. To enjoying the economics of scale, airline timetable at the hub should be constructed around coordinating arrivals and departures of flight. The optimal hub locations and the number of operated hubs on the network have seen considerable amount of research, highlighting the importance of the geographical location of the hub. In the following section we will elaborate on this topic from two perspective; first the temporal coordination, and second the spatial concentration. Such coordination is known as connecting banks or waves of arrival flights from different origins, at specified time interval followed by wave of departures to multiple destinations, in order for airlines to maximizing the number of city pairs and minimizing passenger-waiting time, Dennis, N., (1994).

Yet, to establishing such a timetable, airlines must first decide between maximization of aircraft utilization, manpower and other resources and schedule for passengers' convenience. The timetable must incorporate minimum "turnaround" times required at each airport to deplane and enplane passengers and their baggage, and prepare aircrafts to end destination, Belobaba, P., (2007). The major advantage can be seen as higher revenue, lower number of aircrafts and higher efficiency, The net result of this was to improve the level of service and competitiveness of the airlines and the disadvantages of the hub –and-spoke networks can be seen as airport congestions and delays, around peak times and the uneven use of human resources at the hub and to a higher personnel and operational costs, Radnoti, G., (2002).

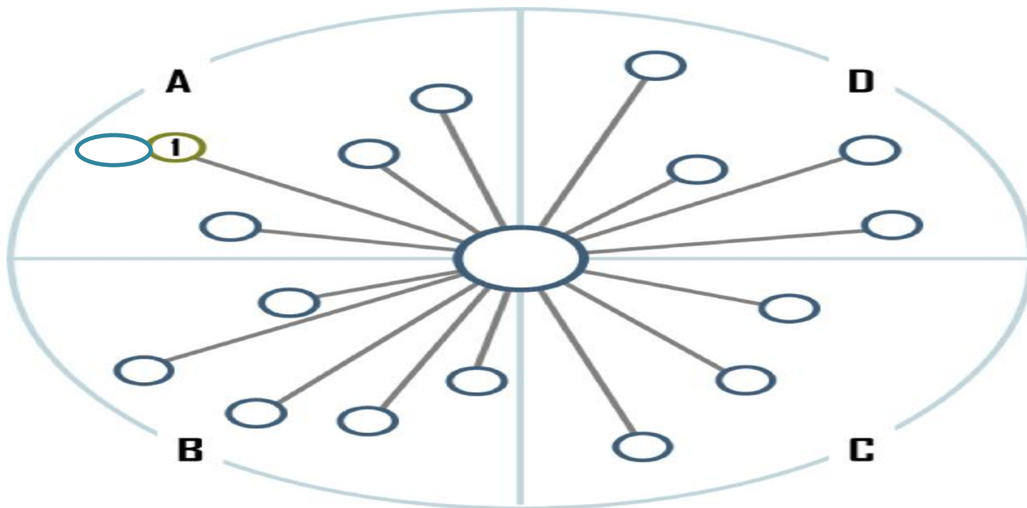


Figure 2.2 A hub and spoke presentation.

A literature review on hub network type, revealed different type of hubs as seen from different perspectives, though these classifications were not always clear to distinguish, for instance, Burghouwt, G., Wit, J., (2005), when analyzing the sub-markets on Europe, they divide the airline hubs into four categories: the all-round hubs, the specialized hinterland-hubs, and the directional or hourglass-hubs, Denis, N., (1994b), classifies hub into hinterland hubs and directional hub only, Burghouwt, G.,pp12, (2007), on his book "Airline Network Development in Europe and its Implications for Airport Planning" He proposed different category and classify hub in accordance with three groups each group was further classified, never the less all the classification were with accordance of two fundamental object , first how passengers were moved in the network through the hub, second point how direct and indirect flights on the hub are related to the hub location and flights movements. Looking at hinterland, hourglass and also Way port hubs per definition of, de Wit and van Gent, pp. 307, (1996), referenced on, Burghouwt, G. pp15, (2007). The work in this dissertation is not intended to be limited by hub classification, nor to adopt new terminology of classification but to examine and investigate the new rival in the Middle East and their operating model as seen in the development of single mega hub (SMH) in that region. As we investigate on the positioning and fast development that these airlines are undergoing, a new shape of competing with the traditional hub carries such as Lufthansa, Air France or Singapore airlines to name few among them exists on the surface of the air transport industry. Middle Eastern airlines are developing their ambitious models to become the new global hubs leaders for long haul connecting flights.

This type of hub per description requires an excellent airport and global location in addition to airport capacity that cans abundant peak hours. For instance Emirates, Qatar and Etihad one can also include Turkish airline, focusing on their excellent locations and newly designed airports and their willingness to shaping the global network routes to pass through their hubs. These airlines rely heavily on transferring passengers through their hubs.

Finally, in their paper, Danesi and Lupi, (2005), mentioned three requirements for airline to develop a hub and spoke network effectively (i) spatial concentration of the network structure, (ii) temporal co-ordination of the flight schedule at hub airports in "waves", and (iii) via-hub service integration (tickets, baggage transfer). The hub network defines the boundary of its wave structure by considering both passengers waiting time and passengers flow volume at the terminal.

Traditionally, airlines operating hub and spoke network design their schedule around minimum waiting time and maximum acceptable time, nevertheless these time tables start seeing a must change for the peaking hours that results from such operations.

Indeed, airlines trends nowadays is shifting toward depeaking hubs, that is spreading the schedule to minimize the effect of peaking caused by operating banks of arrivals and departures, Jiang, H., Barnhart, C., (2006).

An airline with a large presence in a hub airport gains significant customer loyalty advantages through marketing devices such as frequent flyer programs and travel agency commission overrides. The existence of such marketing devices combined with the fact that travelers value H&S network characteristics (higher frequencies of service, wider variety/selection of destinations, etc.); allow an H&S airline to exercise some monopoly power at the hub airport. Airport concentration and airport dominance at a hub ensure a degree of protection from competition - in part due to the control of scarce airport facilities - further exacerbating the market power of an H&S airline, see Borenstein, (1989, 1991, 1992); Berry, (1990). In Berry et al., (1996) paper it provide further empirical evidence of the joint presence of cost-side and demand-side benefits arising from hubbing operations.

The most relevant purpose of any hub wave-system, is to maximize connectivity. Hub connectivity refers to the number and the quality of indirect flights available to passengers via an airline hub, Bootsma, (1997). Hub connectivity depends on:

1) The number of markets linked to the hub with direct services,

2) Service frequencies,

3) Times of arrival and departure of the flights scheduled at the hub.

Large hub airports have a major advantage, because connectivity tends to increase in proportion to the square of the number of flight movements. Nevertheless, smaller airline hubs can try to compensate for this, by offering a higher level of timetable coordination, which does not depend on the size of hub operations, Rietveld, P., and Brons, M., (2001).

2.2.2 Spatial and Temporal Concentration

It is clear by this point, for an airline to operate a hub and spoke network efficiently it requires a concentration of traffic flow in both space and time, Reynolds-Feighan, (2001) which referred to the spatial and temporal concentrations of traffic, Danesi and Lupi, (2005) in addition to these requirement the airline must have the ability and willingness to provide a full service to passengers in terms of ticketing and baggage transfer at the hub.

These concentration requirements are seen from the airline level or perspective. On the other hand, there are critical requirement on the chosen hub (central) airport, these are: (i) geographical location, that is centered around the airline network, this requirement helps airline minimize operational cost and minimizes total travel time of passengers and or waiting time between connected flights (ii) air-side capacity, (iii) land-side capacity, the necessity of these two requirement for a hub to be able to handle peak hours concentrations as a consequences of the waves banks of arrivals and departures, and suitable configuration of the terminal, (iv) an airline willing and prepared to operate hubbing at the airport, (v) satisfactory average weather conditions, and (vi) ideally, strong local demand from/to the hub. These are a summary based on the developments of hub operation on US and Europe.

By examining to what extend the above mentioned requirements are met by the Middle East airlines, as a selfish (single) hub operator airlines, it can be easily concluded the perfect fit of the primary requirements, and how well they handle the secondary requirement into their interest, that enables the Middle East airlines to generate more traffic Danesi, A., (2005).

The space (spatial) concentration, is referred to airlines ability to concentrate their traffic flow around one or more central hub airports in their network, Burghouwt. G, Hakfoort, J., and Jan Ritsema van Eck, (2003), and time concentration on the other hand, is the ability to align connecting flights that are arriving from different origin's to departing flights of within predetermined time interval in order to increase airline connectivity factor.

The aim of such structures, is being to optimize the number and quality of connections offered. On the other hand, for the temporal coordination (i.e., time co-ordination) to be effective, it should be organized according to an ordered pattern, so that connectivity can be enhanced without increasing the number of flights, this is done by concentrating flights in waves as it is the common approach for implementing hub timetable co-ordination, Danesi, A., (2005). There is a large research and empirical studies exploring the degree of connectivity about the spatial and temporal coordination. Figure 2.3 shows the geographical location of the Middle East for airlines to operate HS network.

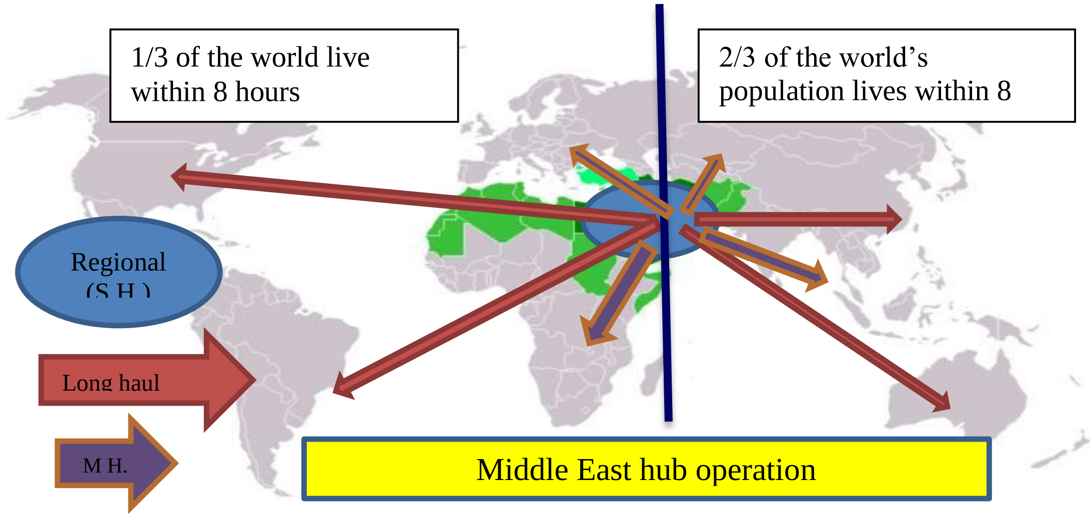


Figure 2.3 Hubs location and passenger's distribution to Middle East.

2.2.3 Wave System Structure

Airlines operating hubs with wave-system structure perform generally better than airline hubs without a wave-system structure in terms of indirect connectivity given a certain number of direct connections. The wave-system structure is in fact a temporal concentration of flights that may result in increasing airline competitive position and increase market share, Burghouwt, G., Wit, J., (2005). In order for an airline to developing wave - system structure, the airline schedule their time tables around banks of arrival flight during specified short period of time, followed shortly by a wave of departure flight. The objective of this configuration is to decrease the waiting time of passengers using the hub on other words increasing connectivity of flights in order to attract passengers particularly if other airlines offer direct flights to the specified destination. For a complete review on indirect flight attractiveness see Veldhuis, J., (1997), just to mention that attractiveness of a flight is decreased with an increase waiting time.

Theoretically, the wave structures depends on three elements, these are: (i) number of flights in the waves, (ii) hub repeated cycle, Dennis, N., (1994b) and (iii) aircraft locations at the end of the day (week), Bootsma (1997), Burghouwt and De Wit (2005), Figure 2.4 shows different wave structure examples.

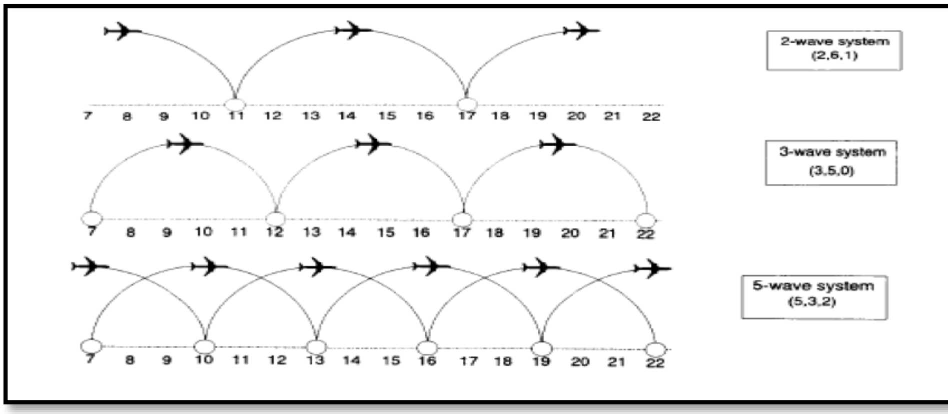


Figure 2.4 Examples of wave formulation depicted from Danesi, A., 2005.

Therefore for airlines adopting the wave system and in order to quantify a flight to join a wave structure meaning a particular wave, it has to meet the given criteria; (i) minimum connecting time, (ii) maximum connecting time, and (maximum number of flights that a wave can handle, to meet airport capacity, not all flight can be on one wave. Figure 2.5 details an ideal wave structure. The majority of airline attempt to schedule their flights in such a way to increase connectivity and hence the attractiveness of the flights, nevertheless most of the airlines start realizing the main disadvantage of the wave system. These disadvantages are seen on the peaking hours, the waves of arrivals and departure creates unbalance resource use for both the airlines and the airports resources. In addition, the ground time for an aircraft is increased resulting on low aircraft utilization. In order to overcome these disadvantages airlines move toward depeaking the wave structure on other words spreading their flight schedules evenly. In the next sections, we will further discuss the new trend of the continuous (rolling) hub.

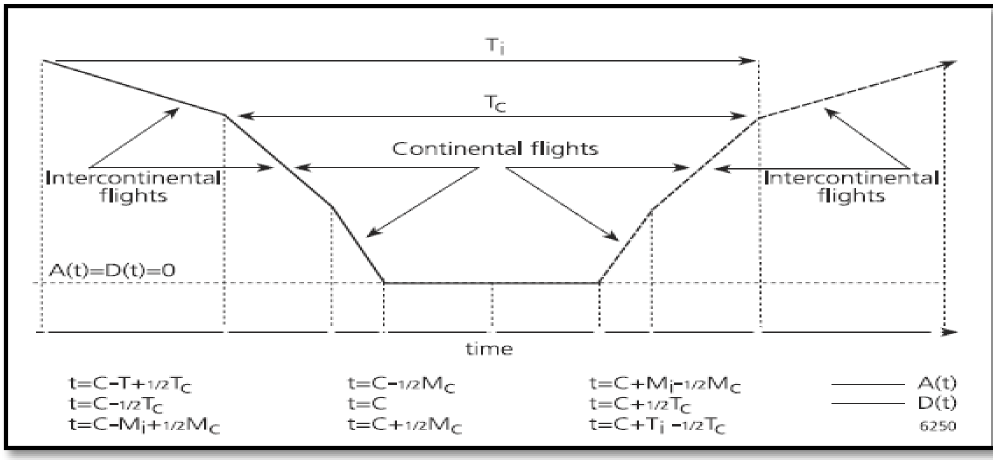


Figure 2.5 Ideal wave structure. A (t) = number of flights that still have to arrive at the hub at time t; D (t) = number of flights that still have to depart from the hub at time t; C = wave center; $\boldsymbol{M_i}$ = minimum connecting time for intercontinental flights; $\boldsymbol{M_c}$ = minimum connecting time for continental flights; $\boldsymbol{T_i}$= maximum connecting time for intercontinental time for flights; $\boldsymbol{T_c}$ = maximum connecting time for continental flights. *Source: Bootsma, 1997, p.57.*

2.2.4 Continuous (rolling) hub

With increasing competition between airlines operating a hub and spoke network, and the added pressure from the low cost carriers, airline trend nowadays, shift toward continuous (rolling) hub formulation, Jiang, H., Barnhart, C., (2013) argues the benefits gained using rolling hub schedule design, and introduces the dynamic scheduling supported by robustness, they apply the refleeting and retiming techniques to achieve an increase in revenue, their retiming assumptions were based on a classification of four periods of time (morning, afternoon, evenings and night), on the other hand, Warburg et al., (2008) extended the work and defined departure time around each departure time of the original schedule, their methods in adopting a preferred departure is restricted with $\pm$ 30 minutes. The attempt is to reduce airline cost by increasing fleets utilizations.

One of important conclusion obtained by, Lederer, P. and Nambimadom, R., (1999), in their paper “airline network design”, it is optimal for the airline to design its network and scheduling for profit maximization by minimizing both cost, airline operating cost and passengers cost.

2.3 The Middle East Mega Hub Network Features

Most of the works that have been done in investigating airline level or airport level operating characteristics of a hub and spoke network were done in US market as results of the deregulation act in 1978, as liberalization spread to Europe the research area have expanded the scope to cover the characteristic in the European market. Despite the similarity of the overall operation of the network configuration, there are some specific differences with the region where it is implemented. As Gulf airlines in the Middle East carrier start competing in the global market, we start seeing a new type of hubbing that based solely on transferring passengers in all directions. The new rivals operating model bases are; (i) the geographical location driver, the location of the middle east region plays an important factor to the success of the ME3, equidistance on the world, (ii) any destination of the globe from the region requires only one stop of about 8 hours, and (iii) willingness to operate one hub airport per the airline 24 hours.

The above bases have influence the aviation growth in the Gulf region, in fact this will affect and reshape global traffic patterns, Table 2.1 below shows the regional yearly market share, passenger traffic, capacity growth and load factors. As reported by, ICAO news release, PIO 28/11, (January 6/2012), the growth of international passenger sector was registered by airlines of the Middle East. The Gulf region is positioned for routes between Europe and Asia and between North America and Asia.

Table 2.1 Regional Yearly Market Share, Passenger Traffic, Capacity Growth and Load Factors

Passenger Traffic (PKP's)	**International**		**Domestic**		**Total**			
Region	Traffic Growth	Market Share	Traffic Growth	Market Share	Traffic Growth	Market Share	Capacity Growth (ASK's)	Load Factor
Africa	4.6	3.7	5.4	0.8	4.7	2.6	6.1	66.7
Asia Pacific	4.3	24.8	9.0	31.4	6.3	27.4	5.8	75.8
Europe	9.5	40.5	4.5	9.2	8.9	28.5	9.7	75.9
Middle East	**11.9**	**11.6**	**11.6**	**1.7**	**11.9**	**7.8**	**13.4**	**73.2**
North America	4.3	15.5	2.3	51.3	2.9	29.1	3.1	83.5
Latin America Caribbean	9.0	3.8	6.0	5.7	7.5	4.6	2.2	78.5
WORLD	**7.4**	**100**	**4.9**	**100**	**6.4**	**100**	**6.5**	**77.5**

Source: ICAO news release, PIO 28/11, January 6/2012.

The ME3 has capitalized in their location and the growth in passengers by starting force their business model into the aviation industry, airports in the regions are under constructing of the new mega hub airports design to compete and force the redirecting of passengers flow into their hubs, from a theoretical perspective, Middle Eastern carriers are not expanding the network in a way that additional airports (‘‘nodes”) are taken into the overall network. The network is rather expanded in a way that new routes (‘‘edges”), i.e., alternatives of going through the network are offered to the customer (for example London–Dubai–Sydney as opposed to London–Singapore– Sydney). It's seen that ME3 are capitalizing in reshaping the route through focusing on: (i) secondary airports and, (ii) markets that have been largely unconnected to the global air transport network.

On the other hand, multi-hub network systems may be less cost efficient than mega hubs. Furthermore, the airline might take off its own customers from its hubs to other airports and therefore cannibalize its own network. As a result, the hub-and-spoke system of the airline may become less effective, for example initiate measures to reduce delays or provide additional offers like shopping opportunities and areas to relax within the hub airports. The effectiveness or feasibility of a network per description, is the ease of travelling equally in any direction with no reference to overall cost or unit cost, Malighetti, P. (2010).

2.4 Airports – Airline Relationship

The liberalization and deregulation in the aviation industry have led to increasing competition between airlines and at hub airports operated by airlines, adding an increasing trend on the traffic volumes and travel behavior changing, had led to requiring flexible responses from all actors in the aviation industry airlines and airports should explore possible cooperation between them yet the majority of these cooperation when exist are built upon contractual agreements, with a period of defined scope, Auerbach, S., Koch, B., (2007).

In a press release no.: 54, 11/2/ 2011.The International Air Transport Association (IATA) encourages innovation for new methods and relationship between the airlines and airports to keep growing, as mentioned by Tony Tyler, IATA's Director General and CEO.

This research, is focusing on improving performance and operating efficiency of an airport by manipulating an airline existing schedule through partnership relation with the main operating airline. The achievement of such a partnership does not require a sophisticated optimization techniques rather it a simulation tools that facilitate the process.

CHAPTER 3

FLIGHT SCHEDULING OBJECTIVES IN AN AIRPORT – AIRLINE PARTNERSHIP

3.1 The Classical Approach

The air transport industry has traditionally been structured as a customer – supplier relationship between airlines and airport operators. Typically, both of these organizations have their own planning and optimization activities. In addition to these two entities, there are two other stakeholders in airport operations: passengers and government agencies. As illustrated in Figure 3.1, all four entities have separate but often overlapping objectives in their use of the airport.

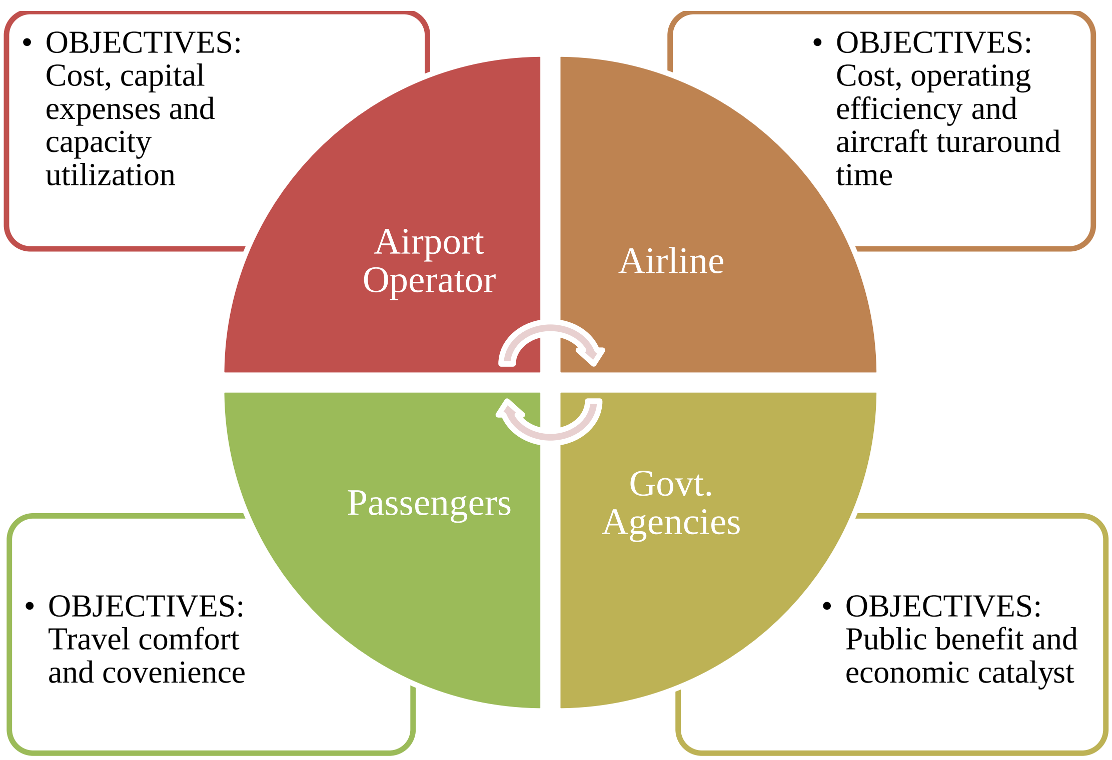


Figure 3.1 The four stakeholders in airport operation.

Most research methods and textbooks on airport operations are based on this four-entity model. A key area of focus has been the role of airports in the airlines flight networks, and this has been one of the most extensive areas of research and model development. Most traditional, or legacy U.S. airlines operate a hub-and-spoke network which is defined as "denoting a network of air transportation in which local airports offer flights to a central airport through which passengers can connect to other local airports". The alternate network is a point-to-point model in which an airline operates flights primarily to serve the Origin and Destination (O/D) traffic. This means that the airline is more interested in transportation of passengers originating from one city (A) to another city (B) and vice versa, but not in connecting passengers between C and B via A. Low Cost Carriers are considered to be pioneers of this paradigm with a classic example being Southwest Airlines.

This research focuses specifically, on a special configuration of the hub-and-spoke (H&S) network. A single hub and zero to minimal O/D traffic characterize this special network. Later in Section 3.3, we provide a detailed description of this network. In the context of the more classical H&S network we discuss next some of the network design objectives of the different entities.

3.1.1 Network Schedule Design Objective – Airlines

The primary capital asset of an airline is the aircraft fleet, and in the flight schedule design process, airlines want to optimize aircraft deployment and utilization. Additionally, schedules are designed to maximize revenue generation and to targeting passenger convenience. Flight operations are subject to a wide range of uncertainties and unpredictable events, and the schedule process will attempt to mitigate the effect of these uncertainties. Since airlines operates in multiple airports each of which is managed by a different entity and different community/jurisdiction codes, scheduling problem is quite complex. The airline industry is notoriously challenged by rapid changes and that affect the way airlines optimize their schedules and operate at hub airports. Frequently, schedule optimization models result in a sub-optimal solution, as decision fixed early on the process can limit flexibility in subsequent stages. Common traits of these sub-optimal schedules are banked arrival/departures that meet the constraints imposed by a specific hub airport.

3.1.2 Network Schedule Design Objective – Airport Operator

For airport management, the key objectives are to provide the necessary resources, and facilities for both airlines and passengers. The majority of airports are owned or managed by government agencies and catalysts for the regional economy and the best use of public monies are their charter objectives. Typically, efficiency improvement is a lower focus objective unless it affects the direct operational targets of the airport. Forward-looking trends in deregulation and privatization will though challenge to increase their focus on operations efficiency and reduce their operating cost.

Recently, a number of research papers and conferences addressing airport capacity suggested the use of demand management tools to address existing capacity at airports effectively by encouraging higher capacity aircraft and by better utilizing the times when airport capacity is not fully used. For example; pricing of peak flights to encourage shifts to the off peak, and auctions, but most of these either proved unworkable or had only a small impact on freeing capacity, Zupan, J. pp13 (2011).

3.2 The Cooperative Airline-Airport Flight Scheduling Systems

Traditionally, flight schedules are created by airlines to meet passenger’s time sensitive demand subject to the given slot constraints from airports. This research finds that in SMH airports there is a significant level of cooperation between the airline and airport in creating flight schedules. In Figure 3.2 we describe our prescribed process for developing these cooperative flight schedules.

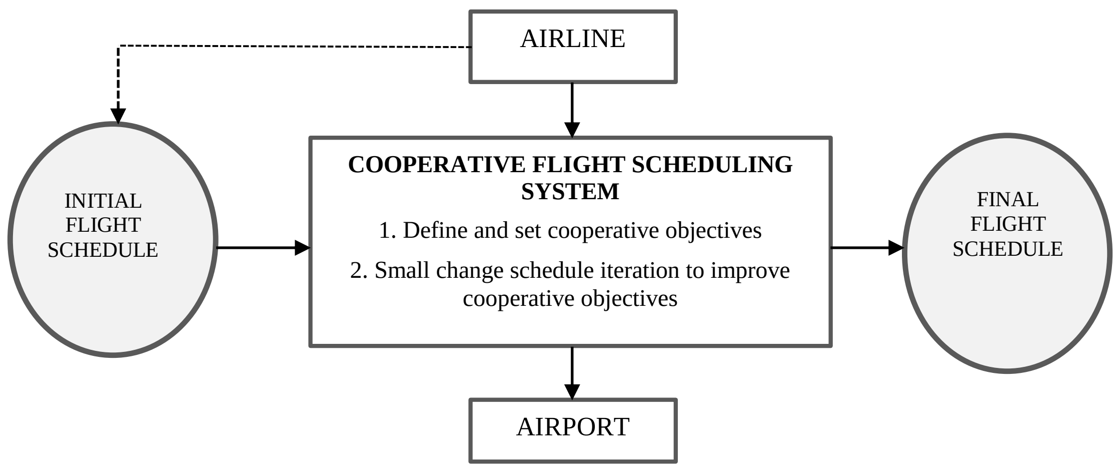


Figure 3.2 The proposed cooperative flight scheduling system.

In this system, there is an initial flight schedule created independently by the airline, using traditional methods and objectives. This initial schedule is then cooperatively modified by the airline and airport with a specific focus on the operating costs and efficiency of the SMH. We developed two novel methods to support these systems as identified in Figure 3.2. First we define the cooperative objectives function, and second, we developed a heuristic procedure to generate the final optimized schedule from the initial schedule.

A key assumption here, is that the small changes that are made by the cooperative systems do not result in a significant deterioration in the objectives of the initial schedules.

This is supported by the selfish perspective, that is the airport operational benefits, can to a certain extent outweigh passenger time-sensitivity objectives and other airport objectives. Evidence shows that the ME3 carriers are already exercising this strategy in their schedules.

We are developing a procedure that addresses these concerns from the airport perspective side at the same time adding value and sufficiency to airline industry in terms of lower operating cost and higher resources and equipment's utilization. Our procedure is designed in order to promote efficient and cost-effective airport terminal operation subject to airport capacity constraints. The development method is applicable to airlines operating rolling schedules as well as banked schedules at their hubs, as we will show later in this chapter. Hence we looked at the latest theory in designing new airports and examine the factors included in these designs, in terms of airport capacity and terminal operation. In addition, we examine the type of data collection that is recommended for research committee when investigating airports cost behaviors and operating efficiency.

We utilize the dynamic airline scheduling mechanism in order to manipulating the departure time of a flight to improving airport efficiency and reduce operational cost. The retiming of flight schedule, is a new technique; it was used first by American Airlines in the year 2002, Ott, J. (2003).

American Airline attempt to reducing cost at their two main hubs in (Chicago O'Hare, and Dallas/ Fort-Worth International Airport) by de-peaking the bank of arrival and departure structure from peak and valley into a smoother banks to maintain the hub and spoke operations, their act was followed by several other major airlines in US and Europe (e.g., Lufthansa, Continental). Academically, Etschmaier has introduced the concept sporadically and Mathaisel (1985), Jiang, H., (2006), uses the concept in his research for his PHD dissertation, exploring both retiming and refleeting techniques in order to increase airlines revenues through dynamic and robust scheduling of airline schedule. In last decades many major airlines in the world including American Airlines, Continental Airlines, United Airlines, Delta Airlines, and Lufthansa Airlines have de-banked one or more of their hubs, Warburg (2008). In literature, the retiming as well refleeting of timetable schedule referred to de- peaking strategy. De-peaking (rolling hubs) is used in recent research to optimize and minimize airline cost and improve revenues by retiming either departure or arrival time. Research has covered objective functions such as:

i. Improving airport ground operation; Swiss airline
ii. Improving arrival punctuality, to address declared capacity; Lufthansa airlines
iii. Improving airline profit by designing dynamic schedule that includes some infeasible flights and apply re-timing mechanism to yield a feasible solution that capture higher demands.
iv. Reducing Cost of energy at the airport and hence environmental impact.
v. Airport activity cost.

From a strategic perspective, this motivation to forming a partnership leads to an advantage for the participating companies in gaining and sustaining competitive Das and Teng, (1999), this idea is further explored and explained by Albers, S., et al., (2005), looking at possible potential benefits that can arise from alliances between passenger airlines and their hub-airports, Figure 3.3 list a number the potential areas for strategic partnership. The quality of service in the air transportation is seen as a function of punctuality, reliability and service. Traditionally each player is planning and managing to achieve the same goal separately which creates some conflicts despite that the same goal is to be attained, Table 3.1, highlighted a typical relationships between airlines and airports in key countries and Table 3.2, list of factors that affect the choice of airports.

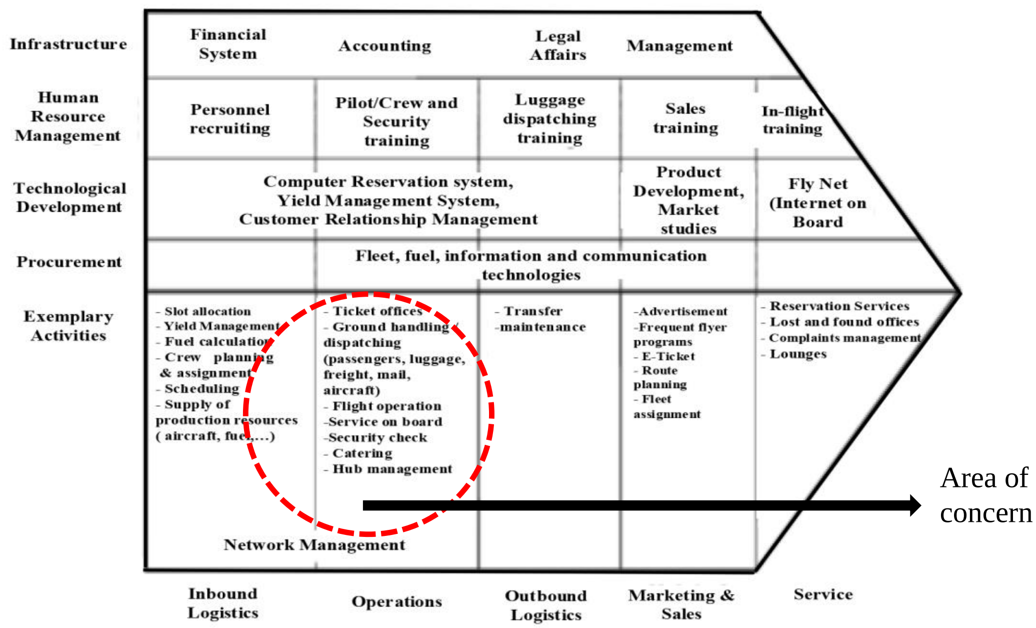


Figure 3.3 Areas of possible partnership between airlines and airports.
Source: Albers, S., Koch, B., and Ruff, C., (2005).

The partnership between airline and airports will help reduces uncertainty for both partners, Albers, S., Koch, B., and Ruff, C., (2005), Auerbach, S., Koch, B. (2007), explore two possible cooperation between airports and airline air service development (ASD) and collaborative decision making (CDM), in order to increase additional traffic and better optimization of airport infrastructure and air space. In Japan the government outsources two airports serving Osaka to private sector. ITTA (2013), according to the government this will help in making these facilities more competitive, the privatization of airports become well known around the globe, it is seen in key cities in Europe, for these movement to last with benefits for all parties involved, there should be a closer coordination between airports and airline. Another sort of corporation through financial participation is seen between Lufthansa and the Star Alliance partners for Munich airport.

Table 3.1 Typical Relationships between Airlines and Airports in Key Countries

Country	Airline-airport relationship
USA	Airport as landlord and coordinator of services Airlines build their own terminals and facilities
Spain	One central, public airport operator company, owing and developing all (or most) airports of the country Airlines as customers to the airports
France, United Kingdom	Mixture of private and public airport companies, owning and developing their airports Airlines as customers to the airports
Emirates, Qatar (Gulf states)	Airports are owned and managed by the government Airlines take advantages of close partnership with airport management

Source: Modified from Albers, S., Koch, B., and Ruff, C., 2005.

Table 3.2 Factors Affecting the Choice Airports

Passengers	Airlines
Destination of flights	Slot availability
Image of airport	Network compatibility
Flight fare	Airport fees and availability of discounts
Frequency of service	Other airport cost (e.g. fuel handling)
Flight availability and timings	Competition
Image and reliability of the airline	Marketing support
Airline alliance policy and frequent flyer program	Range and quality of facilities Ease of transfer connections
Range and quality of shops, catering and other commercial facilities	Maintenance facilities Environmental restrictions
Surface access cost and ease of access to airport car parking facilities	

Source: Albers, S., Koch, B., and Ruff, C., 2005, Source: (Graham, 2001).

3.3 Single Mega Hub Airport

Global airlines have traditionally operated multi-hub network systems. Optimization models for these networks typically focus on schedule convenience, fleet utilization and local operating constraints. Recently we have seen a new type of flight network model being deployed by some new airlines. We label these as Single Mega Hub (SMH) networks, and they have a significantly different operating cost structure and objective when compared to the more classical H&S network. The most well-known examples of SMH networks, are the following three airlines and the associated mega hub city:

- Emirates → Dubai (DXB)

- ❖ Qatar → Doha (DOH)
- ❖ Etihad → Abu Dhabi (AUH)

These are located in Middle East and are commonly referred to as the ME3. As a note Dubai is now the highest passenger volume international airport in the world. Other less dominant examples are noted below, these are not strict SMH networks since they may have a few feeder or mini hubs.

- ❖ Copa Airlines → Panama City (PTY)
- ❖ Air Asia → Kuala Lumpur (KUL)
- ❖ Turkish → Istanbul (IST)

The research literature on SMH networks, is relatively limited, and it is the ME3 airlines that have been reluctant to provide much operational details to the research community. Analysis of their published schedules show that SMHs operate more of a continuous flow model as opposed to a peak and valley schedule. Further O/D traffic at the mega hub is minimal. We identify the following classifying features of the SMH airport:

1. There are no peak arrival/departure periods; the airport operates on a 24-Hour schedule with a close to uniform passenger throughput rate.

2. Flights schedules do not assign a strong priority to arrival/departure times at destination cities (selfish strategy). Unless specific constraints are imposed by the spoke city.

3. The O/D traffic at the hub is less than 5% of the total traffic, with the vast majority of passengers just transiting through the airport.

4. Operates only non-stop flights to multiple destinations.

5. There is only one hub in the network.

6. Flight schedules are organized into a series of arrival/departure banks or waves.

7. The airline and airport operator are closely aligned in a tight partnership.

8. Typically one airline accounts for 95+% of traffic.

Figure 3.4 below illustrates the SMH network structure and a typical hub operation. As noted a key aspect of this type of airport is a close partnership between the airline and airport operator. Very small disruptions could lead to significant upswings in transit passenger counts and flight delays.

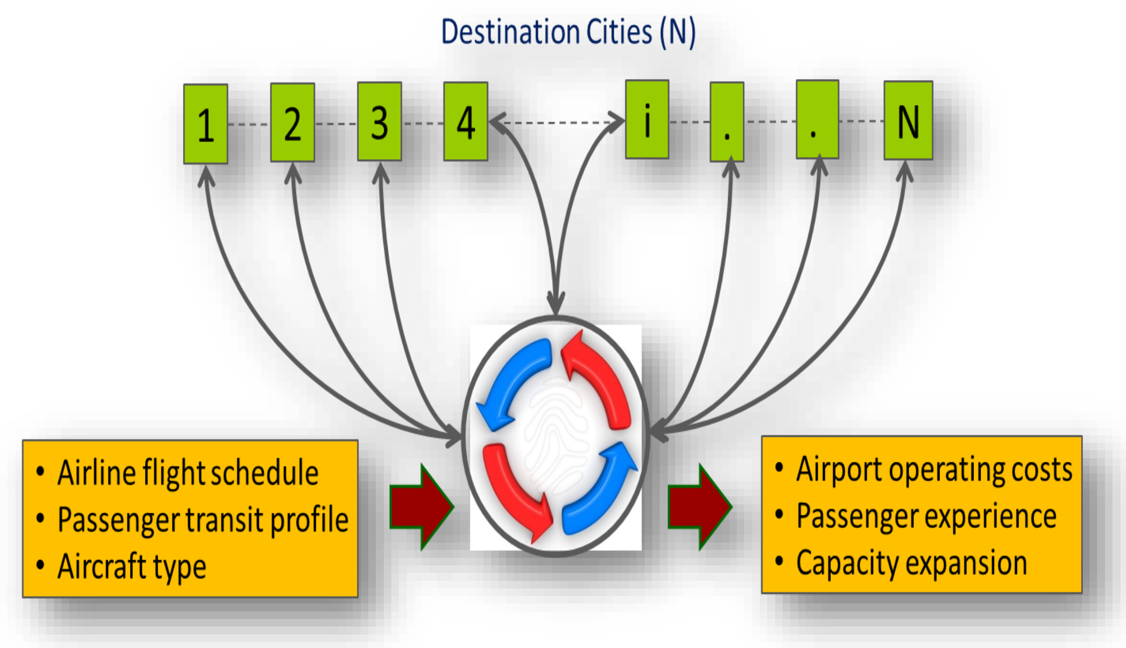


Figure 3.4 Illustrates the SMH network structure.

3.3.1 SMH Airline Airport Partnership

Koch and Ruff (2005), noted that significant schedule planning interaction between the airline and airport is required for a SMH to be successful. The airport has a responsibility to the airline by offering an appropriate level of capacity to conform to its network ambitions. We propose here a framework for developing a flight schedule, which is beneficial to both the airline and airport operators. Our research will capitalize on balancing resources for both airline and airport by using the mechanism of retiming flights. Figure 3.5 show a suggested flow of information between the two parties in a SMH network. This flow of information leads to the developments of the Selfish Mega hub.

Selfish mega hubs are characterized by its own operations feature as results of airline – airport coordination. In chapter 4, we will enumerate and discusses the features of mega hub under the model assumptions.

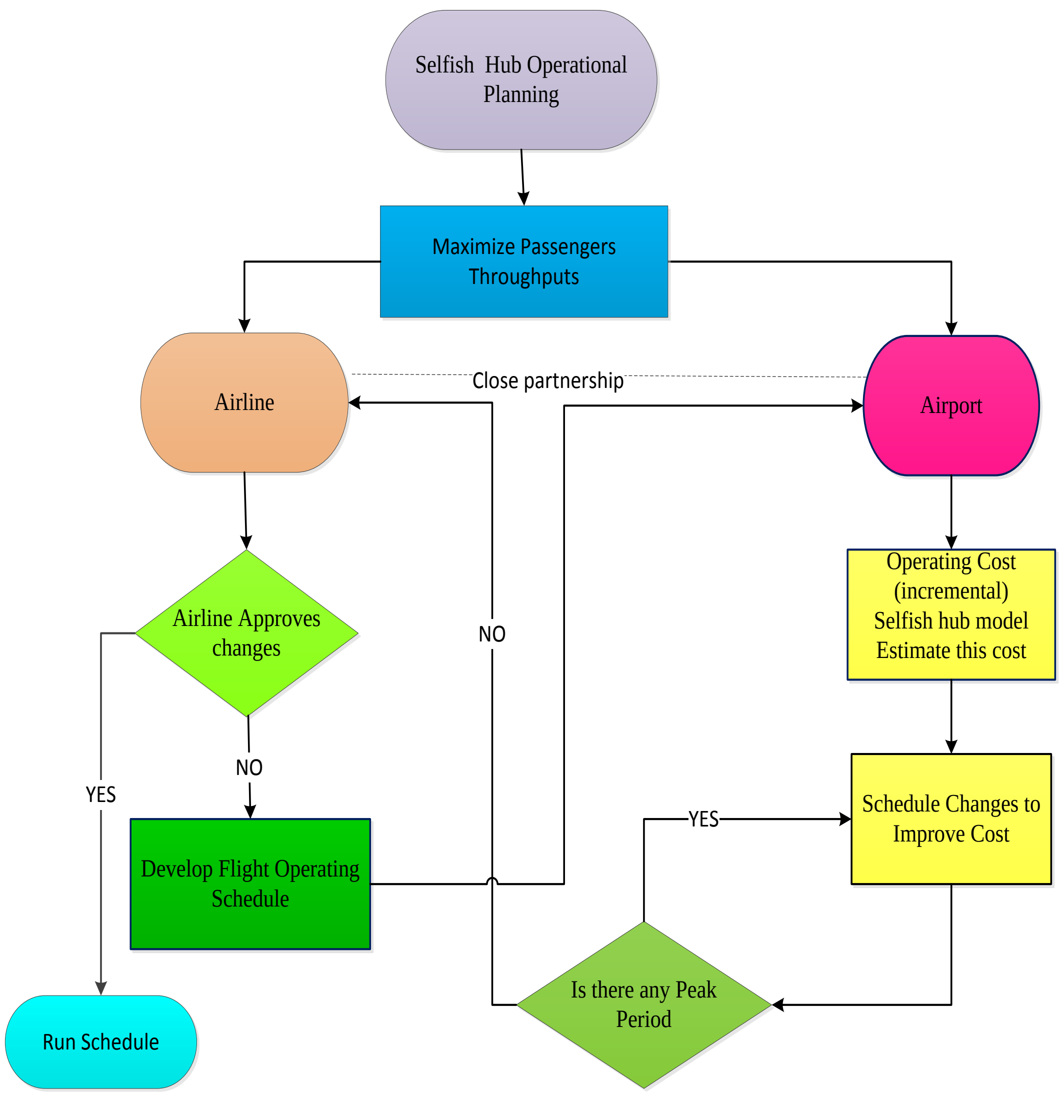


Figure 3.5 Suggested partnership flow of information between airports and airlines.

3.3.2 Cooperative Scheduling Objectives

As noted, SMH networks have a significantly different operating cost structure, and objective. The nature of continuous operations at these hubs required different cost tools for tracking passengers flow as well as aircraft movements inbound and outbound the hub airport. Traditional objective functions are designed for classical H&S network model. A key differentiator is the balanced activity level in a SMH allowing for greater utilization of equipment resources.

In this research, we address this imbalance impacts on operating mega hub airport; that is characterized by continuous passengers' transit by introducing a novel cost function to address and integrate airport capacity. Airport capacity are seen on; (i) physical space available for passengers at the terminal, (ii) physical space for aircraft at the ground, and (iii) capacity control for arrivals and departure rate to and out of the airport.

We will first start with, defining our cost functions individually, and provide a justification for selecting each of these cost function as the proper matrices to improve airport efficiency and operational cost. To address airport capacity constraints, we defined our matrix inputs entities based on passengers flow and aircrafts movements into the hub. For, first according to ACRP Report 23,pp.v (2009), the most common entities in collecting data for planning future passengers' terminals in an airport are passengers and bags, passengers and their belongings flow rates specially enplaning (i.e., boarding) and deplaning (offloading) rates are key factors in airport operational efficiency. As mentioned earlier after deregulation and privatization in US, airlines globally adopted the hub-and-spoke network. Many of the international airlines start using their hub mainly for international passenger transfer, as seen nowadays by the airlines existing in Middle East region, thus the importance of transfer passengers have been increased. This requires the airlines to understanding and catering the specific needs of transferring passengers, the transfer passengers' needs are fundamental in achieving growth in today's competitive airport environment, Jin-Woo, P., and Se-Yeon, J., (2011), in his study "Level of Service Analysis and Airport Terminal Development (Case Study: Soekarno-Hatta International Airport, Indonesia)", Adisasmita, S., A., (2012), uses FAA and IATA standard for terminal area techniques analysis concluded that the expected distribution of the number of passengers and aircrafts is more prevalent when managing the traffic (passengers and aircrafts flow) and schedule frequency. FAA and IATA standards for airport terminal building is planned to serve the number of passengers at peak hours with an estimated for long-term period. This is a fact in designing airports terminal, yet the economic operation and efficiency of running the airport are in the shoulder of airport managements.

Airports can boost economic growth in the communities they serve, when these airports are well defined to serve under the complexity of shifting needs. The airport industry has to meet several traveler's combinations of needs as some travelers wish to experience the airport almost as a destination into itself, with many options for leisure and entertainment, dining, fitness and shopping, Others just want moving as quickly as possible through the airport facility before and after their flight, with endless traveler's needs. The challenge for the airport is to deliver the experience that each type of passenger wants, consistently and cost-effectively, despite the inherent complexity in meeting a wide variety of traveler's needs.

Our research, identifies and proposes three objectives for the collaborative flight-scheduling problem. Note that both airlines and airport operators have many other operating objectives. The three objectives highlighted here are what we see in the intersecting space between the two entities.

1. *Passenger Waiting Time* - Represents (i) the cost of providing services and amenities that minimize the effects of the wait or transit time at the SMH airport and (ii) the pricing discount the airline has in-built into the fares to make the SMH transit attractive to passengers.

2. *Passenger Volume in Terminal* – Represents (i) the scaled-up cost of providing in-terminal waiting spaces, passenger services and amenities as a function of the number of passengers currently in the terminal and (ii) the cost of additional resources associated with meeting people logistics, queueing delays, and congestion effects as a result of larger in terminal passenger volumes.

2. *Flight Activity Wave Imbalance* – Represents (i) the cost of underutilized flight activity resources due to imbalance in the arrival/departure waves (ii) the cost of aircraft ground time delays during the wave peaks.

A detailed characterization and formulation of the three objectives is developed and provided in the next sections.

3.4 Passenger Waiting Time Cost

Passenger waiting time refers to the time interval between connecting flights that each passenger spends in the airport, this is also referred to as transit. It is calculated using the arrival time of a flight to the hub and the departure time of the passenger connected flight. SMH airports by design will require passengers to have both a longer travel time and waiting time at the SMH Airport compared with other network types. Structurally travel times will be shorter in a direct flight or multi-hub H&S network. For a SMH to sustain passenger volumes it must provide a comfortable transit experience, which mitigates the wait time effect.

Figure 3.6, shows the flowcharts of the transit process for a passenger at a hub airport, Gatersleben and van der Weij, (1999). In a SMH airport the landside arrival/departures are not of significance since there is little to no O/D traffic. As shown below the airport operator needs to build an efficient transfer process and provide extensive lounge and other passenger comfort facilities. Transfer passengers at a SMH airport require different needs and handling process, since very little of the airport is designed for the O/D traffic (De Barros et al., 2007).

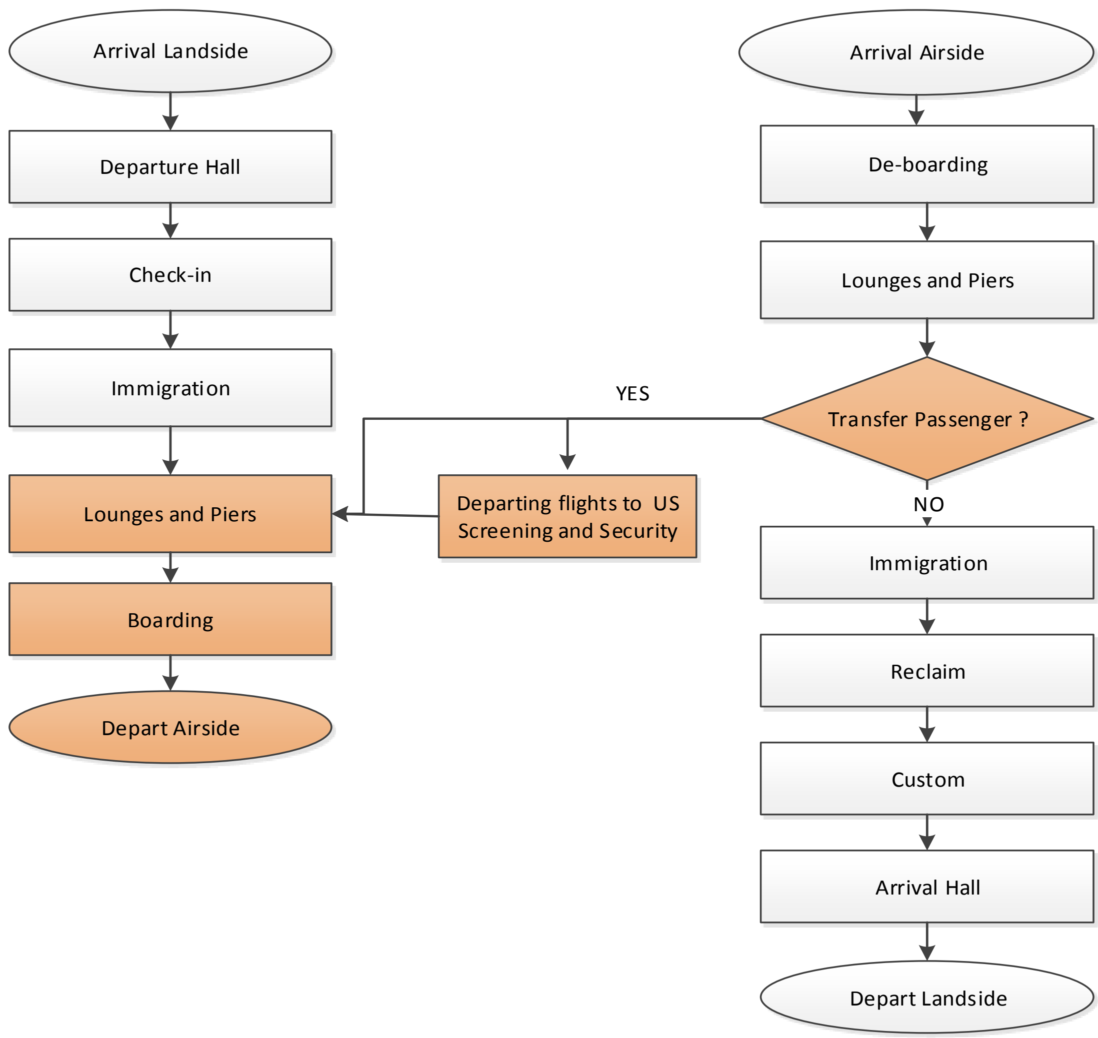


Figure 3.6 The process of transit process for passenger at a hub airport.
Source: Modified from Gatersleben and Van der Weij, pp.1229 (1999).

The dynamic nature of passenger flows will cause congestion bottlenecks in the process of transferring passengers and their bags. These congestion in walkways, long queue lengths or walking distances, Gatersleben and van der Weij, pp. 1229 (1999). Figure 3.7 shows a detailed airport departing passenger process, adopted from ACRP Report 23, (2009).

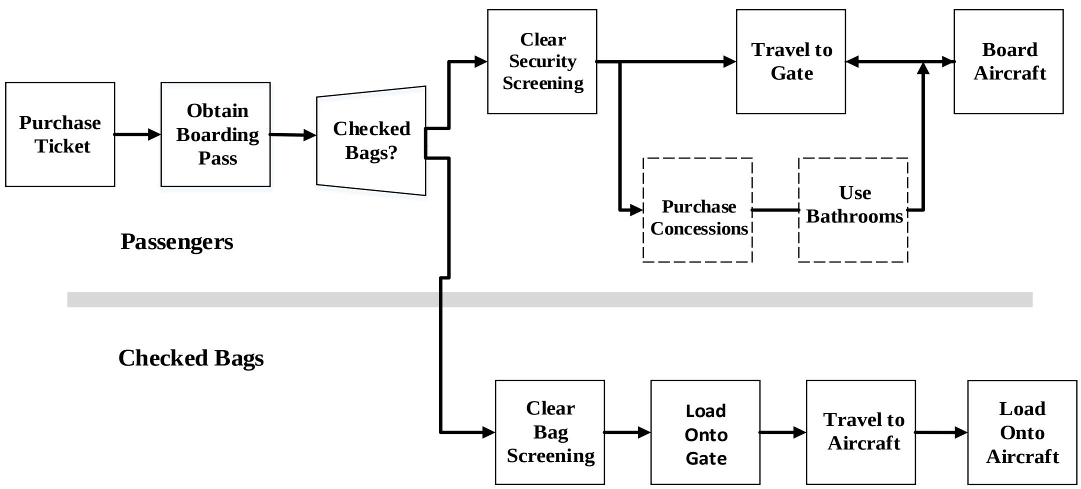


Figure 3.7 Generalized airport passenger departing process.
Source: ACRP Report 23 pp.7.

In traditional flight scheduling methods, the wait time penalty is formulated as a linear utility model. That is if the wait time is τ then the decrease in passenger utility is given by $w\ \tau$ for some $w > 0$. For the joint airline-airport model we expand this traditional wait time cost function. Specifically our research shows that passenger wait time cost function can be divided into three segments, these segments are: (i) Short Transfer where $B_0 \leq \tau \leq B_1$, where B_0 is the minimum transfer time the airport will allow, (ii) Medium Transfer where $B_1 \leq \tau \leq B_2$, and (iii) Long Transfer where $B_2 > \tau$. Passenger transit activities and movements inside the airport terminal can generally be summarized as; deplane, walk, wait, and board as depicted in Figure 3.8. For the SMH each segment represents a different class of passengers' requirements and facility resources hence incurred different cost by the hub airport.

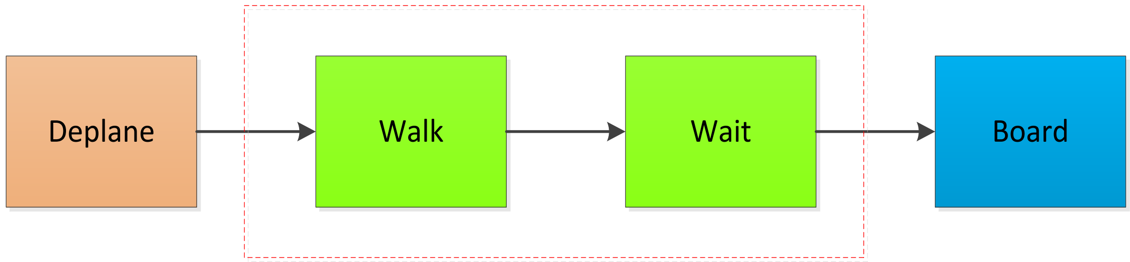


Figure 3.8 Transfer passenger movements inside the hub in general.

In general, the first and last activities are similar to all segments and hence, we will focus inside the walking and waiting activities to justify the use of the proposed U cost function for the different segments, it is concluded that manpower, equipment's and facility requirements to accommodate all type of connected passengers are different for the segments.

3.4.1 Short Transfer where $B_0 \leq \tau \leq B_1$

This segment includes passengers who have a very short time to transit between their arrival and departure gates. The activities in their flow path will only be; deplane, walk, and board, see Figure 3.9. The exact value of B_0 and B_1 varies between airports. In international hubs, common settings are B_0 – 60 to 90 minutes and B_1 – 90 to 120 minutes. At a highly efficient airport such as DXB, from flight schedule data we project $B_0 = 30$ minutes and $B_1 = 60$ minutes. In contrast another large more traditional hub such as London Heathrow it is reported $B_0 = 60$ minutes and $B_1 = 120$ minutes.

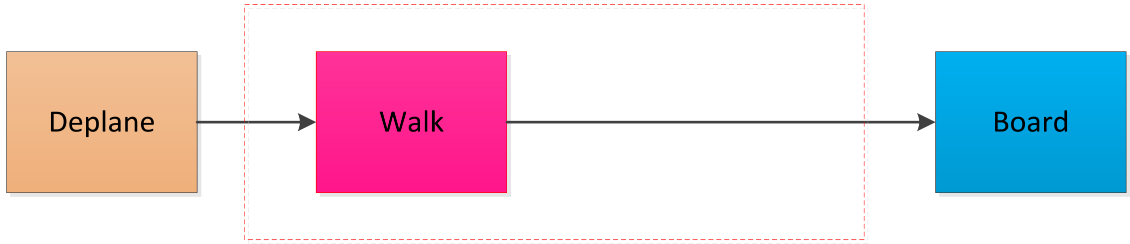


Figure 3.9 Transfer passenger movements inside the hub representing short transfer passengers.

The airport operator will build and install the infrastructure to provide the services and channels for short transfer. This includes special equipment to minimize their walking distances and hence the travelling distance, e.g., escort (car) movers, walking escalators, see Figure 3.10, these add-ins needs rapid maintenance, power consumption and operators.

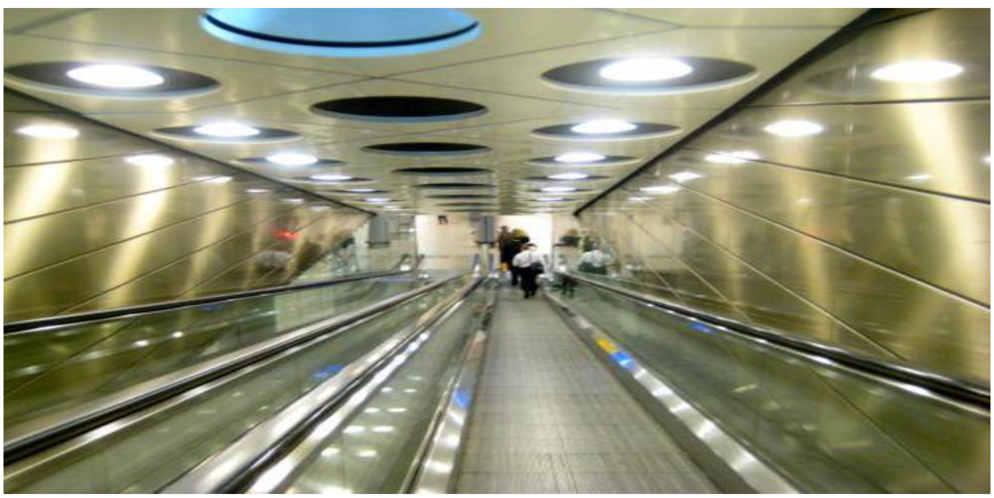


Figure 3.10 An example of infrastructure's, from Amsterdam airport.

On the other hand, these express services require additional manpower and customer services personnel to provide guidance and quick response related to these passengers segment, which increases airport operating cost. Another sort of cost incurred by the airport for the short leg passengers come from their baggage transfer, more resources and equipment are used to assure passengers satisfaction for their baggage's transfers, for that, this cost is declining with time hence it is modeled with a negative slope line.

3.4.2 Medium Transfer where $B_1 \leq \tau \leq B_2$

This segment typically represents the largest component of passengers transiting through the SMH. For these passengers the deterioration in the utility function is dependent on the quality of the wait experience. But the utility deterioration rate is not for high (less than 20%). For a SMH the operational design objective is to maximize the length of the B_1 to B_2 interval, since the utility deterioration rate rises sharply after B_2. For example at Dubai B_2 = 300 minutes for a B_1 to B_2 interval of 4 hours, while at London the projection is that B_2 = 200 minutes for a B_1 to B_2 interval of 1.5 hours.

To achieve a long B_2, airport operators and airlines must build and operate an attractive transit or wait area with a wide range of services, this will be crucial to keep the deterioration rate low. This will include eating in a food court, using bathroom, taking some rest, do some shopping and spend some time using internet or other communication tools, Figure 3.11 summarizes transfer passenger demand for this segment. For a SMH the target utility deterioration rate is zero for this segment, and our understanding is that Dubai is close to achieving this target.

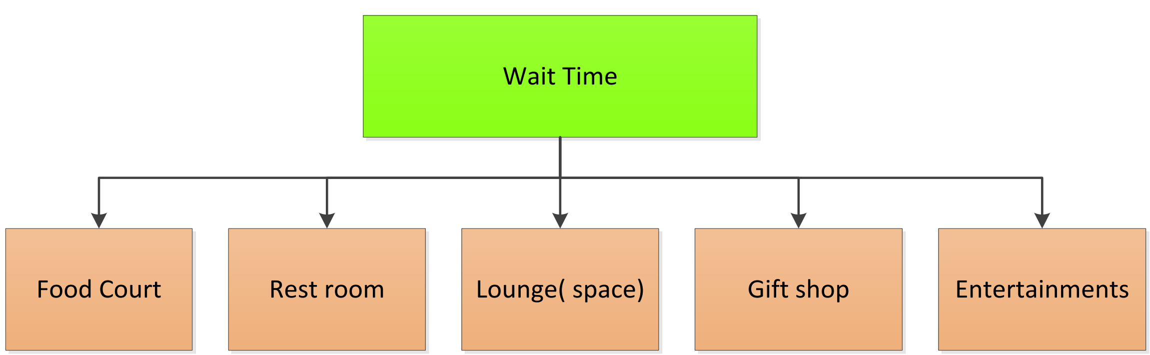


Figure 3.11 Nominal transfer passenger demands.

3.4.3. Long Transfer where $B_2 > \tau$

This last segment, covers passengers with a significant increase in the utility deterioration rate. Though passengers at this segment are aware of the long waiting hours when purchasing tickets, they will expect a steep price discount to make the selection. The airport needs to offer more services and entertainments facilities to assure passengers are comfortable and can spend their time with a positive experience. These can be in a more luxurious and higher level services to mention, lounges and rest area furniture's are different and accessed by boarding tickets, see Figure 3.12 to assure occupancy for this segments, court food for instances are restaurants and includes varieties of international cuisines, Figure 3.13 show example of cost spend by airport management to attract long leg transfer passengers.

In addition the airport may offer some touring trip to the city outside the airport. This is only possible for transfer traffic, if there is a complete coordination between the airport and the airline. It is very important to mention that the U function cost will be different for different hubs; the tradeoff is between how much the airport management is willing to invest and how big is the airline network size.

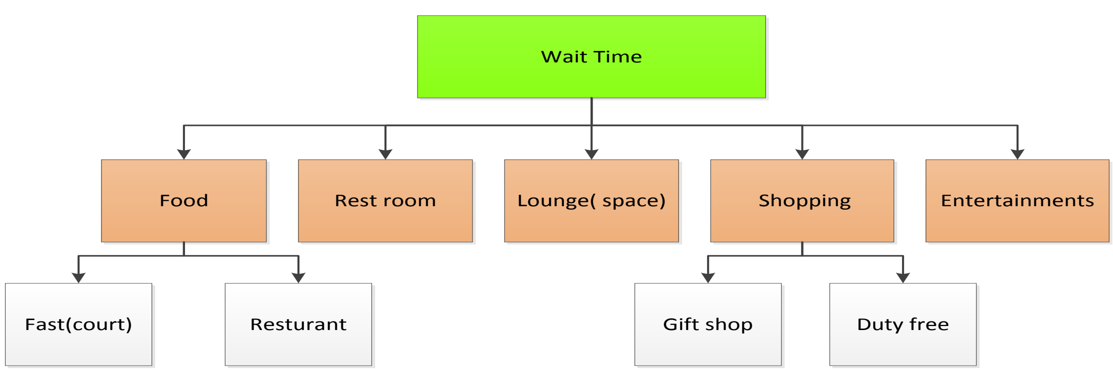


Figure 3.12 Long leg transfer passenger demand.

Figure 3.13 Long leg transfer passengers rest areas.

3.4.4. The Passenger Waiting Time Objective Function

Our objective, is to develop a cost function which represents (i) the cost of providing services and amenities that minimize the effects of the wait time and (ii) the pricing discount in-built into the fares to make the SMH transit attractive to passengers. Clearly, the waiting time cost for each passenger is dependent on their specific wait time which is described by:

τ Passenger waiting time at the airport defined by |A-D| where A is the scheduled arrival time and D is scheduled departure time.

MODEL NOTATION & FORMULATION

B_0 Minimum allowable passengers waiting (transit) time

B_1 Threshold waiting time between short and medium segments

B_2 Threshold waiting time between medium and long segments

B_3 Long waiting time benchmark

$\beta_{w,0}$ Passenger waiting time cost benchmark at B_0

$\beta_{w,1}$ Passenger waiting time cost benchmark at B_1

$\beta_{w,2}$ Passenger waiting time cost benchmark at B_2

$\beta_{w,3}$ Passenger waiting time cost benchmark at B_3

$\delta_{w,0}$ Short leg waiting time utility deterioration rate

$\delta_{w,1}$ Medium leg waiting time utility deterioration rate

$\delta_{w,2}$ Long leg waiting time utility deterioration rate

The deterioration rates are then given by:

$$\delta_{w,0} = \{\beta_{w,0} - \beta_{w,1}\}/\{B_1 - B_0\} \tag{3.1}$$

$$\delta_{w,1} = \{\beta_{w,2} - \beta_{w,1}\}/\{B_2 - B_1\} \tag{3.2}$$

$$\delta_{w,2} = \{\beta_{w,3} - \beta_{w,2}\}/\{B_3 - B_2\} \tag{3.3}$$

Note that τ is not bounded by B_3. The waiting time cost for a passenger is then defined by the U - Convex piece wise linear function as follow:

$$\gamma(\tau) = \begin{cases} \beta_{W,0} + \delta_{W,0}(\tau - B_0) & | \quad B_0 \le \tau < B_1 \\ \beta_{W,1} + \delta_{W,1}(\tau - B_1) & | \quad B_1 \le \tau < B_2 \\ \beta_{W,2} + \delta_{W,2}(\tau - B_2) & | \quad B_2 \le \tau \end{cases} \tag{3.4}$$

Passenger waiting time cost function is unique cost for every airport and described by the vector { B_0, B_1 , B_2 , B_3 , $\beta_{W,0}$, $\beta_{W,1}$, $\beta_{W,2}$, $\beta_{W,3}$ }. In Figure 3.14, the cost functions for three airports ranging from a high to low cost are illustrated, while Table 3.3 shows the accompanying cost function vectors. An ideal SMH, will have an operational airport design and implemented passenger flow infrastructure to exhibit the low cost behavior. Table 3.4 shows the waiting time utility deterioration rate for the different designs.

Table 3.3 The Cost Function Vectors

AIRPORT DESIGN	B_0	B_1	B_2	B_3	$\beta_{W,1}$	$\beta_{W,2}$	$\beta_{W,3}$	$\beta_{W,4}$
Low Cost	0.5	1	5	10	$10	$4	$6	$20
Mid Cost	1	2	3.33	10	$16	$7	$8	$35
High Cost	1	1.5	4	10	$19	$13	$14	$40

Table 3.4 Waiting Time Utility Deterioration Rate

AIRPORT DESIGN	$\delta_{W,0}$	$\delta_{W,1}$	$\delta_{W,2}$
Low Cost	$12.00	$0.38	$2.90
Mid Cost	$9.00	$0.75	$4.05
Low Cost	$12.00	$0.40	$4.33

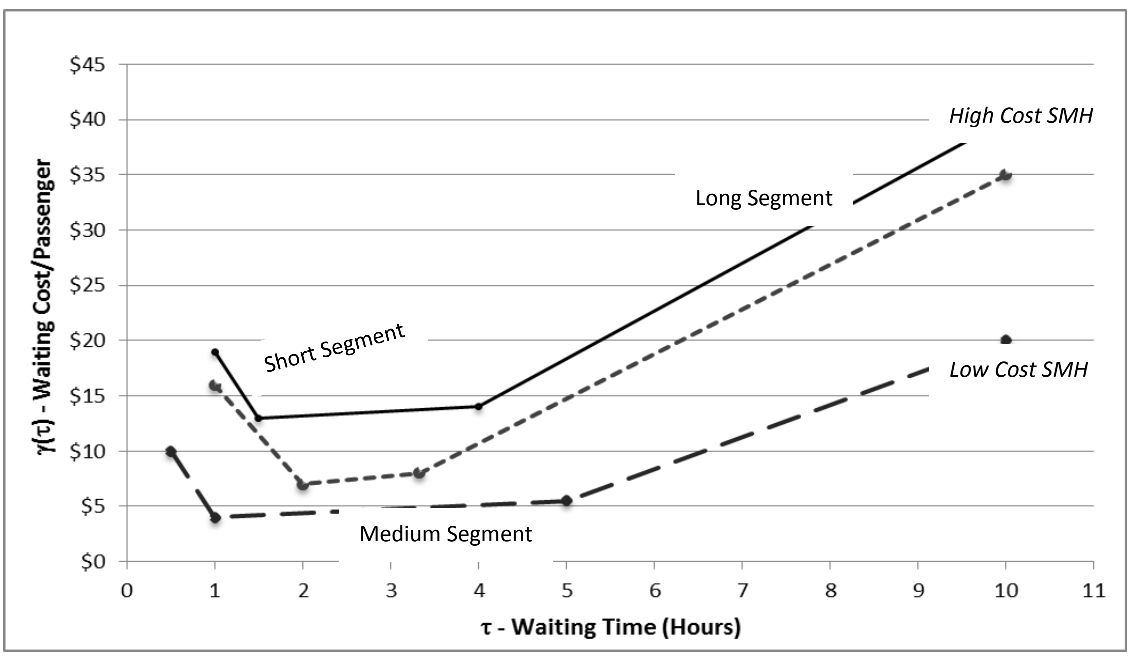


Figure 3.14 Different airports incur different passenger waiting time cost.

3.5. Number of Passenger in Terminal Cost

The previous cost objective considered, the costs associated with the flow process of individual passengers. It is well know that in any flow process the service cost increases with the number of entities currently held in the system. This also applies to the number of passengers in the airport terminal building at any instant. A review of passengers' complaints and airport redesign projects, reveals that issues related to increasing levels of flow congestion are most important. This congestion is caused by three interrelated problems; the first level of congestion comes from fluctuations of demand, second cause of congestion is related to network and scheduling practices and the third cause of congestion in check-in areas is related to flight scheduling, Ahyudanari, E., and Vandebona, U. (2005). A traditional scheduling method adopts peak and valley banks scheduling practice, which causes congestion pattern associated with these banks. This imbalance in return affects the allocation of airport personnel used in addition to airport infrastructure used Luethi, M., Kisseleff, B., and Nash, A.,(2009), Airports developers and planners require data on airline passenger volumes and their rates of flow at which these passengers can be served at ticket counters, baggage check-in, passenger security screening, and other processing points, these data to be used in designing new airports or expanding existed terminal facilities, and or used to enhance airport efficiency and operational cost, ACRP report 23, (2009).

Airport developers, design passenger terminal facility sized to accommodate the peak hour passenger volumes of a design day, different airports has different distinct peaking characteristics, these differences variation are due in airline schedules; business or leisure travel; long or short haul flights; the mix of mainline jets and regional/commuter aircraft; originating/terminating passenger activity or transfer passenger activity; and international passenger or domestic passenger use, Aspen/Pitkin County Airport Master plan, (2003). That is said, then the airport capacities are set in advance and is fixed, but future demand for airlines transportation is growing rapidly, for instance in US market it is projected that by 2015 there will be 1.1 billion travelers yearly, airport expansion and technology enhancement are not easily obtained yet these expansions alone are not enough to cope with the competition-driven scheduling practices of the airline industry, Loan, L., Donohue, G., It is airport management responsibility to run the airport economically at lower cost at the same time provide satisfaction for airport users (airlines as well as passengers). Since these are important avenues to generate revenues and stay competitive. IATA Airport development manual, (2004), defines the level of services (LOS) for airport planner see Table 3.5 below, it states that LOS C or higher is a standard design goal. For a mega hub that is relays on transfer passenger airport should provide a LOS A or a minimum of LOS B.

Table 3.5 Airport Development Service Levels

LOS A	Excellent level of service; condition of free flow; no delays; excellent level of comfort
LOS B	High level of service; condition of stable flow; very few delays; high level of comfort
LOS C	Good level of service; condition of stable flow; acceptable delays; good level of comfort
LOS D	Adequate level of service; condition of unstable flow; acceptable delays for short period of time; adequate level of comfort
LOS E	Inadequate level of service; condition of unstable flows; unacceptable delays; inadequate level of comfort
LOS F	Unacceptable level of service; condition of cross - flows; system breakdown and unacceptable delays; unacceptable level of comfort

Source: IATA Airport Development Manual (2004).

Terminal planning and design involves balancing a variety of goals, including enhancing safety, security, convenience, efficiency, and aesthetics at the same time it must provide a cost-effective means of providing passengers and the public with a comfortable and pleasant travel experience. For passenger terminals, LOS measures space requirements and passenger comfort in terms of wait times and space per person, Spokane International Airport Master Plan (June 2013).

We align the use and design requirement of LOS, which does not consider operational and economic goals with our objective, cost function for operating mega hub. One should not be conflicted with the fact that airports objective is to maximize passenger volume using the facility, with our objective of minimizing the total volume at any time, we are proposing a solution that only reorder the passenger volume distribution to accommodate with nominal operating resources and constraint of the airport and hence gain operational efficiency for the hub airport and reduce hub cost. Significant crowding within Terminal building is expected to occur upon traditional scheduling practices, see Figure 3.15. Those have an effect in passenger's choice of airports, by avoiding airports that luck of comfort. Today passengers review airports on a variety of standard, as examples of typical passenger review questionnaire for airports see SkyTrax. From the passenger's point of view, the terminal is the most important element of the airport. At the terminal building passenger handles the majority of formalities related to their journey, passengers always compare their time waiting in the terminal to the time of the flight itself. The quality of service during any process at the airport and the comfort provided to the passengers is an important criteria used by passengers for evaluating the airports facilities, Skorupski, J., ARGE Simulation News, No. 35 Proceedings Mathmod (2009), that have an effect in passengers' choice of airport luck of comfort, the redistribution of flight in such away using passenger volume criteria will have a better impact in passengers comfort, as well as in increasing airport throughput. Recent airport designs are characterized by spacious design to ensure: i) a smooth circulation of passengers, ii) adequate waiting areas for large aircrafts at the gate (e.g. Airbus 380) and iii) bear a calming effect on passengers. The new design can be tracked back to Chek Lap Kok Air terminal main concourse; Hong Kong, which was opened in 1998. Airports are designed in such that, there are a percentage of passengers will be seated and the rest will be standing during any period of time, (e.g., 80% are seated and 20 % standing, on other design manuals it is stated as "Area/seated passenger: 17 square feet and Area/standing passenger: 12 square feet", (TRB Airport Design Manual).

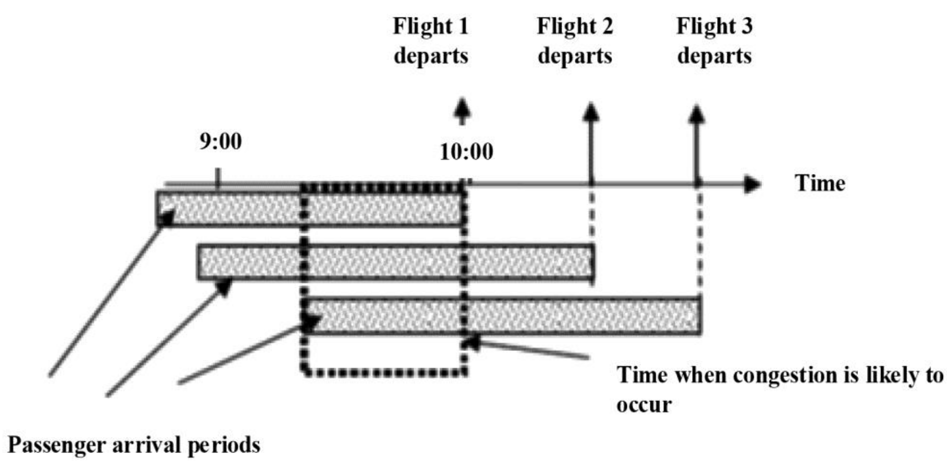


Figure 3.15 display the congestion caused by overlapping passenger arrival periods of three aircraft.
Source: depicted from Ahyudanari, E., and Vandebona, U., (2005).

3.5.1. Passenger in Terminals Objective Function

Our objective is to develop a cost function which represents (i) the airport's cost of maintaining and increasing the number of servers such the passenger service level and overall flow efficiency is not compromised and (ii) the airline's cost due passenger flow delays as a result of the congestion. Clearly, this cost is a function of the number of passengers in the terminal which are described by:

η Total number of passenger waiting time at the airport between their scheduled arrival and departure times.

In traditional flight scheduling methods η is rarely integrated in the modeling practice, but we find it to be of critical importance in SMH operations. Since airports experience varying levels of passengers' volume during the day and during the year analytical models typically focus on the peak hourly passenger loadings that the terminal and its various systems may have to cope with. These loadings are also referred to as "*design hour passengers*", the standard approach is to define the design hour as the 90th (or 95th) percentile busiest hour of the year. Our model uses the design hour to define a three segment objective function (i) Baseline cost – This is the minimum hourly operating cost for passenger flow systems and amenities and is applicable up to 60% of the design hour passenger volume (ii) Low Congestion cost – This is an increasing cost up to 80% of the design hour passenger volume and (iii) High Congestion cost – This is also an increasing cost up to the design hour passenger volume.

V_0 In terminal passenger volume equal to 60% of design hour volume

V_1 In terminal passenger volume equal to 80% of design hour volume

V_2 In terminal passenger volume equal to 100% of design hour volume

$\beta_{V,0}$ Hourly terminal operating cost benchmark at V_0

$\beta_{V,1}$ Hourly terminal operating cost benchmark at V_1

$\beta_{V,2}$ Hourly terminal operating cost benchmark at V_2

$\delta_{V,1}$ Low congestion cost increase rate

$\delta_{V,2}$ High congestion cost increase rate

The congestion cost increase rates are then given by:

$$\delta_{V,1} = \{\beta_{V,1} - \beta_{V,0}\}/\{V_1 - V_2\} \quad (3.5)$$

$$\delta_{V,2} = \{\beta_{V,2} - \beta_{V,1}\}/\{V_2 - V_1\} \quad (3.6)$$

Note that η is not bounded by the volume V_2. The passengers in terminal cost at a given hour are then defined by the increasing piece wise linear function:

$$\phi(\eta) = \begin{Bmatrix} \beta_{V,0} & | & \eta < V_0 \\ \beta_{V,0} + \delta_{V,1}(\eta - V_0) & | & V_0 \leq \eta < V_1 \\ \beta_{V,1} + \delta_{V,2}(\eta - V_1) & | & V_1 \leq \eta \end{Bmatrix} \quad (3.7)$$

Figure 3.16 the cost function $\phi(\eta)$ for three airports ranging from a high to low cost are illustrated. The first airport has a lower infrastructure investment and hence the lowest $\beta_{V,0}$ but as the passenger volume η increases the higher $\delta_{V,1}$ results in a quickly increasing $\phi(\eta)$. The other two airports display other design strategies with both having a higher $\beta_{V,0}$ but $\phi(\eta)$ is lower compared to the first airport. In seeking the optimal flight schedule the objective would be to balance η such that it is primarily in the baseline cost segment.

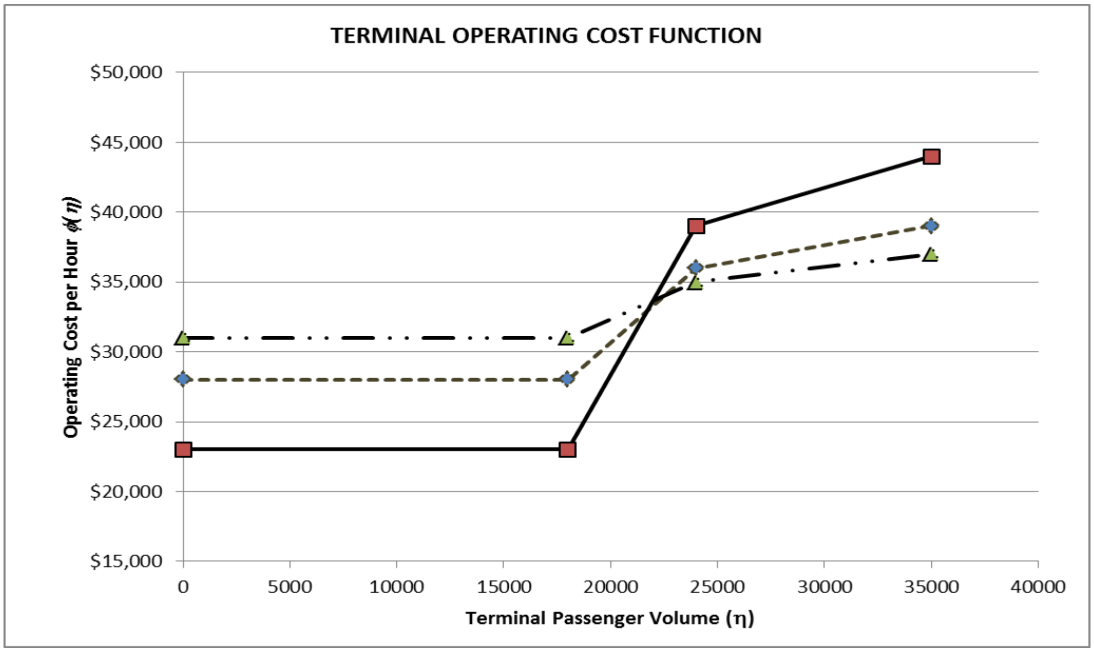


Figure 3.16 Different Airports have different Terminal Operating cost function in terms of passengers' volume.

In addition to a higher cost for building these mega hub airports facilities, the cost associated with it is also higher and will increase dramatically when airlines operates a peak and valley schedule's, as example, cleaning and maintenance cost, energy consumption cost are all dependent in the total number of passengers.

3.6 Ground Traffic Cost to Airport

The ground traffic cost function is developed to balance flight activity through daily operations by attempting to balance the rates of arrivals and departure flights into the hub. A mega hub attempts to achieve temporal co-ordination of the flight schedules airports in waves such that the sum of arrivals and departures in a time block is constant or balanced.

This balance is to enabling flight from/to an airport into available airspace, safely separate flights from other traffic, not to exceed capacity limits, and to make optimum use of the scarce system resources. Perfect balance ensures maximum utilization of flight infrastructure, with little need for surplus capacity. Assigning available capacity of the system with demand to smooth the flows of traffic is a challenging task, imbalances in flight activity volume will result in peak capacity and higher operating costs, as it causes the system airside components to be congested and becoming saturated, e.g., gates, aprons, taxiways, runways, or airspace. For example, departure gates and boarding are responsible for 5-8% of flight delayed as a consequences of congestion on the system, see Table 3.6 below extracted from Schultz, M., and Fricke, H., (2011); the 5 top categories that causes system to become congested, which will results on imbalance of aircrafts activities as well. As gates are fully utilized a significant congestion with the terminal building is expected to occur. Ahyudanari, E., and Vandebona, U., (2005).

Table 3.6 Top 5 Category Causing System Congestion

category : terminal infrastructure and handling processes	**Delayed flights at top 5 airports per category**
Terminal building capacity	Not validated
Baggage handling	2 %
Check – in area / ticket desk	1 – 2 %
Security check	5 – 12 %
Departure gates and boarding	5 – 8 %

Source: Taken from Michael Schultz and Hartmut Fricke.

This congestion or the saturation on airport landside or airside increases airline operating costs for delays require airport to spend additional resources for the handling of aircraft when these vehicles must be held in line ups awaiting takeoffs or landings. In addition, the passengers are adversely affected wasting time as result of these queues, García, A., H., and Moreno Quintero, E., (2011). In today's competitive environment aircraft and airport operations should form an integral part for planning airport activities to ensure greater operational flexibility and improving airport throughput, Miaillier, B., (2011).

As aircraft utilization goes down, a higher penalty is incurred for more resources will be needed. For instance, an aircraft at the gate beyond nominal time will have an impact on the whole system, depending on how much time it needs to further proceeds, Figure 3.17 exhibit a typical Boeing 757 aircraft turn time, on the other hand, runways require supporting taxiways to clear arriving aircraft to the gates, while also providing the flexibility for aircraft to navigate throughout the airport, during peak times these resources are fully equipped hence, arriving aircraft will not be permitted to land unless available resources are ready to handle these aircraft, another sort of low utilization could occur when operators need aprons to store aircraft or else gates and taxiways become de facto parking lots and congestion is likely to occur, the result is unbalancing the flow of traffic to and from the runways, There might be sufficient runway and ancillary airfield capacity, but no available gates, Zupan, J., page 21 (2011).

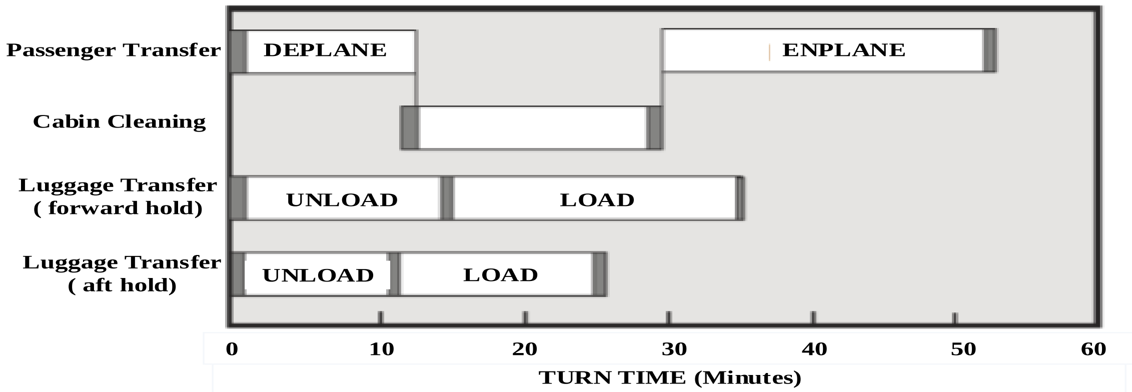


Figure 3.17 Typical aircraft turn time (Boeing 757-200 with 201 passengers) Extracted from ACRP Report 23.

3.6.1. Ground Traffic Objective Function

Our objective is to develop a cost function which represents (i) the airport's cost of maintaining sufficient capacity for aircraft handling and servicing at the design hour rate such that the aircraft turn around efficiency is not compromised and (ii) the airline's cost due aircraft flow delays as a result of the congestion. Clearly, this cost is a function of the current flight activity level, which is described by:

χ Total number of flight arrivals and departures in a given hour.

In traditional flight scheduling methods, χ is typically not a variable of significance. The airline is assigned a slot and will assume the airport is responsible for providing the needed services. In the collaborative model proposed here, χ becomes a key controllable variable. Our model uses the range between balanced and design hour activity rates to define a three segment objective function (i) Balanced Activity cost – This is the lowest ground activity cost and occurs at a volume equal to the perfectly balanced activity rate (ii) Average Imbalance Activity cost – This is the activity rate corresponding to a volume midway between the perfectly balanced and design hour rate and (iii) Design Hour cost – This is the highest activity cost rate corresponding to the peak flight volumes.

F_0	Perfectly balanced hourly flight activity
F_1	Average imbalanced hourly flight activity
F_2	Hourly flight activity at the design hour
$\beta_{F,0}$	Hourly ground equipment operating cost benchmark at F_0
$\beta_{F,1}$	Hourly ground equipment operating cost benchmark at F_1
$\beta_{F,2}$	Hourly ground equipment operating cost benchmark at F_2
$\delta_{F,1}$	Low imbalance cost increase rate
$\delta_{F,2}$	High imbalance cost increase rate

The balanced activity rate is given by:

$$F_0 = \{\textit{Total Number of Daily Arrivals/Departures}\}/24 \tag{3.8}$$

F_1 is defined as the mean point between the balanced and design hour and is given by:

$$F_1 = \{F_0 + F_2\}/2 \tag{3.9}$$

The imbalance cost increase rates are then given by:

$$\delta_{F,1} = \{\beta_{F,1} - \beta_{F,0}\}/\{F_1 - F_0\} \tag{3.10}$$

$$\delta_{F,2} = \{\beta_{F,2} - \beta_{F,1}\}/\{F_2 - F_1\} \tag{3.11}$$

Note that χ is not bounded by the flight activity rate F_2. The ground activity cost at a given hour is then defined by the increasing piece wise linear function:

$$\Psi(\chi) = \begin{Bmatrix} \beta_{F,0} & | & \chi < F_0 \\ \beta_{F,0} + \delta_{F,1}(\chi - F_0) & | & F_0 \leq \chi < F_1 \\ \beta_{F,1} + \delta_{F,2}(\chi - F_1) & | & F_1 \leq \chi \end{Bmatrix} \tag{3.12}$$

In Figure 3.18, the cost function $\Psi(\chi)$ for three SMH airports ranging from a low to high installed infrastructure are illustrated. The first airport has a lower ground infrastructure investment and hence the lowest $\beta_{F,0}$, but as the hourly flight activity χ increases the higher $\delta_{F,1}$ results in a quickly increasing $\Psi(\chi)$. The other two airports, display other design strategies with both having a higher $\beta_{F,0}$, but we can see that the high infrastructure airport has lower flight activity and at higher flight activity levels $\Psi(\chi)$ is lower compared to the other airports. In seeking the optimal flight schedule the objective would be to balance $\Psi(\chi)$ such that it is primarily in the average balance segment.

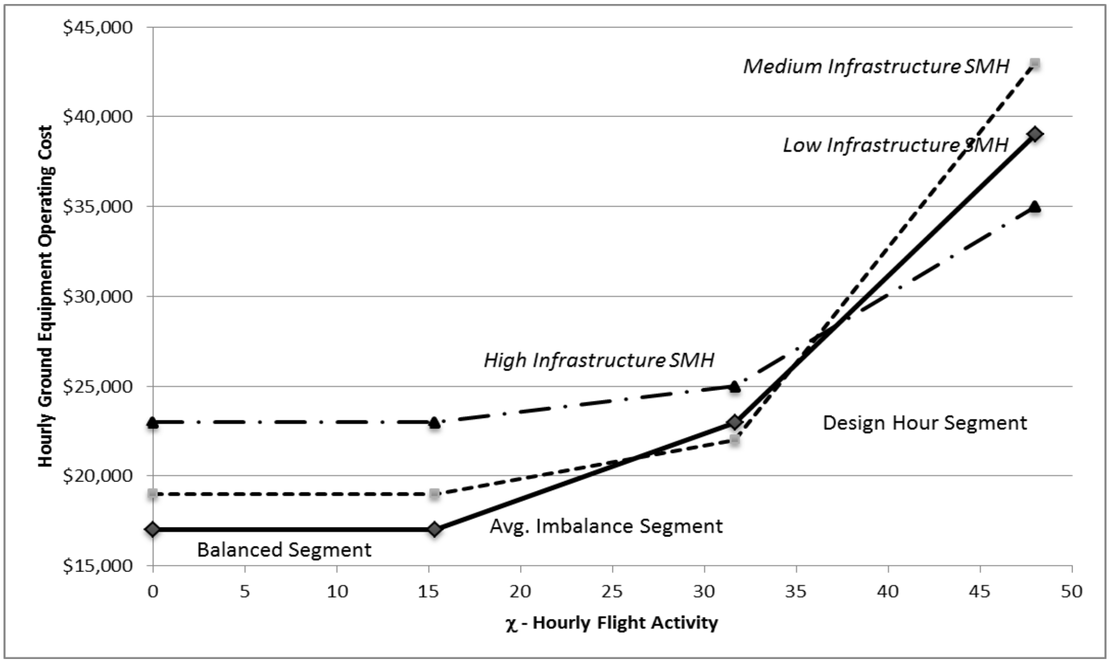


Figure 3.18 Ground Traffic Operating cost function.

3.7 Combined Objective Function

We have presented a three-component objective, which combines passenger-waiting times, number of passengers in the terminal and the ground activity associated with the flight movement levels. The state of the airport at any hour is then given by the vector $\{\mu\tau, \eta, \chi\}$ where $\mu\tau$ is the mean waiting time of the passengers currently in the airport.

Note that η and χ are calibrated in hours and are changing during the day, likewise there are many passengers. To index these state variables, we introduce the subscripts:

k 1 to P, individual passengers transiting through the SMH

t 1 to T where T=24, hourly blocks in the daily schedule, Midnight to 1 am etc.

The expanded state variables are then τ_k, η_t and χ_t. The overall objective function for a given day is then described as:

$$\Pi\{\tau_k, \eta_t, \chi_t\} = \sum_{k \in P} \gamma(\tau_k) + \sum_{t \in T} [\phi(\eta_t) + \Psi(\chi_t)] \tag{3.13}$$

Any effort to improve the flight schedule in a cooperative manner will attempt to minimize the above objective function. In the next chapter we build a simulation model to derive the SMH state vector and hence derive $\Pi\{\tau_k, \eta_t, \chi_t\}$ for a given flight schedule.

CHAPTER 4

DESCRIPTIVE MODEL OF OPERATING COST AT A SELFISH MEGA HUB

This chapter illustrates, the developments and analysis characteristics of the simulator model. The simulator integrates two components; (i) generating passenger volumes, (ii) producing daily schedule cost. The simulator is a tool that is intended to serve as an evaluation tool that helps airport management to run the airport hub efficiently by increasing airport resources utilization. The remainder of this chapter is organized as follows. In Section 4.1, introduction to the simulator and the simulator components. In Section 4.2 the passenger generating matrix component is discussed and illustrated with the key assumptions and related relationship, followed by section 4.3 that illustrate the model objective cost simulator. The objective function components are illustrated in section 4.4. Finally we will discuss the validation process of our work.

4.1 Introduction

Scheduling models are complicated task and researchers are faced with difficulties obtaining certain data such as total number of passengers inflow and outflow around the day to the various spokes using a hub airport, the lack of real data on classifying connected passengers is either these information is kept confidential as a result of the stiff competition between airlines, or luck of interest by parties involved on aviation industry in summarizing the passenger movement data on such categories. This motivated us to develop a cost simulator that will generate the necessary data to validate our cost functions under different scenarios and added realism for the analysis, for instant our research aims to using the retiming of flight techniques to tracking the schedule during `manipulating a flight departure time on the entire time table in order to minimize airport operating cost.

In this section, we present the simulator structures and components. The simulator utilizes the discrete events simulation techniques. The simulator consists of two major components; (i) passenger matrix generator, this tool is used to artificially generates passenger volume for the entire network, and (ii) the objective cost simulator, that calculate the initial daily cost based on airline input, it tracks any changes on the time table instantly and evaluate the cost associated with the proposed changes. The excel based simulator consists of several stages to accurately model the following (i) passenger transits between city pairs, this stage is called passenger generating volume, (ii) accumulated in-terminal passenger volumes at any time, (iii) ground activity cost to track ground cost and maintain aircraft feasibility as we proposed any changes to airline time table, (iv) a daily passenger volumes cost that tracks passengers at any instant during the day.

The excel simulator model is setup to supporting an iterative methodology techniques that is able to identifying candidates flight for rescheduling, which will be discussed later in chapter 5. The excel simulator model is consisting of several worksheets that are connecting together using advanced formula of excel and visual basic applications (VBA).

The first component, is the passenger matrix generator, at this stage passengers volume distribution is generated between the city pair, the passenger distribution volume consist of two subroutines or phases, (i) identify the network regions to generate random numbers accordingly, and (ii) the final passenger volume between the city pairs. The second component of the simulator is the objective daily cost simulator which consists of the three key operating variables (i) passengers waiting time cost, (ii) passenger in terminal cost, and (iii) ground traffic cost. The objective cost simulator is used to generate the daily airport operating cost report as related to flight schedule and tracking the airline schedule feasibility. In addition the supporting subroutines that calculate each individual cost elements is shown in Figure 4.1, the high level of the simulator flowchart.

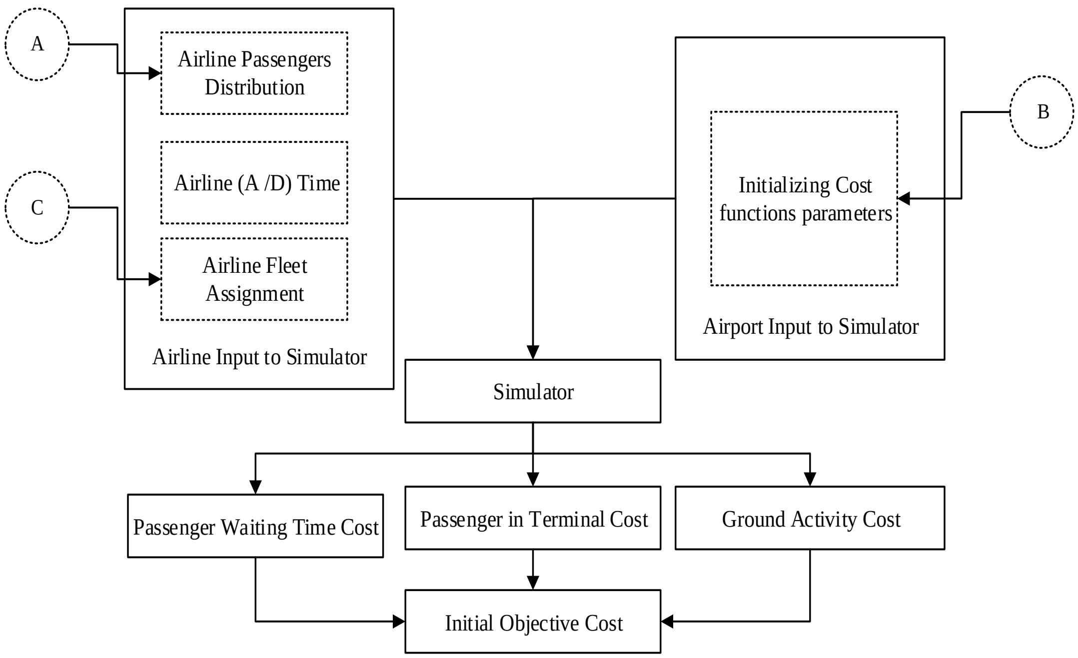


Figure 4.1 The simulator high level flowchart.

The mechanism and the type of input data for the process flow for the combined simulator model is shown in Figure 4.2. In the following sections a detail analysis for these generators and it is combined subroutines A, B, and C are fully explained.

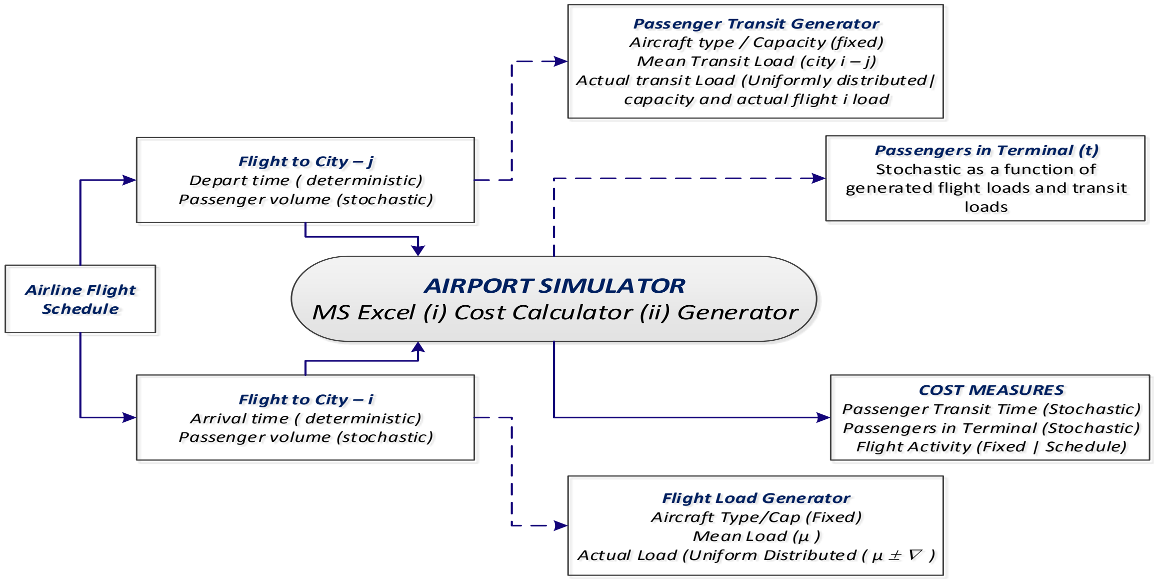


Figure 4.2 Mega hub Cost Simulator Structure.

4.2 Passenger generating Matrix

In this section, we provide a detailed procedure of how to generate passenger volume between the city pairs and give a detail explanation for the methodology of building the passenger volume matrix simulator model and examine all relationship between the equations that were used in developing the passenger volume generator matrix. As mentioned earlier, due to the highly competitive in the aviation sector, the passenger data distribution from the hub to the various cities is not ready and available for our specific use. The purpose of this generator is to provide passenger volume at each city arriving to the airport hub and departing throughout the network. The generated passenger volume will then be used as one of the inputs that are provided by the airline to the airport as previously illustrated in Figure 4.1.

The passenger volume generator matrix, consist of two parts, (i) the generation of random numbers matrix, this matrix is also used to define active arcs from any city, the passenger distribution takes two phases of operation (i) phase 1, at this step a predetermined factors are identified to obtaining active arcs that specified the network size, and (ii) phase 2 generating the final passenger volume from each city in the hub network. Complete details of the two phases are illustrated in Figure 4.3, and Figure 4.4. The two phases are the A subroutine of Figure 4.1 that form one of the airline basic inputs to the simulator.

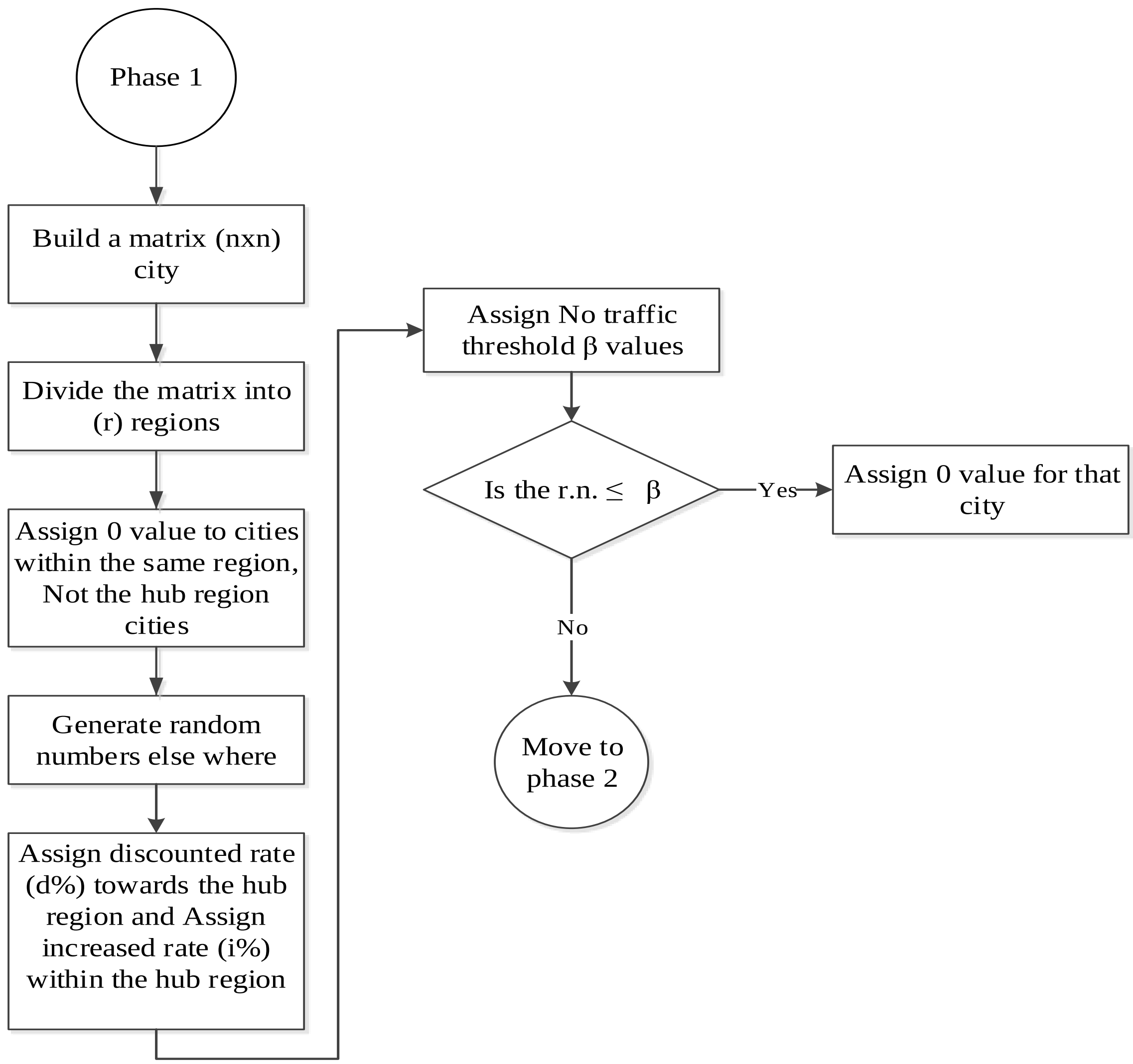


Figure 4.3. Passenger volume generator and distribution for phase 1.

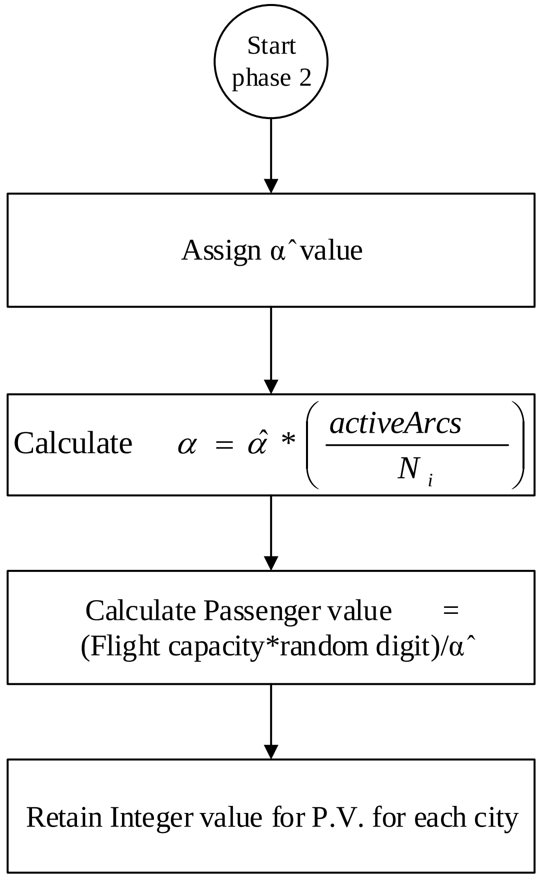


Figure 4.4 Passenger volume generator and distribution for phase 2.

In the process of building the passenger volume simulator, the model assumptions and parameters are first identified as follow; (i) the first step is to define the network size of the airline operating in the hub, this will define the N x N passenger matrix size and the N x N generated random number matrix, (ii) second, divide the passenger matrix into regions, see Figure 4.5 for illustrations, the division of network into region and the serving passenger flow movements. The choice of passenger flow through the hub can be into any direction. The importance of this step is to distinguishing between the active and inactive arcs in the network, for inactive arcs we assign a zero (0) value to the pair city, to offset the waiting time between the city pairs as it will be calculated in the objective cost simulator. In general the inactive arcs are the arcs within same regions such as long haul to long haul, medium haul to medium haul and also long haul to medium haul and vice versa, as an example consider two adjacent city in one region, see Figure 4.6, we exclude passenger traveling between these cities using the hub airport, two reasons behind this assumption, first, the waiting time these passengers will spend at the hub will be longer than direct flights within the same region and hence passengers are discouraged to buy these tickets.

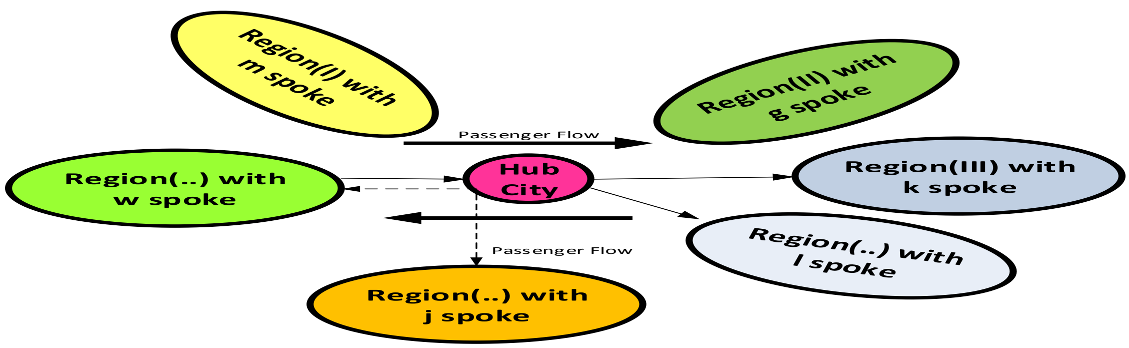


Figure 4.5 Illustration of regions connection through the hub city.

The second argument, related to our assumption regarding the selfish mega hub airports, it is designed to provide a one connection between the different spoke; this connection is passing through the hub only for flights between the spokes of the different region. Once these assumptions are completed the second step is to generate random numbers for all other arcs, which are called active arcs.

A uniformly distributed random numbers on the interval [0, 1] are used, other probability distributions can be used to describe passenger volume movement but our argument behind the use of uniform distribution is to generate passengers volume that will help in analyzing the cost functions and providing analytical illustration for the cost concept of this dissertation and not on studying or analyzing passenger behavior in the system nor to be used as a forecasting tool.

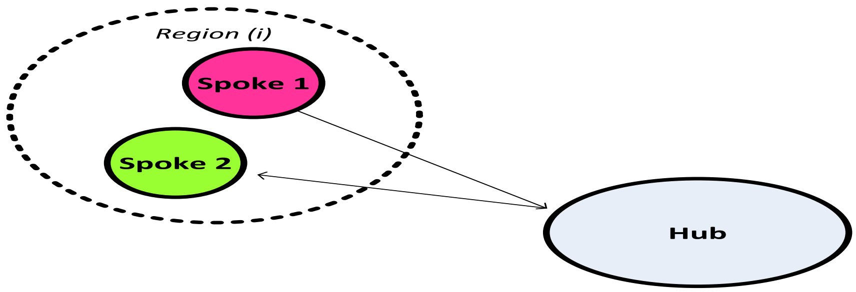


Figure 4.6 Illustration of inactive arcs definition.

The third step consist of imposing additional restrictions on the passenger matrix as follows; (i) a discounted value of *(d %)* is applied to all medium and long haul cells (cities) moving towards the hub city, and (ii) an increased value of *(i %)* which is applied to flights within the hub region. This restriction on passenger volume supports our assumption of the selfish mega hub operation as well as the hub and spoke concepts as more of the traffic is usually generated at the hub than any other spoke in the network.

Finally is to define the no traffic threshold beta (β) value, and a passenger volume concentrator alpha (α) value.

Beta is an input for calculating passenger volume in any city, the assigned beta value is compared to the generated random number at each cell as follow; (i) if beta value is lower than or equal the corresponding generated random number on the generated random number matrix then there will be no traffic and the generated passenger volume at that city is assigned a zero value, (ii) on the other hand, if beta value is higher than the corresponding generated random number then there will be a generated volume at that cell which will be converted into a passenger volume through imposing a function to return an integer value that represent the passenger volume.

Beta can be modified to adjust to any fluctuation to producing a passenger flow volume between the city pairs to be used for the analysis of this dissertation, the choice of beta will affect the current load as higher beta value will produce less passenger distribution concentration through the hub and vice versa.

The other elements of the passenger volume generation matrix is alpha, alpha functionality is another concentrating factor, alpha can be find by

$$\alpha = \hat{\alpha} * \left(\frac{\text{active arcs}}{\mathrm{N_i}}\right) \tag{4.1}$$

where, N_i= total number of active arcs served by city i, cities on the network

Finally passenger traffic between cities pair is obtained by:

$$Passenger\ volume\ = \frac{Flight\ capacity*random\ digit}{\hat{\alpha}} \tag{4.2}$$

The alpha and Beta values are obtained by a trial and error method to accommodate with aircraft capacity between city pairs and it is a unique value for each case under study.

It is important to emphasize again on the use of passenger generating simulator as a substitute for airline real data. If airline real data are available then it will be used as input anywhere we used the passenger distribution data. Also our procedure calls on airlines and airports authorities to categorize future data in such a way that is compatible to our simulator to enable a more accurate analysis. Table 4.1 exhibits passenger matrix output.

Table 4.1 Sample Output of the Passenger Generating Matrix

PASSENGER TRAFFIC BETWEEN CITY PAIRS (100S)									
LOAD RATE	CAP	CURR LOAD	ALPHA	FROM/TO	1	2	3	....	N
0.92	475	398	28.99	1		10	0	......	12
0.96	496	492	40.40	2	11		9	......	9
0.87	316	315	39.26	3	7	6		......	0
......	......	......	......	...	......	......	......		5
0.94	261	246	42.00	N	9	0	3	4	

4.3 Model Objective Cost Simulator

The objective cost simulator consists of the three key operating variables (i) passengers waiting time cost, (ii) passenger in terminal cost, and (iii) ground traffic cost. It also contains a sub-routine to track the airline fleet capacity and locations during any time of the day, this will assure flight schedule feasibility. The above components of the simulator process are all organized within the airport cost analysis simulator (ACA), which will return the initial cost of a given airline input of flight timetable and passengers flow to the hub. The other part of the simulator is the wave gain loss (WGL) optimizer, in chapter 5 we will discuss how both simulator works together to obtaining a potential final cost in more details.

The three key operating variables mentioned above are used to generate the daily airport operating cost report as related to flight schedule. The cost simulator output is organized to return a cost comparison between cost of current timetable (initial airline input) and the potential new timetable (after implementing WGL optimizer solution). Table 4.2 exhibits an example output repot.

Table 4.2 Daily Output Report Sample from 184 Network Size

SINGLE HUB NETWORK MODEL OBJECTIVE				
#	COMPONENT	NEW COST	ORIGNAL COST	COST SAVINGS
1	Passenger Waiting Time	$1,317,517	$1,688,581	22.0%
2	Passengers in Terminal	$481,137	$544,572	11.6%
3	Flight Activity Balance	$471,348	$428,283	-10.1%
	TOTAL	$2,270,002	$2,661,436	14.7%
FLIGHT SCHEDULE INFEASIBILITY				0

The ACA simulator consists of two main parts. The first part contain information that are obtained from the airline, the airline time table, the passengers forecasted volume in flight legs and itineraries, and the fleet assignment, this information is stored on the flight data sector, and is entered at the first stage for the ACA simulator to analyzed it and prepare the basic calculations that are needed on calculating; (i) passenger waiting time, (ii) passengers volume in the terminal and (iii) ground activity at the hub. The second part consist of generating passenger level during the day, his information is used for allocating passenger volume cost on an hourly basis. And the flight activity and flight status on a day on an hourly basis, this information is used to track the infeasibility hours during manipulating departure time as given by the WGL optimizer process.

4.3.1 Arrival Time at the Hub

At this point, it important to mention that there are three sub-problems to the MCFR Problem (i) Both D_{i} and H_i are decision variables, (ii) H_i is fixed and only D_i is a decision variable and (iii) D_i is fixed and only H_i is a decision variable. In this dissertation we explore only a solution to the second problem, that is the case where only D_i is a decision variable. The simulator is built to work under this case.

The arrival time is obtained by adding the departure time to the flight cycle for each spoke is given by the relationship (4.3)

$$\mathrm{A_i} = \mathrm{D_i} + \mathrm{E_i} \quad , \forall\ \mathrm{i} \in \{\mathrm{I}\} \tag{4.3}$$

where, *i* and *j* cities in the network such that $i \in M$ and $j \in M$, departure time D_i of flight to city *i* arrival time A_i of flight from city *i*, and E_i flight cycle time to city ***i***, the time interval between departure and arrival.

Once arrival times from all spoke to the hub are set, the simulator is coded to follow up by calculating waiting time between all spoke in the network, at this point we assumes passengers can travel anywhere in the network using the hub regardless of origin and destination being from the same region, however this restriction is imposed at the cost level calculation of the passenger waiting time cost, the waiting time between connecting pairs *(i, j)* is calculated as follow:

$$w_{i,j} = \begin{cases} D_j - A_i & , \quad if \quad A_i < D_j \\ 24 - (A_i - D_j) & , \quad if \quad A_i > D_j \end{cases}, \ i \neq j \ and \ i,j \in I \tag{4.4}$$

This step is followed by summing up the total number of passenger inflow and outflow at the hub from city *i*, these passengers interested to connect to spoke *j*. The total number of passengers at any time of the day is then found by first identifying airports status in terms of passengers in and out of the terminal, see Figure 4.7 illustrate this idea, passenger at terminal status is then multiplied by the passenger volume to and from city *i*.

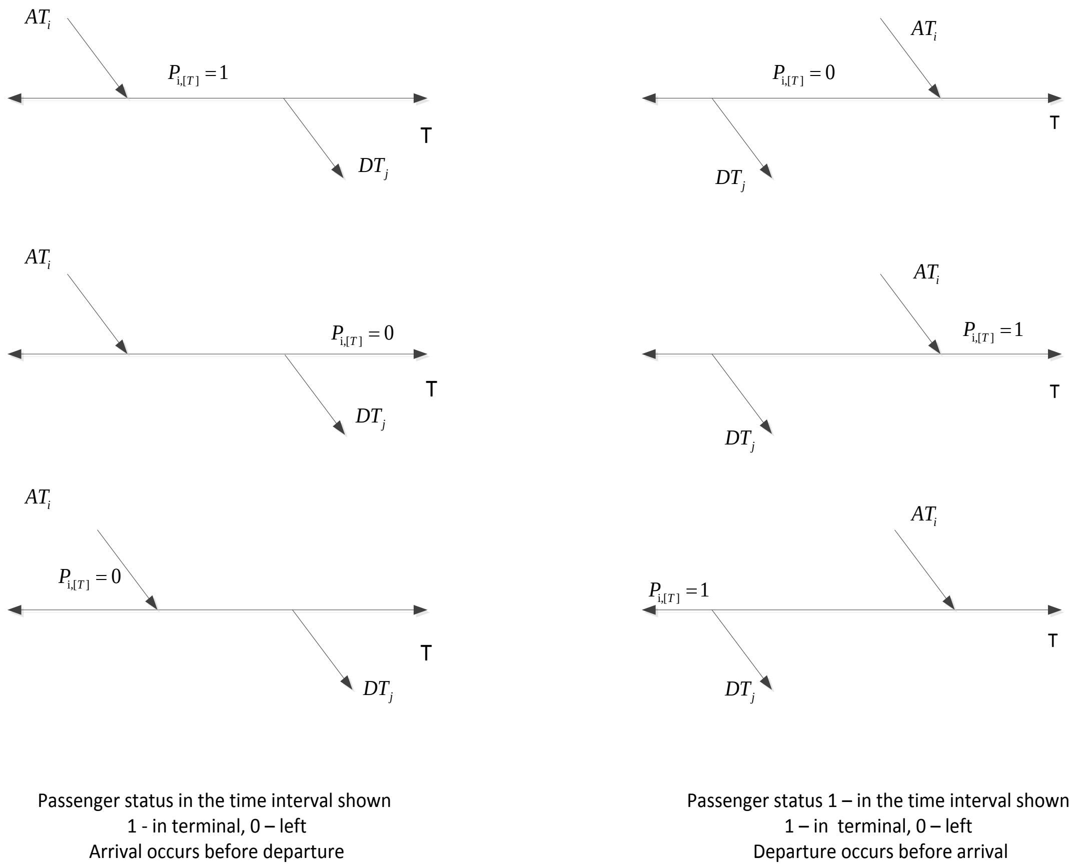


Figure 4.7 Passenger status at any time interval during the day.

In addition, the simulator will take all input data from airline to perform daily summation for (i) full load from city ***i***, (ii) actual load departing to city ***i***. The above calculation form the basic input blocks for the cost simulator to proceeds to the next steps. Figure 4.8 depict the waiting time calculation at the first stage.

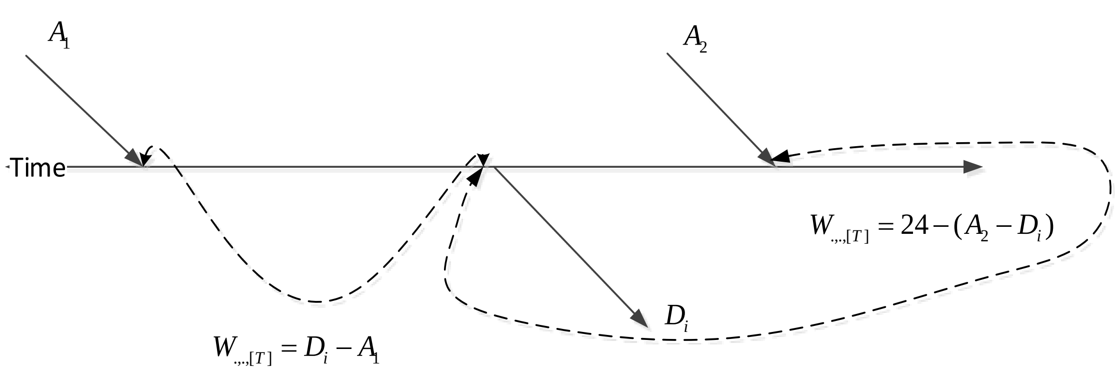


Figure 4.8 Waiting time calculations between city pairs.

4.3.2 Passengers waiting time subroutine simulator

In the process of developing the waiting time cost function, we formulate the followings using the following relationship and results obtained on the previous stage.

We begin with finding the daily frequency count; by summing up the total passengers in time interval. We use an increment of one hour per time interval to facilitate the calculations without losing the essential illustration of the concept of the waiting time operating sub - cost function. Here we define the total passengers that have a waiting time less than specified by the time interval. In order to track these passengers we first identifies city pairs with waiting time specified by the time interval and then sum up passengers corresponding to these city pairs, the daily frequency is then the summation of passengers in all these time intervals. Table 4.3 show sample of passenger waiting time data organization.

Table 4.3 Passenger Waiting Time Cost Distribution Data Collection and Summary

PASSENGER WAITING TIME COST DISTRIBUTION					
PASS WAIT TIME (< Interval)		FREQUENCY COUNT		COST	
Numeric	Hours	Cumulative	Block	Per Pass	Block Total
1.00	1:00	1190	1190	$8.00	$9,520
2.00	2:00	3799	2609	$4.00	$10,436
24.00	23:59	56832	934	$70.86	$66,181
DAILY TOTAL FOR FLIGHT SCHEDULE			56832		$1,688,581

The process of simulating the passenger waiting time are summarized in the flow chart represented in Figure 4. 9 below.

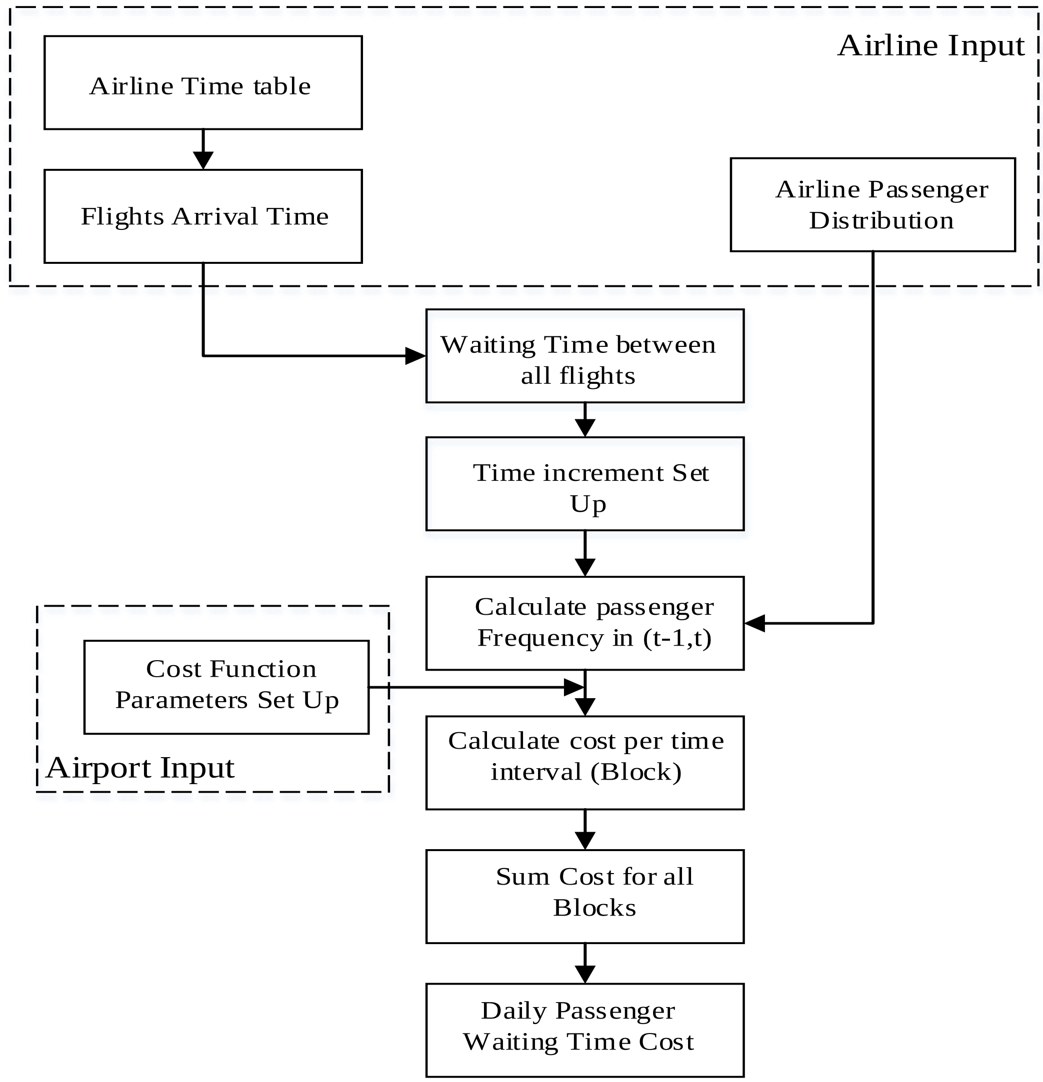


Figure 4. 9 Passenger waiting time sub-routine simulator.

4.3.3 Passengers in terminal sub-routine simulator

The passenger status at any time were calculated during the waiting time cost function and then the total passenger were summed to represent the total waiting time at any instant during the day. In finding the total number of passenger the passenger status is modified to represent an hourly status. At this stage the status will be multiplied by the corresponding passenger volume and summed up. The simulator through passenger level sheet will repetitively find the sum for the airline input time table and updates passenger in terminal calculation. The total for each block time intervals is summed and cost is done according to parameters penalties resulting in the passenger volume daily cost. The process of simulating the passenger waiting time are summarized in the Figure 4. 10.

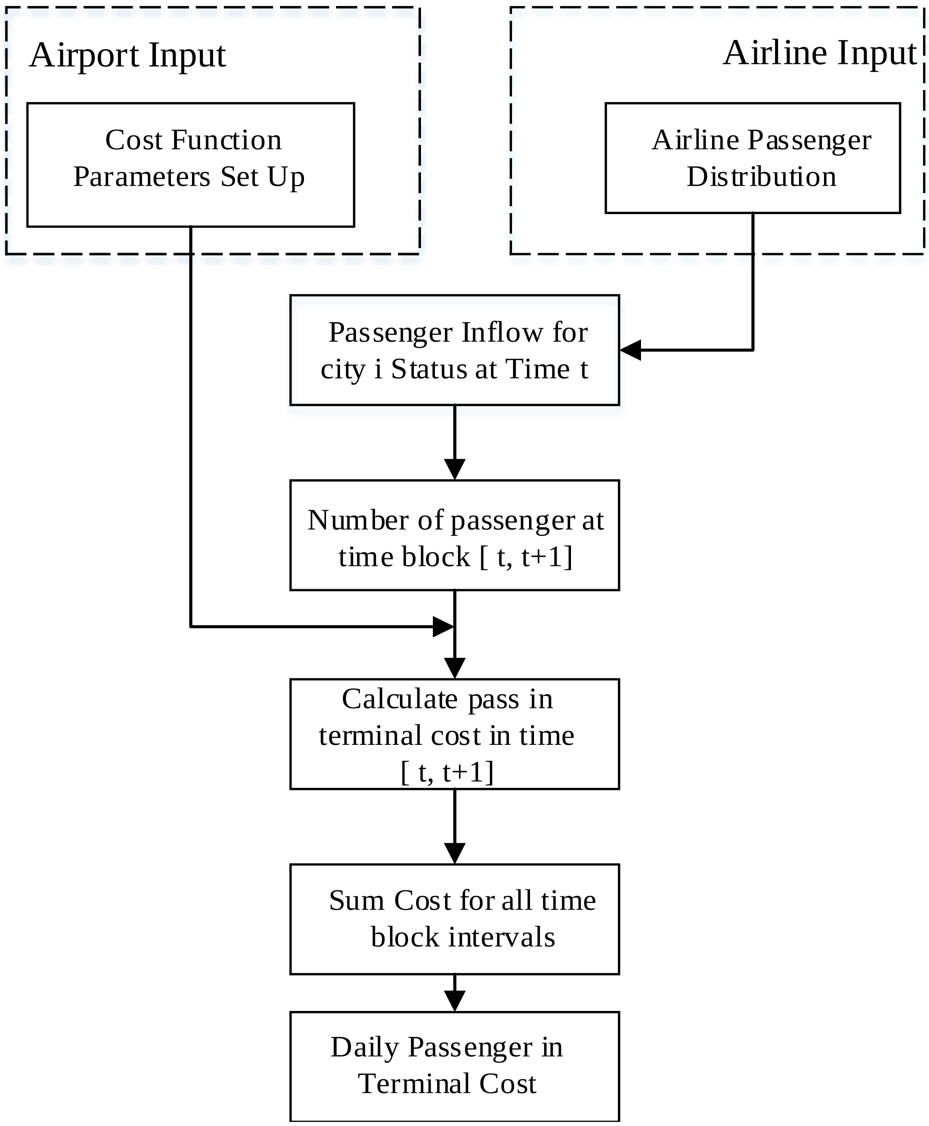


Figure 4.10 Passenger in terminal sub routine simulator.

Table 4.4 below show a sample of passenger status worktable and Table 4.5 show a sample summary table for total passenger in terminal cost during a day.

Table 4.4 Sample of Passenger Status Worktable

passenger status					1 – pass.in terminal 0 – passenger left		given α=0
PASS WAITING	1:00	0.0417	<< Terminal Time				
	City	1	2	3	4	....	N
446	1		1	1	1	....	1
141	2	0		0	1	....	1
116	3	1	0		1	....	1
....	4	1	1	1		....	1
....	5	....	....	....	....		....
....	6	1	1	1	1	1	
35687	TOTAL	114	77	73	175	77	176

Table 4.5 Passenger in Terminal Volume Distribution Data Summary

TERMINAL PASSENGER VOLUME DISTRIBUTION		
CLOCK TIME	PASS COUNT	COST
1:00	35687	$35,961.80
2:00	35008	$35,011.20
3:00	29450	$27,230.00
0:00	28628	$26,079.20
TOTAL COST		$544,572.00

Average Pass Volume	26110
Maximum Pass Volume	38849
Minimum Pass Volume	19284

4.3.4 Ground traffic sub-routine simulator

As mentioned in chapter 3, the ground traffic cost function is developed to balance flight activity through daily operations by attempting to balance the rates of arrivals and departure flights into the hub. A mega hub attempts to achieve temporal co-ordination of the flight schedules airports in waves such that the sum of arrivals and departures in a time block is constant or balanced, the flight activity sub-routine gather the fleet information by a sequence of operations to return the cost at any instant, Table 4. 6 exhibit data collection and cost summary.

Table 4.6 Flight Arrival and Departure Wave Analysis

FLIGHT ARRIVAL DEPARTURE WAVE ANALYSIS						
FLIGHT ACTIVITY DISTRIBUTION						AIR TRAFFIC COST
PASS WAIT TIME (< Interval)		DEP FREQUENCY		ARRIVAL FREQUENCY		
Dig Time	Hours	Cumm	Block	Cumm	Block	
0.04	1:00 AM	0	0	22	22	$19,761
0.08	2:00 AM	7	7	29	7	$16,500
0.13	3:00 AM	23	16	30	1	$17,315
…..	…..	…..	….	…..	….	……….
0.96	11:00 PM	182	7	163	6	$16,500
1.00	11:59 PM	184	2	184	21	$20,250
DAILY TOTAL FOR FLIGHT SCHEDULE			184		184	$428,283
MAXIMUM FLIGHT ACTIVITY			24		24	

Another feature in this subroutine, is aircraft flight schedule infeasibility analysis to track the movement of individual aircrafts within each fleet group, this is done in an hourly bases. At each hour of the day a matrix to return the location of the aircraft either in the hub or active (out of the hub), Table 4.7 below show an example of this matrix, from the information in Table 4.7 we calculate the utilization by dividing total aircraft active (out) by total number of aircrafts.

Table 4.7 Aircraft Flight Schedule Infeasibility Analysis

Aircraft Flight Schedule Infeasibility Analysis											
Clock Time	Aircraft Type										
	1		2		3		4		5		
	Fleet =	12	Fleet =	5	Fleet =	12	Fleet =	15	Fleet =	6	Total
	Flights =	15	Flights =	7	Flights =	8	Flights =	12	Flights =	8	50
	IN	OUT	IN	OUT	IN	OUT	IN	OUT	IN	OUT	Total
1:00	10	6	5	4	4	8	12	7	4	4	29
2:00	10	6	5	4	6	6	12	7	4	4	27
3:00	10	6	5	4	5	7	10	9	6	2	28
4:00	10	6	5	4	2	10	8	11	6	2	33
5:00	8	8	5	4	0	12	7	12	5	3	39
6:00	8	8	5	4	2	10	8	11	4	4	37
7:00	9	7	5	4	3	9	8	11	5	3	34
8:00	8	8	6	3	3	9	7	12	4	4	36
9:00	7	9	6	3	3	9	5	14	3	5	37
10:00	5	11	6	3	3	9	5	14	3	5	42
11:00	4	12	5	4	3	9	5	14	2	6	45
12:00	5	11	5	4	3	9	5	14	3	5	39
13:00	6	10	6	3	3	9	6	13	4	4	39
14:00	6	10	6	3	3	9	7	12	4	4	38
15:00	7	9	6	3	2	10	7	12	4	4	38
16:00	6	10	6	3	2	10	6	13	4	4	40
17:00	6	10	5	4	2	10	5	14	3	5	43
18:00	5	11	4	5	2	10	5	14	3	5	45
19:00	5	11	4	5	2	10	4	15	4	4	40
20:00	6	10	5	4	2	10	4	15	3	5	44
21:00	7	9	5	4	2	10	6	13	3	5	41
22:00	7	9	5	4	2	10	7	12	3	5	40
23:00	10	6	5	4	2	10	7	12	3	5	37
0:00	10	6	5	4	3	9	9	10	4	4	33
DAY ACTIVE CYCLE		1		2		4		7		0	**14**
INFEASIBLE HRS		0		0		0		0		0	**TOTAL**
INF INDEX		0		0		0		0		0	**0**

In order for the simulator to fill this matrix another matrix called flight status at any time summary, see Table 4.8 next. The procedure of ground activity traffic sub-routine cost is summarized in Figure 4.11.

Table 4.8 Sample Table of Flight Status at any Time Summary

Aircrafts Positions at any Time (t)										**0** INDICATES FLIGHT IS ACTIVE
❖ Digital value indicate fleet family										
	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00
	0.0417	0.0833	0.1250	0.1667	0.2083	0.2500	0.2917	0.3333	0.3750	0.4167
FLTSEQ	1	2	3	4	5	6	7	8	9	10
1	4	4	4	4	4	4	4	0	0	0
2	0	0	0	0	0	0	4	4	4	4
3	0	0	0	0	0	0	0	0	4	4
4	6	6	6	0	0	0	0	0	0	0
5	0	0	0	0	0	0	7	7	7	7
6	5	5	0	0	0	0	0	0	0	0
7	7	7	7	7	7	7	7	7	0	0
8	4	4	4	4	4	4	4	0	0	0
9	0	0	0	0	0	0	0	7	7	7
10	7	7	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...
ACTIVE	56	57	73	89	89	66	43	53	103	91

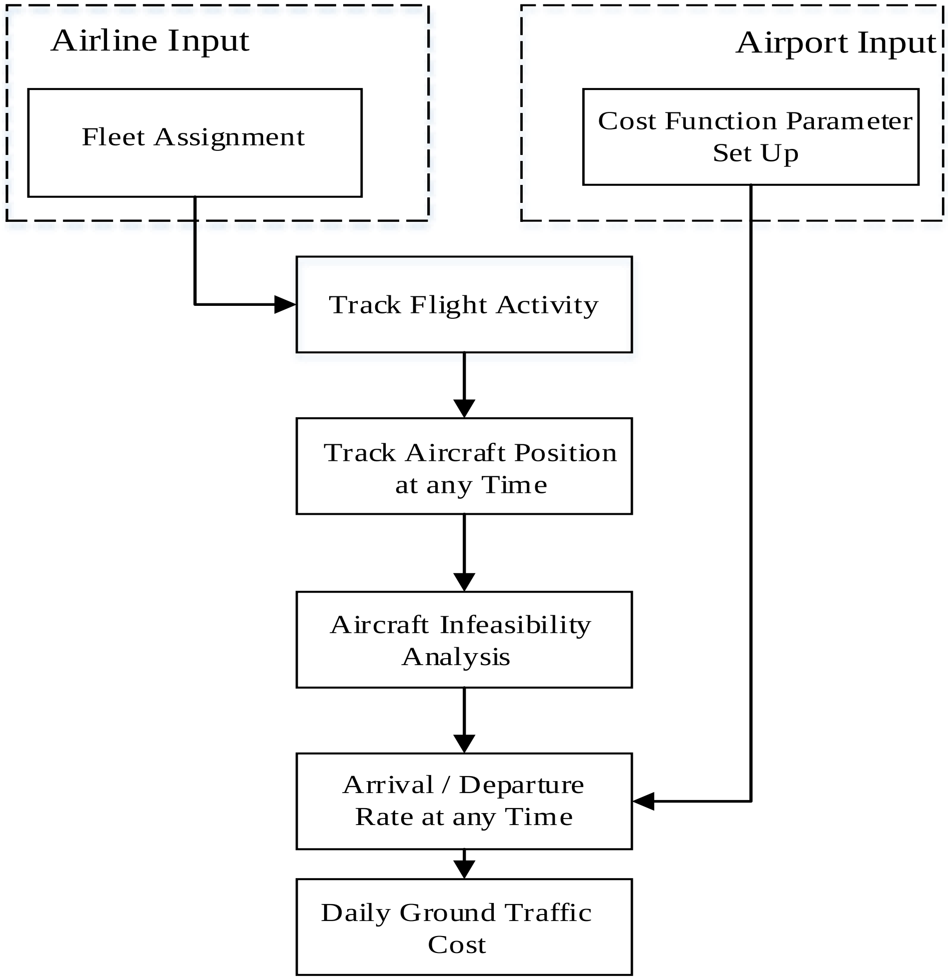


Figure 4.11 Ground activity traffic sub-routine simulator.

The above formulations, are used to manipulate the departure times for flight legs or itineraries that will result on a potential cost reduction. Our cost functions are based on passengers flow into the hub and aircrafts activities on the ground. Airport authorities will be able to reduce the airport operating cost and run the airport more efficiently, at the same time, the airline that is operating at the airport (hub) will manage to spread out it is peaked flights based on actual passengers flow.

4.4 Model Process Validation

As described in the previous sections, these functions varies according to several hub factors and parameters, such as size of airport, size of network, passenger concentration as the main factors in addition to other parameters such as the location, cost of labor and so on. It is essential to prove that this model can work independently from the hub taken into consideration (i.e. with different gradients and offsets of the cost functions).

Due to the difficulty in collecting data of airports cost structure, in order to validate the model, several sets of gradients and offsets has been chosen within a range representative of reality. Thus, to prove that the model can work under different conditions, around 500 combinations of parameters has been generated. For simplicity's sake only five changes in the network were considered, shapes are different, as it will be the daily cost and the optimized schedules that the models in the following chapters will produce. All the optimized schedules, under the 500 sets of different cost functions, have proved to produce a positive savings. The range of savings in percentage of the initial daily cost has shown significant cost reduction. This proves that the model is not sensitive to the type of hub taken into account.

The model has been implemented with the procedures described in the following chapters. In order to validate the model, different airport sizes have been considered with 50, 80, 100, 149 and 184 daily flights of the main airline operating in the hub.

CHAPTER 5

WAVE GAIN LOSS HEURISTIC FOR MEGA-HUB FLIGHT SCHEDULING

This chapter illustrate the developments of the WGL heuristic and analysis characteristics of the simulator model. This chapter is organized as follows. In section 5.1, definition and introduction of the Mega-Hub Collaborative Flight Rescheduling Problem (MCFR). In section 5.2 we explore the WGL approach, followed by section 5.3, that illustrate the WGL heuristic. Finally section 5.4 is implementation of the WGL heuristic.

In chapter 3, we introduced a new objective function $\Pi\{\tau_k, \eta_t, \chi_t\}$ for the collaborative flight scheduling problem between airlines and airport operators. In chapter 4, we developed a simulation based descriptive model which allowed us to estimate the performance metrics τ_k, η_t, χ_t for a given airport and its associated flight schedule. The next research question then following the airport-airline collaboration shown in Figure 3.5, is to develop a method that can iteratively change the initial schedule. This would result in a final schedule that would result in an improvement in Π. In this chapter we develop the Wave Gain Loss (WGL) heuristic to achieve this objective. The WGL heuristic exploits the inherent wave structure of the flight schedules to identify cost reduction opportunities. A key component of the WGL heuristic is an intelligent and intuitive objective functions which looks at the effect of a flight schedule shift on all three components of the objective function $\Pi\{\tau_k, \eta_t, \chi_t\}$.

5.1 Defining the Mega-Hub Collaborative Flight Rescheduling Problem

The starting point for this analysis, is the initial flight schedule developed by the airline. In chapter 4, we described this schedule by the following notation, Note that all time variables are denoted on a 24 hour clock format:

i and j Cities in the network such that $i \in M$ and $j \in M$

D_i Departure time of flight to city i

A_i Arrival time of flight from city i

η_i Days later arrival, η_i= 0, 1 or 2

E_i Flight cycle time to city $\boldsymbol{i}$, the time interval between departure and arrival

The associated passenger flow between city pairs is described by:

$N_{i,j}$ Number of passengers travelling from j to i on a given day and are normally distributed.

The passenger traffic $N_{i,j}$ for a given day is assumed to be normally distributed with parameters $\mu N_{i,j}$ and $\sigma N_{i,j}$. Since there is a single mega-hub all passengers will travel through the mega-hub airport. The flight cycle time is made of two components and defined by:

$$E_i = 24\eta_i + (A_i - D_i) = F_i + H_i \tag{5.1}$$

Where F_i is the sum of the outbound and inbound flying times, and H_i is the hold or ground time at the destination city. There are therefore two controllable or decision variable in the flight schedule: D_i and H_i. Note that H_i will typically have a minimum value dictated by the minimum time required to turnaround the aircraft.

The Mega-Hub Collaborative Flight Rescheduling (MCFR) Problem is then described as determining the flight schedule decision variables D_i and H_i such that the expected value of the schedule sensitive airport operating cost is minimized. The associated objective function has been previously defined in chapter 3 (3.19) as follows:

$$Minimize\colon\ \Pi\{\tau_k, \eta_t, \chi_t\} = \sum_{k\in P} \gamma(\tau_k) + \sum_{t\in T}[\phi(\eta_t) + \Psi(\chi_t)]$$

Where the decision space is constrained such that the number of operating flights by aircraft type, does not exceed the fleet capacity. The effect of D_i and H_i on the objective function variables $\tau_k,\ \eta_t,\ \chi_t$ is determined from the simulation model developed in chapter 4. This can then be used to evaluate the quality of the decision policy generated from any solution method.

As mentioned in chapter 4, there are three sub-problems to the MCFR Problem (i) Both D_{i} and H_i are decision variables, (ii) H_i is fixed and only D_i is a decision variable and (iii) D_i is fixed and only H_i is a decision variable. In this dissertation we explore only a solution to the second problem, that is the case where only D_i is a decision variable.

5.2 Exploring the Wave Gain Loss Approach

In chapter 3, we introduced the different functions which specify the relationships between passengers' flows, flight schedules and the objective function Π. Based on the non-linear nature of these functions our strategy has been to use a heuristic approach to iteratively improve the initial flight schedule. Specifically, we investigated different strategies which would improve Π and then built a heuristic to operationalize the strategy. The strategy investigation leads us to the Wave Gain Loss (WGL) strategy, since this positively impacts the components $\gamma(\tau_k)$ and $\phi(\eta_t)$. The impact on the third term $\Psi(\chi_t)$ is less pronounced.

Iterative strategies are known to be very effective in the scheduling literature and in machine scheduling and we commonly see heuristics whereby a single or pair of entities is manipulated to improve the schedule performance. Here we manipulate one flight at a time. For every departing flight ***i*** there is an associated arrival wave of passengers who will connect to this flight. We assume that every flight is bound to a unique city, which implies that, the arrival wave is 24 hours long, or $\tau \leq 24$ hours for all passengers. Likewise there is a departure wave representing the waiting time for passengers connecting from ***i*** to all other flights. Figure 5.1 illustrates the wave gain loss behavior when there is positive or delayed flight schedule shift, likewise Figure 5.2 illustrates the case when there is a negative or early flight schedule shift. In Figure 5.1 the upper waves show the number of passengers arriving at the mega hub from all flights at time t and connecting to flight i. The lower waves show the number of passengers arriving on flight i and departing at time t. How is the objective function Π affected by a shift in D_i?. Passengers arriving immediately after the departure will have a long wait time, similarly, passengers whose connecting flights departed just after A_{i} will also have a long wait time. An optimization strategy would then be to shift D_{i} such that Π is reduced. Introducing:

Δ_i Shift in the flight departure time such that the new departure time is $D_{\mathrm{i}} + \Delta_i$

For a given Δ_i, Figure 5.1 shows the passengers who will have a resulting gain and those who will have a resulting loss effect on Π for both the arrival and departure waves. For a given schedule and a specific flight we need to prescribe Δ_i such that:

$$\text{Maximize:} \quad \{\Pi \mid D_i\} - \{\Pi \mid D_i + \Delta_i\} \tag{5.2}$$

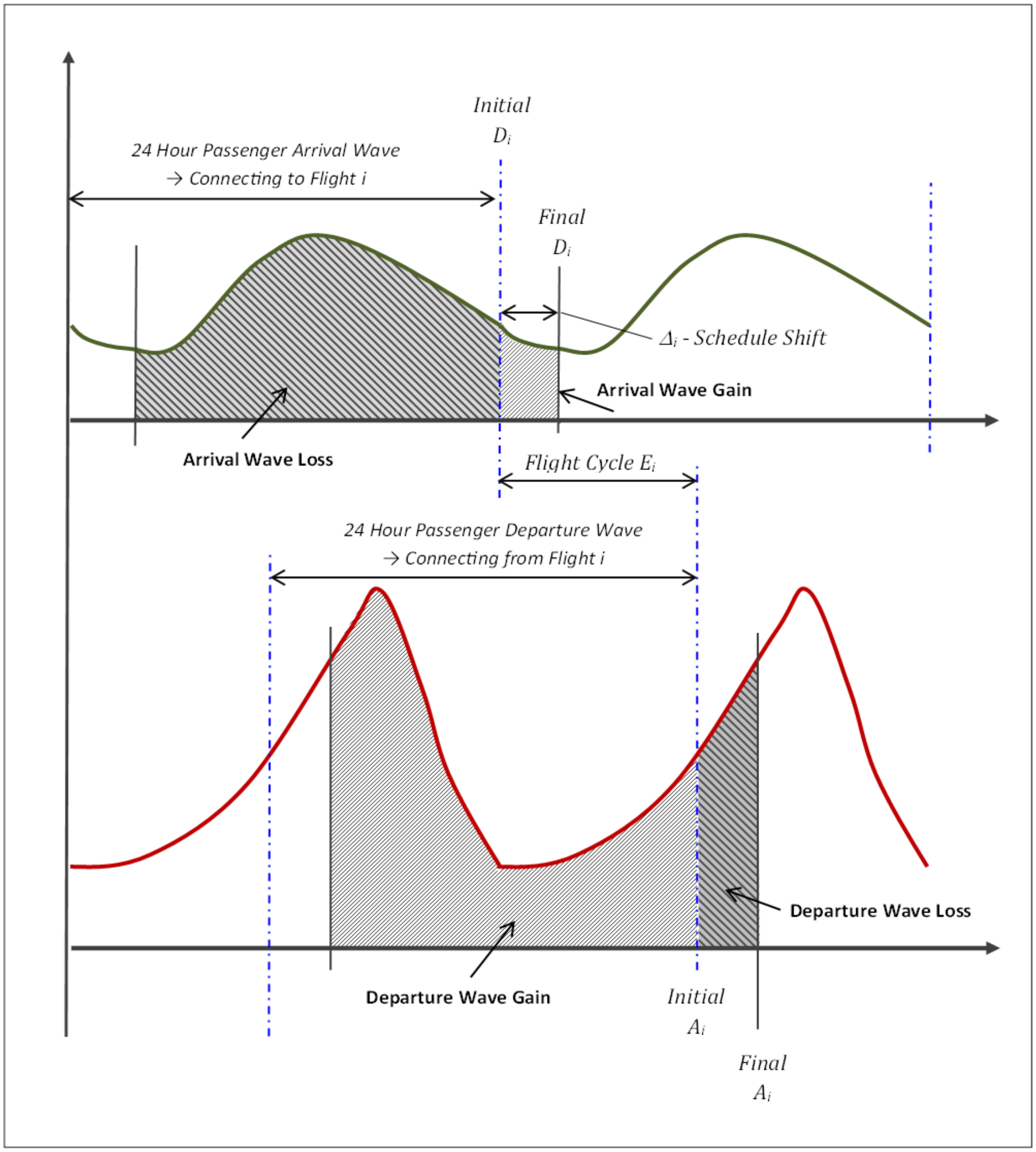


Figure 5.1 Passenger wave gain loss with a positive (delayed) flight departure shift.

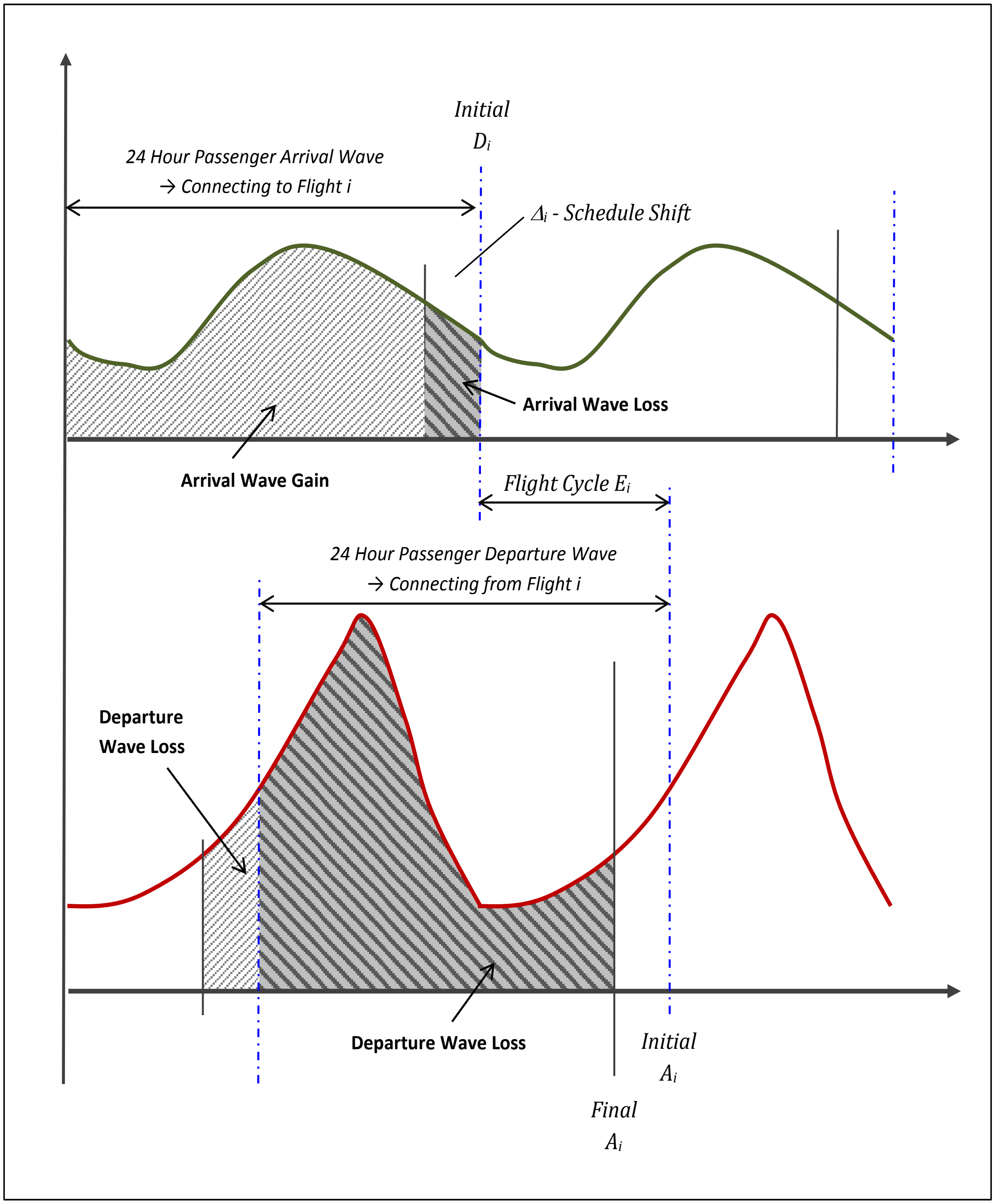


Figure 5.2 Passenger wave gain loss with a negative (early) flight departure shift.

Notice that depending on the wave patterns the numbers of passengers affected are quite different in the departure and arrival sides. We also see from Figure 5.1 and Figure 5.2 that the gain/loss behaviors are inversed between a positive and negative schedule shift. Note that Figures 5.1 and Figure 5.2 only show the number of passengers affected not the overall waiting time or passengers in the terminal. That curve is derived by the product of the X-axis differential and the Y-axis.

5.3 The Wave Gain Loss (WGL) Heuristic

We present the WGL heuristic as a solution to the Mega-Hub Collaborative Flight Rescheduling Problem introduced in section 5.1. We consider only $D_i \mid i \in M$ as decision variables and set H_i at the original holding time. The WGL heuristic is designed as an iterative procedure that reschedules one flight at a time, with the process ending once a stopping condition is reached. At each iterative step the following two decision actions are made:

(i) ***Select*** $\boldsymbol{i^*}$ - the flight that is currently being rescheduled

(ii) ***Identify*** $\Delta_{\boldsymbol{i^*}}$ - the current best flight departure time shift

Since H_i is fixed then A_i is a dependent variable and derived directly from the new D_i. The following notation is introduced in the development of the WGL heuristic:

$W_{i,j}$ Waiting time in transit for passengers arriving from *j* and departing to *i*

$L_{D,i}$ Passenger wait time loss by departure time shift of flight *i*

$G_{D,i}$ Passenger wait time gain by departure time shift of flight *i*

$L_{\mathrm{A,i}}$ Passenger wait time loss by arrival time shift of flight *i*

$G_{A,i}$ Passenger wait time gain by arrival time shift of flight *i*

For a given instance of N_i and the prescribed value of the decision variable Δ_i, then the wave loss and gains are given by:

$$G_{D,i} = \sum_j \{N_{i,j}(24 - \Delta_i) | W_{i,j} > (24 - \Delta_i), W_{i,j} > B_0\} \quad (5.3)$$

$$L_{D,i} = \sum_j \{N_{i,j}\Delta_i | W_{i,j} \leq (24 - \Delta_i)\} \quad (5.4)$$

$$G_{A,i} = \sum_j N_{j,i}\{W_{j,i} - \Delta_i | W_{j,i} > \Delta_i, W_{j,i} > B_0\} \quad (5.5)$$

$$L_{A,i} = \sum_j N_{j,i}\{W_{j,i} + 24 - \Delta_i | W_{j,i} \leq \Delta_i\} \quad (5.6)$$

The above equations account for the U-flat nature of the $\gamma(\tau_k)$ objective and the B_0 condition accounts for the short segment waiting time case where the waiting penalty is inversed. In the next few sections we progressively build up the WGL heuristic, first assuming a condition of independence and then adding other modelling attributes.

5.3.1 WGL Flight Independence Formulation

When a single flight is rescheduled, then it affects only the waiting time of the passengers that are transported on that flight. This allows us to model the isolated problem of shifting a single flight i^* as a non-linear program which prescribes Δ_{i^*} for all flights in the network assuming independence. The flight rescheduling problem when limited to just passenger wait time can then be defined as:

$$Maximize\ Z = \sum_i (Z_i) \tag{5.7}$$

$$\text{where, } Z_i = \left(G_{D,i} - L_{D,i} + G_{A,i} - L_{A,i}\right), \quad \forall i \in M$$

Where gain and loss equations are given in (5.3) - (5.6). The above formulation assumes that the gain loss associated with each flight is independent, but this is not really the case. But in an iterative procedure in which one flight is updated at a time, the above approximation is valid. The above problem is non-linear due to the non-smooth nature of the constraints, but it is amenable to solution using a good non-linear optimizer. In chapter 6, we executed a range of experiments to solve this problem. We used the MS Excel-Solver with the Evolutionary method.

The output of this problem is a rank ordered flight list, which identifies the gains, associated with each flight, the flight with maximum Z_i is ranked highest. An immediate solution to the MCFR problem would be to iteratively implement the flight shifts per this list.

5.3.2 Flight Traffic Affinity – Opportunity Cost

The next step is to extend the above solution by relaxing the independence condition. When a flight i^* is rescheduled, then it may limit the rescheduling gain Z_i of other flights. This could potentially lead to a locally optimal solution and eliminate the opportunity for much larger gains. To account for the lost opportunity cost, we introduce the traffic affinity index between flights, which is the traffic volume on the flight pair that is common to both flight. The traffic affinity index for a pair of flights *i* and *j* is then given by:

$$\rho_{ij} = \left\{ \frac{N_{ij} + N_{ji}}{\sum_{i \epsilon M} N_{ij} + \sum_{j \epsilon M} N_{ji}} \right\} \tag{5.8}$$

When a flight has a high traffic affinity with other ranked flights, as identified in the list generated in section 5.3.1., then the possible lost opportunity is greater. The WGL Heuristic should, therefore be biased towards flights with a lower affinity to higher ranked flights. The objective function in the problem formulated in the previous section is then expanded to:

$$Maximize\ Z = \sum_i \{ Z_i - \sum_j (\rho_{ij} Z_j \mid 0.75 Z_i < Z_j < 1.25 Z_i) \} \tag{5.9}$$

The above non-linear program penalizes flights if they have a high affinity with other flights clustered near them (± 25% range) in the rank order list. Note that the Z_i for each flight remains the same. Flights are now ranked using the above function, as a result flights with a higher Z_i maybe ranked lower. The WGL heuristic is now less likely to generate a local optimum solution.

5.3.3 Integrating the Number of Passengers Objective

The above formulations directly consider only the passenger waiting time objective $\gamma(\tau_k)$, next we extend the WGL heuristic to consider all the number of passengers in the terminal $\phi(\eta_t)$. When a flight i^* is rescheduled then this will shift the transit profile of passengers associated with it and as a result effect η_t in the window $t + \Delta_{i^*}$ for both positive and negative shifts. To improve the efficiency of the WGL heuristic we add the term $\phi(\eta_t)$ to the Z function above.

The WGL solution strategy is summarized by the behavior as exhibited in Figure 5.3 below. For flight i^* the likely impact can be projected from the local gradient of η_t in a time window around the associated departure and arrival points D_{i^*} and A_{i^*}. Note that without loss of generality we track η_t on an hourly clock.

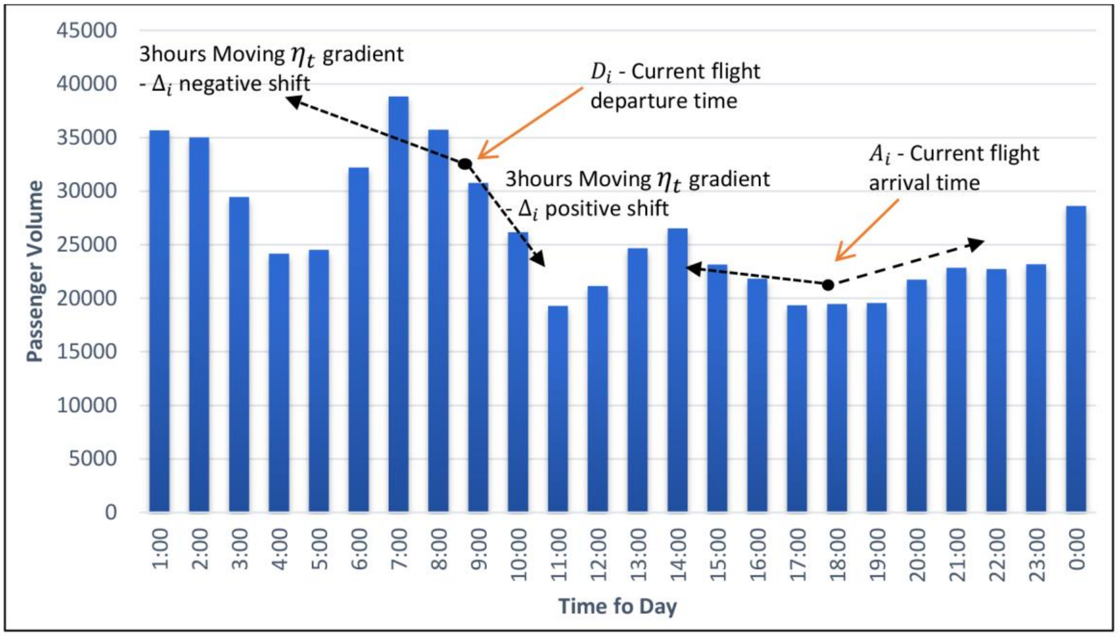


Figure 5.3 Projected effect on η_t by a Δ_i shift.

In Figure 5.3 we see that if flight i^* is rescheduled then it can and will cause a change in η_t on both the front end and back end of D_{i^*}. To integrate the recalculation of η_t for every potential Δ_i shift is not feasible, rather as noted earlier the WGL strategy is to derive the projected impact of a Δ_i shift. In Figure 5.3 a linear model of the projected impact is given from the moving gradient of η_t in the immediate vicinity of *t*. The following notations are introduced:

ω_t	Length of moving window at time *t*
ξ_{t+}	Moving average gradient of η_t in the *t* to $t + \omega$ window
ξ_{t-}	Moving average gradient of η_t in the *t* to $t - \omega$ window

A key factor in the derivation of the gradients is the moving window ω. A short window makes the WGL short sighted while a long window dampens the potential gains since the gradient would progressively tend to become horizontal. By investigating the behavior of η_t we find that ω should be related to the wave length of the arrival/departure wave that flight *i* is a part off. In Figure 5.3 we exhibited the arrival/departure wave pattern typically seen in mega-hubs. When the arrival/departure waves are approximated by a smoothed function then the amplitude for each wave can be explicitly determined. Since the WGL is expected to make flight reschedules which keep the flight within the current wave or the next wave, then ω should be restricted by the wave length, and we set it as follows:

$$\omega_t = {}^{1}/_{2}\ \textit{(Wave length of the arrival/departure wave associated with time t)} \quad (5.10)$$

For every hour in the day the gradients are then derived using the $\omega_t$value for the arrival/departure waves active at time *t*. These are then defined as follows:

$$\zeta_{D_i+} = \left\{\frac{\eta_{D_i+\omega_{D_i}} - \eta_{D_i}}{\omega_{D_i}}\right\} \quad (5.11)$$

$$\zeta_{D_i-} = \left\{\frac{\eta_{D_i-\omega_{D_i}} - \eta_{D_i}}{\omega_{D_i}}\right\} \quad (5.12)$$

$$\zeta_{A_i+} = \left\{\frac{\eta_{A_i+\omega_{A_i}} - \eta_{A_i}}{\omega_{A_i}}\right\} \quad (5.13)$$

$$\zeta_{A_i-} = \left\{\frac{\eta_{A_i+\omega_{A_i}} - \eta_{A_i}}{\omega_{A_i}}\right\} \quad (5.14)$$

For a proposed flight reschedule then the WGL heuristic considers both the passengers level at time *t* and the gradient at that time. The projected impact on $\phi(\eta_t)$ and consequently on Z is estimated by:

Relative impact on Z for a Δ_i shift =

$$\frac{1}{\eta_{Avg}}\left\{\left(\eta_{D_i}\zeta_{D_i+}+\eta_{A_i}\zeta_{A_i+}\middle|\Delta_i>0\right)+\left(\eta_{D_i}\zeta_{D_i-}+\eta_{A_i}\zeta_{A_i-}\middle|\Delta_i<0\right)\right\} \quad (5.15)$$

where, η_{Avg} is the average passengers in terminal value for the day.

The motivation here is that at low values of η_t the overall impact of a flight shift is lower on $\phi(\eta_t)$.

The next step is to translate this impact on a common cost scale relative to the passenger waiting cost, since our Z function above is measured passenger waiting time. This is a derived by scaling the gradients of the $\gamma(\tau)$ and $\phi(\eta_t)$ cost functions introduced in chapter 3.

Relative Cost of Passengers in terminal to Waiting Time =

$$\left\{\left(\frac{B_2-B_0}{\beta_{W,2}-\beta_{W,0}}\right)\left(\frac{\beta_{V,2}-\beta_{V,0}}{V_2-V_0}\right)\right\} \quad (5.16)$$

This relative costs scaling allows us to integrate the impact of passengers in terminal and waiting time into the same Z function. The objective function in the problem formulated in the previous section is then expanded to:

$$Maximize\ Z=\sum_i\left\{Z_i-\sum_j\left(\rho_{ij}Z_j \mid 0.75Z_i<Z_j<1.25Z_i\right)+\right.$$

$$\left.\left\{\left(\frac{B_2-B_0}{\beta_{W,2}-\beta_{W,0}}\right)\left(\frac{\beta_{V,2}-\beta_{V,0}}{V_2-V_0}\right)\frac{1}{\eta_{Avg}}\left\{\left(\eta_{D_i}\zeta_{D_i+}+\eta_{A_i}\zeta_{A_i+}\middle|\Delta_i>0\right)\left(\eta_{D_i}\zeta_{D_i-}+\eta_{A_i}\zeta_{A_i-}\middle|\Delta_i<0\right)\right\}\right\}\right\}$$

(5.17)

The above non-linear program now considers the likely effect of a Δ_i shift on the $\phi(\eta_t)$ component of the objective function.

5.3.4 Integrating the Ground Traffic Objective

The above formulations directly consider only the passenger waiting time objective $\gamma(\tau_k)$ and number of passengers in the terminal $\phi(\eta_t)$ objectives. Next we extend the WGL heuristic to consider the ground traffic activity objective $\Psi(\chi_t)$. Similar to the previous objective when a flight i^* is rescheduled then this will cause a change in χ_t. To improve the efficiency of the WGL heuristic we add the term $\Psi(\chi_t)$ to the Z function above.

The WGL solution strategy here is the same as that used in the previous section, and is summarized by the behavior as exhibited in Figure 5.4 below. For flight i^* the likely impact can be projected from the local gradient of χ_t in a time window around the departure and arrival points D_{i^*} and A_{i^*} as part of the wave it is associated with.

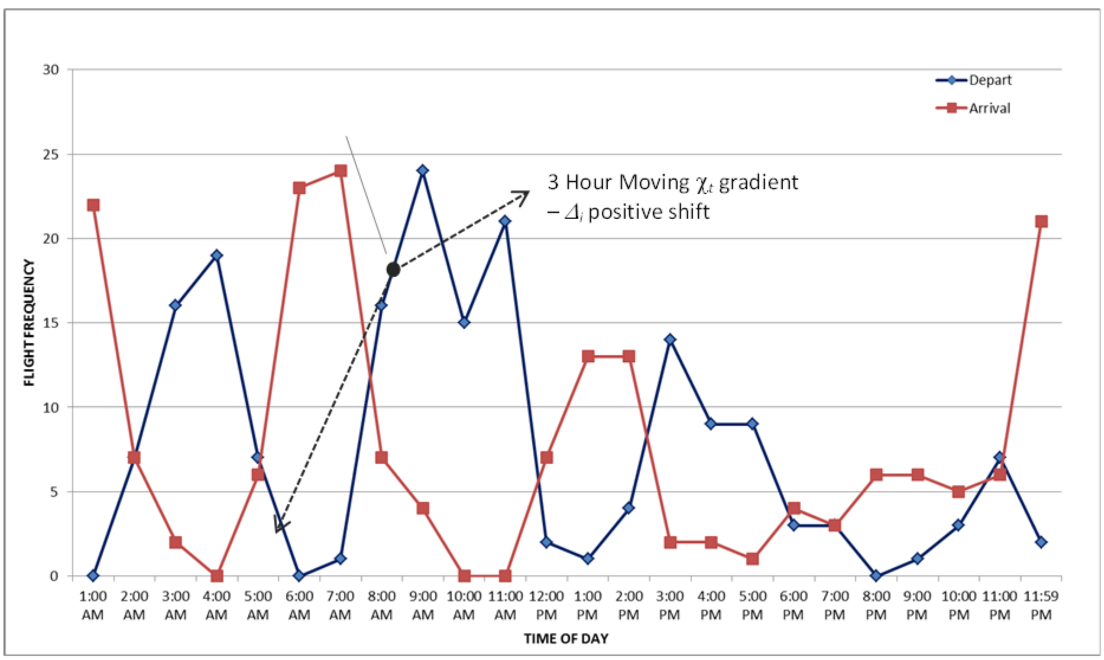


Figure 5.4 Projected effect on $\Psi(\chi_t)$ by a Δ_i shift.

In Figure 5.4 we see that if flight i^* is rescheduled then it can and will cause a change in χ_t on both the front end and back end of D_{i^*}. To integrate the recalculation of χ_t for every potential Δ_i shift is not feasible, rather as noted earlier the WGL strategy is to derive the projected impact of a Δ_i shift. In Figure 5.4 a linear model of the projected impact is given from the moving gradient of χ_t in the immediate vicinity of *t*. The following notations are introduced:

ξ_{t+} Moving average gradient of χ_t in the *t* to $t + \omega$ window

ξ_{t-} Moving average gradient of χ_t in the *t* to $t - \omega$ window

The derivation of the moving window ω was discussed in the previous section and the same holds here. For every hour in the day the gradients are then derived using the ωt value for the arrival/departure waves active at time *t*. These are then defined as follows:

$$\xi_{D_i+} = \left\{\frac{\chi_{D_i+\omega_{D_i}} - \chi_{D_i}}{\omega_{D_i}}\right\} \tag{5.18}$$

$$\xi_{D_i-} = \left\{\frac{\chi_{D_i-\omega_{D_i}} - \chi_{D_i}}{\omega_{D_i}}\right\} \tag{5.19}$$

$$\xi_{A_i+} = \left\{\frac{\chi_{A_i+\omega_{A_i}} - \chi_{A_i}}{\omega_{A_i}}\right\} \tag{5.20}$$

$$\xi_{A_i-} = \left\{\frac{\chi_{A_i+\omega_{A_i}} - \chi_{A_i}}{\omega_{A_i}}\right\} \tag{5.21}$$

For a proposed flight reschedule then, the WGL heuristic considers both the ground traffic at time *t* and the gradient at that time *t*.

The projected impact on $\Psi(\chi_t)$ and consequently on Z is estimated by:

Relative impact on Z for a Δ_i shift

$$= \frac{1}{\eta_{Avg}} \left\{ \left(\chi_{D_i}\xi_{D_i+} + \chi_{A_i}\xi_{A_i+} \middle| \Delta_i > 0 \right) + \left(\chi_{D_i}\xi_{D_i-} + \chi_{A_i}\xi_{A_i-} \middle| \Delta_i < 0 \right) \right\} \quad (5.22)$$

where, χ_{Avg} is the average ground traffic per hour for the day.

The motivation here is that at low values of χ_t the overall impact of a flight shift is lower on $\Psi(\chi_t)$.

The next step, is to translate this impact on a common cost scale relative to the passenger waiting cost, since our Z function above is measured in passenger waiting time. This is a derived by scaling the gradients of the $\gamma(\tau)$ and $\Psi(\chi_t)$ cost functions introduced in chapter 3.

$$\textit{Relative Cost of Ground Traffic to Waiting Time} = \left\{ \left(\frac{B_2 - B_0}{\beta_{W,2} - \beta_{W,0}} \right) \left(\frac{\beta_{F,2} - \beta_{F,0}}{F_2 - F_0} \right) \right\} \quad (5.23)$$

This relative cost scaling, allows us to integrate the impact of passengers in terminal and waiting time into the same Z function. The objective function in the problem formulated in the previous section is then expanded to (5.24) next

$$Maximize\ Z = \sum_i \Bigg\{ Z_i - \sum_j \big(\rho_{ij} Z_j \mid 0.75 Z_i < Z_j < 1.25 Z_i \big) +$$

$$\Bigg\{ \left(\frac{B_2 - B_0}{\beta_{W,2} - \beta_{W,0}} \right) \left(\frac{\beta_{V,2} - \beta_{V,0}}{V_2 - V_0} \right) \frac{1}{\eta_{Avg}} \left\{ \left(\eta_{D_i} \zeta_{D_i+} + \eta_{A_i} \zeta_{A_i+} \middle| \Delta_i > 0 \right) + \right.$$

$$\left. \left(\eta_{D_i} \zeta_{D_i-} + \eta_{A_i} \zeta_{A_i-} \middle| \Delta_i < 0 \right) \right\} \Bigg\} -$$

$$\Bigg\{ \left(\frac{B_2 - B_0}{\beta_{W,2} - \beta_{W,0}} \right) \left(\frac{\beta_{F,2} - \beta_{F,0}}{F_2 - F_0} \right) \frac{1}{\eta_{Avg}} \left\{ \left(\chi_{D_i} \xi_{D_i+} + \chi_{A_i} \xi_{A_i+} \middle| \Delta_i > 0 \right) + \right.$$

$$\left. \left(\chi_{D_i} \xi_{D_i-} + \chi_{A_i} \xi_{A_i-} \middle| \Delta_i < 0 \right) \right\} \Bigg\} \Bigg\} \qquad (5.24)$$

The above non-linear program now considers the likely effect of a Δ_i shift on the $\Psi(\chi_t)$ component of the objective function.

5.3.5 Fleet Feasibility of a Flight Reschedule

The airline is constrained in the number of aircraft by aircraft type that it operates in its fleet. In chapter 4 we modelled the aircraft type associated with each flight. The simulation model monitors the number of aircrafts by that are active at time *t*, and in a feasible solution this number is less than the fleet size. The above non-linear program formulation does not consider this constraint. While it is possible to integrate this constraint into the model we find that it would significantly affect the solution efficiency. Rather the WGL heuristic evaluates feasibility in a separate step after the above program is run. When a flight reschedule is found to be infeasible then it is deleted from the flight change list.

5.4 WGL Heuristic Implementation Steps

Using the above formulation as a basis, we propose the Wave Gain Loss (WGL) heuristic to solve the flight rescheduling problem. The WGL heuristic assumes that the primary driver of the objective function is the passenger waiting time. If this time is decreased then correspondingly the passengers in terminal will also decrease. The logic behind the WGL is to identify the flight, which has the maximum potential gain from a flight departure time shift, and to determine the length of the shift Δ_i.

The WGL is formulated as an iterative solution, which identifies a target flight, then makes a departure shift for the flight, utilizes the Airport Cost Analysis (ACA) simulator to recalculate the objective function and check for feasibility. The procedure stops when a user defined stopping conditions is achieved or no further target flights can be identified. The procedural steps are described as follows:

1. Initialize the heuristic with the original flight schedule described by $\{D_i, A_i, \mu N_{i,j}, \sigma N_{i,j} \mid \text{for } i \in M \text{ and } j \in M\}$.
2. Generate the passenger traffic flow $N_{i,j}$ for a random day assuming the flow is normally distributed.
3. Run the baseline simulation using the original flight schedule and the generated passenger traffic flow $N_{i,j}$. Record the $\Pi_{\text{Base}}\{\tau_k, \eta_t, \chi_t\}$ cost and set $\Pi_{\text{new}} = \Pi_{\text{Base}}$
4. Solve the non-linear optimization problem described by the objective function Z formulated in (5.24).
5. Select C (a solution strategy parameter), which the number of flight changes that will be simultaneously implemented. Higher C values reflect a solution strategy which assumes higher independence between flights reschedules. C is between 1 to M.
6. Create a Z_i ranked list (highest to lowest) of C flight changes $\{i, \Delta_i\}$ from the results of the solution generated in step 4. Note that C is the number of flights to be updated before the WGL regenerates the ranked list of target flights.
7. Repeat steps 8 to 9 below for c = 1 to C.

8. Let i^* be the c *th* flight in the ranked list, then update $D_{i*} = D_{i*} + \Delta_{i*}$ and $A_{i*} = A_{i*} + \Delta_{i*}$.

9. Check the updated flight schedule fleet feasibility. If infeasible skip the flight, since it cannot be rescheduled. Reset the flight times changed in step 8 and return to step 7.

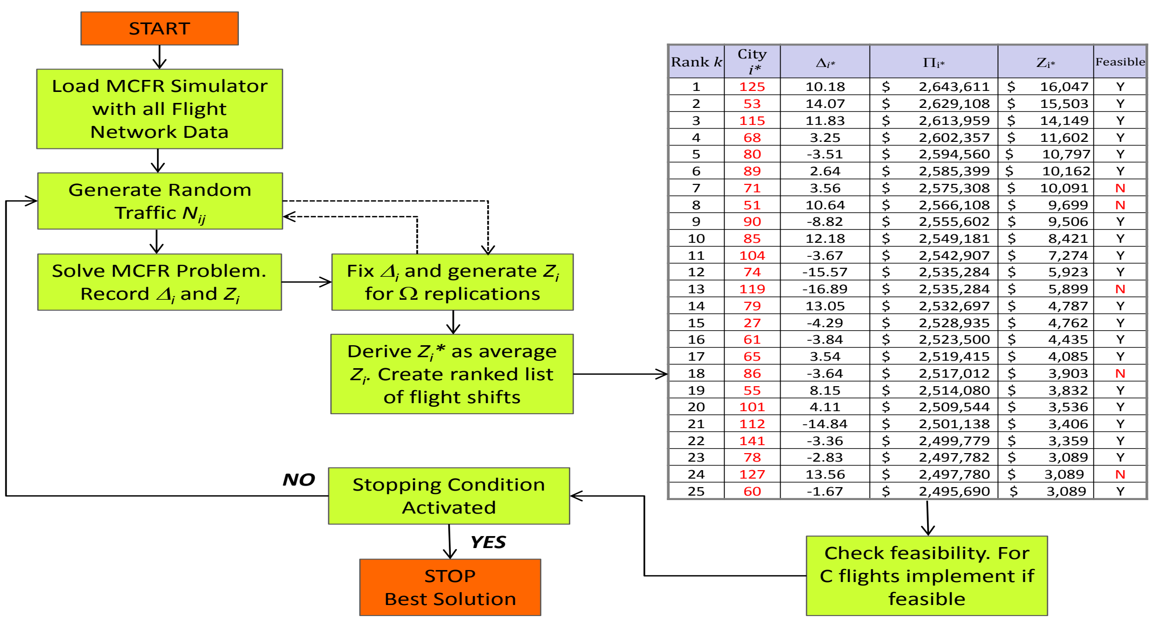
10. For a feasible flight update the schedule for flight c, such that and run the simulator to generate the $\Pi_i\{\tau_k, \eta_t, \chi_t\}$ cost

11. If $\Pi_i < \Pi_{New}$ then the flight reschedule is confirmed. Update $\Pi_{New} = \Pi_{i*}$. Else, the expected gains from a Δ_{i*} shift cannot be realized and the reschedule is retracted. Reset the flight times $D_{i*} = D_{i*} - \Delta_{i*}$ and $A_{i*} = A_{i*} - \Delta_{i*}$.

12. Stopping condition, if the reduction from the last cycle C flight changes was less than 0.5% then further benefits from the WGL heuristic are minimal and the iterative process is stopped.

The WGL heuristic can also be extended to include the limit $\Delta_i \leq W$. For instance if we wish to only consider changes within the same wave, and the wave period is 4 hours then we could set W=4.

Figure 5.5 exhibit the flow chart of the WGL heuristic and working sheet mechanism.



Rank k	City i^*	Δ_{i^*}	Π_{i^*}	Z_{i^*}	Feasible
1	125	10.18	$ 2,643,611	$ 16,047	Y
2	53	14.07	$ 2,629,108	$ 15,503	Y
3	115	11.83	$ 2,613,959	$ 14,149	Y
4	68	3.25	$ 2,602,357	$ 11,602	Y
5	80	-3.51	$ 2,594,560	$ 10,797	Y
6	89	2.64	$ 2,585,399	$ 10,162	Y
7	71	3.56	$ 2,575,308	$ 10,091	N
8	51	10.64	$ 2,566,108	$ 9,699	N
9	90	-8.82	$ 2,555,602	$ 9,506	Y
10	85	12.18	$ 2,549,181	$ 8,421	Y
11	104	-3.67	$ 2,542,907	$ 7,274	Y
12	74	-15.57	$ 2,535,284	$ 5,923	Y
13	119	-16.89	$ 2,535,284	$ 5,899	N
14	79	13.05	$ 2,532,697	$ 4,787	Y
15	27	-4.29	$ 2,528,935	$ 4,762	Y
16	61	-3.84	$ 2,523,500	$ 4,435	Y
17	65	3.54	$ 2,519,415	$ 4,085	Y
18	86	-3.64	$ 2,517,012	$ 3,903	N
19	55	8.15	$ 2,514,080	$ 3,832	Y
20	101	4.11	$ 2,509,544	$ 3,536	Y
21	112	-14.84	$ 2,501,138	$ 3,406	Y
22	141	-3.36	$ 2,499,779	$ 3,359	Y
23	78	-2.83	$ 2,497,782	$ 3,089	Y
24	127	13.56	$ 2,497,780	$ 3,089	N
25	60	-1.67	$ 2,495,690	$ 3,089	Y

Figure 5.5 WGL heuristic flow chart.

CHAPTER 6

EXPERIMENTAL DESIGN ANALYSIS AND RESULTS

This chapter, summarizes results of our experiments for this research, we will explain in details the planning process for the designing the procedures and configurations that were used to analyze the solutions and draw a conclusion to the MCFR Problem. The remainder of this chapter is organized as follows. In Section 6.1, we define the problem size and space. In Section 6.2 the experimental results and the validation process. Finally, we will draw our conclusions and recommendations.

6.1 Defining Problem Size and Space

The evaluation plan was to generate the MCFR Problem for a diverse set of problems, and then generate the performance measure Ω using the ACA simulator and the WGL Optimizer developed in chapter 4. A simulation optimization approach is used to solve the MCFR problem. We define the problem size and the problem space during the planning process. At this stage, of our research we define the main factors of the MCFR Problem that will influence the solution and the performance of WGL heuristic, using Table 6.1 and 6.2. We also define the following factors, to examine their effects on the define cost functions:

(i) Number of Cities in the Network (N), known as network size, here we define 5 different network sizes (levels) these levels are define as (50, 80, 100, 149, and184). Mean Concentration number for each city *i*. This factor is the level of passengers in the network, we define three different levels of passenger flow networks, characterized by low, medium and high traffic concentrations.

(ii) Number of candidate (opportunity) flights (C) to manipulate departure time per iteration, here we define four different control levels as (C = 10, C = 25, C = 50, and C = N).

Table 6.1 Set of Benchmark Problems A

Prob #	# of Cities in Network	Fleet Size	RCN (Routing Concen. No.)	Mean Concen.	Average Load Rate	Total Waiting Time
A1	50	50	5	31%	89%	16937
A2		50		52%	89%	16282
A3		50		64%	89%	4518
B1	80	72	6	35%	90%	19327
B2		72		45%	90%	20696
B3		72		53%	90%	18602
C1	100	94	7	42%	89%	22200
C2		94		52%	89%	23060
C3		94		59%	89%	23662
D1	149	129	8	39%	88%	41126
D2		129		44%	88%	41302
D3		129		56%	88%	39050
E1	184	156	9	35%	87%	56835
E2		156		55%	87%	49630
E3		156		60%	87%	45919

Table 6.2 Set of Benchmark Problems B

Prob #	Passenger in Terminal (volume)			DAILY Flight Activities					
				SCHEDULE RATE		MAXIMUM		Median Activity	
	Avg Pass	Max Pass	Min Pass	Dept. Rate	Arrival Rate	Dept. Activity Rate	Arrival Activity Rate	Dept	Arrival
A1	7800	10870	5627	50	50	6	5	1.5	2
A2	7497	10143	5351	50	50	6	5	2	2
A3	2139	2938	1508	50	50	6	5	2	2
B1	9421	12995	7194	80	80	8	8	3	3.5
B2	10135	13654	7683	80	80	8	8	3	3.5
B3	8975	12078	6664	80	80	8	8	2	3.5
C1	10608	13435	8311	100	100	9	9	3.5	4.5
C2	10928	13968	8438	100	100	10	9	3	4.5
C3	11238	14472	8399	100	100	9	9	3.5	4.5
D1	18666	28695	13089	149	149	21	21	4	3.5
D2	18812	28622	12950	149	149	20	20	4	3
D3	17870	25881	12169	149	149	21	17	3	4.5
E1	26110	38849	19284	184	184	24	24	5.5	6
E2	23021	33725	17401	184	184	21	25	5.5	6
E3	21583	30189	16077	184	184	20	23	5.5	6

The above factors set at the different levels give a total of 57 different problem. Figure 6.1, shows the hierarchy of the problem. In order to minimize the statistical bias in the experiment, and to draw a valid statistical conclusion about the performance of the WGL, we plan to run the defined problem in a random order. We use Minitab statistical software to aid in designing the sequence orders run, and in analyzing output. Table 6.3 shows the sequence of running all experiments.

Table 6.3 Design Table (Randomized)

Run	Blk	A	B	C	Run	Blk	A	B	C	Run	Blk	A	B	C	Run	Blk	A	B	C
1	1	5	1	3	16	1	5	2	1	31	1	5	2	3	46	1	3	2	3
2	1	4	2	4	17	1	4	1	1	32	1	3	1	3	47	1	3	1	4
3	1	2	1	1	18	1	1	2	2	33	1	2	2	3	48	1	4	2	1
4	1	2	2	4	19	1	2	1	4	34	1	5	3	1	49	1	3	3	1
5	1	1	2	4	20	1	4	1	3	35	1	3	2	4	50	1	4	3	3
6	1	5	3	2	21	1	1	3	2	36	1	2	2	2	51	1	3	2	1
7	1	1	1	1	22	1	3	2	2	37	1	4	2	3	52	1	5	1	1
8	1	2	1	2	23	1	4	2	2	38	1	5	1	4	53	1	3	3	2
9	1	1	3	3	24	1	2	1	3	39	1	3	3	4	54	1	1	3	4
10	1	2	3	3	25	1	1	1	4	40	1	1	2	3	55	1	5	2	4
11	1	2	3	2	26	1	4	3	2	41	1	5	2	2	56	1	1	3	1
12	1	2	3	1	27	1	3	3	3	42	1	2	2	1	57	1	1	1	3
13	1	5	1	2	28	1	4	1	4	43	1	4	3	4	58	1	1	1	2
14	1	4	1	2	29	1	1	2	1	44	1	4	3	1	59	1	5	3	3
15	1	5	3	4	30	1	3	1	1	45	1	3	1	2	60	1	2	3	4

Network size defined by the randomized table as factor A and it is set on five levels as follows: 1 for network size 50, 2 for network size 80, 3 for network size 100, 4 for network size 149 and 5 for network size for 184. The mean concentration factor, is define as B and is set in three levels as follow: first level for passenger concentration is A1, the second level for passenger concentration is A2, and the third level for passenger concentration is A3. Finally, the number of flight change factor, is define as C and is set at four levels as follow: level one, for C = 10, level two, for C = 25, level three, for C = 50 and level four, for C = N. As an example, the first experiment run we conducted is indicated by the code (last 3 digits) 5 1 3 as Network size 184 the A2 level of passenger concentration and C = 10.

We planned to conduct four hypothesis tests to evaluate the performance of the WGL, The hypotheses we plan are as follows: (i) evaluate the performance of WGL as we change the network size, (ii) evaluate the performance of the WGL as passenger concentration change, (iii) evaluate the performance of WGL as the number of flights (C) changes, and (iv) compare the performance of WGL other heuristics.

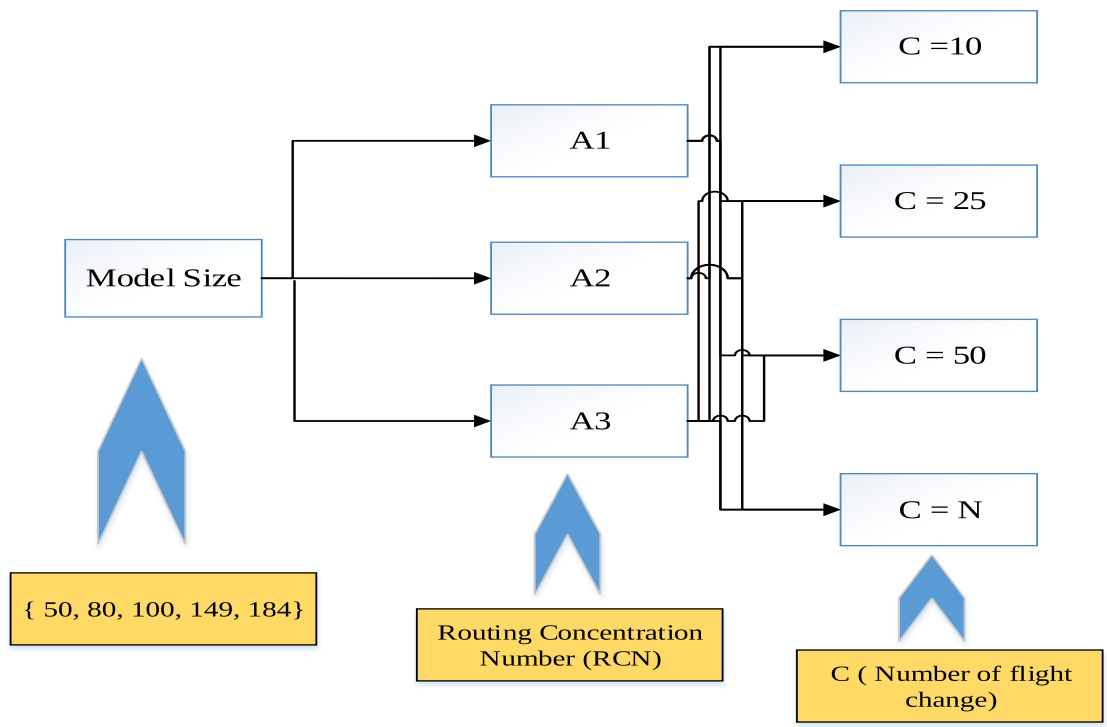


Figure 6.1 Problem space.

6.2 WGL Test and Experimental Analysis

In this section, we provide computational results for all sets of experiments. Results obtained from each simulation run, is then summarized in a table, the final output table is first examined using basic statistic charts done by excel, then moved to Minitab for statistical tests of our hypotheses. We first start by running initial 10 replication for each set of problem, the order of the run follow the design of experiment shown in Table 6.3.

6.2.1 Replication Estimate for the Experiments

Simulation experiments are inherently characterized by errors or measure variance. For a valid study the simulation replication number should be estimated to get more accurate experimental results. To estimate the valid number of replications under certain half width, the following definitions and equations are used. Standing as the most direct output value, half width is just showing everywhere after mean value in the simulation experiment. If a value is returned in the Half Width category, this value may be interpreted by saying "in 95% of repeated trials, the sample mean would be reported as within the interval sample mean ± half width." The half width can be reduced by running the simulation for a longer period of time, or by running more replications as not enough replication times will lead to "insufficient" in the half width. In this experiment we design to run a number of replications as indicated by. Experiments with baseline problems an initial simulation run of 10 replications, 95% half-width were conducted to report Ω and half width. Then using the above formulas the number of replication is find and reported in Table 6.4.

Table 6.4 Simulation Replication for Test Problems

Prob #		A			B			C			D			E		
		1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
# of Replications	m = 10	196	185	189	196	187	162	147	135	131	115	189	159	114	154	147
	m = 25	172	195	139	190	199	175	144	163	182	163	181	144	182	168	159
	m = 50	128	153	120	146	136	177	137	165	121	178	172	146	164	130	137
	m = N				152	108	155	101	143	168	121	132	174	184	175	109

The first half is about the mathematic equation for half width which would derive to an equation which has "n" on both sides (*). Introducing the following notation:

N = number of simulation replications

$\bar{x}$ = sample mean

s = sample standard deviation

$t_{n-1,1-\alpha/2}$ = critical value from t tables, or using excel function [T.INV.2T (probability, n)], the confidence interval is then obtained using: $\bar{X} \pm t_{n-1,1-\alpha/2}\frac{s}{\sqrt{n}}$

The first half is about the mathematic equation for half width which would derive to an equation which has "n" on both sides (*). The second half is an approximation method to estimate the "n" which is the number of replications.

Approximation:

- Replace t by z, corresponding normal critical value
- Pretend that current "s" will hold for larger samples
- Get $n \cong {z^2}_{1-\alpha/2}\frac{s^2}{h^2}$ (where s=sample standard deviation from "initial" number n_0 of replications. Table 6.5 summarizes results obtained from the simulation.

Table 6.5 Summary Data Output from the Simulation

Model Size	Prob #	% of Gain							
		m = 10		m = 25		m = 50		m = N	
		Ω Mean	Ω Half Width	Ω Mean	Ω Half Width	Ω Mean	Ω Half Width	Ω Mean	Ω - Half Width
50	A1	3.533%	0.372%	5.896%	0.359%	7.520%	0.521%		
	A2	3.366%	0.255%	6.761%	0.495%	7.963%	0.508%		
	A3	2.038%	0.199%	3.211%	0.301%	3.564%	0.375%		
80	B1	2.977%	0.071%	4.369%	0.107%	5.324%	0.118%	6.117%	0.150%
	B2	3.012%	0.092%	3.995%	0.314%	5.145%	0.220%	6.351%	0.917%
	B3	2.084%	0.087%	5.509%	0.196%	6.505%	0.217%	6.592%	0.258%
100	C1	8.203%	0.300%	9.234%	0.337%	14.027%	0.394%	12.969%	0.476%
	C2	8.244%	0.372%	11.681%	0.471%	14.029%	0.614%	14.794%	0.728%
	C3	8.979%	0.587%	11.349%	0.733%	16.196%	1.170%	16.969%	1.004%
149	D1	9.754%	0.122%	12.260%	0.093%	12.674%	0.099%	13.458%	0.139%
	D2	10.682%	0.132%	11.666%	0.140%	10.623%	0.174%	12.454%	0.182%
	D3	9.816%	0.227%	13.237%	0.206%	14.878%	0.297%	13.594%	0.275%
184	E1	14.708%	0.166%	12.124%	0.336%	16.294%	0.141%	14.997%	0.121%
	E2	6.089%	0.122%	10.237%	0.494%	13.200%	0.189%	15.358%	0.134%
	E3	11.498%	0.147%	15.370%	0.253%	13.521%	0.181%	15.794%	0.290%

6.2.2 Simulation Output Results Using the WGL heuristic

The simulator will use the passenger waiting time matrix obtained from the airline input as mentioned in chapter 4 , using excel solver with evolutionary option as this problem is a non-smooth, non-linear, the output results are then summarized in Table 6.6. The simulator will transfer these results immediately to Table 6.7. The output is then transferred to ACA cost simulator using VBA codes.

Table 6.6 Summary output of WGL Optimizer

DELAY =	19:50	22:45	4:57	23:35	3:05	18:52	0:31
	4:09	1:14	19:02	0:24	20:54	5:07	23:29
D-GAIN =	1032.4	342.9	1637.9	130.8	1401.2	875.2	681.0
D-LOSS =	634.8	0.0	1293.1	0.0	790.2	1548.3	144.7
D-NET =	397.7	342.9	344.8	130.8	611.0	-673.1	536.3
A- Net =	1398.4	-298.0	872.9	173.6	351.0	1291.6	112.6
Final GAIN =	1796.1	44.9	1217.7	304.4	962.0	618.5	649.0

Table 6.7 Ranking Output Sample from the WGL Optimizer

RANK	9	41	19	33	21	30	28
FLIGHT #	1	2	3	4	5	6	7
OLD TIME	9:30 AM	8:25 AM	9:10 AM	5:25 AM	9:35 AM	5:24 AM	5:30 AM
NEW TIME	5:20 AM	7:10 AM	2:07 PM	5:00 AM	12:40 PM	12:16 AM	6:01 AM

The ACA simulator will set up to monitor the iterative process per single flights Table 6.8 is an example of this table layout.

Table 6.8 ACA Simulator Sample Monitoring Flights Iterations

Total Cost Z_k	Start	$ 1,275,199	CURRENT SOLUTION - *k*	
	End	$ 1,228,949	TOTAL	$1,228,949
	GAIN	$ 46,250	INFEASIBILITY	0
	% GAIN	3.63%	INF SOLNS	0

The simulator will summarize the WGL progress by providing different charts Figure 6.2 is an example of one of the solved problems, this figure shows the progress of the WGL for different C policies.

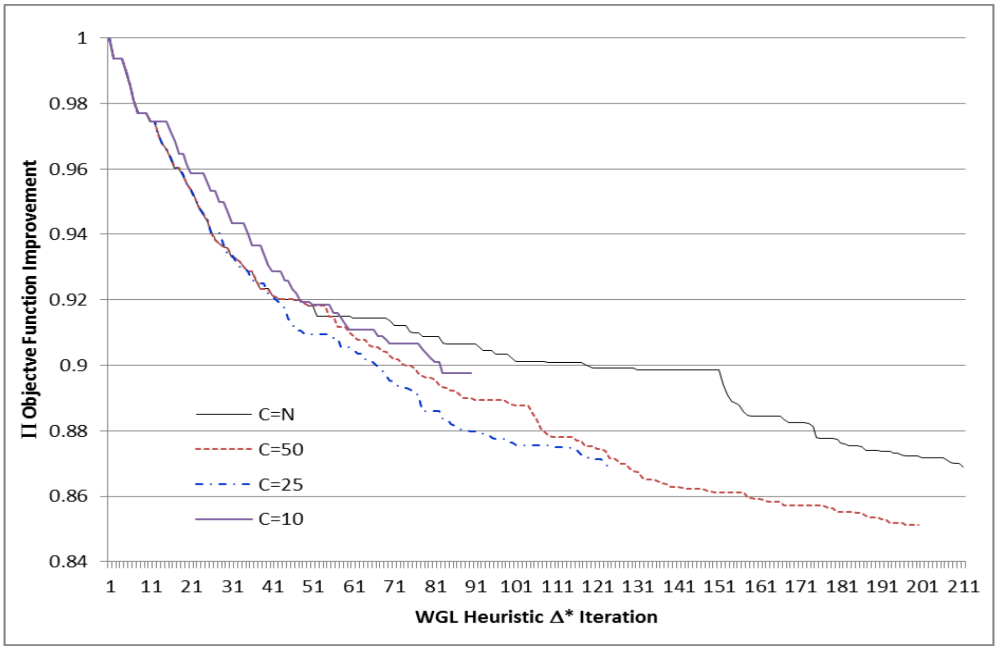


Figure 6.2 WGL heuristic progress chart under different C policies.

6.2.3 Hypotheses evaluation of the WGL heuristic

As mentioned earlier, we planned to conduct four hypothesis tests to evaluate the performance of the WGL. The hypotheses to be tested are as follows: (i) evaluate the performance of WGL as we change the network size, (ii) evaluate the performance of the WGL as passenger concentration change, (iii) evaluate the performance of WGL as the number of flights (C) changes, and (iv) compare the performance of WGL other heuristics. In this section we also use Minitab 17 statistical software for further analyzing the four mentioned hypotheses, in addition the ACA cost simulator results and graphs are used.

I. Evaluating the performance of WGL as network size change

The output results of the ACA Cost Simulator, are summarized and shown graphically in Figure 6.3 shows network size under the three different levels of the RCN and C = 10. In

Figure 6.4 network size under the 3 different levels of the RCN and C = 25, and Figure 6.5 it shows network size under the 3 different levels of the RCN and C = 50. Examining the graphs thoroughly indicate that the network size could possibly have an effect on the performance of the WGL. The various graphs of network size versus the number of city change show a possible increasing trend of percentage of gain. The graph also show a consistent behavior through the 3 different mean concentration as indicated by A1, A2, A3 which are the different level of passenger concentrations in our experiment. But to draw a valid statistical conclusion we take the results and further investigate the effect of the network size.

Under this hypothesis we want to examine the performance and behavior of the WGL as the network size change, we set up the hypothesis as follow:

H_0: The performance of WGL – Change as network size change

H_1: The performance of WGL – Do not change as network size change

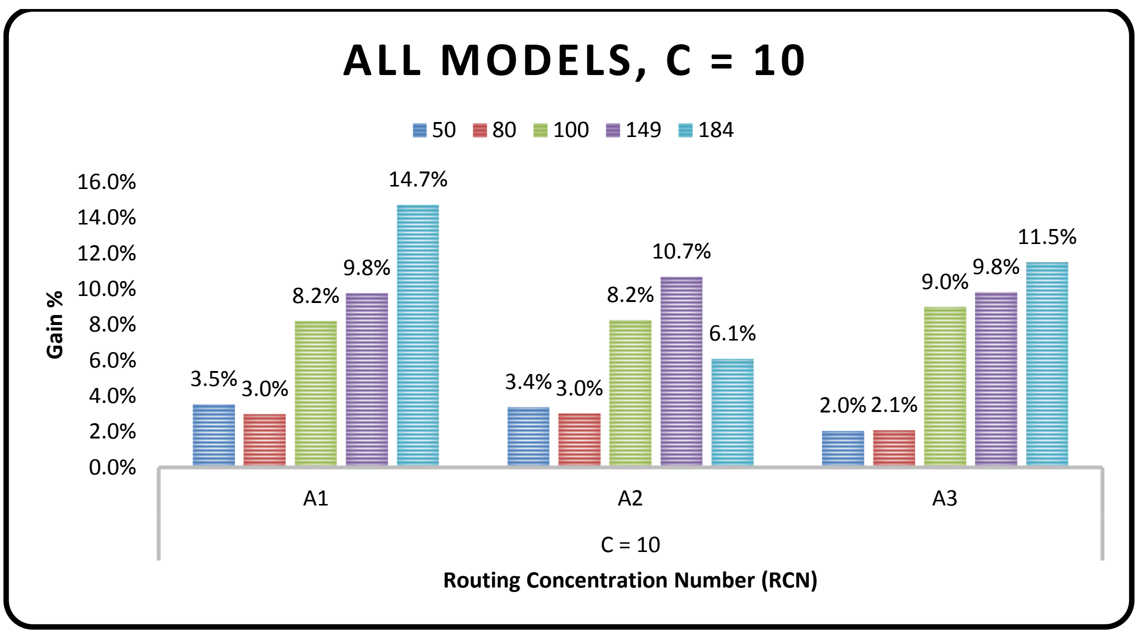


Figure 6.3 Network size under different levels of RCN and different levels of C=10.

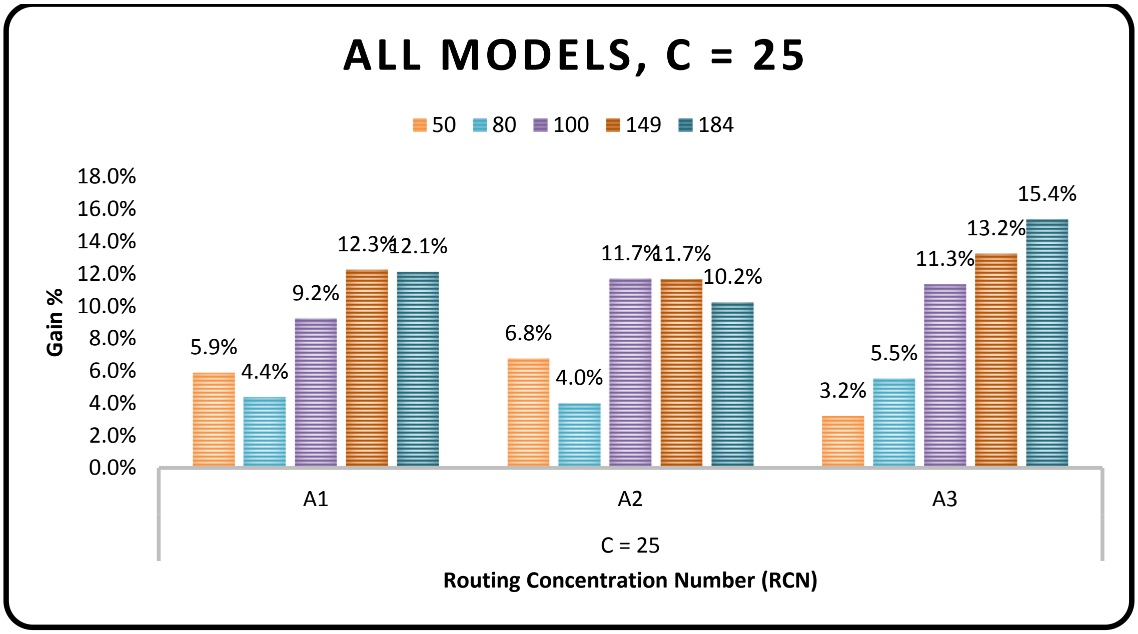


Figure 6.4 Network size under different levels of RCN and different levels of C=25.

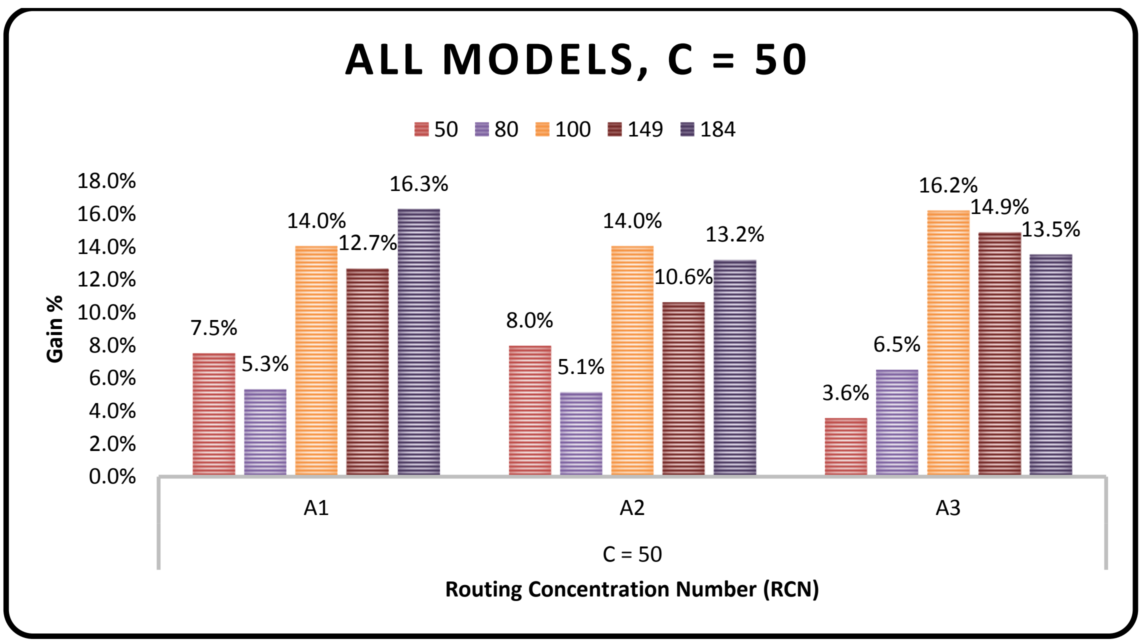


Figure 6.5 Network size under different levels of RCN and different levels of C=50.

We use ANOVA (One-Way) methods by defining the Network size as the factor and gain percentage is the experiment response output for this hypothesis. The results obtained from Minitab 17 are summarized in in Table 6.9. From the results obtained from

Minitab, we reject the hypothesis of equal mean as indicated by the low P- value. This conclusion leads us to accept our null hypothesis that as the network size increase the percentage of gain also increase. The analyses were set at a significant level alpha of ($\alpha = 0.05$).

Table 6.9 Minitab Report of Network size factor and various levels of C

One-way ANOVA: % Gain versus Network Size

Factor Information

Factor	Levels	Values
Network Size	5	50, 80, 100, 149, 184

Welch's Test

Source	DF Num	DF Den	F-Value	P-Value
Network Size	4	26.9947	47.23	0.000

Model Summary

R-sq	R-sqr (adj)	R-sq (pred)
72.55%	70.55%	67.33%

Means

Network Size	N	Mean	StDev	95% CI
50	12	5.250	2.231	(3.832, 6.668)
80	12	4.838	1.528	(3.867, 5.808)
100	12	12.217	3.093	(10.252, 14.182)
149	12	12.108	1.617	(11.081, 13.136)
184	12	13.267	2.940	(11.399, 15.135)

As indicated by the residual plot shown in Figure 6.6, the model shows a reasonable normality considering the sample size, the data are also considered independent as indicated in the residual chart as evidence of lack of any pattern.

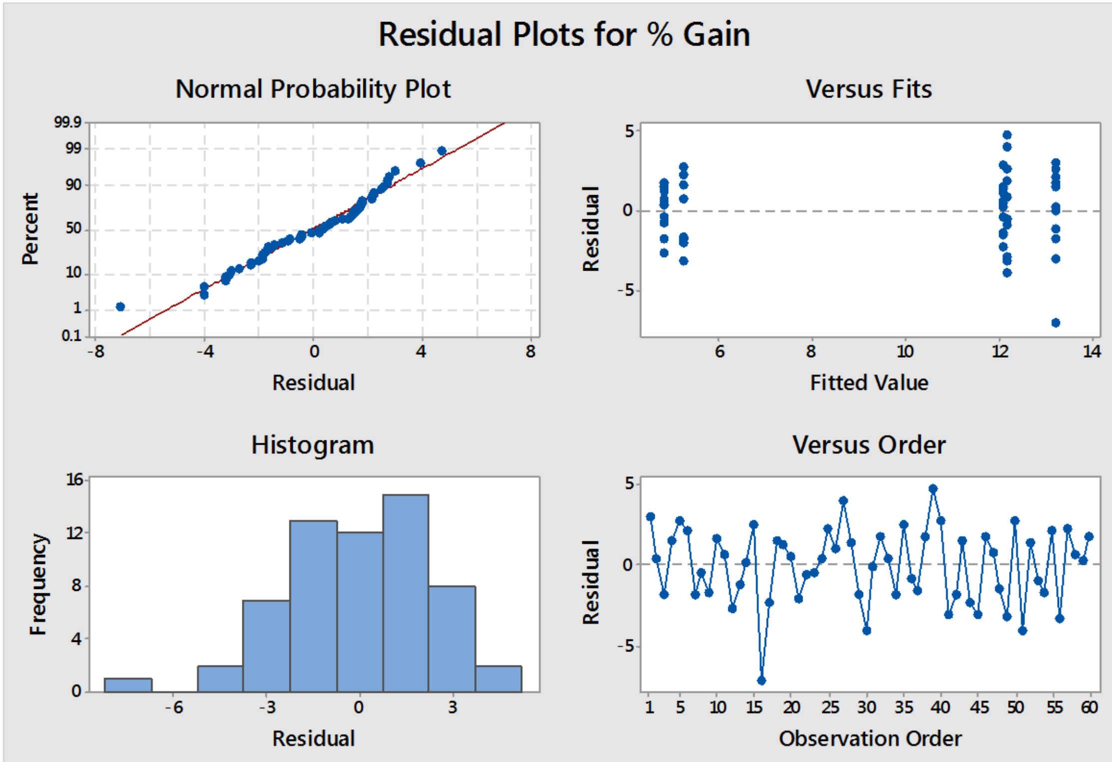


Figure 6.6 Residual plots for gain percentage of network size.

The interval plot for the various network size are shown in Figure 6.7, Table 6.10, summarizes the main differences data.

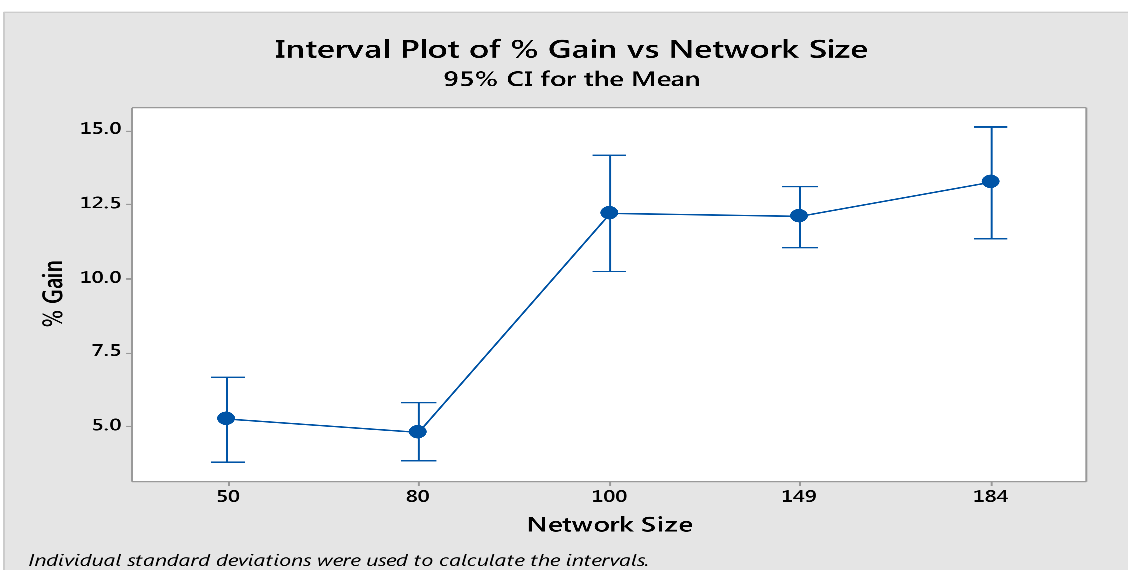


Figure 6.7 Interval plot of % gain by each network.

The main effect plots of the model is shown in Figure 6.8, clearly the gain percentage is increasing as the network size increase. The individual value plot of gain % versus the network size can be seen in Figure 6.9.

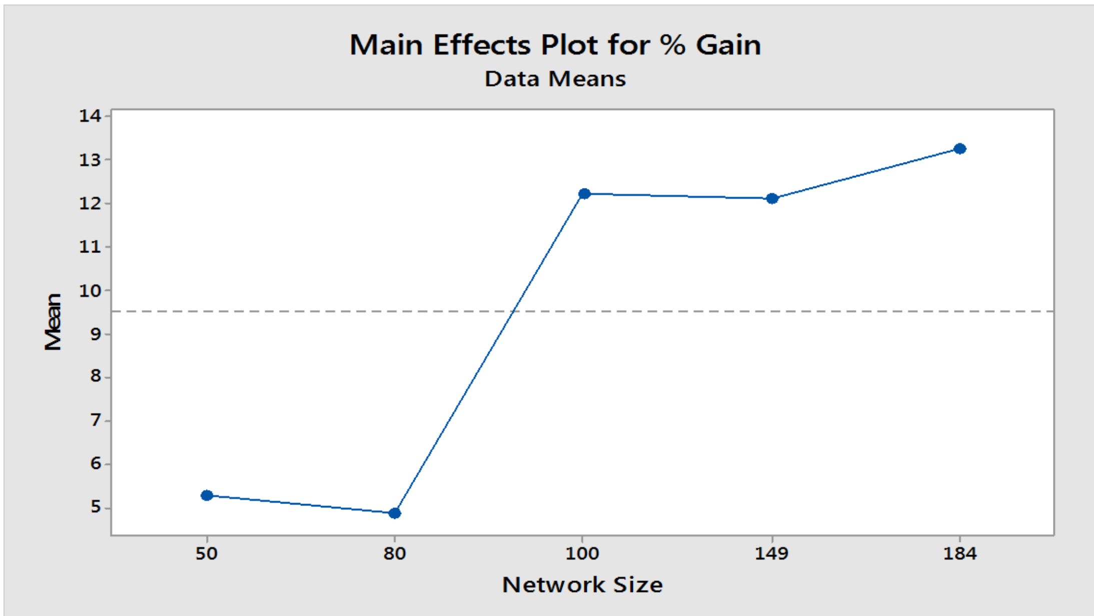


Figure 6.8 Main effect plot of the network size on the gain %.

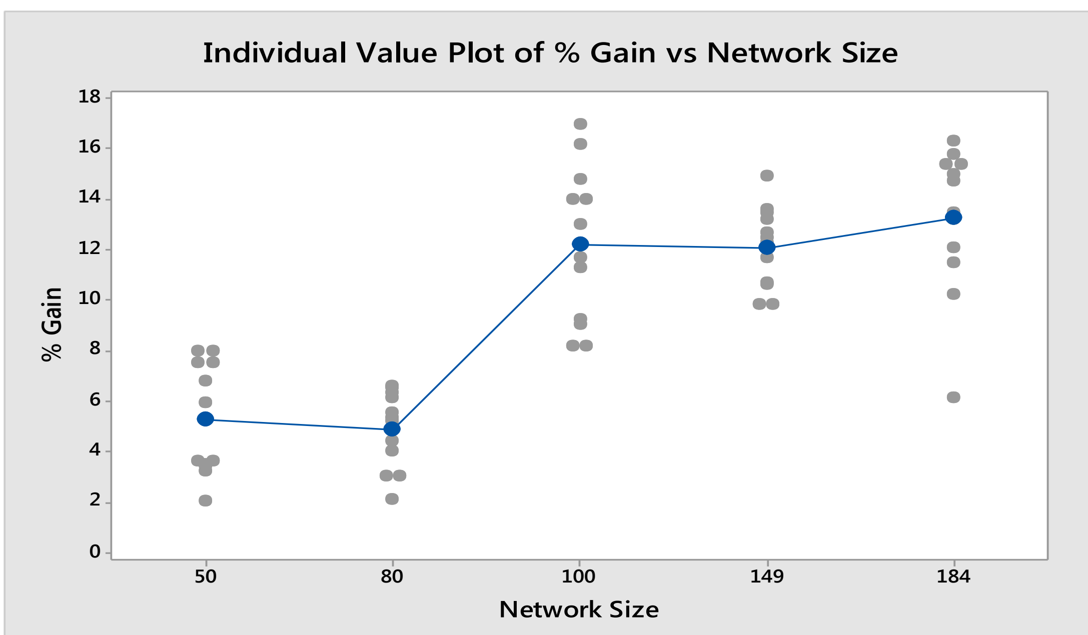


Figure 6.9 Individual value plot of the network size on the gain %.

Table 6.10 Minitab Results of Pairwise Comparison of Mean Gain Data

Games-Howell Pairwise Comparisons

Grouping Information Using the Games-Howell Method and 95% Confidence

Number of Flight Change	N	Mean	Grouping
250	15	11.25	A
50	15	10.77	A B
25	15	9.127	A B
10	15	7.00	B

Means that do not share a letter are significantly different.

Games-Howell Simultaneous Tests for Differences of Means

Difference of Levels	Difference of Means	SE of Difference	95% CI	T-Value	Adjusted P-Value
25 - 10	2.13	1.43	(-1.78, 6.03)	1.49	0.458
50 - 10	3.77	1.52	(-0.39, 7.92)	2.47	0.087
250 - 10	4.25	1.53	(0.08, 8.42)	2.78	0.045
50 - 25	1.64	1.50	(-2.45, 5.73)	1.10	0.695
250 - 25	2.12	1.50	(-1.99, 6.24)	1.41	0.503
250 - 50	0.48	1.59	(-3.86, 4.83)	0.30	0.990

Figure 6.10, shows the differences in mean for the gain percentage.

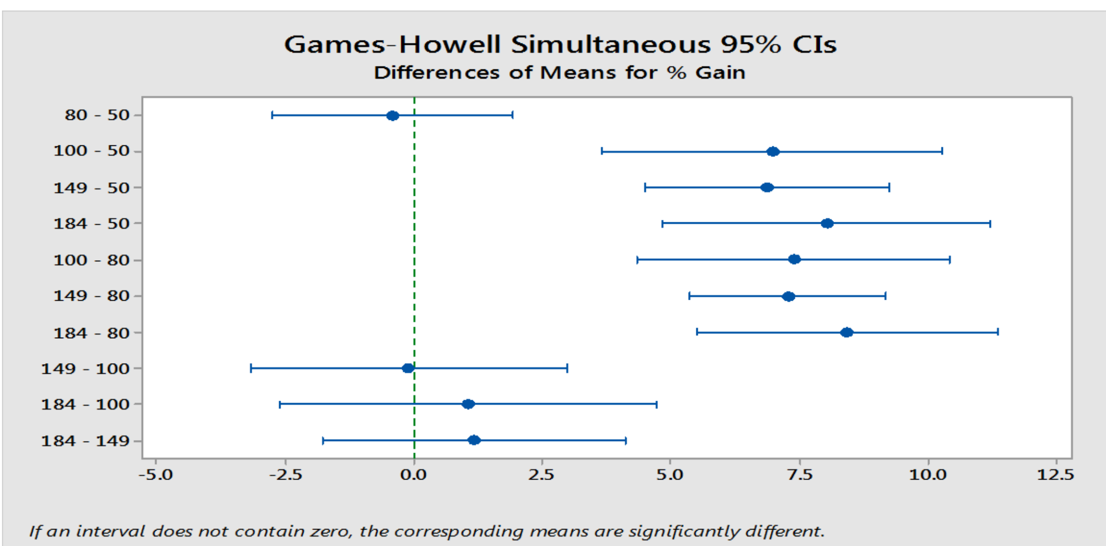


Figure 6.10 Differences in mean of network size on gain %.

II. Evaluating the performance of WGL as number of flight change

The output results, of the ACA Cost Simulator are summarize and shown graphically in Figure 6.11, for model size 50, Figure 6.12, for model size 80, Figure 6.13, for model size 100, Figure 6.14, for model size 149 and Figure 6.15, for model size 184. In all figures, the number of flights change under the three different levels of the RCN. The graph of the number of city change does show a possible increasing trend of percentage of gain within each mean concentration level, but the last part of Figure 6.11, at A3 level show a sharp drop in the percentage gain, a further investigation predict that the total number of passenger can have an effect, this will be analysis later in this chapter. ANOVA analysis, will look first at the effect of the number of flight change in the performance of WGL as a single factor, and also as a group of factors and explore the effect of each factor as an individual and their interaction together.

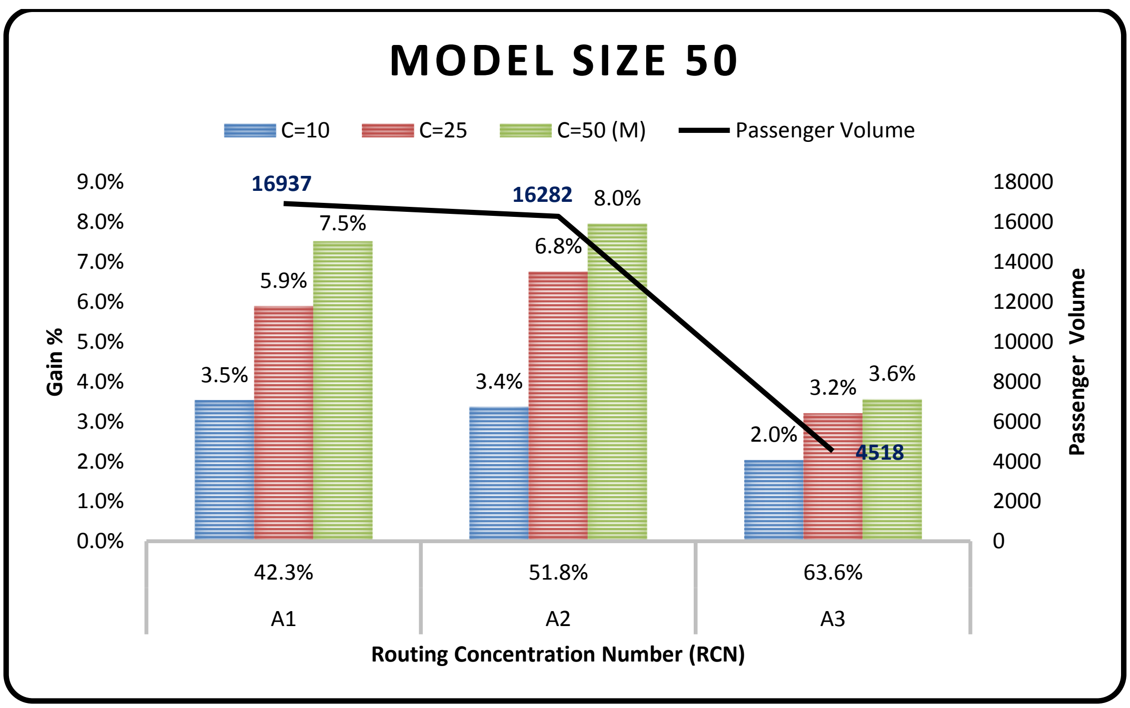


Figure 6.11 The number of flight change with different levels for model 50.

Figure 6.12, shows the number of flights change under the three different levels of the RCN and model size 80. The graph of the number of city change does show a possible increasing trend of percentage of gain within each mean concentration level, as group there is evidence of percentage increase, we can't draw a strong conclusion before a further analysis using ANOVA.

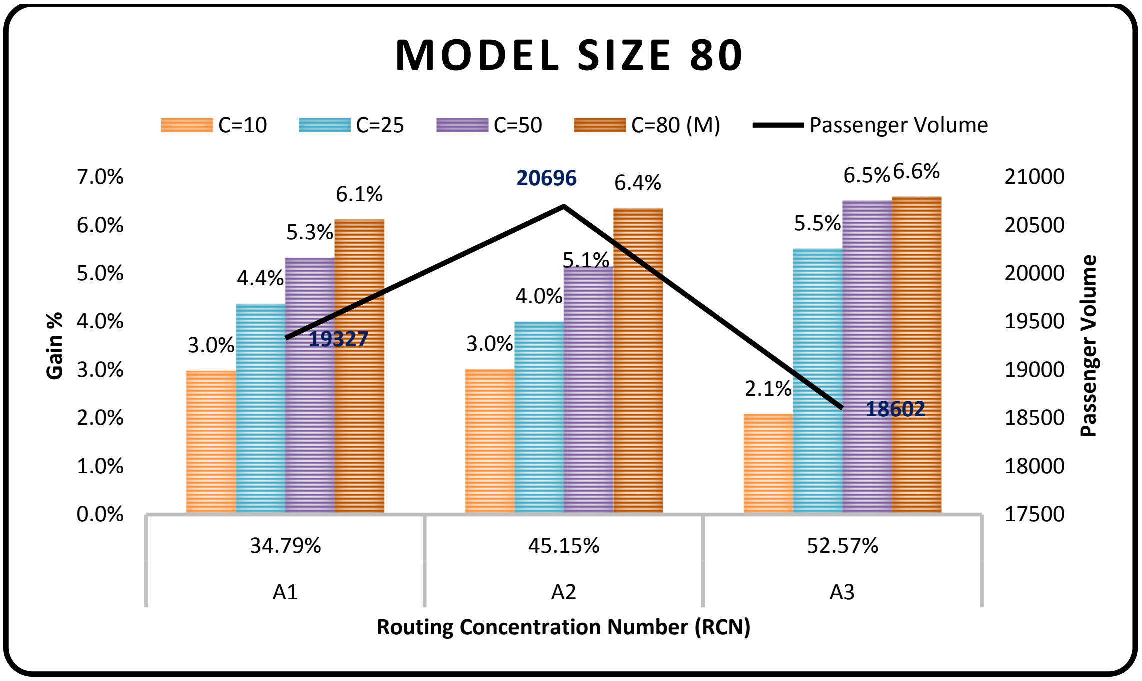


Figure 6.12 The number of flight change with different levels for model 80.

Figure 6.13, shows the number of flights change under the three different levels of the RCN and model size 100. The graph of the number of city change does show a possible increasing trend of percentage of gain within each mean concentration level, as group there is evidence of percentage increase, we can't draw a strong conclusion before a further analysis using ANOVA.

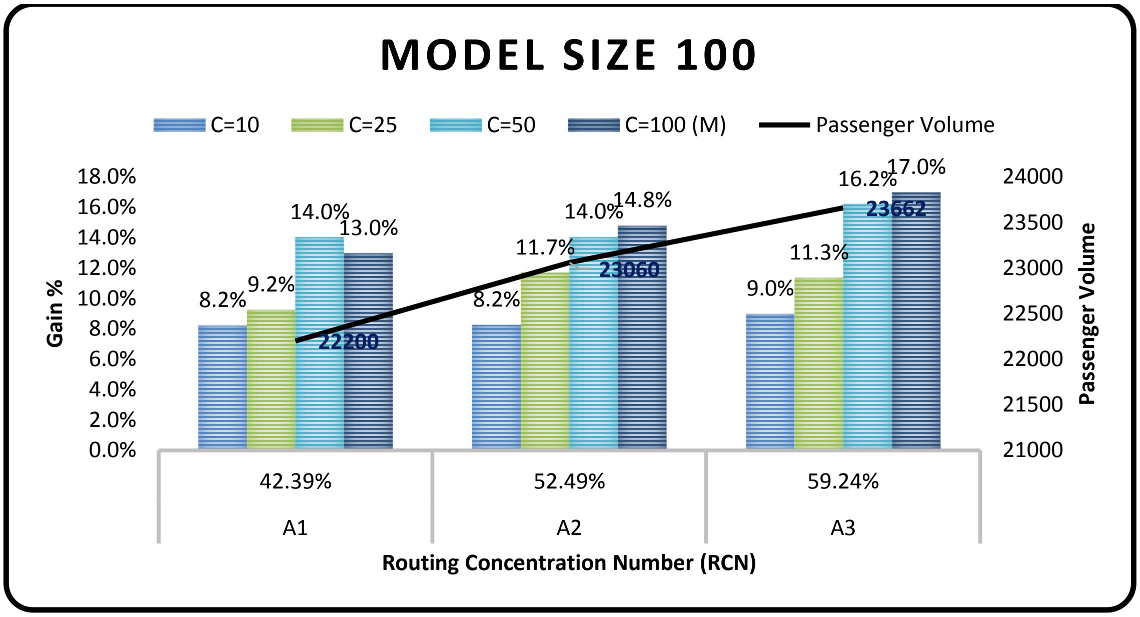


Figure 6.13 The number of flight change with different levels for model 100.

Figure 6.14, shows the number of flights change under the three different levels of the RCN and model size 149. The graph of the number of city change does show a possible increasing trend of percentage of gain within each mean concentration level, as group there is evidence of percentage increase, we can't draw a strong conclusion before a further analysis using ANOVA.

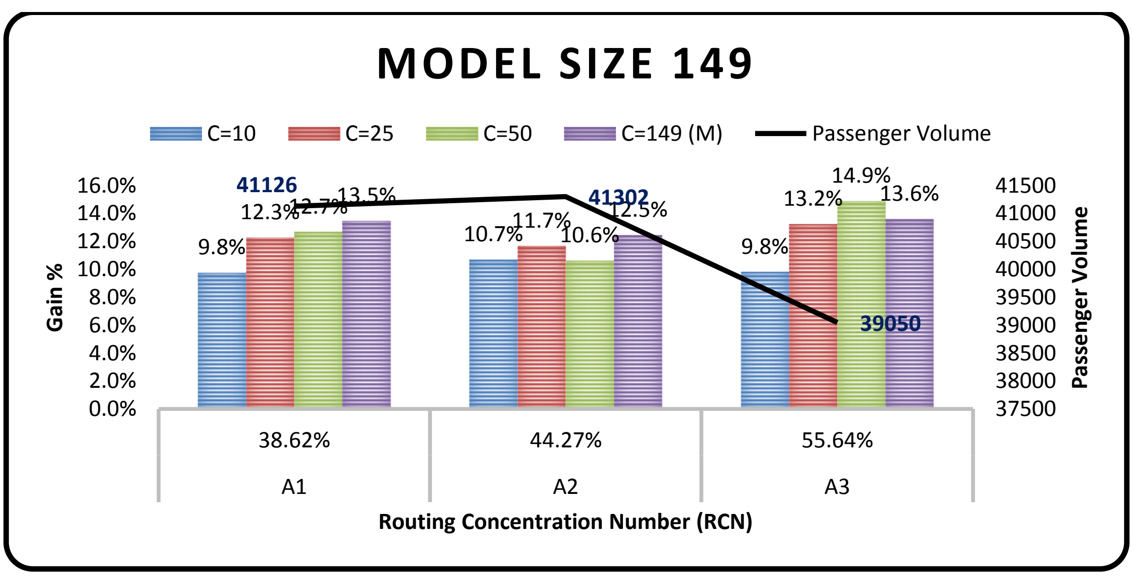


Figure 6.14 The number of flight change with different levels for model 149.

Figure 6.15, shows the number of flights change under the three different levels of the RCN and model size 184. The graph of the number of city change does show a possible increasing trend of percentage of gain within each mean concentration level, as group there is evidence of percentage increase, we can't draw a strong conclusion before a further analysis using ANOVA.

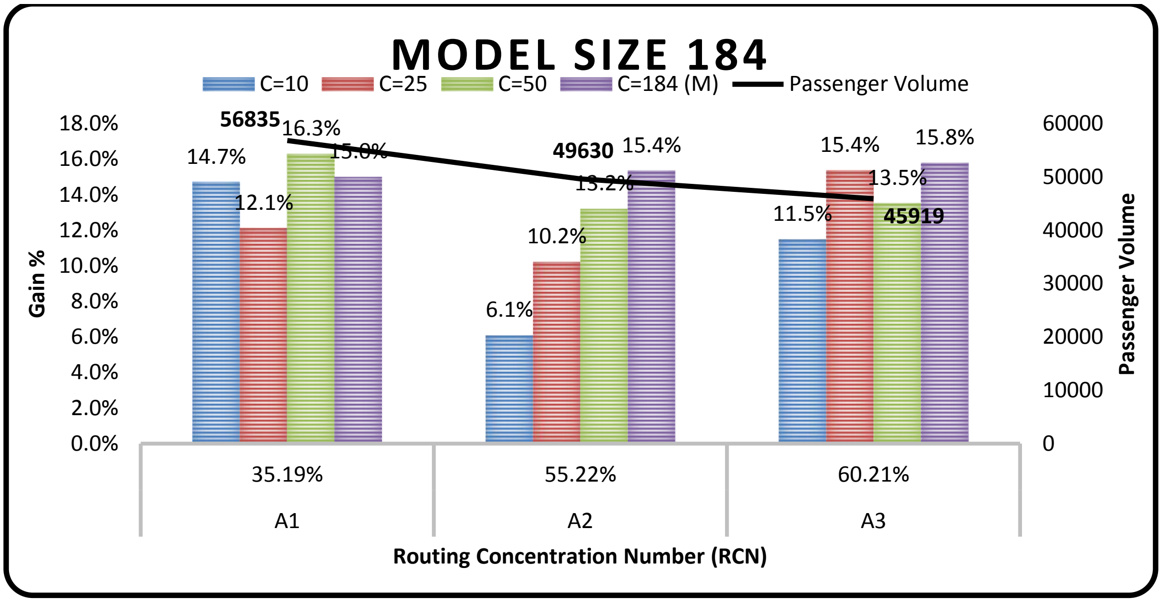


Figure 6.15 The number of flight change with different levels for model 184.

At this point, we state our hypothesis to examine the effect of increasing the number of flight change on the performance of the WGL as indicated by the percentage gain. The hypothesis is stated as follow:

$\boldsymbol{H_0}$**:** The performance of WGL – Change as the number of flight change

$\boldsymbol{H_1}$**:** The performance of WGL – Do not Change as the number of flight change

Table 6.11 summarizes the results obtained from Minitab, The number of flight changes is statistically significant at (α = 0.05) versus the percentage gain. The P-value is slightly close to α = 0.05. This suggest to perform an in-depth analysis on this factor interaction with other factor. Later in this chapter, we will show the interaction of the various factor together using two way ANOVA and general methods analysis.

Table 6.11 Minitab Report of Number of Flight Change Effect on the Percentage Gain

One-way ANOVA: % Gain versus Number of Flight Change

Factor Information

Factor	Levels	Values
Number of Flight Change	4	10, 25, 50, 250

Welch's Test

Source	DF Num	DF Den	F-Value	P-Value
Number of Flight Change	3	31.0682	3.09	0.041

Model Summary

R-sq	R-sq(adj)	R-sq(pred)
14.70%	10.13%	2.08%

As indicated by the residual plot shown in Figure 6.16, the model shows a reasonable normality condition exit for the number of flight change data considering the sample size also independency can be concluded as no pattern in the residual chart.

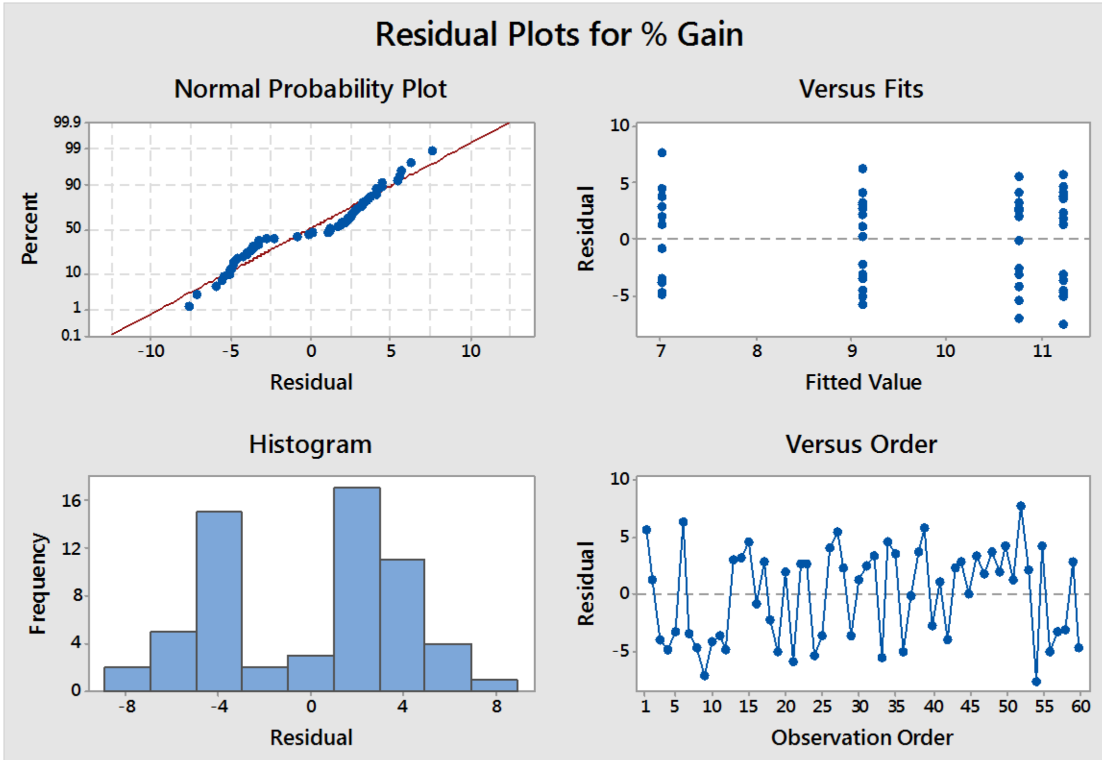


Figure 6.16 Residual plots for gain percentage of different C.

The interval plot for the various C are shown in Figure 6.17.

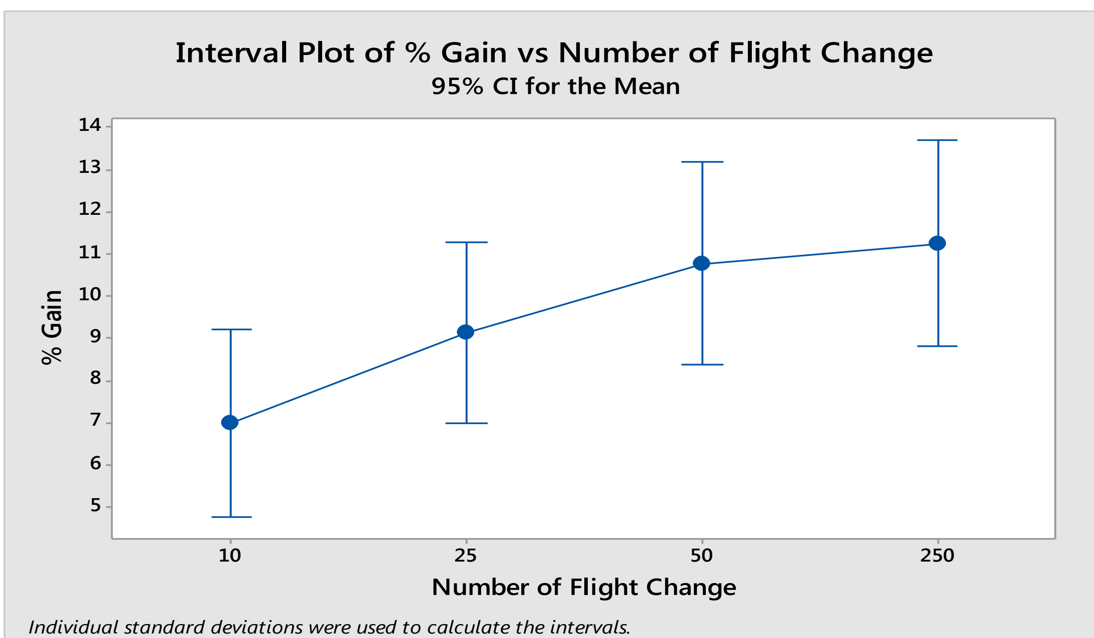


Figure 6.17 Interval plot of % gain by each C.

The main effect plots of the model is shown in Figure 6.18, clearly the gain percentage is increasing as the network size increase. The individual value plot of gain % versus different C can be seen in Figure 6.19.

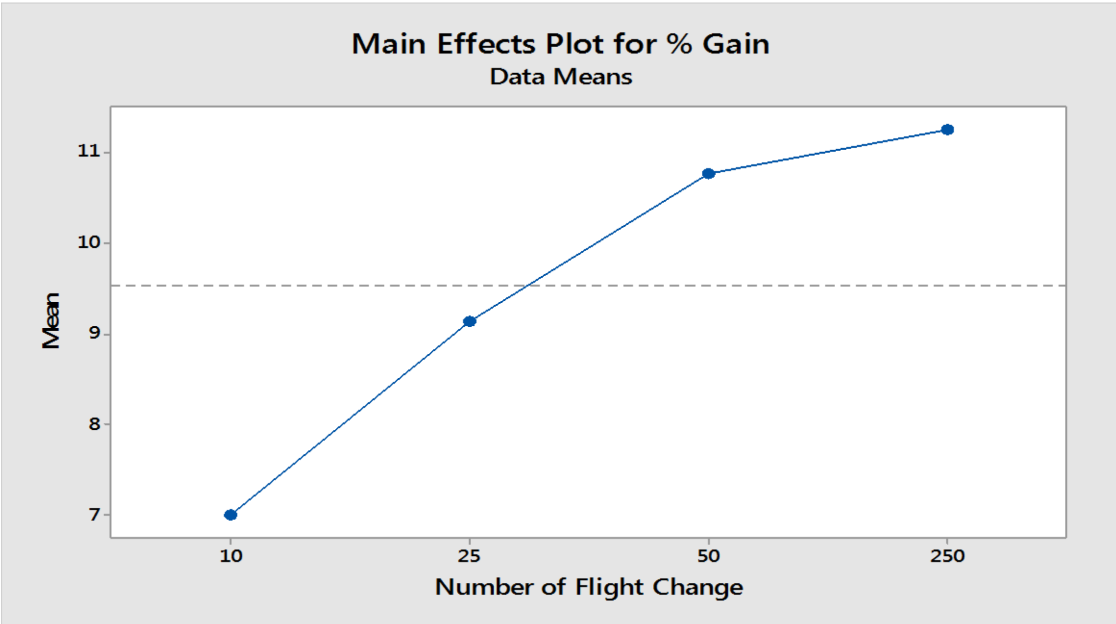


Figure 6.18 Main effect plot of different C on the gain %.

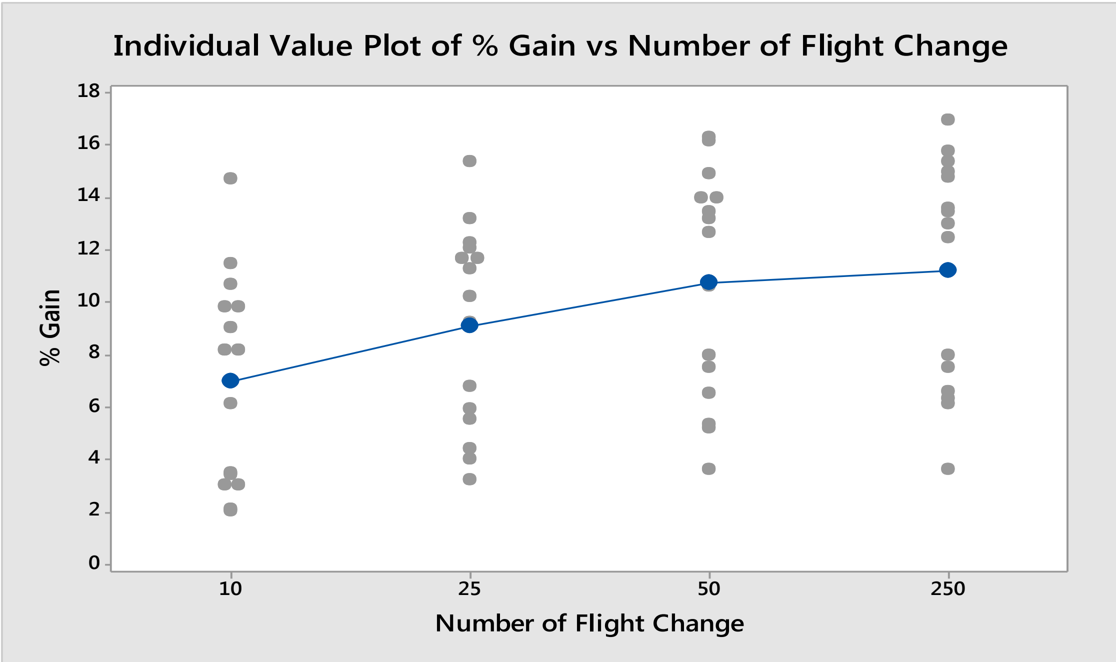


Figure 6.19 Individual value plot of different C on the gain %.

Table 6.12 Minitab Results of Pairwise Comparison of Mean Gain Data

Games-Howell Pairwise Comparisons

Grouping Information Using the Games-Howell Method and 95% Confidence

Number of Flight Change	N	Mean	Grouping
250	15	11.25	A
50	15	10.77	A B
25	15	9.127	A B
10	15	7.00	B

Means that do not share a letter are significantly different.

Games-Howell Simultaneous Tests for Differences of Means

Difference of Levels	Difference of Means	SE of Difference	95% CI	T-Value	Adjusted P-Value
25 - 10	2.13	1.43	(-1.78, 6.03)	1.49	0.458
50 - 10	3.77	1.52	(-0.39, 7.92)	2.47	0.087
250 - 10	4.25	1.53	(0.08, 8.42)	2.78	0.045
50 - 25	1.64	1.50	(-2.45, 5.73)	1.10	0.695
250 - 25	2.12	1.50	(-1.99, 6.24)	1.41	0.503
250 - 50	0.48	1.59	(-3.86, 4.83)	0.30	0.990

Figure 6.20 shows the differences in mean for the gain percentage of different C.

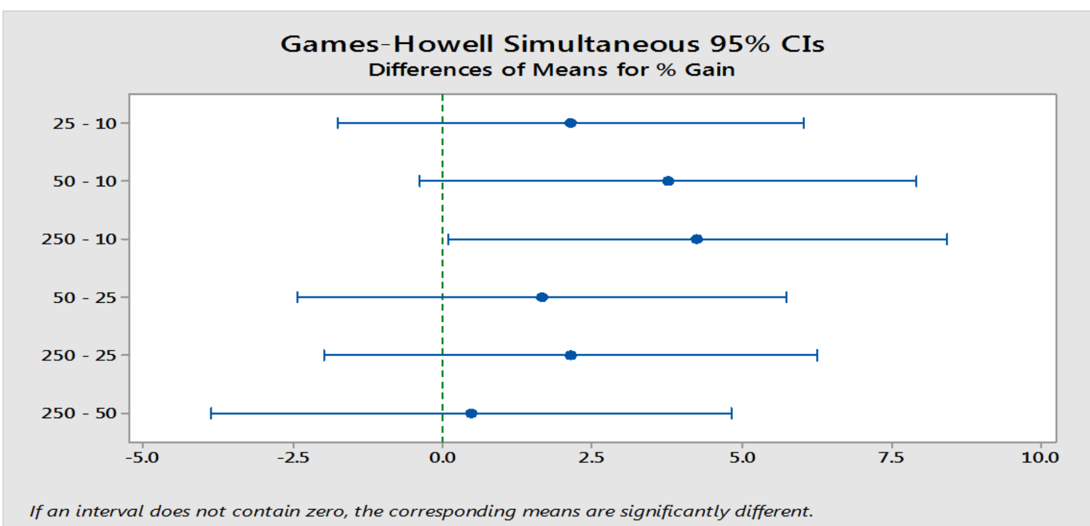


Figure 6.20 Differences in mean for different C on gain %.

III. Evaluating the performance of WGL as passenger mean concentration change

In this hypothesis, we want to examine the effect of mean passenger concentration change on the performance of the WGL as indicated by the percentage gain. The hypothesis is stated as follow:

$\boldsymbol{H_0}$**:** The performance of WGL – Change as the mean passenger concentration change

$\boldsymbol{H_1}$**:** The performance of WGL – Do not Change as the mean passenger concentration change

Table 6.13, summarizes the results obtained from Minitab, The mean passenger concentration is not statistically significant at ($\alpha = 0.05$) versus the percentage gain. The P-value is high compared to level of significant $\alpha = 0.05$. This suggest to perform an in-depth analysis on this factor interaction with other factor. Later in this chapter we will show the interaction of the various factor together using two way ANOVA and general methods analysis.

Table 6.13 Minitab Report of Mean Passenger Concentration on the Percentage Gain

```
One-way ANOVA: % Gain versus Mean Concentration

Factor Information

Factor              Levels  Values
Mean Concentration       3  1, 2, 3


Welch's Test

                     DF
Source              Num   DF Den  F-Value  P-Value
Mean Concentration    2  37.4795     0.10    0.903


Model Summary

 R-sq  R-sq(adj)  R-sq(pred)
0.31%      0.00%       0.00%


Means

Mean
Concentration   N   Mean  StDev       95% CI
1              20  9.700  4.182  (7.743, 11.657)
2              20  9.192  3.838  (7.396, 10.989)
3              20   9.71   5.19  ( 7.29,  12.14)
```

As indicated, by the residual plot shown in Figure 6.21 the model shows a reasonable normality condition exit for the number of flight change data considering the sample size. The output data is independent as no clear pattern as concluded from the residual chart.

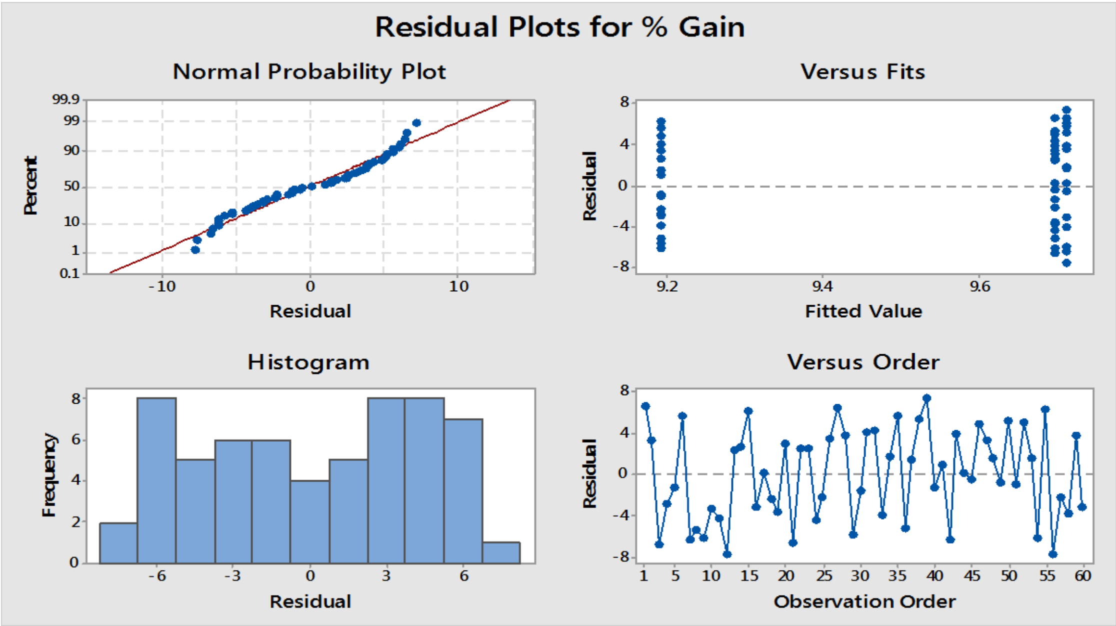


Figure 6.21 Residual plots for gain percentage of mean concentration.

The interval plot for the various passenger concentrations are shown in Figure 6.22.

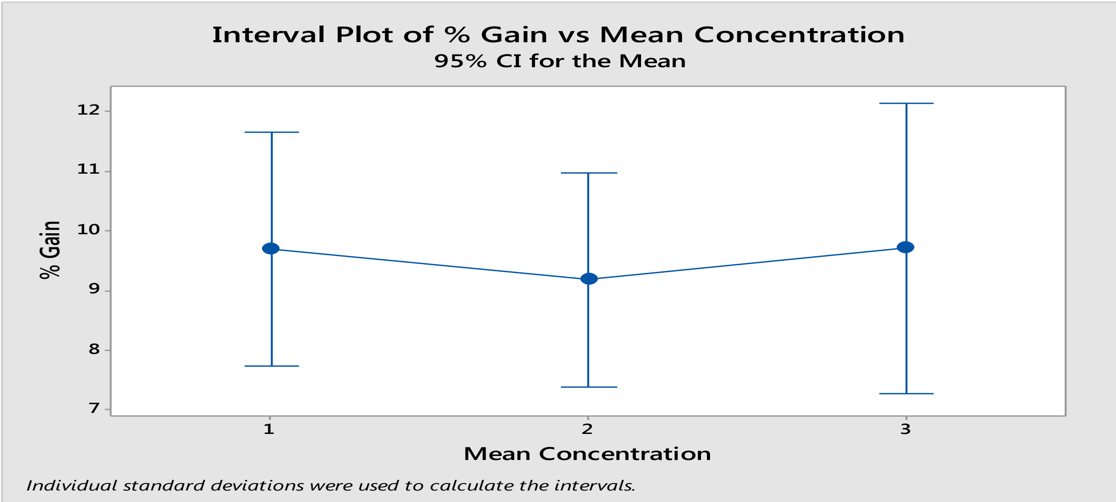


Figure 6.22 Interval plot of % gain at different level of mean concentration.

The main effect plots of the model is shown in Figure 6.23, clearly the gain percentage is not depending on mean concentration. The individual value plot of gain % versus the mean concentration can be seen in Figure 6.24.

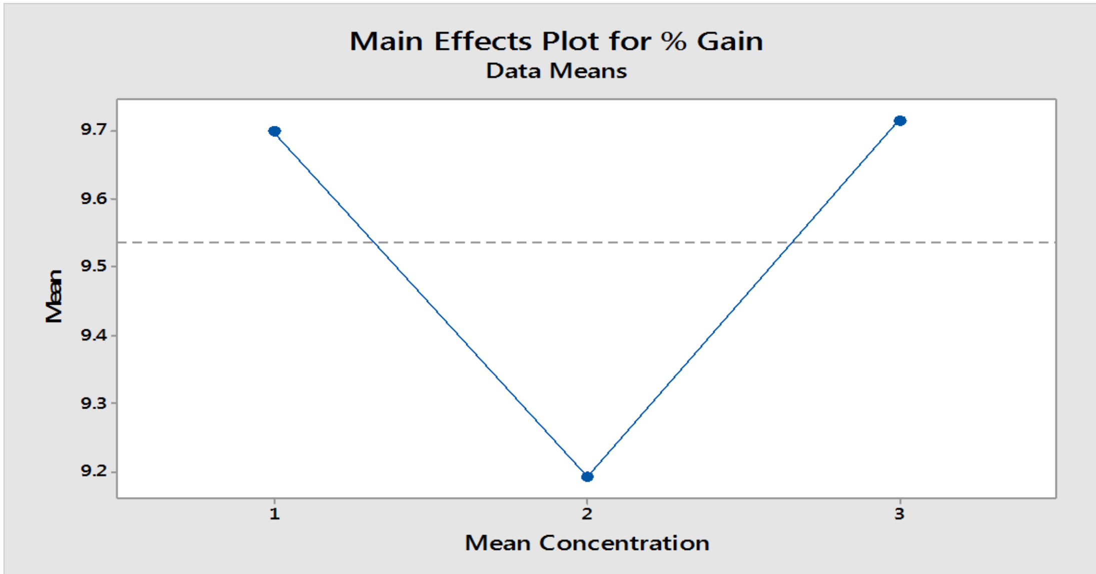


Figure 6.23 Main effect plot of the different levels of mean concentration on the gain %.

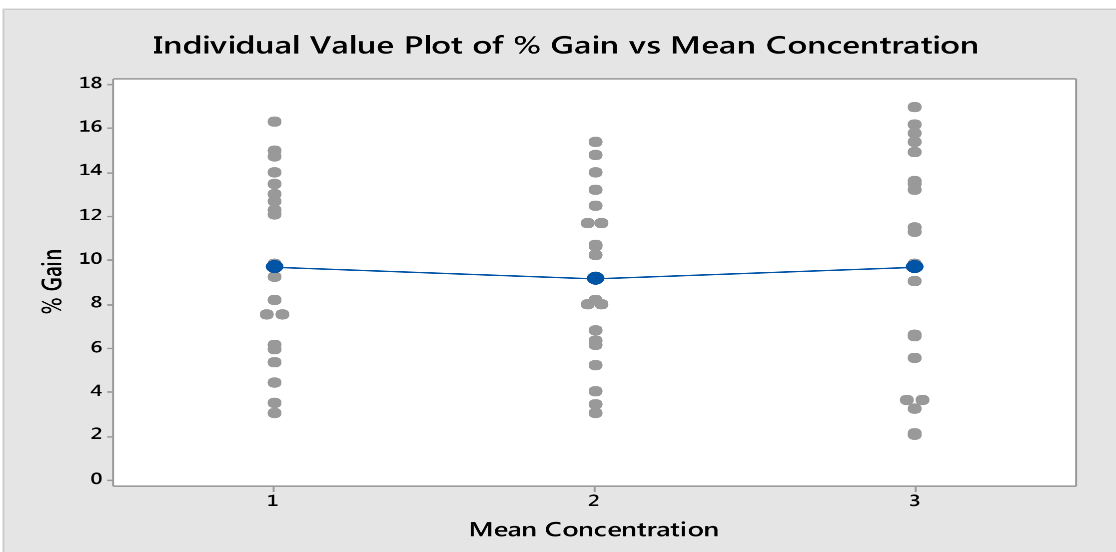


Figure 6.24 Individual value plot of different levels of mean concentration on gain %.

Table 6.14 Minitab Results of Pairwise Comparison of Mean Gain Data

Games-Howell Pairwise Comparisons

Grouping Information Using the Games-Howell Method and 95% Confidence

Mean Concentration	N	Mean	Grouping
3	20	9.71	A
1	20	9.700	A
2	20	9.192	A

Means that do not share a letter are significantly different.

Games-Howell Simultaneous Tests for Differences of Means

Difference of Levels	Difference of Means	SE of Difference	95% CI	T-Value	Adjusted P-Value
2 - 1	-0.51	1.27	(-3.60, 2.59)	-0.40	0.916
3 - 1	0.02	1.49	(-3.63, 3.66)	0.01	1.000
3 - 2	0.52	1.44	(-3.01, 4.05)	0.36	0.930

Figure 6.25, shows the differences in mean for the gain percentage of different levels of mean passenger concentration.

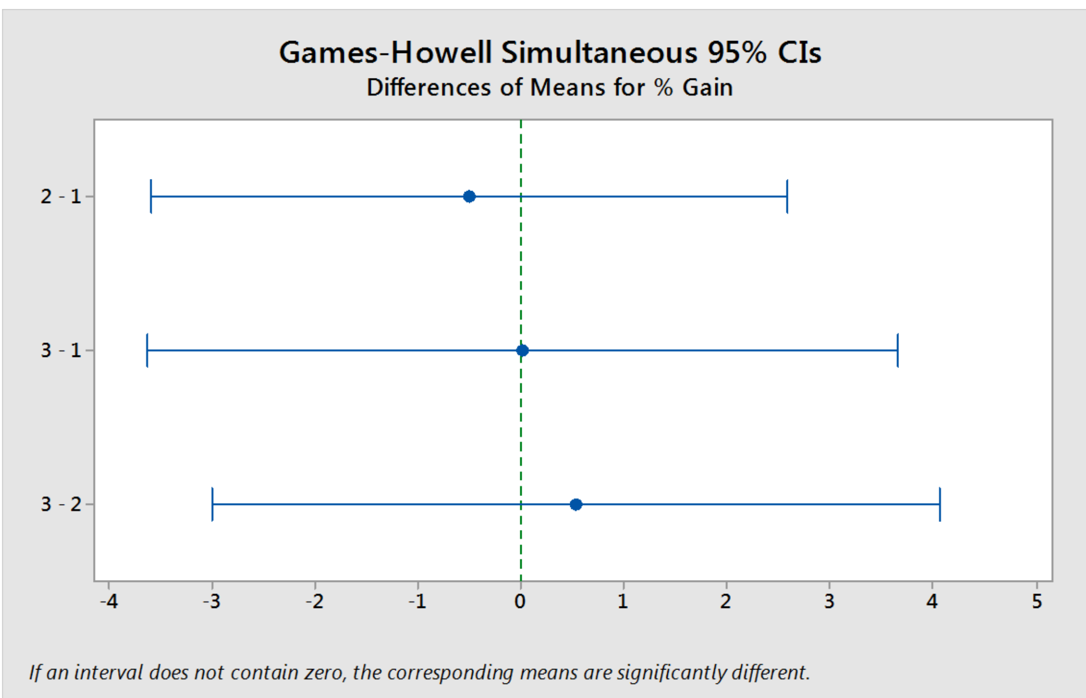


Figure 6.25 Differences in mean for passenger concentrations on gain %.

One way ANOVA analyzes the individual factor at different level as set by the experimenter but it can't show the main effect of different factors and their interaction on the experiment. In the following discussion, we will conduct the analysis using the general linear model, to investigate the different interaction between the main factors, and the impact of this interaction on the performance of WGL as indicated by the percentage of gain.

Table 6.15, summarizes the results obtained from Minitab, the summary statistics confirms our previous analysis as we find both the network size and number of flight change are statistically significant at ($\alpha = 0.05$) versus the percentage gain. This is indicated by the low P-value for both factors. The mean passenger concentration in not significant as seen by the high P-value compared to level of significant $\alpha = 0.05$.

Table 6.15 Minitab Results of General Linear Model

General Linear Model: % Gain versus Network Size, Number of Flight Change, Mean Concentration

Factor Information

Factor	Type	Levels	Values
Network Size	Fixed	5	50, 80, 100, 149, 184
Number of Flight Change	Fixed	4	10, 25, 50, 250
Mean Concentration	Fixed	3	1, 2, 3

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Network Size	4	818.00	204.499	72.93	0.000
Mean Concentration	2	3.54	1.769	0.63	0.536
Number of Flight Change	3	165.77	55.256	19.70	0.000
Error	50	140.21	2.804		
Total	59	1127.52			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
1.67459	87.56%	85.33%	82.09%

Fits and Diagnostics for Unusual Observations

Obs	% Gain	Fit	Resid	Std Resid	
9	3.600	6.660	-3.060	-2.00	R
16	6.100	10.387	-4.287	-2.80	R
52	14.700	10.895	3.805	2.49	R
54	3.600	7.143	-3.543	-2.32	R

R Large residual

The model data are normally distributed as the normal probability plot indicates in Figure 6.26. The data is also independent as indicated by the residual chart.

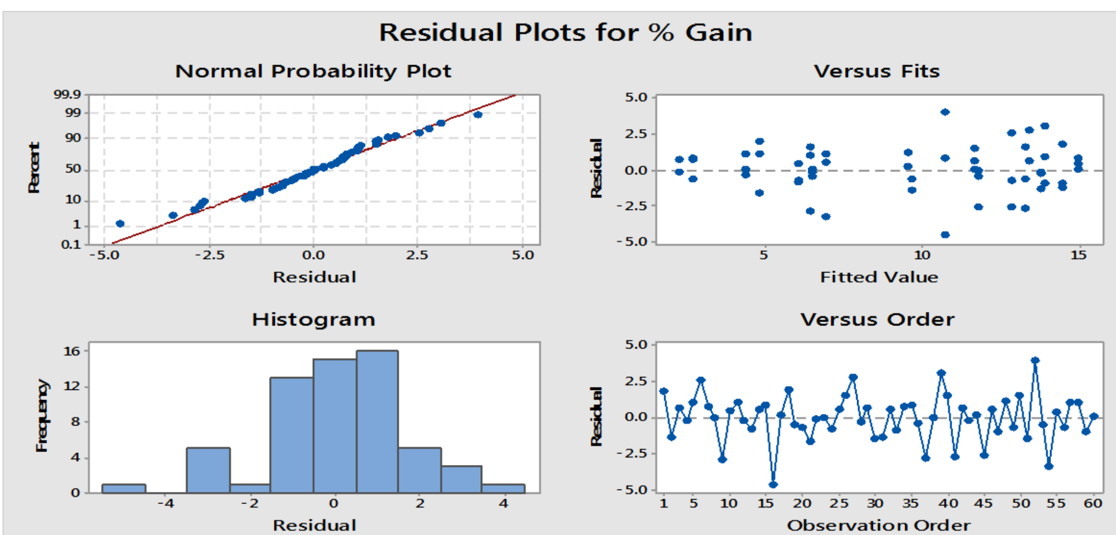


Figure 6.26 Model residual plots for all factors on % gain.

Figure 6.27, show the interaction between the three factors network size, number of flight change and the mean passenger concentration, the chart shows how these factor interacting together.

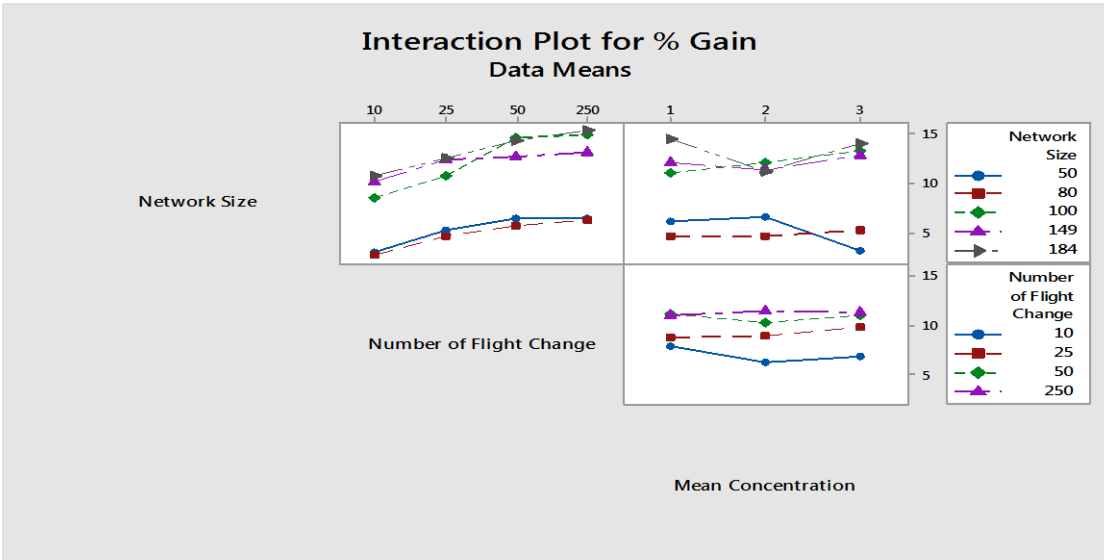


Figure 6.27 Interaction plot for % gain and the 3 factor of the experiment.

In the following discussion, we choose to show the interaction between two factors with respect to the percentage gain separately. Figure 6.28 – Figure 6.33 exhibit the interaction between each two factors.

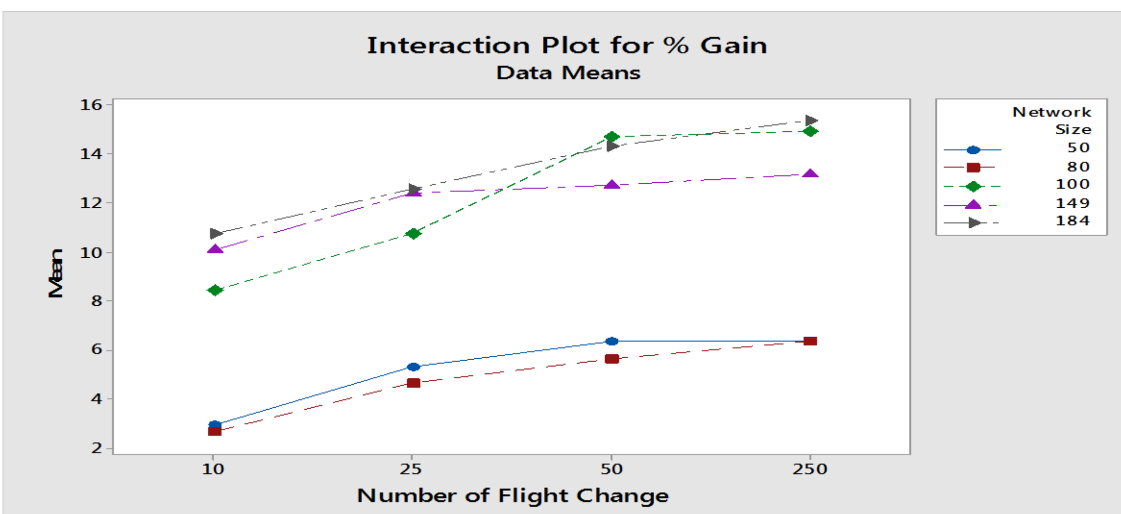


Figure 6.28 Interaction plot for % gain between C and network size.

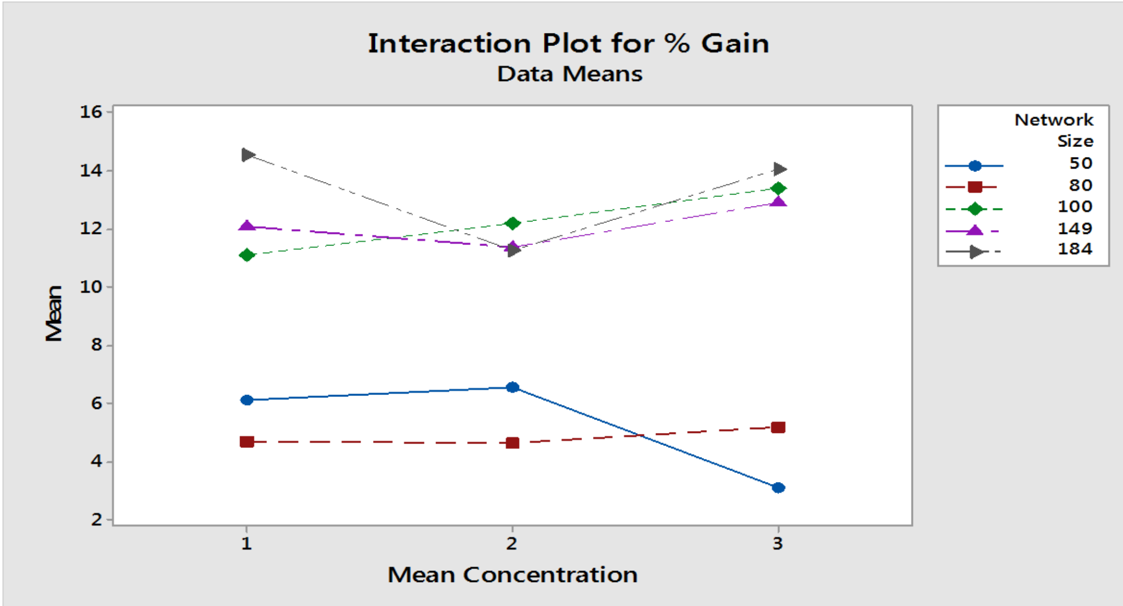


Figure 6.29 Interaction plot for % gain between network size and mean concentration.

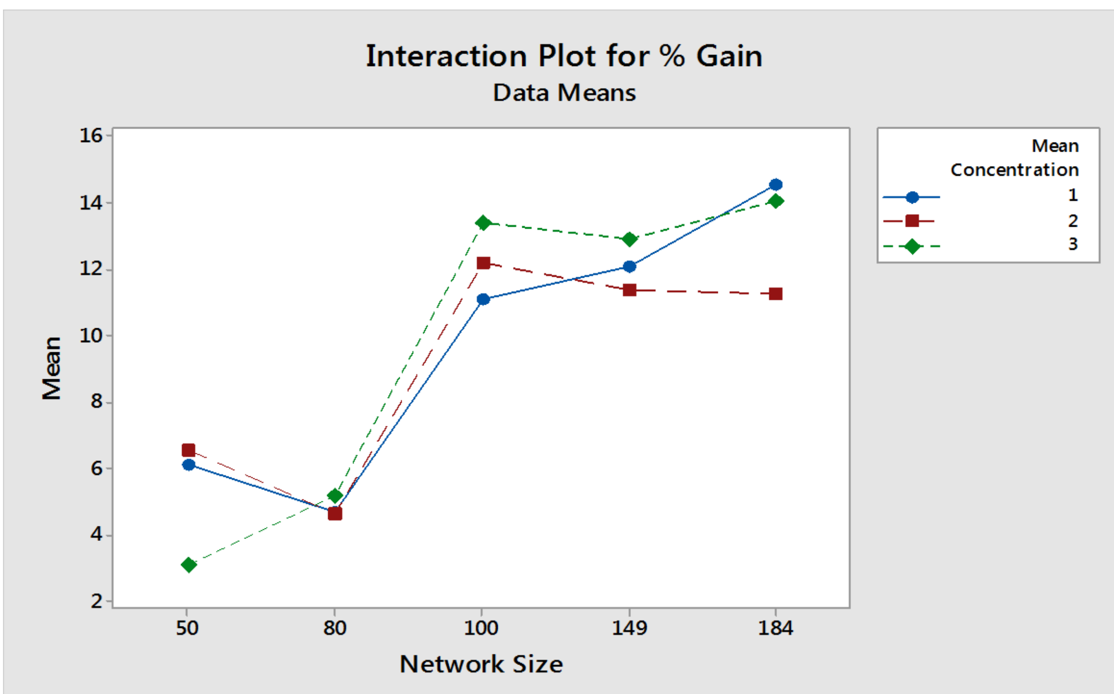


Figure 6.30 Interaction plot for % gain between mean concentration and network size.

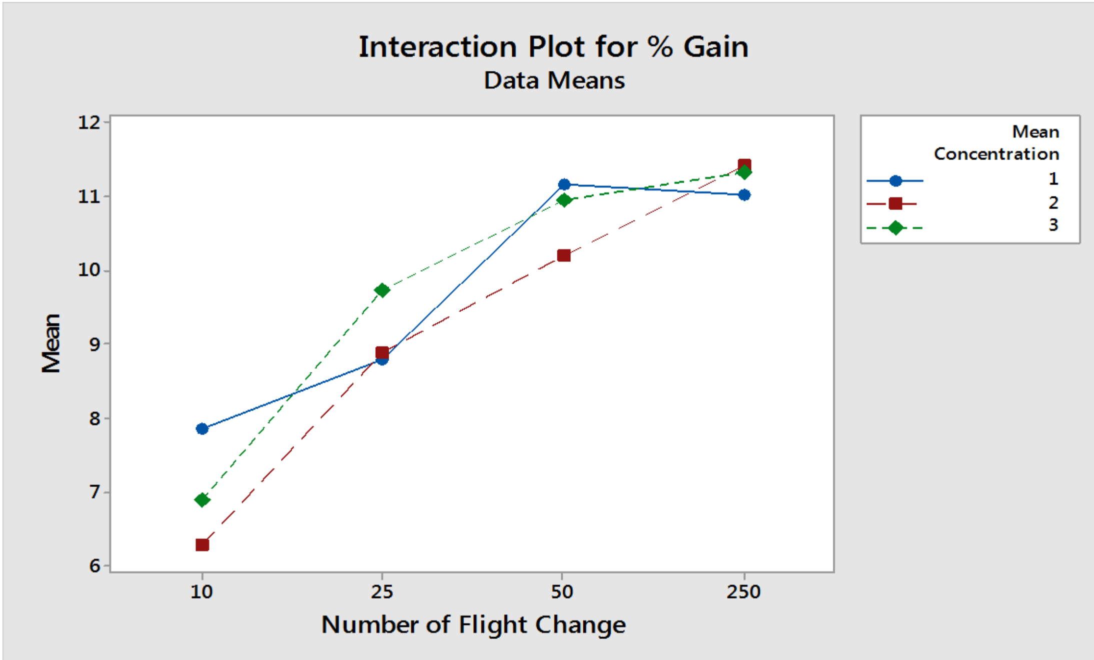


Figure 6.31 Interaction plot for % gain between mean concentration and C.

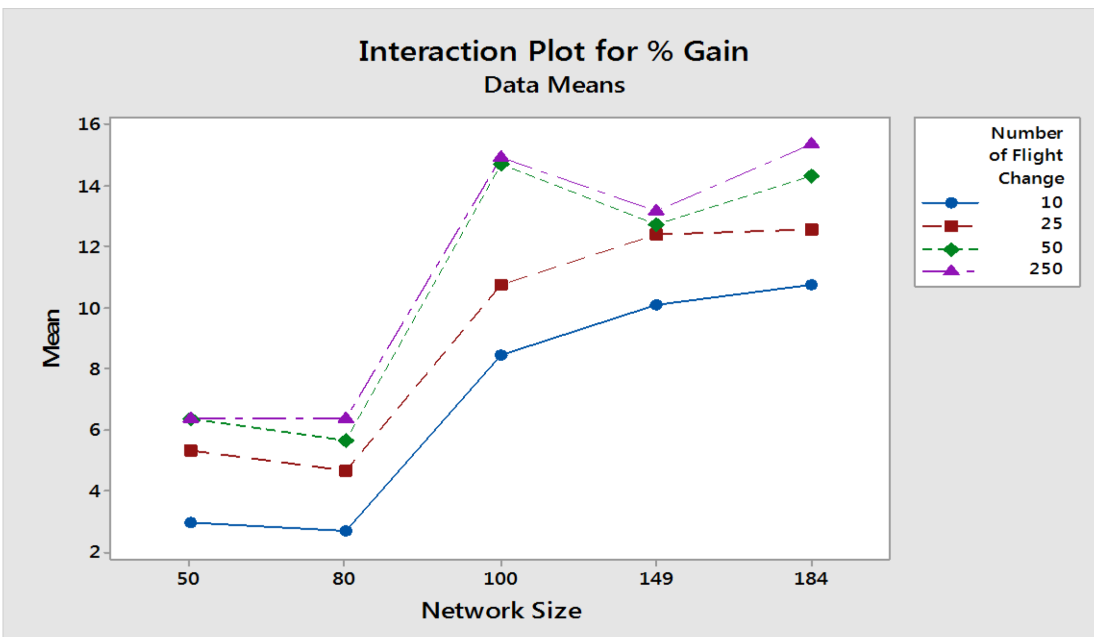


Figure 6.32 Interaction plot for % gain between C and network size.

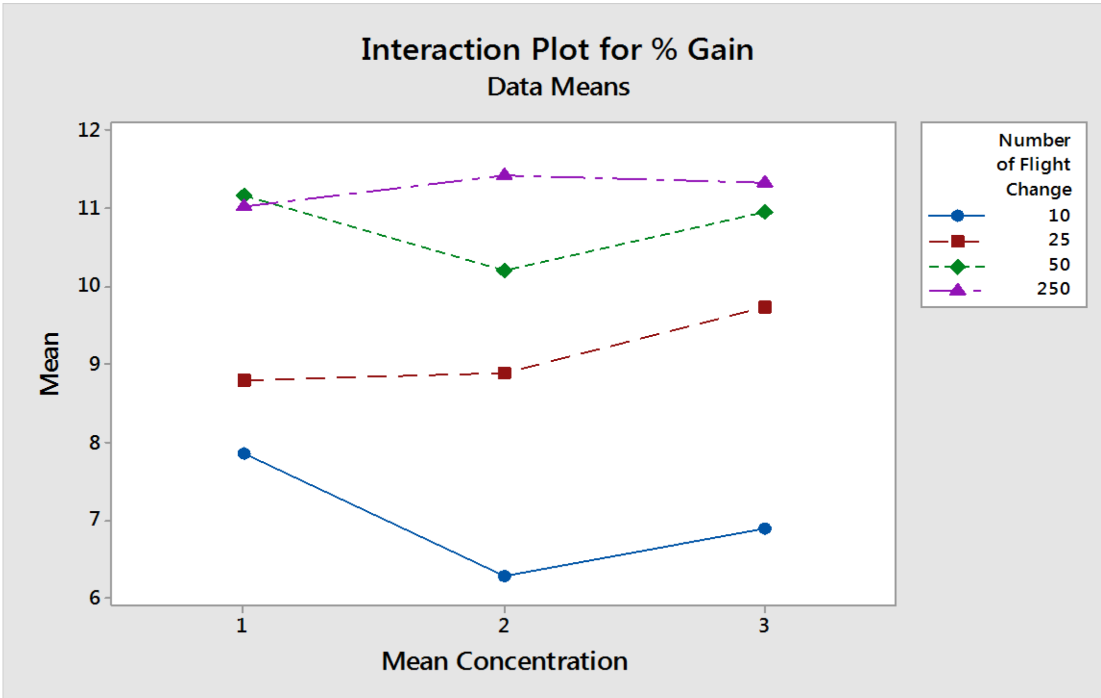


Figure 6.33 Interaction plot for % gain between C and mean concentration.

Finally, we show that the WGL heuristic that we integrate with the EXCEL/VBA simulator is capable of generating significant costs reduction in an efficient time. The data we test were done on a set of five flight network problems, each with three different passenger flow networks characterized by low, medium and high traffic concentration.

CHAPTER 7

SIGNIFICANT FINDINGS AND FUTURE WORK

Significant Findings The research conducted in the production of this dissertation accomplishes the following significant research objectives:

1. We create a quantitative model to represent this relationship, identifying both objective functions, controllable decision variables, and equations to model the analytical relationships.

2. We present a descriptive model to capture the cost behavior of these networks by defining (i) passenger wait times cost (ii) hourly passenger levels at the hub cost and (iii) hourly ground flight activity cost to Mega-Hub airports.

3. Creates An Excel + VBA based model which accurately models (i) passenger transits between city pairs (ii) accumulated in-terminal passenger volumes at any time instant (iii) aircraft schedule feasibility and (iv) normalized generation of daily passenger volumes.

4. Investigative research on the key dependencies between the operating costs of a mega-hub airport and the airline flight schedule and the associated passenger traffic.

5. Develop an optimization procedure that iteratively reschedules flights to solve the Mega-Hub Collaborative Flight Rescheduling (MCFR) Problem.

6. Develop and test a Wave Gain Loss (WGL) heuristic for optimizing the airline-airport collaborative objective function.

7. Develop a simulation based experimentation analysis of the WGL Heuristics as a solution to the MCFR problem.

Future Work The research conducted in the production of this dissertation has laid the groundwork for the future research opportunities.

As mentioned in chapter 3 there are three sub-problems to the MCFR problem, in this dissertation we focused in the case where departure time (D_i) is the decision variable. Extend the problem to include the other decision variables by fixing D_i and solving Hi as the decision variable, another extension is by solving a two dimensional problem where both D_i and H_i are the decision variables. A new formulation to the problem will then requires a proposing new heuristic solution to deal with new design and that should be capable of producing better solution.

Improve the cost function model to include other hidden or minor costs, such as cost of holding all airlines coming to the hub and the impact on the cost function.

Extend the airport + airline collaboration model during the planning periods so it is possible to for this partnership relation to include, reassignment of aircraft type due to gate availability, it can also include air side cost to ground side cost, another potential area for such collaboration can be extended to risk analysis of adding new spokes (markets) to the network.

Generalize cost function model by defining a detail derivers to assign cost parameters to be used by different airport

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