MAKERERE UNIVERSITY

STOCHASTIC OPTIMISATION MODELS FOR AIR TRAFFIC FLOW MANAGEMENT

By

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Declaration

I, Wesonga Ronald, hereby declare that the work contained in this thesis is my original work and has not previously in its entirety or in part been submitted at any University for a Degree Award.

Signature: .... Date: 24th November, 2010

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PHD CANDIDATE

Approval

'his is to certify that this thesis has been submitted as a fulfillment of the requirements for the ward of the Degree of Doctor of Philosophy in Statistics of Makerere University with my ıpproval.

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Dedication

I dedicate this work to my departed parents, Mr. John Wambette and Mrs. Margaret Wabule Wambette. May God rest their souls in Eternity. My dedications also go the family of Mr. Mohammed Watuwa and Mrs. Madina Nambuya Watuwa for the timely moral and financial roles played in supporting my academic endeavours.

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List of Acronyms

ABBREVIATION	MEANING
AAR	Airport Acceptance Rate
AHP	Air Holding Programme
AIC	Akaike Information Criteria
AOC	Airline Operation Centre
ARTCC	Air Traffic Radar Control Centre
ARIMA	Autoregressive Integrated Moving Average
ATC	Air Traffic Control
ATFM	Air Traffic Flow Management
ATM	Air Traffic Management
CAA	Civil Aviation Authority
CDM	Collaborative Decision Management
DC	Developing Countries
DSS	Decision Support System
EIS	Executive Information System
ENHAS	Entebbe handling service
ES	Expert System
FAA	Federal Aviation Administration
GDP	Ground Delay Programme
GDSS	Group Decision Support System
GHP	Ground Holding Programme
HUEN/EBB/EIA	Entebbe International Airport
ICAO	International Civil Aviation Organization
IFR	Instrument Flight Rules
LP	Linear Programming
MAGHP	Multi-Airport Ground Holding Programme

ABBREVIATION	MEANING
MDG	Millennium Development Goal
MIS	Management Information System
NAS	National Aviation System
NMC	National Meteorological Centre
OOA	Object-Oriented Authoring
PAX	Passenger
QNH	Queen's Nautical Height
SAGHP	Single Airport Ground Holding Programme
SFA	Stochastic Frontier Analysis
TFM	Traffic Flow Management
TFMP	Traffic Flow Management Problem
TMI	Traffic Management Initiative
TRACON	Traffic Radar Control
VFR	Visual Flight Rules
VIP	Very Important Person
WMO	World Meteorological Organization

ABSTRACT

Air traffic delay is not only a source of inconvenience to the aviation passenger, but also a major deterrent to the optimisation of airport utility. Many developing countries do less to abate this otherwise seemingly invisible constraint to development. The overall objective of this study was to investigate the dynamics of air traffic delays and to develop stochastic optimisation models that mitigate delays and facilitate efficient air traffic flow management.

Aviation and meteorological data sources at Entebbe International Airport for the period 2004 to 2008 on daily basis were used for exploratory data analysis, modelling and simulation purposes. Exploratory data analysis involved logistic modeling for which post-logistic model analysis estimated the average probability of departure delay to be 49 percent while that for arrival delay was 36 percent. These computations were based on a delay threshold level at 60 percent which presented more significant predicators of nine and ten for departure and arrival respectively. The proportion of aircrafts that delay was established to follow an autoregressive integrated moving average, ARIMA (1,1,1) time series.

The stochastic frontier model estimates show the average inefficiencies of aircraft operations as 15 and 20 percent at departure and arrival respectively. The final category of output of the study was three stochastic optimisation models developed by relating airport utility and the interaction effects of daily probabilities of delay and airport inefficiency estimates. The three models measure daily airport utility at aircraft departures, arrivals and aggregated aircraft departures and arrivals. In this formulation, the stochastic frontier model inefficiency estimates and the post-logistic delay probability estimates were used as inputs into the stochastic optimisation models to enforce the models' theoretical underpinning.

Model sensitivity analysis adduced that the utility level for a given time period at an airport with higher levels of inefficiency was significantly less than the utility level with lower levels of inefficiency. Furthermore, lower estimates of probabilities for departure and arrival delay resulted into a higher operational utility level of the airport. Further analysis suggests that Entebbe International Airport operates at almost the same utility levels for aircraft departures, 92 percent and aircraft arrivals, 91 percent. To maximise airport utility over a time period, measures have to be developed to improve overall timeliness of aircraft operations at departures and arrivals respectively.

Keywords: *Arrival delay, departure delay, proportions, stochastic optimisation models*

Table of Contents

Content **Page**

List of Figures

List of Tables

CHAPTER ONE
INTRODUCTION

This chapter presents a discussion of the background to the study from which the motivation and problem statement are derived. Consequently, the objectives of the study are stated including its scope.

1.1 Background to the Study

Air traffic has greatly increased over the last decade and is predicted to continue to increase at a rate of 15 to 20 percent over the next decade Civil Aviation Authority (2007) . This great increase in air traffic relates to an increase in the demand for airport and airspace resources. Unfortunately, airspace and airport capacities in Africa region as a whole and Uganda in particular are not increasing at a rate adequate to meet its rising demand. The continued level of inefficiency in the air transport sector especially in Uganda has created the need for more robust solutions in averting the situation through developing appropriate approaches to abate the situation in order to promote a sustainable global partnership, MFPED & UNDP (2003), (2007); UN Devinfo Team (2009) .

It is vital that new methodologies and tools be developed to address the inevitable likely effects associated with general high traffic rates as recommended for road traffic flow management Kakooza *et al.* (2005) . Given this tendency in air traffic flow and the ever growing demand for aviation services in the country, there is need to develop tools that optimise the available resources so as to edge towards effective air traffic flow management.

Figure 1.1 is the map of Uganda showing the location of airstrips and the Entebbe International Airport. Uganda is a landlocked country, bordered by Sudan to the North, Democratic Republic of Congo to the west, Rwanda and Tanzania to the south, Kenya in the East. The EIA is located at Entebbe on the shores of Lake Victoria 32 km from Kampala, the capital city. The Civil Aviation Authority (CAA), in partnership with Government is mandated to manage Entebbe International Airport including the thirteen airfields in the country. With the East African Confederation, more air traffic flow is expected which at this rate will cause a surge in air traffic at Entebbe International Airport.

Figure 1.1 Map of Uganda showing the distribution of airports[1]

[1] Map of Uganda, Courtesy of Google Imagery as at the 25th October, 2009

Figure 1.2 shows an aerial view of the exact location of Entebbe International Airport. There are two runways namely; runway 12/30 (2,408 metres) and runway 17/35 (3,658m). However, only runway 17/35 is operational because it has the Instrument Landing System (ILS). The ILS refers to a ground-based instrument approach system that provides precision guidance to an aircraft approaching and landing on a runway, using a combination of radio signals and, in many cases, high-intensity lighting arrays to enable a safe landing during instrument meteorological conditions (IMC), such as low ceilings or reduced visibility due to fog or rain.

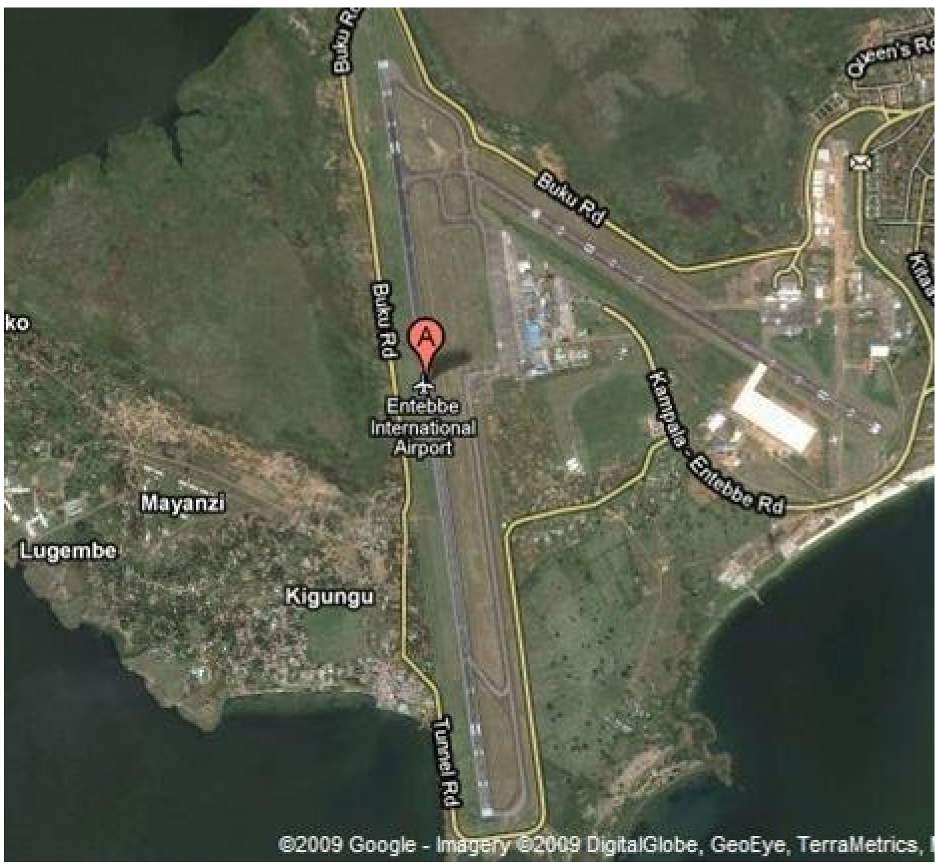

Figure 1.2 Aerial view of the location of Entebbe International Airport[2]

[2] Location of Entebbe International Airport, courtesy of Google Imagery as at the 25th October, 2009

As of the year 2007, sixteen international airlines had scheduled operations to and from Entebbe International Airport, serving fourteen different destinations. The airlines also offer connection to the rest of the world. Uganda's geographical location in the heart of Africa, has given Entebbe International Airport greater advantage for hub and spoke operations in the Eastern and Southern African region according to the website of civil aviation authority of Uganda website *Air Operations* (2007) accessed on the *25th October, 2007*.

During instances of capacity-demand imbalances, air traffic management (ATM) in achieving efficiency and safety is of prime importance as noted by Brooker (2005) . Any given airspace is composed of flight paths, control facilities, sectors and airports. The overall goal of traffic flow management, TFM, is to strategically plan and manage entire flows of air traffic, provide the greatest and most equitable access to airspace resources, mitigate congestion effects from severe weather and ensure the overall efficiency of the system without compromising safety. In the United States' National Airspace System (NAS), for example, there are 21,000 daily commercial flights that are monitored and controlled by 21 Air Route Traffic Control Centers (ARTCCs), 462 airport towers and 197 Terminal Radar Approach Control Facilities (TRACONs). The entire United States airspace is monitored by a central Federal Administration Agency (FAA) facility known as the Air Traffic Control System Command Center (ATCSCC) located in Herndon, Virginia. Therefore, a fundamental capability of all TFM centers globally is the ability to monitor airspace for potential capacity-demand imbalances.

The airspace capacity demand imbalance although constantly monitored by the Air Traffic Control System, at certain times requires human intervention. However, in order to facilitate the human input, sufficient and timely statistical information has to be availed.

The traffic flow management problem (TFMP) can be defined as managing traffic flow during capacity-demand imbalances. As observed by Hansen (2004), the TFMP has become increasingly more important and difficult as the amount of air traffic has increased. Thus, the seriousness of this problem has resulted into a steady increase in delays. Ground holding procedures are a principal tool used to address TFMP. The two main ground holding procedures employed are ground stops and ground delay programs (GDPs). A ground stop is an extreme initiative taken when arrival capacity drastically drops suddenly or when it is greatly underestimated. In a ground stop, flights are held on the ground at their airports until it is determined that the capacity-demand imbalance has abated.

Collaborative Decision Making (CDM), now known as Collaborative Traffic Flow Management (CTFM), was motivated by a need for increased information sharing and distributed decision-making Hoffman R *et al.* (1999) . They further noted a desirable shift from a central planning paradigm to a collaborative TFM paradigm in which airlines, through their airline operational control centers (AOCs), would have more control, flexibility and input into the air traffic flow management decision-making processes. The philosophy of CDM is that with increased data exchange and collaboration comes better and more effective decisions on the part of the traffic flow managers. Collaborative decision making goes hand-in-hand with the air traffic control, ATC concept of Free Flight Architecture (FFA) in which more responsibility for flight maneuvering and aircraft separation is given to the aircraft and pilot.

Air traffic delays are broadly categorized as terminal or en route delays. Terminal delays are incurred as a result of conditions at the departure or arrival airport, and are charged to the appropriate airport. En route delays occur when an aircraft incurs airborne delays of 15 minutes or more as a result of an initiative imposed by a facility to manage traffic. The delays are recorded by the facility where the delay occurred and charged to the facility that imposed the restriction.

1.2 Motivation for the Study

No research has so far been done about air traffic delay at Entebbe International Airport and none has so far published about the same subject at airports in the Southern and Eastern Africa region. It was therefore necessary to assess the extent of air traffic delays at EIA. In the process, it was established that more information would result from an in-depth assessment of delay separately for departure and arrival delay dynamics.

In order to improve the management of air traffic flow at Entebbe International Airport, it was important to analyse the performance of aircraft delay over a period of time. Billy (2009) argued that air traffic delay are not only a source of inconvenience, but also cost New York City $2.6 billion a year. Ehrlich (2008) estimated the total cost due to domestic air traffic delays in the United States of America to be $41 billion for the year 2007 that included higher airline operating costs, lost passenger productivity and time and losses to other industries. Evans *et al.* (2008) agreed that to improve air traffic management during severe convective weather, model need to be applied to facilitate timely decision-making in difficult environments.

The study was guided by five general impacting conditions to air traffic flow management Bauerle N. *et al.* (2007) namely:

i. Weather: the presence of adverse weather conditions affecting operations. This includes wind, rain, snow/ice, low cloud ceilings, low visibility, and tornado/ hurricane/thunderstorm.

ii. Equipment: an equipment failure or outage causing reduced capacity. Equipment failures are identified as to whether they are FAA or non-FAA equipment, and whether the outage was scheduled or unscheduled.

iii. Runway/Taxiway: reductions in facility capacity due to runway or taxiway closure or configuration changes.

iv. Traffic Management Initiatives (TMI): national or local traffic management imposed initiatives, including ground stops/delays, departure/en route spacing, fuel advisory, mile/minutes in trail, arrival programs, and airport volume.

v. Other: emergency conditions or other special non-recurring activities such as an air show, VIP movement or radio interference. International delays are also included in this category.

1.3 Problem Statement

Optimization of air traffic flow at airports is one of the fundamental ways through which airlines maintain operational and economic efficiency. However, weather, equipment, runway and other anomalous conditions disrupt air traffic flow leading to significant costs as a result of aircraft delays. The occurrence of these conditions creates unpredictable situations that require stochastic approach to solve. Automated systems for optimizing air traffic flows are unable to effectively reconfigure when path planning must account for dynamic conditions such as moving weather systems and unpredictable movements of very important persons.

Human intervention is needed and could be provided to enhance the automated decision making for aircraft route planning and reconfiguration. Specifically, there is lack of such intervention at Entebbe International Airport that can mitigate delays so as to enhance Air traffic flow Management to boost efficiency of aircraft operations. Statistics are the basic ingredients of human interventions and these are derived mainly from operational data and data simulations where necessary to facilitate modeling for problem solving. Although, some operational data are available at the Entebbe International Airport, they are not maximally being utilized to abate air traffic delays for sustained efficient air traffic flow management. Subsequently, there are not enough tools to inform the human intervention into air traffic management automation process in order to lead to sustainable air traffic efficiency.

1.4 Research Objectives

The main objective of this research study was to investigate the dynamics of aircraft delays and hence develop stochastic optimisation models that mitigate delays and facilitate timeliness of aircrafts for efficient air traffic management.

The specific objectives of the study were the following:

1. To analyse the air traffic delay at Entebbe International Airport;
2. To assess the dynamics of air traffic delay;
3. To determine air traffic operational inefficiency;
4. To develop stochastic models for aircraft operational utility optimisation;
5. To develop algorithms for sensitivity analysis so as validate the model

1.5 Research Questions

The study addresses the following research questions:

i) Is there a trend in the proportion of aircraft delays at Entebbe International Airport?

ii) How significant do the factors associated with aircraft delays actually determine air traffic delays at Entebbe International Airport?

iii) Can we determine air traffic operational efficiency using the available data?

iv) How is aircraft operational utility related to departure and arrival delays?

1.6 Significance of the Study

The study produced outputs that are very important to the aviation industry including. Firstly, the study derived departure delay determinants of aircrafts at Entebbe International Airport and those with similar characteristics especially in Eastern and Southern Africa region. Similar determinants were derived for evaluating the dynamics of aircraft arrival at the airport. Secondly, a model for aircraft operational technical inefficiency at the airport was determined using stochastic frontier model approach. The significance of these two major study outputs, one and two is to empower the decision making process of air traffic flow management by filling the knowledge gap and emphasizing the need for integration in the decision making process of air traffic flow management. The knowledge gap is informed through evaluating the determinants of aircraft delays and the ability to forecast the delay based on aggregated daily historical data.

Thirdly, the stochastic optimisation models developed recognise the negative effects of delays in the daily operations of aircraft flow and also based on the knowledge, established an optimal aircraft operational level over time. In these models, the number of aircrafts that delay per day are minimised, without necessarily compromising the lives of passengers, the crew board and machinery losses.

Fourthly, computer algorithms have been developed for the stochastic models that render them easy to adapt for implementation through computer programming and automation. Sensitivity tests performed show that the models are adaptable to different scenarios both in the known very busy and moderately busy airports in the world. Furthermore, because of the aggregation of the number of aircrafts delaying to depart or arrive per day, these model are geared towards performing better than the previous models even for the worst case scenario where the inputs are practically too large. The previous models have always considered the duration of time delayed, however, the proportions of aircrafts that delay either to depart or to arrive was the primary parameter used in this study.

1.7 Research Contribution

Stochastic optimization models are presented for the single airport delay programme (SADP) at EIA in which airport utility is computed based on ground and arrival delays assigned to various flights respectively. In the models, constraints that can capture any generalized scenario representing evolving information about airport operating conditions typical to an airport are specified. For all instances of the problem, numerical solutions are obtained directly from the relaxation of the models; hence the computational times are in order of a few seconds even for large scale problems. An additional advantage of this formulation is that it handles a wide range of objective functions ranging from the basic to more complex problems. In addition to the standard linear delay cost function with different weights for airborne and ground delay, an estimation of airport daily utilities and a maximum of the utilities for all the sampled days during departure and arrival at a given airport is computed.

This study also applied a data-driven approach to modeling whereby statistical models based on ground and airborne delay programs are developed to aid management in making appropriate and timely decisions as presented in Chapter Three.

Based on simulation of different airport performance, different scenarios and their probabilities of occurrence were generated. An optimal scenario-based probability of the optimal utility was then generated. Data simulations through well planned design of experiments on the model are also presented in Chapter Four of this thesis.

Finally, this study extended its scope to develop algorithms based on the new object oriented paradigm that enable the air traffic management by using the current object-oriented software technology that provides for human intervention into the system of traffic management at an airport.

1.8 Delimitations of the Study

The empirical study does not focus on the Civil Aviation Authority in its entirety, but only on one Department under the Directorate of Air Navigation Services that specifically handles air traffic management. It does not analyze the technical details for example, the construction and materials of the runways, but rather focuses on the process of managing and improving air traffic flow efficiency at the airport. It analyses the dynamics of the aircraft delay at zero tolerance performance of Entebbe International Airport. The study does not analyze aircraft delay based on the length of duration of the delay as a unit of measurement; rather the daily proportion of aircraft delay was used in the analysis.

1.9 Limitations of the Study

The research had a number of limitations that either acted to slow down its progress or deviate the methodology to the research approach. Nevertheless, the research proceeded to the fulfillment of the researcher's expectations. Some of the research limitations included; firstly, security limitations to access the case study area, Entebbe International Airport; secondly, the high level of data confidentiality attached to the data at the case study; thirdly the unexpected data incompleteness for the proposed time duration and lastly the uncertainty of data compatibility since dual sources of data were used for this study. However, it is worth to note that in no significant way did these limitations affect the research output because each of those limitations mentioned was appropriately overcome.

The first limitation was overcome by getting a security pass to enable me access necessary offices at the airport. This research did not require use of identity names for airlines and aircrafts; hence dropping those variables did not affect the output of this research in anyway. Although, the study aimed at using all the available delay data at the airport, the daily hourly data collected from both the airport and the meteorological briefing office for five years resulted into 1827 daily aggregated records that formed a sufficiently large data set for this research to meet its specific objectives. Finally, the experience of the researcher in data management played a big role in aptly managing and handling data from different data sources, hence this limitation was overcome hustle free.

1.10 Ethical Considerations

The nature of this research required that operational data of Entebbe International Airport were used. As such issues pertaining data confidentiality and integrity were treated with high ethical regard. All variables that tended to identify and classify individuals, airlines or aircrafts involved were dropped. Aircraft registrations and countries where they are registered from were also dropped for the purpose of maintaining high ethics and confidentiality.

1.11 Structure of the Thesis

The thesis has six chapters. Chapter 1 is an introduction to the research outlining the research problem and the objectives of the research. Chapter 2 is literature review and a theoretical and conceptual framework in order to understand the research context and to identify relevant theories and concepts. Chapter 3 is devoted to the statistical models for air traffic delay, detailed exploratory data management approach, data parameters from two sources, statistical analyses, the R statistical computing language and other customized code for statistical model development and sensitivity analysis. Models presented under different sections include: sequence charts, ARIMA models and Logistic models for aircraft delays and the stochastic frontier model for aggregated aircraft delay. Chapter 4 presents the stochastic optimization models deriving from this study. The stochastic optimisation model for maximizing aircraft utility is presented. Sensitivity analysis based on the available data at the Civil Aviation Authority at EIA and data simulations are used to ascertain the resilience of the model. Chapter 5 provides discussions based on the results from the study. Chapter 6 comprises of the conclusions and recommendations as generated from the preceding chapters.

CHAPTER TWO

LITERATURE REVIEW

Review of relevant literature was considered in this Chapter to assess the extent to which solution finding research, using the modeling approach, has reached as far as air traffic management. Consequently, existing knowledge gaps were discovered, thus confirming the relevance of this research as its findings will go a long way in filling the existing knowledge gap in air traffic management in Uganda and the world at large. The choice of sections in this chapter is two pronged, that is, informative and exploratory.

2.1 Airport Capacity

Airport capacity, the primary determinant for resource allocation at a given airport, is the number of aircrafts that can be accommodated given the resources available at the airport. The capacity of a runway or a set of simultaneous active runways at an airport is defined as the expected number of movements (landings and take offs) that can be performed per unit time in the presence of continuous demand and without violating air traffic control (ATC) separation requirements. This is often referred to as the maximum throughput capacity. This definition takes into account the actual number of movements that can be performed per unit of time and is a random variable.

Airports consist of several subsystems, such as runways, taxiways, apron stands, passenger and cargo terminals, and ground access complexes, each with its own capacity limitations Ball Michael *et al.* (2006) . At major airports, the capacity of the system for runways is the most restricting element in the great majority of circumstances. This is particularly true from a long-run perspective. While it is usually possible – albeit occasionally very expensive – to increase the capacity of the other airport elements through an array of capital investments, new runways and associated taxiways involve big expenses in land and they may also have environmental and other impacts that necessitate long and complicated approval processes, often taking a couple of decades or even longer, with uncertain outcomes. The capacity of runway systems is also one of the major causes of the most extreme instances of delays that lead to widespread schedule disruptions, flight cancellations and missed flight connections. There have certainly been instances when taxiway system congestion or unavailability of gates and aircraft parking spaces have become constraints at airports, but these are more predictable and stable. The associated constraints can typically be taken into consideration in an adhoc way during long range planning or in the daily development of ATFM plans. The capacity of the runway system can vary greatly from day to day and the changes are difficult to predict even a few hours in advance. This may lead to an unstable operating environment for air carriers on days when an airport operates at its nominal, good weather capacity. Flights will typically operate on time, with the exception of possible delays due to 'upstream' events, but with the same demand at the same airport, schedule reliability may easily fall on days when weather conditions are less than ideal.

2.2 Air Traffic Management, Global Perspective

The arrivals, departures and general day-today flow of aircrafts in a given airport is facilitated and controlled by a number of parameters that include airport capacity and weather parameter dynamics Zhengping *et al.* (2004). Therefore, for an efficient, smooth and optimal operations, there is need to strengthen air traffic management tools for accurate air traffic flow management decisions.

2.3 Air Traffic Management on the African Continent

Africa is one of the continents that are dominated largely by developing economies. These economies are characterized by underdevelopment in all major sectors including health, agriculture, communication, environment and transport. In September 2000 the 8th UN General Assembly adopted the Millennium Declaration which was signed by 189 countries including 147 Heads of State to facilitate the betterment of the livelihood of inhabitants in the developing countries. However, MDG eight that is central in strengthening the partnership between the developed and developing economies has not been given sufficient attention by governments in the developing economies. Since over 50 percent of budgets of most African countries are financed by the developed nations, achievement of goal eight is not only a necessary, but to a greater extent a sufficient condition to their economic development.

2.4 Air Traffic in Uganda

Air traffic in Uganda is dominated by international passengers mainly due to the fact that although most convenient, it is the most expensive means of transport as such there are comparatively fewer locally derived domestic passengers. A majority of the country's population of about 80 percent is involved in subsistence agriculture whose financial gains are so meagre that they cannot afford sustain air traffic costs. However, the conclusion of the bilateral air service agreements with thirty three countries is indicator for continued increased aviation activities at Entebbe International Airport.

Air traffic management in Uganda is under the umbrella of the Department of Air Navigation Services under the Directorate of Air Navigation Services of the Civil Aviation Authority (CAA) Uganda. CAA is an arm of the International Civil Aviation Organisation (ICAO) in Uganda.[3] The cardinal objective of CAA is to promote the safe, regular, secure and efficient use and development of civil aviation inside and outside Uganda.

2.5 Domestic Air Traffic in Uganda

The number of airfields has been increasing in order to boost domestic air traffic. There are currently thirteen airfields Civil Aviation Authority (2007) , indicates that domestic air traffic increased drastically between the years 1996 and 2008 (see Figure 2.1). This increase in domestic air traffic in the country is mainly attributed majorly to the increased number of international tourists. Presently, the Civil Aviation Authority, CAA manages thirteen airfields located in the following districts: Arua, Gulu, Kasese, Kidepo, Soroti, Mbarara, Pakuba, Masindi, Jinja, Lira, Moroto, Tororo and Kisoro. These upcountry airfields form part of Uganda's domestic air links and serve mainly small general aviation aircraft. In order to promote East African region as one tourist destination, five upcountry airfields that include; Arua, Kasese, Gulu, Kidepo, and Pakuba were designated as entry and exit points to specifically handle cross boarder air traffic flow within the region.

[3] http://www.caa.co.ug/index1.php?pageid=64&pageSection=CAA%20Statute Accessed 25th October, 2008

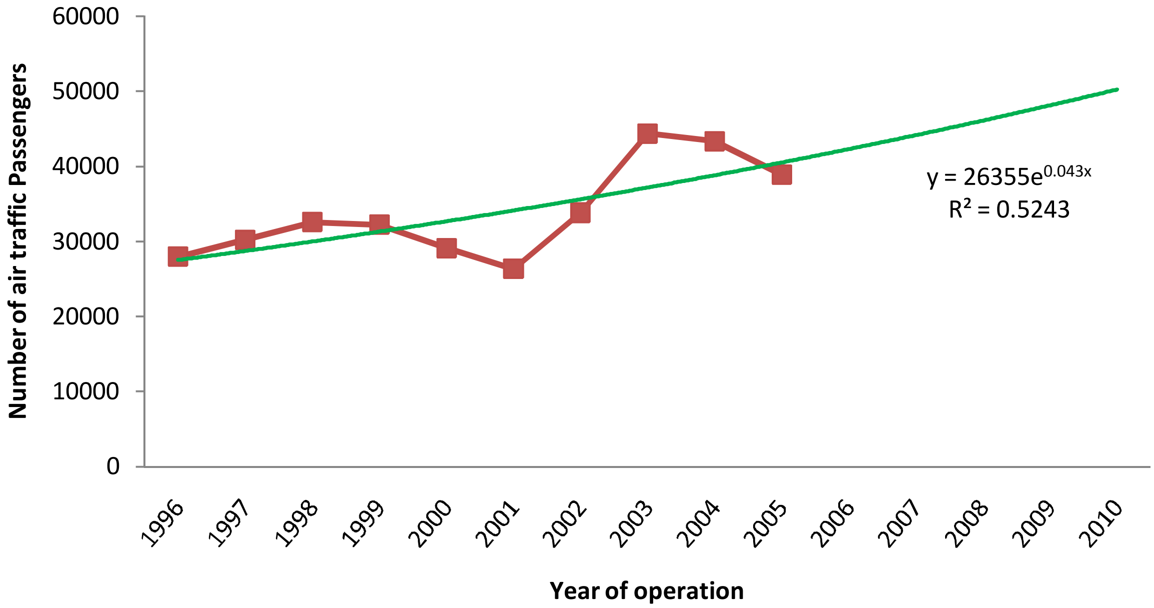

Figure 2.1 Trend of Domestic Passengers at Entebbe International Airport
(Data Source: Uganda Civil Aviation Authority Air Traffic Statistics)

According to the Civil Aviation Authority (2007), an arm of the International Civil Aviation Organisation, a section of the United Nations Organisation responsible for monitoring and management of air traffic, the findings show that the number of domestic passengers in Uganda has almost doubled since the year 1996. This increase is due to the ever increasing number of foreign tourists and the expansion of the number of aerodromes across the country. A forecast of the number of domestic passengers for the year 2010 showed that the country will have to prepare to accommodate over 50,000 domestic civil aviation passengers.

2.6 International Air Traffic in Uganda

Entebbe International Airport is the only international airport in the country and acts as a hub in the Eastern and Central Africa region. In the year 2007, Uganda held the Commonwealth Heads of Government Meeting (CHOGM) that overwhelmed the only international airport's operations with a large number of international passengers. The airport, however, benefitted from some renovations including physical facilitation on improvement of air traffic flow were made.

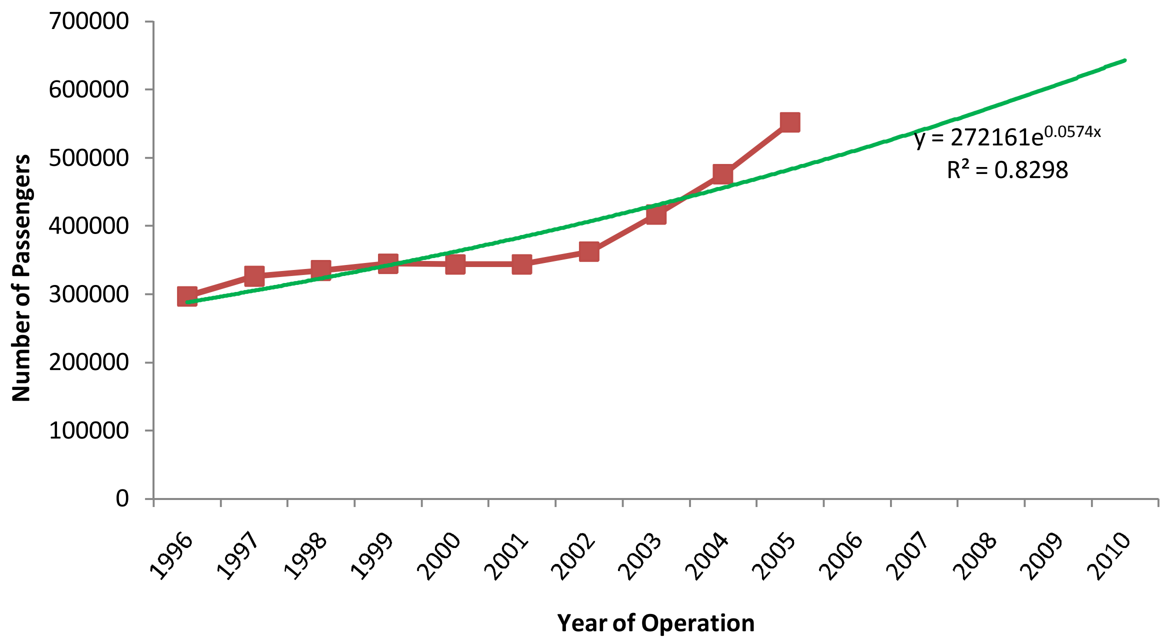

Figure 2.2 Trend of International Passengers at Entebbe International Airport
(Data Source: Uganda Civil Aviation Authority Air Traffic Statistics)

The number of International passengers has also almost doubled since the year 1996. This is due to the increasing number of tourists and the relative improvement in facilities at EIA besides workshops and international conferences.

2.7 Air Traffic Management in Uganda

The rapid restructuring of the global transport system taking place is likely to have a profound impact on processes of globalization, not only in the industrialized, but also industrializing world, including Africa, (Pedersen, 2001) . Pedersen also investigate some of the changes taking place in the global transport system and discussed their impact on African development.

From an individual, national and global point of view, international tourism and air travel are critical factors in achieving global sustainability (Susanne, 2001). This, therefore, clearly indicates that for developing countries to have a sustainable development, they have to improve their air traffic flow management in order to attract and sustain a constant flow of tourists in their countries.

It is interesting that in the event of ICT, air traffic controllers still record data for each flight on strips of paper and personally coordinate their paths. This becomes a great challenge because streamlining this process manually on strips of paper without the assistance of necessary software is not efficient. However, it is noted that in many airports around the world and in Africa, unlike Entebbe International airport by the year 2007, flight progress strips had not yet been replaced by electronic data presented on computer screens.

Besides the global endeavors, air traffic management in Uganda has not received the attention it deserves to improve its operations for efficient traffic flow management. Therefore, this forms the premises for this research.

2.8 Effect of Weather Parameters on Air Traffic Management

Like in the US and other developed countries, air traffic delays are affected by weather parameters such as visibility, cloud cover and thunderstorm-related impacts as confirmed (Wesonga *et al.,* 2008) . Moreover, convective weather delays continue to increase, even though a number of new weather information systems and traffic flow management (TFM) decision support tools have been deployed. In area control centers, the major weather problem is thunderstorms which present a variety of hazards to aircrafts. An aircraft will deviate around storms, reducing the capacity of en-route system by requiring more space per aircraft, or causing congestion as many aircraft try to move through a single hole in a line of thunderstorms. Occasionally, weather considerations cause delays to aircrafts prior to their departure as routes are closed by thunderstorms.

Evans *et al.* (2008) state three major reasons why thunderstorms present a very difficult air traffic management (ATM) problem:

- En route capacities are significantly reduced by phenomena that are difficult to predict in advance.
- Developing and executing convective weather impact mitigation plans is difficult when actions taken in response to the weather disruptions in one spatial region may cause significant air traffic management problems in another spatial region. The task is further complicated by the fact that plans must be developed and executed quickly to take advantage of short lived opportunities.
- There may be subtle differences between any two weather events that pose particular decision-making challenges and there are no agreed-upon approaches for traffic

management of convective weather impacts. As a result, personal decision-making styles on the part of individual decision makers, along with the person's background and experience, are important determinants of the overall use of the traffic and weather information to achieve goals appropriate for a given air traffic control (ATC) facility.

- Furthermore, in tactical (less than 2 hour) decision making, there is no one decision maker who can order the others to comply.

Weather is a also a major factor in traffic capacity dynamics causing runway capacity issues (Markovic *et al.,* 2008) . Rain or ice and snow on the runway cause landing aircraft to take longer to slow and exit, thus reducing the safe arrival rate and requires more space between landing aircraft. Fog also causes a decrease in the landing rate. These in turn, increase airborne delay for holding aircraft. If more aircraft are scheduled than can be safely and efficiently held in the air, a ground delay program may be established, delaying aircraft on the ground before departure due to conditions at the arrival airport.

Statistical models to determine the weather impacts on punctuality of aircrafts have also been developed (Markovic *et al.,* 2008) . They applied a hybrid regression/time series modeling to relate the total daily punctuality at Frankfurt Airport, Germany, to weather, the traffic flow and the airport system state. The selected modeling approach was then applied to the annual, the multi-annual and seasonal data. Their findings showed that the portion of the variability that could be explained by the model after correction of autocorrelations in the residuals using autoregressive (AR) models was between 60 and 69 percent. In this study autoregressive integrated moving average (ARIMA) models presented in Chapter Four.

2.9 Ground Delay Program as an Approach to Air Traffic Management

The ground delay program (GDP) is an air traffic flow management mechanism used to decrease the rate of incoming flights into an airport when it is projected that arrival demand will exceed capacity. Under GDP, a set of flights destined for a single airport is assigned ground delays, (Adilson & Arnaldo, 2000) .

GDPs essentially place CAA service users into a state of irregular operations. Airlines respond by rescheduling, cancelling, or substituting flights. The cancellation and substitution processes allow scheduled airlines to mitigate the adverse effects of ground delays. Cancellation and substitution are specific GDP processes. The process of delaying flights while preserving their order is known as Grover Jack. Furthermore, a bartering solution was suggested whereby inter-airline slot exchanges may be viewed as a bartering process, in which each round of bartering requires the solution of an optimization problem, (Thomas & Ball, 2005) .

The effectiveness of a GDP is contingent upon accurate demand profile and true representation of airport's available capacity during inclement weather conditions. Collaborative decision making (CDM) procedures are said to contribute greatly to an increase in the accuracy of aggregate demand at airports. But these have done little to determine the actual available capacity at congested airports. An airport's capacity or airport acceptance rate (AAR) is directly related to good weather conditions through an airport's runway configuration and its landing procedures. Weather conditions at an airport are used to determine which runway configurations to institute and which landing procedures to implement (Tasha, 2001) . There are two major types of landing procedures: Instrument Flight Rules (IFR) and Visual Flight Rules (VFR). IFR are required when a cloud ceiling of less than 1000 (one thousand) feet or a visibility of less than three miles exists. VFR refers to weather conditions that have a ceiling that exceeds 1000 (one thousand) feet and a visibility that exceeds three miles.

The effective assignment of delay to flights during a GDP is a crucial element to the effectiveness and fairness of a GDP. Fairness of a GDP refers to equitable allocation of delay to each airline. There is a constant hedging between conservative policies of assigning more ground delay. This could lead to the underutilization of arrival resources and the liberal policies of assigning less ground delay that could lead to more costly airborne holding delays (Ball *et al.,* 2006) . Thus, the ground delay problem (GDP) seeks to determine an optimal balance between these policies for assigning delay in a GDP.

The first discussion and description of GDP, referring to the deterministic GDP as the flow management problem in which travel times and capacities are deterministic, the existence of a discrete time horizon whereby the only capacitated element is the arrival airport (Odoni, 1987) . He further established that there are three main assumptions required by the ground holding model, which are based on the assumptions of the flow management problem. The assumptions are (1) a discrete time horizon, (2) deterministic demand and (3) deterministic capacity.

A dynamic programming algorithm for the single-airport static stochastic ground holding problem, GHP for at most one time period was developed (Andreatta & Romanin, 1987) . This was the first paper written that developed an algorithmic approach to determining the amount of ground delay to assign to flights bound for a congested airport. The authors considered a single destination airport and flights bound for the airport. The dynamic program resulted in an optimal delay strategy that minimized total expected delay for the flights. The model in their paper is a static, stochastic version of the GDP because it is assumed that airport capacity information is known at the beginning of the day and is summarized using a random variable.

Airport capacity can be summarized by a random variable k that takes on 0,1,...,n with probability p(0), p(1), ..., p(n), (Terrab & Odoni, 1993) developed a more efficient algorithm to solve the single-airport static deterministic GHP optimally and heuristics for the single-airport stochastic GHP. While Richetta & Odoni (1993) developed heuristics for the single-airport dynamic stochastic GHP.

Terrab *et al.* (1993) formulated single-airport static stochastic GDP with multi-periods as a dynamic programming problem. They proposed heuristics to solve their version of the GHP and to handle large problem instances that occurred in practice. Since the authors were unable to prove that the formulation would yield an integer solution directly from the linear programming (LP) relaxation, they developed a decomposition method to exploit the fact that the constraint matrix could be partitioned into network matrices. Since this was a static stochastic version of the GHP, the authors described airport capacity in the following manner: Capacities are random variables that are given a probabilistic forecast that can be thought of as a number of scenarios, each scenario representing a particular instance of the random capacity vector with an associated probability.

Stochastic linear programming with one stage to solve the single-airport static stochastic GHP with multi-periods optimally were first used (Richetta & Odoni, 1994), who expanded previous work by including the dynamic case. They were able to overcome the limitations of the dynamic programming formulation in their paper (Terrab *et al.,* 1993). Previous work determined amount of delay to assign on a flight-by-flight basis.

The single-airport static stochastic GDP as an integer programming problem that can be solved in polynomial time was formulated (Hoffman *et al.,* 1999) . They improved on (Richetta *et al.,* 1994) formulation by including fewer decision variables and exploiting the network structure of the problem to an optimal solution using linear programming relaxation. As in other stochastic versions of the GDP, arrival capacities are assumed to be random variables. The most important contribution of their model is the paradigm and procedures of CDM. The trend is towards a formulation of the GDP that is stochastic in nature because it is a better representation of true conditions during a GDP.

2.10 Air Delay Program as an Approach to Air Traffic Management

Air traffic flow management in Europe has to deal as much with capacity constraints in en route airspace as with the more usual capacity constraints at airports (Guglielmo & Amedeo, 2007). The en-route sector capacity constraints, in turn, generate complex interactions among traffic flows. They further illustrated the complex nature of European Union (EU) ATFM solutions, the benefits that could be obtained by purposely assigning airborne holding delays to some flights and the issues of equity that arose as a result of the interactions among traffic flows. Specifically, they showed that in certain circumstances, it is better in terms of total delay and delay cost to assign to a flight a more expensive airborne holding delay than a ground delay.

2.11 The Cumulative Costs of Air Traffic Delay

Milan (2009) defined flight delay as any flight departure or arrival that falls more than 15 minutes behind schedule. Milan also confirmed that flight delays have become an inherent feature of the modern air transport system. Delays are caused by internal and external factors working individually and/or in combination. The main internal factor is the imbalance between the demand for flights and the capacity of the given air transport system component that may happen under both regular and irregular operating conditions. For example, in the former case, capacity may not meet demand because of airline scheduling practice. In the latter case, capacity may not meet demand because of unforeseen shortcomings with certain system component.

The United States Congressional Committee (USCC) stated that with the rising price of oil, flying the friendly skies is not only a costly endeavor, but inefficient as well (Ehrlich, 2008) . They continued to note that delayed flights in the year 2006 alone consumed about 740 million additional gallons of jet fuel, according to the Joint Economic Committee (JEC), totaling to about USD 1.6 billion in extra fuel bills for the commercial airline industry. Furthermore analysis by the committee revealed that air traffic delay-related burning of jet fuel also led to the emission of about 7.1 million metric tons of carbon dioxide in the same year. And those numbers were predicted to go up, with wasted fuel costs potentially topping $2 billion in the year 2007. The committee's report, entitled "*Your flight has been delayed again*" called for an upgrade to the air traffic control system by converting the nation's radar based tracking system to satellite based technology.

Two factors that may explain the extent of air traffic delays in the United States including the network benefits due to hubbing and congestion externalities were reported (Mayer & Todd, 2002) . Although they noted some benefits that accrue from air traffic delays, they also noted that Airline hubs enabled passengers to cross-connect to many destinations, thus creating network benefits that increased the number of markets served from the hub. Delays are the equilibrium outcome of a hub airline equating high marginal benefits from hubbing with the marginal cost of delays. However, congestion externalities were created when airlines did not consider that adding flights may lead to increased delays for other air carriers. In this case, delays represented a market failure.

Analysis based at LaGuardia Airport, found out that prices fell by USD 1.42 on average for each additional minute of flight delay and that the price response was substantially larger in more competitive markets (Silke, 2008) . This implied that for only 100 passengers delayed at an airport, for say, 60 minutes, could result into a cumulative loss by an airline equivalent to USD 8520.

Further analysis by the Partnership for New York City, established that local air traffic congestion cost the US economy $2.6 billion in the year 2008, (Billy, 2009) . Furthermore, delays that stemmed from the one-third of nationwide flights that went through New York ended up having an impact in causing a delay in three-quarters of those nation's flights. The head of the Partnership then, Kathryn Wylde recommended modernization of air-traffic control and routes that planes used nationwide, a move that would cost an estimated $22 billion. However, doing so would allow planes to take full advantage of satellite-based air navigation and no longer only use long and straight arrival paths.

These analyses revealed the impending gap that exists in air traffic management that urgently require a study to assess and develop a dynamic tool that can be used in maximizing aircraft utility at airports especially in the developing countries.

2.12 Justification of Stochastic Models in this Study

There are two main techniques of modeling which are categorized as deterministic and stochastic approaches. The former has been applied more regularly, hence its popularity compared to the latter. Deterministic modeling assumes perfect knowledge of the system inputs under study both in the objective function and its constraints. On the contrary, stochastic models assume uncertainty of parameters either in the objective function or its constraints or even both in the objective function and its constraints. Probability theory therefore plays a fundamental role in the development of stochastic models.

Maybeck (1979) gave three basic reasons why deterministic system and control theories do not provide a totally sufficient means of performing system analysis and design. First, mathematical system model is perfect. Any such model depicts only those characteristics of direct interest to the modeler. Second, those dynamic systems are driven not only by our own control inputs, but by disturbances which we can neither control nor model deterministically. For example, if a pilot tried to command a certain angular orientation of the aircraft, the actual response will differ from his expectation due to wind battering or simply his/her inability to generate exactly his desired response from his/her own arms and hands on the control stick. Third, sensors do not provide perfect and complete data about a system; they only generally provide some of the information one would like to know.

2.13 Stochastic Programming and Air Traffic Management

Stochastic programming (SP) deals with a class of optimization models and algorithms in which some of the data may be subjected to significant uncertainty. Such models are appropriate when data evolve over time and decisions need to be made prior to observing the entire data stream.

Under uncertainty, the system operates in an environment in which there are uncontrollable parameters which are modeled using random variables. Consequently, the performance of such a system can also be viewed as a random variable. Accordingly, SP models provide a framework in which a design can be chosen to optimize some measure of the performance (random variable). It is therefore natural to consider measures such as the worst case performance, expectation and other moments of performance, or even the probability of attaining a predetermined performance goal. Furthermore, measures of performance must reflect the decision maker's attitudes towards risk.

Stochastic programming provides a general framework to model path dependence of the stochastic process within an optimization model. Furthermore, it permits unaccountably many states and actions, together with constraints and time-lags. One of the important distinctions that should be highlighted is that unlike DP, SP separates the model formulation activity from the solution algorithm. One advantage of this separation is that it is not necessary for SP models to obey the same mathematical assumptions.

2.14 Optimization in Air Traffic Flow Management

Air Traffic Flow Management (ATFM) optimization has been a topic of research for about a decade. There are two main categories of published research in this area: (1) optimization models that account for airport arrival and/or departure capacities, but ignore en-route capacity constraints, and (2) those that account for both airport and en-route capacity constraints. The former class of problems is commonly known as ground holding problem (GHP), while the latter is sometimes termed the multi-airport air traffic management problem.

The objective of the ground holding problem class of this problem was to minimize the sum of airborne and ground delay costs in the face of anticipated demand-capacity imbalances at destination airports, by assigning ground delays to flights. Within the domain of GHP, there are two sub-problems: the single airport ground holding problem (SAGHP) and the multi-airport ground holding problem (MAGHP). In SAGHP, the problem is solved for one destination airport at a time. In the MAGHP, a network of airports is considered, so that delay on a given flight segment can propagate to down segments flown by the same aircraft. Some treatments of the MAGHP also consider crew and passenger connectivity effects.

A deterministic model for SAGHP, in which the objective function minimizes the total cost of ground holding set of flights, was proposed (Terrab *et al.,* 1993) . The cost of delaying each flight is represented through a linear cost function with flight-specific parameters, which is supplied as input.

Hoffman *et al.* (1999) proposed a deterministic model for the SAGHP with banking constraints, which imposes the condition that one or more groups of flights must arrive within pre-specified time windows.

An optimization model for mitigating bias from exempting flights from a GDP was then proposed (Thomas Vossen et al., 2002). Deterministic optimization, formulated as an integer program (IP), for multi-airport ground holding programme, MAGHP was first proposed (Vranas *et al.,* 1994) . Their computational study showed exorbitant computing times for solving the IP optimally under realistic cases. Dimitris & Patterson (1998) provided a stronger formulation to the deterministic MAGHP. Uncertainty in airport capacities has been addressed mainly in context of SAGHP; although (Vranas *et al.,* 1994) provided some treatment of stochastic version of MAGHP.

A static stochastic IP formulation for solving the SAGHP under uncertainty in airport arrival capacities was first suggested (Richetta *et al.,* 1994) . Thereafter, (Ball *et al.,* 2003) proposed a modified version of the static stochastic optimization for SAGHP, which solves for optimal number of planned arrivals of aircraft during different time intervals. In the static models, decisions related to departure delays of flights are taken once at the beginning of planning horizon, and not revised later. However, (Richetta *et al.,* 1994) attempted to solve this limitation by formulating a multistage stochastic IP with recourse for SAGHP. In their model, the ground delays of flights are not decided at the beginning, but at the scheduled departure time of the flights. However, ground delays once assigned cannot be revised later in their model.

Deterministic optimization models addressing en-route capacity constraints were formulated as multi-commodity network flow problem (Helme, 1992) , and (Dimitris & Patterson, 2000) . Unlike single-commodity flow network formulations, these models are computationally harder and do not guarantee integer solutions from Linear Programming (LP) relaxations. One of the assumptions made (Helme, 1992) was that each aircraft route is pre-determined before its departure. They established that the model addresses routing as well as scheduling decisions, but it produces non-integer solutions for even small scale problems. Therefore the authors suggested heuristics to achieve integer solutions.

Disaggregated deterministic integer programming models for deciding departure time and route of individual flights were formulated (Dimitris *et al.,* 2000) . Although both formulations produce non-integer solutions from LP relaxation, the latter model achieves integrality in many more instances compared to the former, by virtue of its formulation. An attempt to address weather related uncertainty in en-route airspace congestion was made (Arnab *et al.,* 2003) . Their work focused on dynamically rerouting an aircraft across a weather impacted region.

In summary, stochastic optimization methods for ATFM have been applied to solve the SAGHP, while there is much left to be done. One unexplored area is dynamic models that can adapt to updated information as time progresses, to revise the ground delay decisions of flights. Another is models that address both en-route airspace and airport capacity in a stochastic setting. Finally, to implement dynamic decision making in CDM environment, we must develop models that accommodate both decentralized and centralized decision making.

2.15 Theoretical Framework

A number of variables that impact on air traffic management were identified, the critical variables were identified, and their relationship to air traffic flow management explored in detail.

Figure 2.4 shows the interaction of parameters from which the stochastic optimisation model system is derived. Two basic sources of data used are the aviation and meteorological data sources which generate indicators for air traffic management and subsequently use them to project airport capacity demand. When it is established that the demand does not exceed the airport capacity, normal operations using the preset aircraft schedules are used, otherwise, capacity scenarios, probabilities of aircraft delay at departure and arrival, airport inefficiencies at departure and arrival and subsequently the airborne to ground delay cost ratio. The parameters are then used as inputs into the stochastic optimisation model to compute optimal airport utility level.

Figure 2.6 further demonstrates the relationship between the aviation and meteorological parameters and the airport utility functions. It is argued that timely operations of aircrafts at the airport generate a 100 percent level of airport utility. Hence, delays in aircraft departures and arrival tend to reduce the utility of an airport.

2.15.1 Air Traffic Management Logical Framework

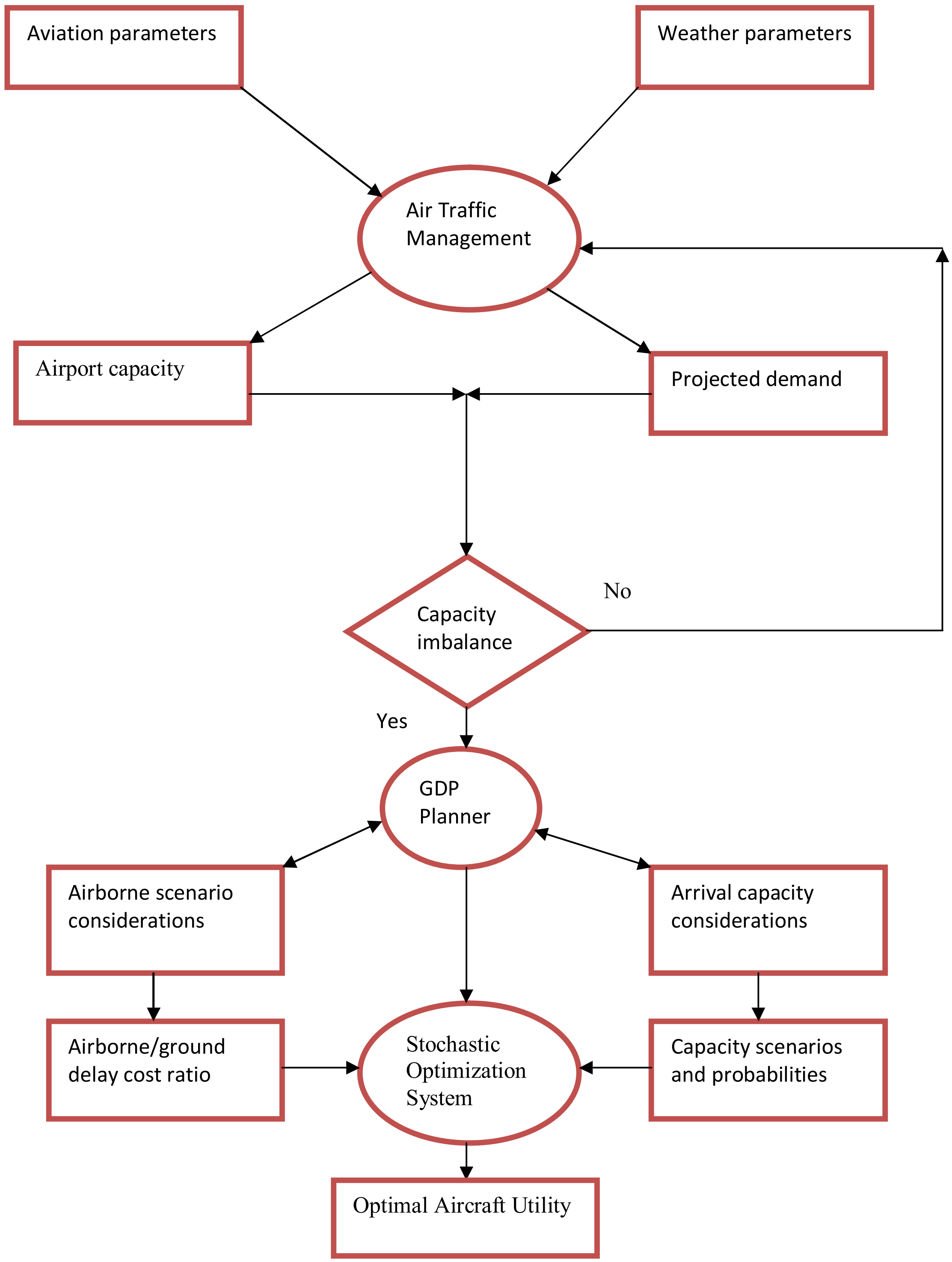

Figure 2.4 Deriving optimal aircraft utility

2.15.2 Conceptual Framework

The conceptual framework below is an illustration of the causal-effect relationship between weather parameters, aviation parameters and the aircraft delay. The effect of the aircraft delay on the airport utility is then derived as indicated in Figure 2.5.

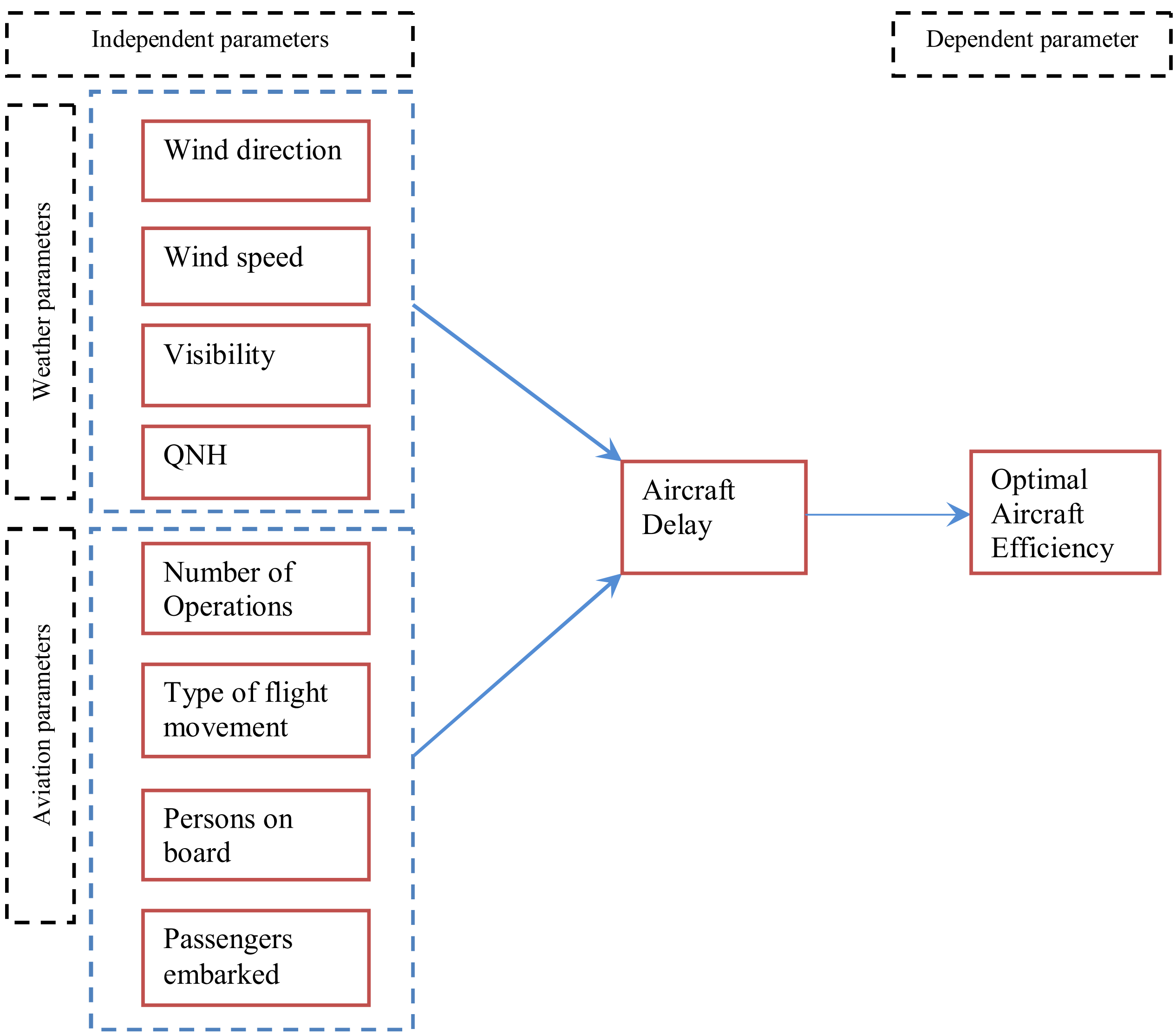

Figure 2.5 Delay based air traffic flow management factors

2.15.3 A detailed Conceptual Framework

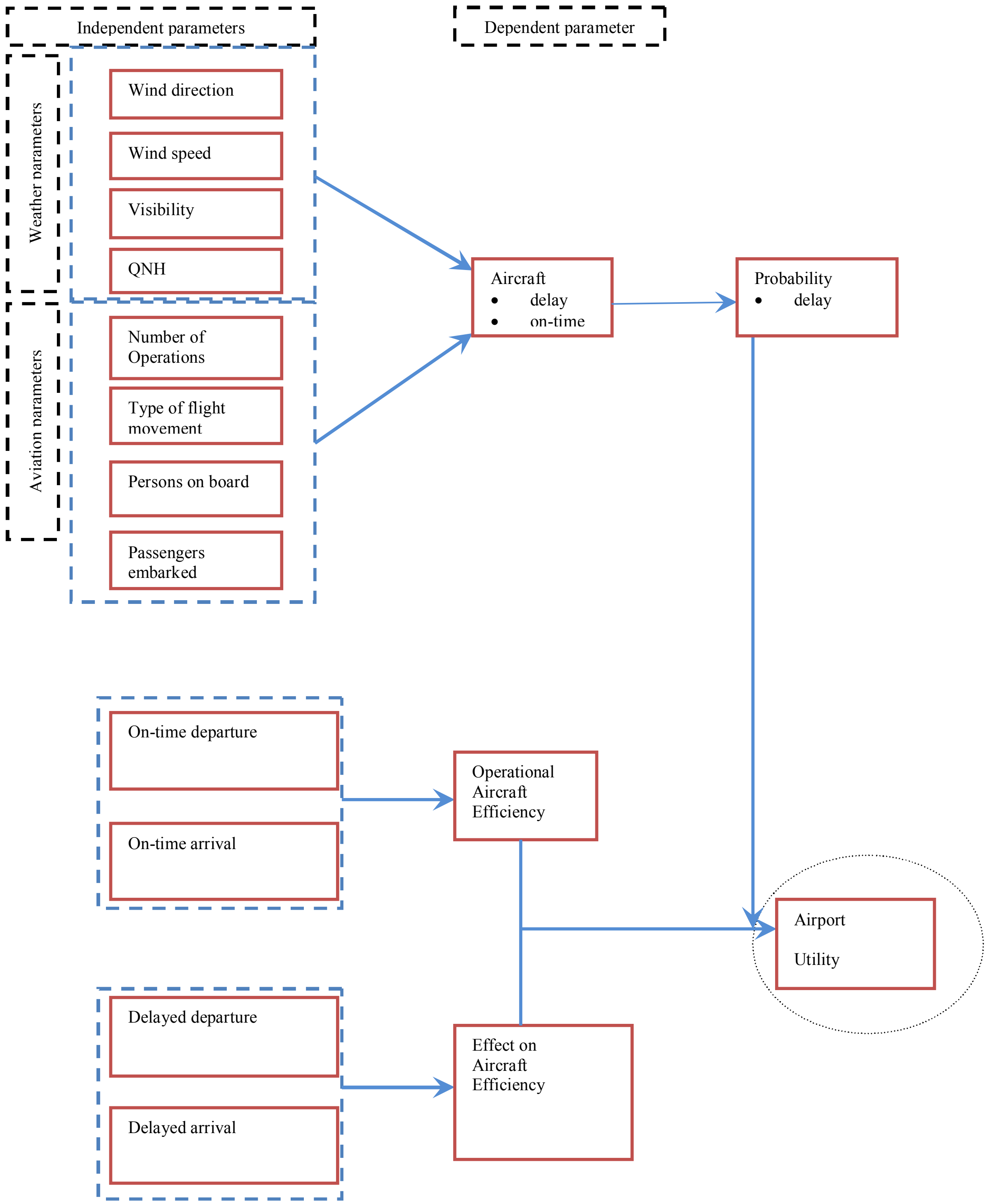

Figure 2.6 Conceptual Framework of the Study

CHAPTER THREE
STATISTICAL MODELS FOR AIR TRAFFIC MANAGEMENT

This chapter presents data sources, specific variables collected, data management process followed by data analysis and challenges encountered both in data collection and during data management process. Specifically, the chapter gives the process of computation of the number of aircrafts that delay both to depart and arrive and also aggregation of the variables on a daily basis. Subsequently, statistical models are developed that can be used to develop informed decisions by the air traffic management. Explicitly, the statistical models developed during the study were logistic regression models, the stochastic frontier models and the ARIMA models. The models are developed using operational data from Entebbe International Airport in Uganda. They are presented in the following order logistic model, the stochastic frontier models and the ARIMA models since one form produces results that invoke the other.

3.1 Data Description: Sources and Preparation

The data for the study were collected from the Civil Aviation Authority (CAA) and the National Meteorological Centre (NMC). Specifically, data collected came from the Statistics Department of the Civil Aviation Authority and the Briefing Office of the Department of Meteorology in Entebbe, Uganda. The reliability of the models is strongly dependant on the amount and quality of data used for model formulation and calibration. Models were formulated using aircraft delay program parameters and weather conditions at Entebbe International Airport.

3.1.1 Aviation Data Logs

On a daily basis, specialists record all facility operations from the beginning of the day until the end of the day on a twenty four hour basis. The main components of these records were the actual and expected times of arrival and departure respectively recorded for every incoming and outgoing flight at the airport. These data commonly referred to as manifest data are then entered and stored in a database and only referred to whenever there is for example an investigation of aircraft accident or incidence. Table 3.1 gives the main variables for the data of interest in this study. The departure delay duration was then computed by obtaining the difference between actual and expected departure time while arrival delay duration was estimated by computing the difference between actual and expected arrival time. In either way, an aircraft is said to delay when actual time is greater than the expected time. Given the variability of operations of aircrafts over the scope of time for the study, the data was aggregated to obtain proportions of delay per day, thus generating 1827 records representing 1827 days in the period 2004 to 2008.

3.1.2 Meteorological Data Logs

Weather related data is of immense application and one of the main uses is to support the aviation industry in its aim to maintain high and reliable aircraft flow. The weather data logs comprised of a number of parameters referred to as a METAR, which is a French abbreviation for *MÉTéorologique Aviation Régulière*, and used to report specific weather data on an hourly basis. A typical METAR report contains information on temperature, dew point, wind speed and direction, precipitation, cloud cover and heights, visibility and barometric pressure all of which contribute to the understanding of the horizontal and vertical stochastic phenomena of weather.

The data in METAR report is coded as a way of international standardization such that it may be understood by anyone irrespective of the language barrier. This coding is managed a United Nations body called the World Meteorological Organisation.

Weather conditions and runway configurations play a major role in determining airport capacities and the smooth flow of aircrafts at an airport. Meteorological data for aviation are collected using the semi-automated method that involves both manual readings and use of the Satellite Distribution System (SADIS) to track weather parameters along the major stages along the aircraft's trajectory. Weather variables were mainly used to determine distributions of Instrument Flight Rule conditions that included ceiling height and visibility. A ceiling below 1000 feet or a visibility less than 3 miles marks Instrument Flight Rule conditions according to ICAO regulations. Table 3.1 gives key variables of interest to this study.

Table 3.1 is a data dictionary showing various characteristics of the variables used in this study, their data types and general description.

Table 3.1: Data dictionary for the model variables

Field name	**Type**	**Upper limit**	**Lower limit**	**Continuous /Discrete**	**Description**
Date	Date	Dec. 2008	Jan. 2004	Discrete	Date of aircraft operation
Scheduled	Integer	Dec. 2008	Jan. 2004	Scale discrete	Number of daily scheduled flights
Non-scheduled	Integer	Dec. 2008	Jan. 2004	Scale discrete	Number of daily non-scheduled flights
domestic	Integer	Dec. 2008	Jan. 2004	Scale discrete	Number of daily domestic flights
International	Integer	Dec. 2008	Jan. 2004	Scale discrete	Number of daily domestic flights
POBin	Integer	Dec. 2008	Jan. 2004	Scale discrete	Number of daily persons on board on the incoming aircrafts
POBout	Integer	Dec. 2008	Jan. 2004	Scale discrete	Number of persons on board on the outgoing aircraft
GDP	Integer	Dec. 2008	Jan. 2004	Scale discrete	Number of aircrafts that have delayed to depart on a daily basis
AHP	Integer	Dec. 2008	Jan. 2004	Scale discrete	Number of aircrafts that have delayed to arrive on a daily basis
Visibility	Float	Dec. 2008	Jan. 2004	Scale continuous	Average daily visibility
Windrecn	Float	Dec. 2008	Jan. 2004	Scale Continuous	Average daily visibility
Windsped	Float	Dec. 2008	Jan. 2004	Scale Continuous	Average wind speed
QNH	Float	Dec. 2008	Jan. 2004	Scale Continuous	Queen's Nautical Height

3.2 Data Management and Analysis

To achieve objectives of the research, a number of tools were applied to the data collected from the Briefing Office of National Meteorological Centre and the statistics office of Civil Aviation Authority of Entebbe International Airport. Aviation data were obtained in an excel format with many files each storing daily data for a specific month. On the other hand weather data were extracted from records stored on hardcopies. Given this scenario, the data had to undergo thorough data processing and cleaning after merging based on date as a key field. The researcher synchronized data from the two sources to obtain uniformity of daily data for the period of five years ranging from 2004 to 2008. The earlier years were not considered because their data either lacked uniformity or were grossly missing vital parameters. The data was further aggregated into daily averages. In the absence of aircraft delay logs in terms of time at the Entebbe International Airport, the number of flights delayed in a day and those on time, both at departure and arrival were computed to obtain the number of aircrafts that experienced delay. From the same variable transformations, other variables were obtained, among which is the dichotomous variable indicating two categories which are 0 = ‘On time’ and 1 = ‘Delayed’.

3.2.1 R Statistical Computing Language

R was inspired by the S language environment which was principally developed by John Chambers, with substantial input from Douglas Bates, Rick Becker, Bill Cleveland, Trevor Hastie, Daryl Pregibon and Allan Wilks (R Development Core Team, 2009) . A number of statistical software exist for data analysis, some of which fairly attempt to provide modeling environment, but R was used in this study because of the more convenient programming environment it provides. R is an integrated suite of software facilities for data manipulation, calculation and graphical display. It includes an effective data handling and storage facility, a suite of operators for calculations on arrays, in particular matrices, a large, coherent, integrated collection of intermediate tools for data analysis, graphical facilities for data analysis and display either on-screen or on hardcopy, and a well-developed, simple and effective programming language which includes conditionals, loops, user-defined recursive functions and input and output facilities. Furthermore, for computationally-intensive tasks, C, C++, C# and FORTRAN code can be linked to R and called at run time.

3.3 Statistical Models in Air Traffic Delay

A strong emphasis is placed on statistical models as they significantly aid to generating reliable decisions and policy formulations. Konishi & Kitagawa (2007) stated that statistical modeling is a big source of information for decision making especially for probabilistic events such as aircraft delay at airports. Wang *et al.* (2002) proposed applications of advanced technology in transportation, but this he said should be integrated with statistical models and simulations to enhance the relevance of advanced technology. This was deemed important because even with satellite enabled systems for management of air traffic flow, inefficient use of statistical modeling and analysis would render such a system incapable of maximum utilization. Wesonga *et al.* (2008) pioneered the development of statistical models for management of air traffic flow by generating statistical models based on air traffic delays at Entebbe International Airport.

3.3.1 Normality Tests of Air Traffic Delay

The Shapiro-Wilk test of normality in R was preferred over the Kolmogorov-Smirnov test because conceptually the Shapiro-Wilk involves arranging the same values by size and measuring fit against expected means, variances and covariances. These multiple comparisons against normality give the test more power than the Kolmogorov-Smirnov test. The test produced the following test analyses ($W_d = 0.9609$, p-value = 2.2e-16, N=1827) and ($W_a = 0.9660$, p-value = 2.2e-16, N=1827) for the proportion of departure and arrival delays respectively. This implied that for both cases of departure and arrival delays, the normality tests failed. Thus, further graphical investigations showed that the data for both proportions of departure and arrival delays are negatively skewed as shown in Figure 3.1. Furthermore, the Welch two sample t-test was applied to test whether the true difference between the means of aircraft proportions of departure and arrival delays was zero. Alternatively, it was used to test the hypothesis that there is no difference between aircraft departure and arrival delay proportions. The test gave ($t = 10.3749$, $df = 3552.125$, p-value < 2.2e-16), implying that the true difference in their means is not equal to zero. It was further established that the proportions of departure delay are on average six percent greater than the proportions of arrival delay.

The two plots in Figure 3.1 represent densities against the natural logarithms for the proportions of departure and arrival delays respectively. They suggest that either of the delays follow the exponential distribution functions. Logarithms were taken so as to standardise the data to enable visual inspection of the deviations from normality of delay proportions.

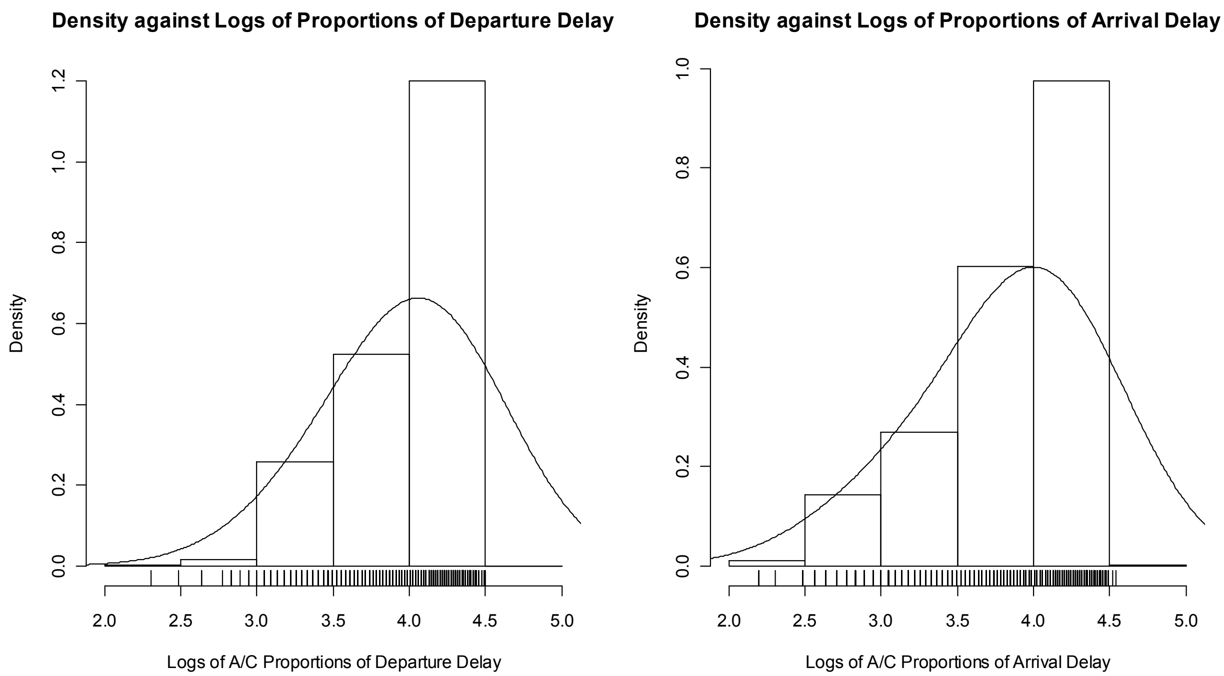

Figure 3.1 Probability density against proportions of aircraft delay

3.3.2 Proportion of Scheduled and Non-scheduled Flights

There are eight types of movements recorded at Entebbe International Airport, they include; private, schedules, freighters, charters, military, training/testing, non-commercial and other non-commercial flights. To achieve the objectives of this study, scheduled aircrafts are defined as those with estimated time of either departure or arrival. It should be noted that the seven types of aircraft movements enumerated above are programmed before their operations are permitted at the airport. It is the duty of the air traffic management to programme these aircrafts accordingly. However, the less time given to plan their movements is what sometimes causes inconveniences to those that have been programmed, say at the beginning of the day. Hence, for this study, all the aircrafts without expected and actual times of departure and arrival are not considered. A simple graphical comparison of the two samples of the number of scheduled and non-scheduled flights using box-plots was generated, as shown in Figure 3.2.

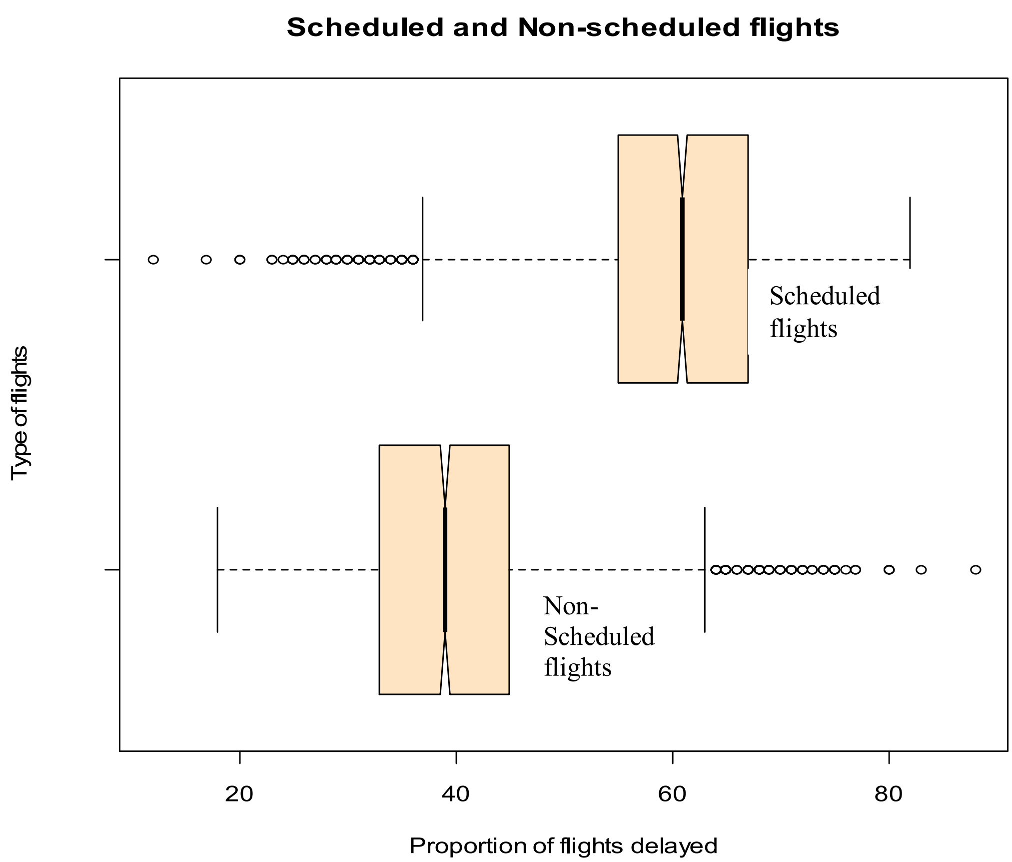

Figure 3.2 Box plot of the proportion of scheduled and non-scheduled flights

Testing further for equality of the sample means using the Welch two-sample t-test resulted into the following statistics that showed high significance levels, t = -54.2232, df = 3651.999, p-value < 2.2e-16, implying that we reject the null hypothesis and conclude that the true difference in the means is not equal to 0 (zero). We further used the F test to test for equality in variances since the two samples are from normal populations. The following results were obtained; (F = 1.0009, num df = 1826, denom df = 1826, p-value = 0.9839), implying that we reject the null hypothesis and conclude that the true ratio of variances is not equal to 1 (one).

The non-scheduled types of flights were found to affect timeliness of aircraft other aircrafts' operations as shall be explained further in due course.

One way to compare graphically the two samples was by using the empirical cumulative distribution functions for the proportion of scheduled flights with the proportion of non-scheduled flights as shown in Figure 3.3.

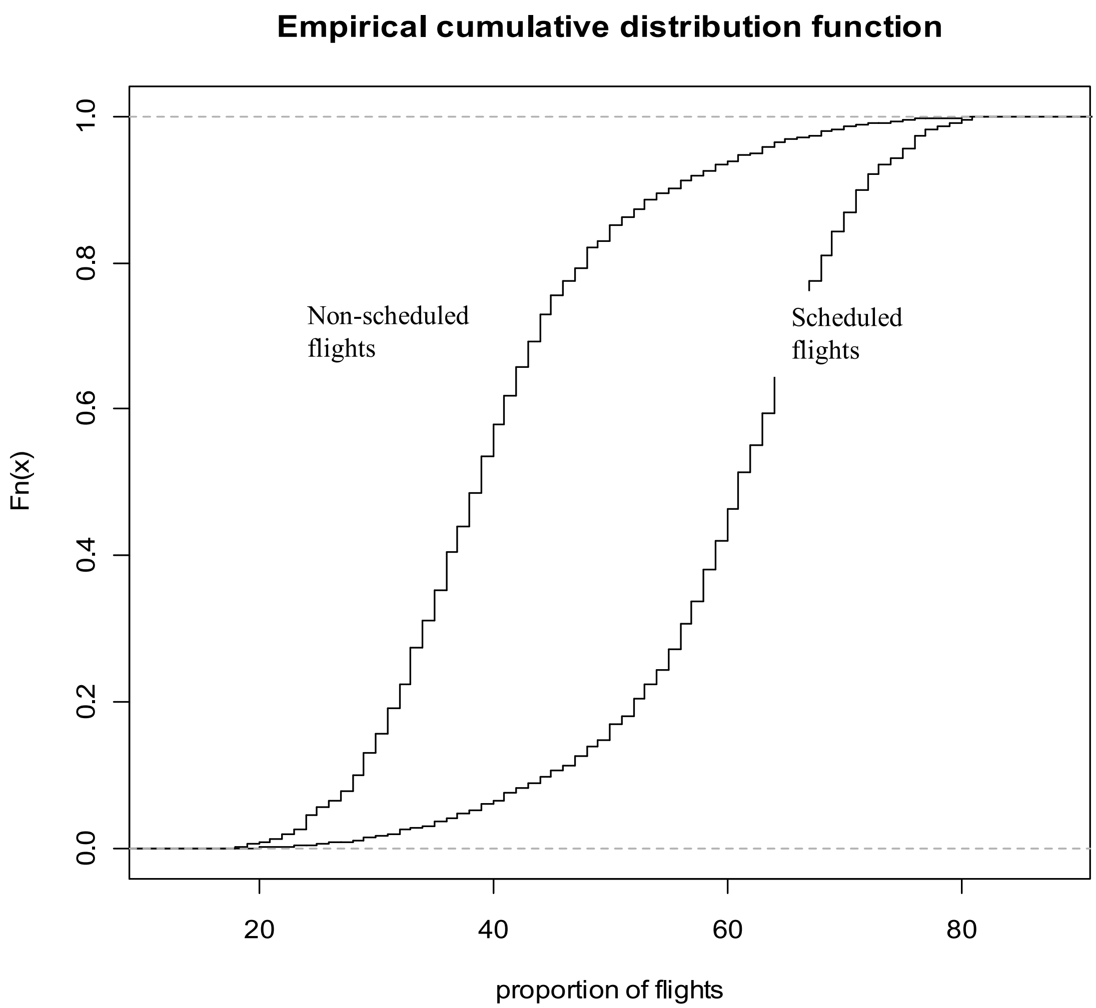

Figure 3.3 Empirical Cumulative Distribution Function for scheduled and non-scheduled flights

The Kolmogorov-Smirnov test is of the maximal vertical distance between the two empirical cumulative distribution functions, assuming a common continuous distribution resulting into (D = 0.0988, p-value = 6.661e-16). Therefore, the null hypothesis was rejected and concluded that the distribution for the proportion of non-scheduled flights is two-sided.

3.4 Logistic Modeling

Logistic regression model is the case that the dependent variable is a dummy variable with value '0' if during a given day aircrafts' operations are classified as being on time and '1' if the day's aircraft operations are classified as delayed, (Konishi *et al.,* 2007) and (Nerlove & Press, 1973) . An aircraft is said to have delayed if the difference between the actual time and the scheduled time of arrival or departure respectively is positive. In this study, the dummy variable of interest captures aircraft delay on the daily basis as '1' if the proportion of aircrafts that delay to depart or arrive was greater than the proportion of aircrafts that arrive or depart on time. Otherwise, the dummy variable takes on the value '0'. Logistic analysis is deemed as useful for this investigation because the study aimed to assess the dynamics of factors that determine aircraft delay at Entebbe International Airport (Equation 3.1). Furthermore, a logistic regression model estimates the probability with which a certain event will happen or the probability of a sample unit with certain characteristics expressed by the categories of the predictor variables, to have the property expressed by the value 1 representing aircraft delay. The estimation of this probability is performed by using the cumulative logistic distribution (Equation 3.2), where $\beta's$ are the regression coefficients of the categories to which the sample unit belongs.

The following formulation was deemed appropriate representation of the model.

$$ln(\pi(X_i)) = \sum_{j=1}^{p} \beta_j x_{ij} \quad \ldots\ldots \quad (3.1)$$

Where:

β_j represent coefficients of the model

$X_i = \{x_{i1}, x_{i2}, \ldots, x_{ip}\}$ represent a set of explanatory variables

The logit, $ln(\pi(X_i))$ on the left hand side of equation 3.1 represent the logarithm of the odds which symbolizes the conditional probability that a certain day is classified as a delay day given all the explanatory variables and its determinants are subsequently tested for significance of the underlying relationship.

$$Odds = \frac{\pi(X)}{1-\pi(X)} = exp^{\sum_{j=1}^{p} \beta_j x_{ij}} \qquad \ldots\ldots\ldots\ldots\ldots \qquad (3.2)$$

This implies that the odds are exponential function of X_i that provides a basic interpretation of the magnitude of the coefficients. When β_j is positive, it implies increasing rate while when β_j is negative, this implies decreasing rate and the rate of climb or descent increases as the magnitude of β_j increases. Conversely, the magnitude of β_j signifies the increasing or decreasing effect of a given determinant on the daily proportion of delay. If $\beta_j = 0$, it would mean that the daily proportion of aircraft delay is independent of X_i.

$$\pi(X_i) = \frac{exp^{\sum_{j=1}^{p} \beta_j x_{ij}}}{1+exp^{\sum_{j=1}^{p} \beta_j x_{ij}}} \qquad \ldots\ldots\ldots\ldots\ldots \qquad (3.3)$$

Where $\pi(X_i)$ represent the probability that on a given day the proportion of the aircrafts that delay to depart or arrive given the influence of meteorological and aviation parameters.

3.4.1 Results of the Logistic Model for Air Traffic Delay

The logistic model with a two-category dummy variable, that is, the proportion of aircrafts delaying their operations and the proportion of aircrafts that operated on time was created with an objective of generating corresponding probabilities for an aircraft operating on time and experiencing delay based on daily. The logistic model for a delay of an aircraft before departure and delay during arrival at the airport were fitted and the results are shown in Table 3.2. The Table shows the logistic model parameters with a category of interest being a 50 percent threshold of proportion that aircrafts experience delay at departure and arrival at Entebbe International Airport.

The logistic model presented in Table 3.2 shows that in both cases the intercepts, number of freighters recorded per day and the number of other non-commercial flights are significant. Other parameters found significant to determine that on a certain day at a 50 percent threshold, the proportion of departure delay included arrival delay as a dummy, number of arrival delays, number of operations, number of scheduled flights and the number of chartered flights per day. The number of arrival delay and number of operations both showed a negative trend implying that their increase results into a decrease in the proportion of departure delay at the rates of 0.11 and 0.39 respectively. Thus the rate of descent in the proportion of daily delay increases more with the number of operations than with the number of arrival delay per day. The other parameters for determining the proportion of departure delay showed that their increase results in an increase in the proportions of daily departure delay. In the order of the strength of their effect they are: arrival delay dummy (0.72), number of freighters (0.59), number of other non-commercial flights (0.57), number of scheduled flights (0.46) and the number of chartered flights (0.32).

Table 3.2 Logistic model dynamics for aircraft departure and arrival delay

Proportion of departure delay				**Proportion of arrival delay**			
DV: dummy daily proportion of departure delay	**Est. of coeffs.**	**S.E**	**Level of sign.**	**DV: dummy daily proportion of arrival delay**	**Est. of coeffs.**	**S.E**	**Level of sign.**
Intercept	1.1	0.44	*	Intercept	0.95	0.31	**
arrival delay dummy	0.72	0.33	*	departure delay dummy	-0.57	0.27	*
number of arrival delay	-0.11	0.01	**	number of freighters	-0.14	0.03	**
number of operations	-0.39	0.14	**	number of other non-commercial flights	0.03	0.01	**
number of scheduled flights	0.46	0.14	**	number of persons on board in	0.01	0.01	**
number of chartered flights	0.32	0.14	*				
number of freighters	0.59	0.15	**				
number of other non-commercial flights	0.57	0.14	**				
[4]*Akaike Information Criterion, AIC= 731.5*				*Akaike Information Criterion, AIC=1732.6*			

*Note: ** significant at 0.01 level; * significant at 0.05 level*

On the other hand to determine the proportion of arrival delay, the explanatory variables found to be significant, but with a negative effect included departure delay as a dummy and number of freighters. The rate of their effect shows that departure delay as a dummy (-0.57) has a greater reducing effect than the number of freighters (-0.14) on arrival delay.

[4] AIC is a measure of the goodness of fit of the estimated statistical model, $AIC = 2k - 2lnL$, where k is the number of parameters in the model and L is the maximized value of the likelihood function for the estimated model.

Since the logistic model has a curve rather than a linear appearance, the logistic function implies that the rate of change in the odds, $\pi(X_i)$ per unit change in the explanatory variablesx_i varies according to the relation $\frac{\partial\pi(X_i)}{\partial(x)} = \beta\pi(X_i)[1-\pi(X_i)]$. This implies that for the odds of the proportion of delay $\pi(X_i) = \frac{1}{2}$ and taking the coefficient of the number of scheduled flights, $\beta = 0.46$ the slope is $\frac{\partial\pi(X_i)}{\partial(x_i)} = 0.46 * \frac{1}{2} * \frac{1}{2} = 0.115$. For example, the value 0.115 represents a change in the odds of departure delay, $\pi(X_i)$ per unit change in the number of scheduled flights. In simpler terms, for every 100 scheduled flights at Entebbe International Airport, 11 will delay to departure.

Post logistic estimation analysis was performed to estimate the probability of the daily proportions of departure and arrival delay by computing mean values of the estimated daily probabilities. This analysis was able to generate estimated probabilities per day, resulting into 1827 probabilities. To obtain an overall probability, an average was computed for each departure delay and arrival delay respectively as shown in Table 3.3.

Table 3.3 Estimated probability for aircraft departure and arrival delay

Category	1st Quartile	3rd Quartile	Mean Probability
Estimated **departure delay** given a 50 percent delay threshold	0.92	0.99	**0.94**
Estimated **arrival delay** given a 50 percent delay threshold	0.77	0.89	**0.82**

Generally, holding other explanatory variables constant at 50 percent threshold level, the probability of aircraft departure delay was established to be relatively higher than for aircraft arrival delay. Based on the collaborative nature of airports, one can conclude that the lower arrival delay compared to departure delay is mainly due to factors that are exogenously determined outside Entebbe International Airport.

Furthermore, post logistic estimation analysis for four different thresholds in the set $\{50, 60, 70\ 80\}$ was performed to estimate the probability of departure and arrival delay. Use of different thresholds generated dependent variables with varying counts of categories. The results are shown in Table 3.4.

Table 3.4: Variation of predicted delay probability with the threshold level

	Probability using logistic model							
	Departure delay				Arrival delay			
Delay Threshold (*percent*)	No. of variables in the model	1st quartile	3rd quartile	Mean	No. of variables in the model	1st quartile	3rd quartile	Mean
50	8	0.92	0.99	0.94	4	0.77	0.89	0.82
60	**9**	**0.17**	**0.83**	**0.49**	**10**	**0.12**	**0.55**	**0.36**
70	7	0.02	0.50	0.26	3	0.01	0.32	0.18
80	2	0.00	0.08	0.05	3	0.00	0.05	0.04

The results show that the predicted delay for aircrafts at departure and arrival reduces as the threshold level is increased as demonstrated in Figure 3.4. Conversely, lowering the threshold of delay increases the predicted probability of delay for both aircraft departure and arrival. In both cases, the mean predicted probability for aircrafts departing and arriving at the Airport that used more predictors were 0.49 with 9 predictors and 0.36 with 10 predictors respectively. However, in both of these cases, there is a visibly characteristic large deviation between the estimates for the 1^{st} and 3^{rd} quartiles, but larger for the departure than arrival estimated probabilities.

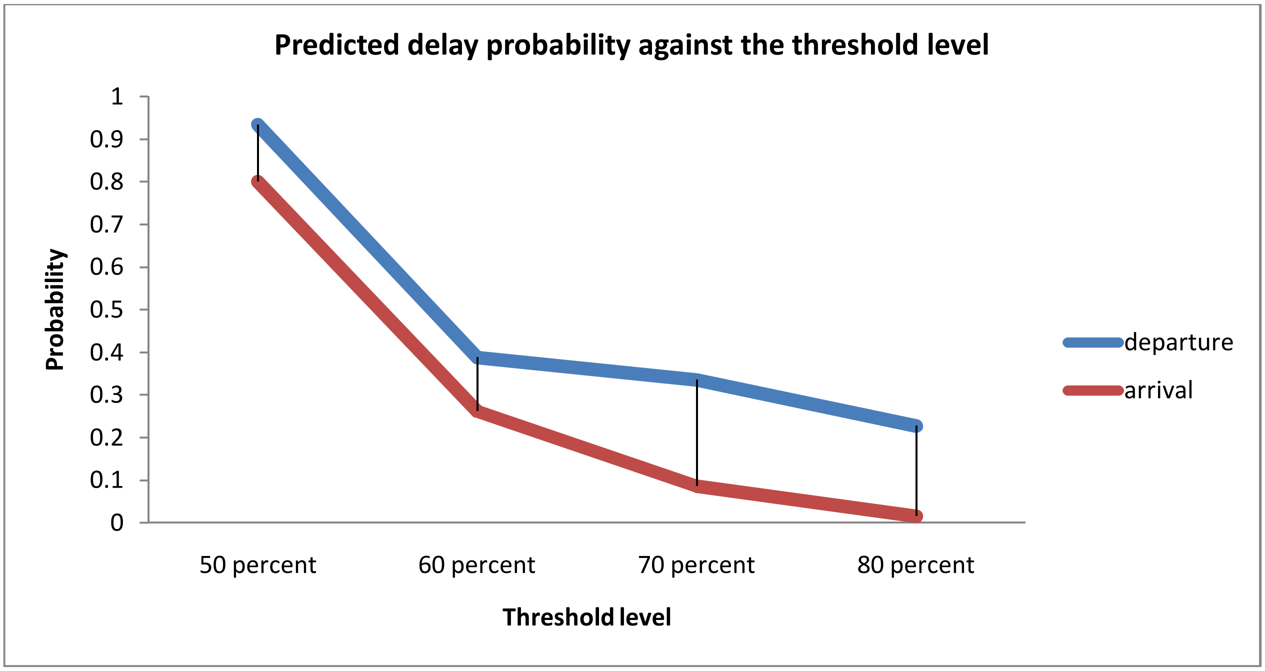

Figure 3.4: Variation of predicted delay probability with the threshold level

3.4.2 Analysis of Probabilities from the Logistic Models

Using the logistic modelling post analyses, probabilities were predicted on daily basis. In this section, a presentation of the characteristic time series behaviour of these probabilities is done for the period 2004 through 2008 covering 1827 records that match with the number of days for the stated period. It is evident from Figure 3.5 that the lower the threshold proportion of delay; the higher are the estimated probabilities that the airport will experience a departure delay. Furthermore, as the threshold is increased, thereby allowing lesser departure delay, the predicted probabilities over time breaks into visibly two trends, at 60 and 70 percentage threshold levels, but tends to smoothen at 80 percentage threshold level. This generally indicates the predicted aircraft departure delay probabilities exhibited a positive trend over the period 2004 to 2008 given the explanatory parameters used in the logistic model.

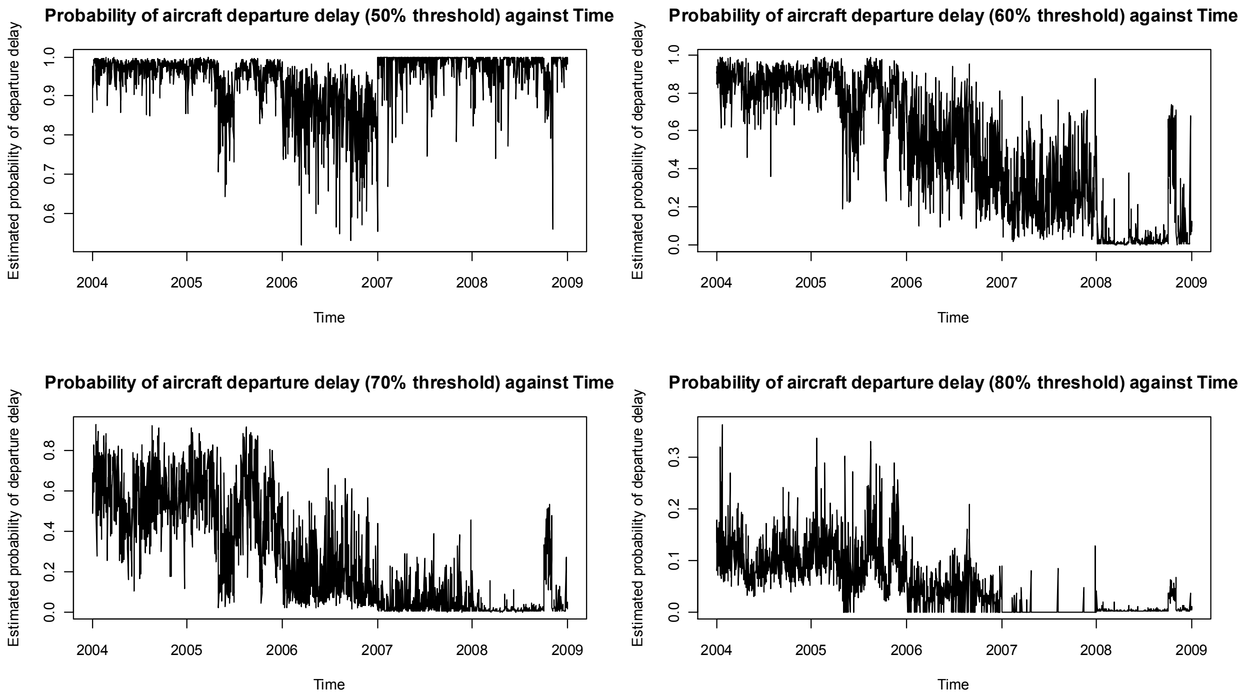

Figure 3.5: Variation of predicted departure delay probability with Time (days)

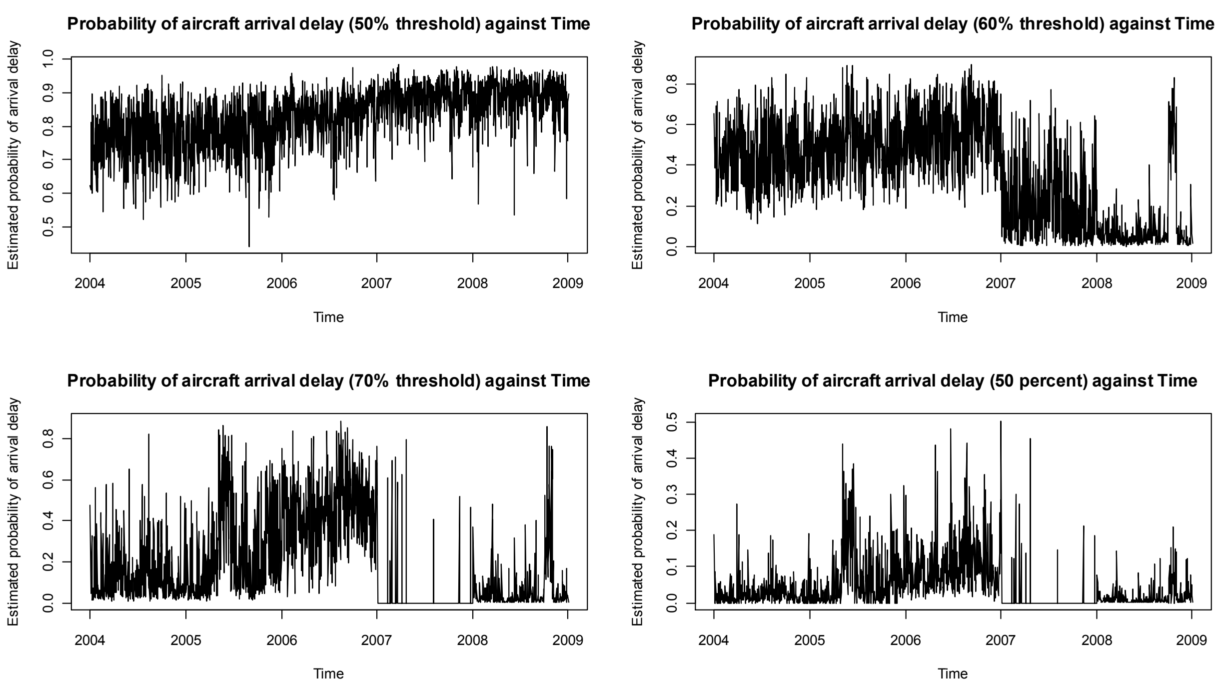

Figure 3.6: Variation of predicted arrival delay probability with Time (days)

Similarly, Figure 3.6 shows that the lower the threshold proportion of delay; the higher are the estimated probabilities that the airport will experience arrival delay. As the threshold is increased, thereby allowing lesser arrival delay, the predicted probabilities over time breaks into two trends from the year 2007 at 60 and 70 percentage threshold levels, but tends to smoothen at 80 percentage threshold level. Generally this indicates that the predicted aircraft arrival delay probabilities exhibited a positive trend with a smaller slope over the period 2004 to 2008 given the explanatory parameters used in the logistic model.

Probabilities of departure and arrival delay were computed annually using the threshold with more predictors. Table 3.5 shows how the probabilities of delay have been varying over years. It should be noted that these probabilities are conditional on a number of predictors of delay at Entebbe International Airport.

Table 3.5 Variation of probability of departure and arrival delay from 2004 to 2008

Year	**Probability of departure delay**	**Probability of arrival delay**
2004	0.9454	0.3443
2005	0.8986	0.4055
2006	0.3534	0.9589
2007	0.2164	0.0931
2008	0.0795	0.0164

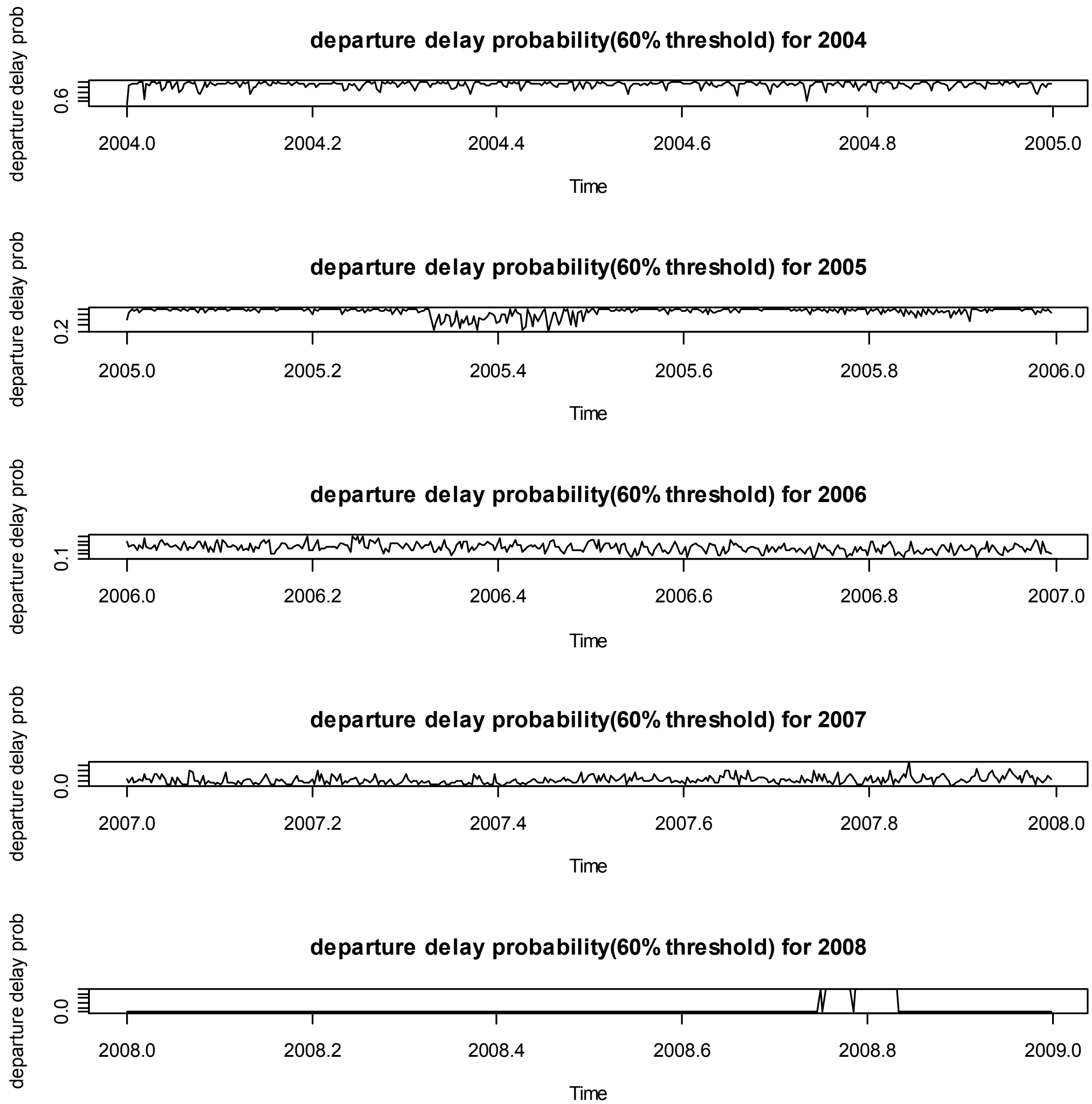

Figure 3.7: Departure delay probability within years for the period 2004-2008

By using a delay threshold of 60 percent, the probability of departure delay as estimated by the logistic model for each year were plotted as shown in Figure 3.7. It shows that over the period 2004 through 2008, the probabilities were diminishing implying a good management performance for the Airport. A delay threshold of 60 percent was applied because its measurement applied more explanatory variables, as shown in Table 3.4.

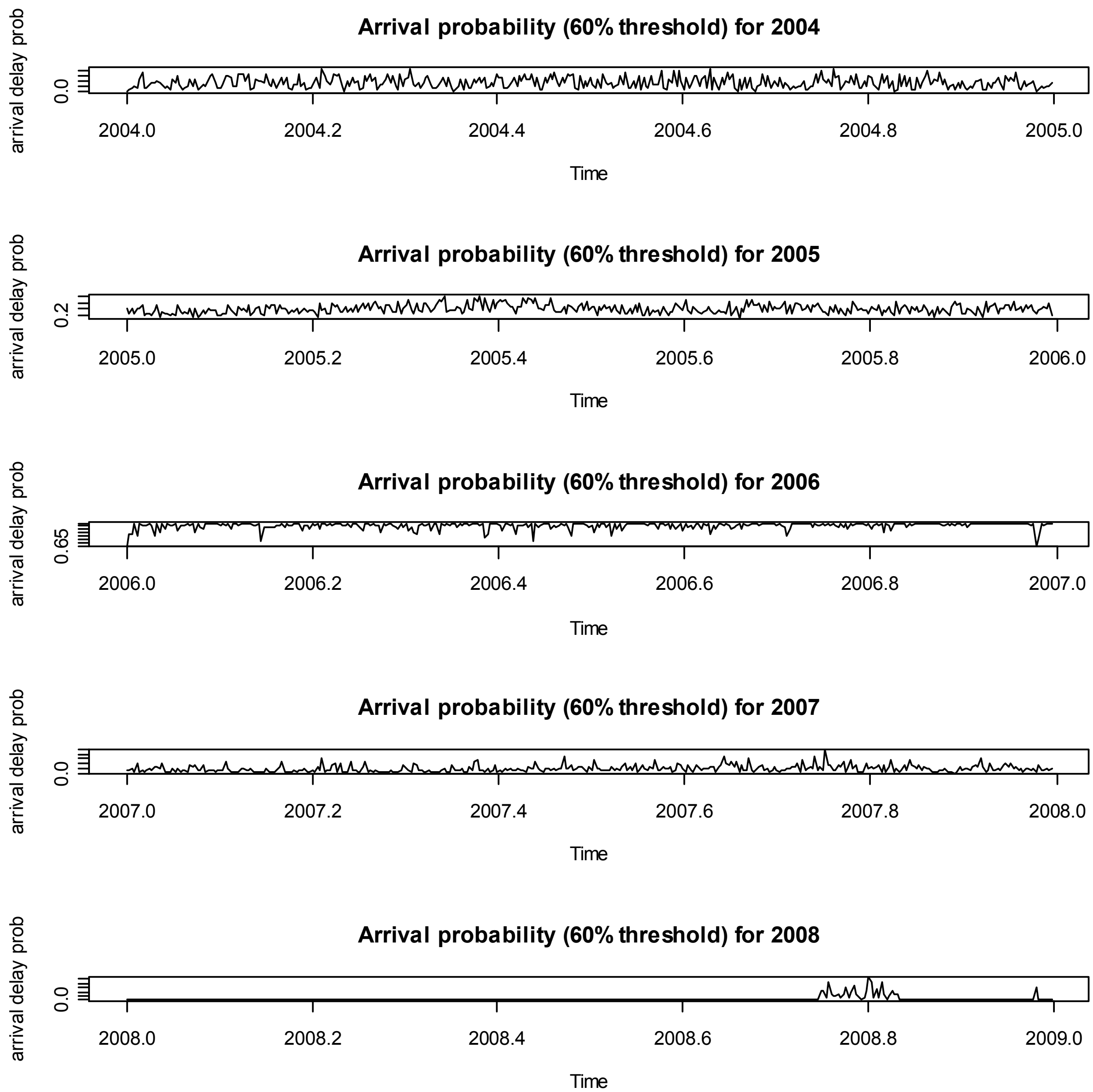

Figure 3.8: Arrival delay probability within years for the period 2004-2008

Similarly, an annualised plot of arrival delay probability was done so as to visualise the variations of probabilities of arrival delay within each year. The plot in Figure 3.8 shows first an increase between the years 2004 and 2006 and a sustained decrease thereafter after. It is possible that CHOGM had some influence on not only the Entebbe International Airport, but also the other airports within the region were aircrafts depart from.

The collaborative nature of air traffic flow management divisions at different airports means that an aircraft's arrival performance may be due to factors outside the arrival airport. The complexity of this collaboration is premised on the fact that for any arriving aircraft, it must have departed from some other airport. Therefore, the timeliness of the arriving aircraft is affected not only by factors at the arrival airport, but also those factors exogenously determined at the arrival airport. Similarly, departing aircrafts are primarily determined by factors within the airport, but also by factors other than those at the departing airport.

3.5 Aircraft Delay Stochastic Frontier Modeling

Findings presented in Section 3.4 using the logistic model post analyses, revealed that there exist an inexplicable deviation between the proportions of daily aircraft delays and the predicted probabilities of delay. This section measures and analyses the efficiency component of aircraft daily departure and arrival delays at Entebbe International Airport in Uganda. Stochastic production frontier model is applied to measure the relative technical efficiency while also shedding light on the factors associated with these efficiency differences based on a framework that has been used in other related studies (Cheng & Caves, 2000; Pels *et al.,* 2001) and (Good *et al.,* 1995) .

The technical efficiency (TE) in production management refers to the achievement of maximum potential output from a given amount of input factors while taking into account the physical production relationship. An airport operating at point A is technically efficient, while that operating at B is technically inefficient. The TE score for the technically efficient firm is 1 or 100 percent, while for the technically inefficient score is computed from q/q^* as shown in Figure 3.9.

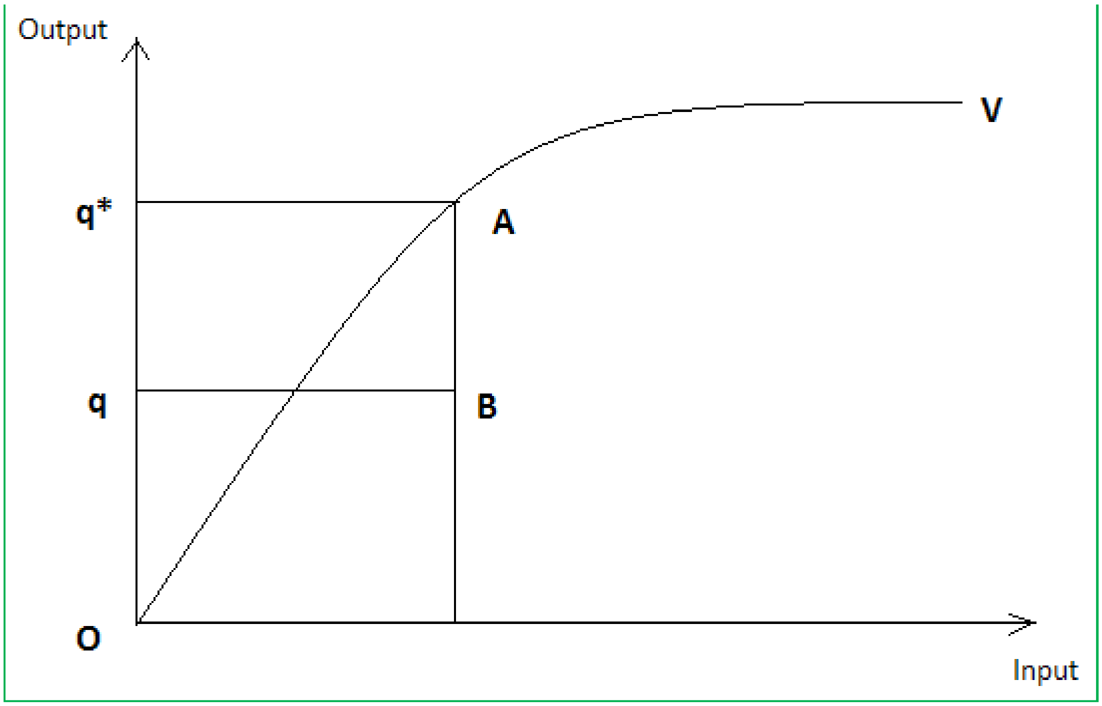

Figure 3.9 Technical efficiency principle

The modelling estimation and application of stochastic production frontier were first proposed by (Aigner *et al.,* 1977) and (Battese & Corra, 1977) .The production frontier analysis models are motivated by the idea that deviations from the production 'frontier' may not be entirely under the control of the production unit under the study. These models allow for technical inefficiency, but they also acknowledge the fact that random shocks outside the control of producers can affect output. They account for measurement errors and other factors, such as weather conditions at other airports, diseases and other anomalous events on the value of output variables, together with the effects of unspecified input variables in the production function. The main virtue of the model is that, at least in principle these effects can be separated from the contribution of variation in technical efficiency. The stochastic frontier approach is preferred for assessing efficiency in aircraft flow management at the airports because of the inherent stochastic characteristics of the parameters, (Sarkis, 2001) .

However, the distribution to be used for the inefficiency error has been source of contention (Griffin & Steel, 2004) . For this scenario, efficiency of aircrafts at airports in developing countries typically fall below the maximum efficiency levels that is possible, the deviation from actual maximum output becomes the measure of inefficiency and is the focus of interest for this study. Increasing the technical efficiency for an aircraft at an airport with due consideration of others would result in overall technical efficiency of a given airport. This way all aircrafts would be competing to be on time so that passengers who are destined to other airports by using other aircrafts are not delayed. At the same time, pressure due to aircraft route planning and optimisation by the air traffic management would be minimised.

The stochastic frontier model proposed by (Aigner *et al.,* 1977) and then extended by (Huang & Liu, 1994) and (Battese & Coelli, 1995) is a good approach to explain the causes of deviations other than the explanatory variables identified in this study. Consider the proportion of aircrafts departing or arriving at an airport on a certain day denoted by i whose proportion of aircrafts delayed per day is determined by the following production function:

$$lnY_i = X_i\beta + \varepsilon_i \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad 3.4$$

Where

$\varepsilon_i = vu_i - mu_i$

$i = 1,2,\ldots,N$ Represents number of days

Y_i Is the proportion of aircrafts that delay (departure or arrival) during the i^{th} day

X_i Is (1xk) vector of explanatory variables

β Is (1xk) vector of unknown scalar parameters to be estimated

vu_i Is an idiosyncratic error term similar to that in conventional regression model and is assumed to be independently and identically distributed as $N(0, \sigma_{vu}^2)$. The term captures random variation in output due to factors beyond control of the airport such as some other parameters of weather not considered in the study and other omitted explanatory variables.

mu_i is a non-negative random variable accounting for the existence of technical inefficiency in the proportion of delay and it is identically distributed as half-normal $mu \sim |N(0, \sigma^2)|)$ or truncated normal $mu \sim |N(\mu_a, \sigma^2)|)$ distributions.

The inefficiency effect of $mu_i$is assumed to consist of both unobserved systematic effects, which vary on different days. Coelli *et al.* (2005) stated that the subtraction of the nonnegative random variable mu_i, from the random error vu_i, implies that the logarithm of the production is smaller than it would otherwise be if technical inefficiency did not exist. However, following Coelli *et al.* (2005) , the inefficiency distribution parameter can also be specified as

$$mu_i = \sigma_0 + z_i\sigma + w_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad 3.5$$

Where

w_i is distributed following $N(0, \sigma_w^2)$

z_i is a vector of airport specific effects that determine technical inefficiency

σ is a vector of parameters to be estimated

Airport specific factors that were found to affect technical efficiency include airport operational level, number of passengers, visibility and QNH, among others. Input variables may be included in both Equations (3.18) and (3.19) provided that technical inefficiency effects are stochastic (Battese *et al.,* 1995) .

The condition that $mu \geq 0$ in equation (3.18) guarantees that all observations either lie on, or are beneath the stochastic production frontier. Following (Battese *et al.,* 1977) and (Battese *et al.,* 1995) , the variance terms are parameterized by replacing $\sigma_{vu}^2$and σ_{mu}^2 with

$$\sigma = \sigma_{vu}^2 + \sigma_{mu}^2 \text{ and } \gamma = \frac{\sigma_{mu}^2}{\sigma_{vu}^2+\sigma_{mu}^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad 3.6$$

The value of γ ranges from 0 to 1, with the value equal to 1 indicating that all the deviation from the frontier are due entirely to technical inefficiency (Coelli T. & Perelman, 1999) . The technical efficiency of aircrafts on the ith day can be defined as:

$$TE_i = \frac{E({}^{Y_i}/_{mu_i}, X_i)}{E({}^{Y_i}/_{mu_i=0}, X_i)} = e^{-mu} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad 3.7$$

Where; E is the expectation operator. According to (Battese & Coelli, 1988) the measure of technical efficiency is based on a conditional expectation given by Equation (3.7), given the value of $vu_i - mu_i$ evaluated at the maximum likelihood estimates of the parameter in the model, where the expected maximum value of Y_i is conditional on $mu_i = 0$. The measure TE_i takes the value between zero and one and the overall mean technical efficiency of the proportion of aircraft delay at the airport on all sampled days is given by:

$$TE = \left\{\frac{1-\varphi[\sigma_{mu} - \left(\frac{mu}{\sigma_{mu}}\right)]}{1-\varphi(\frac{mu}{\sigma_{mu}})}\right\} e^{-mu+\frac{1}{2}\sigma_{mu}^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad 3.8$$

Where;

$\varphi(.)$ represents the density function for the standard normal variable

A variety of distributions for example exponential, truncated-normal and gamma are used to characterize the technical efficiency term mu_i in the existing literature that apply the stochastic production frontier. While models that involve two-distributional parameters for example gamma and truncated normal can accommodate a wider range of possible distributional shape, their application appears to come at a potential cost of increased difficulty in identifying parameters (Ritter & Simar, 1997) . Different simulations exercises carried out by (Greene, 2003) indicated that the most straightforward model, that is, half normal is more appropriate from the statistical point of view. Hence, stochastic frontier analysis on the factors affecting the proportion of aircraft delay on a given day is based both on the truncated normal and the half-normal probability distribution.

3.5.1 Stochastic Frontier Model for Determination of Aircraft Efficiency

The functional forms developed to measure the physical relationship between inputs and outputs include Cobb-Douglas (CD) and the transcendental logarithmic (translog) functions. The translog production function reduces to the CD if all the coefficients associated with the second-order and the interaction terms of aircraft flow inputs are zero. In this study, the generalized likelihood ratio tests are used to help confirm the functional form and specification of the estimated models. The correct critical values of the tests statistic come from a χ^2 distribution at the 5 percent level of significance and a mixed χ^2 distribution, which is drawn from (Kodde & Palm, 1986) . This study employed the translog stochastic frontier function in Equation (3.9) for the proportion of aircraft departure delay and Equation (3.10) for the proportion of aircraft arrival delay.

$$ln(GDP)_i = \beta_0 + \beta_1 \ln(AHP)_i + \beta_2 \ln(NOPS)_i + \beta_3 \ln(SCH)_i + \beta_4 \ln(CHA)_i + \beta_5 \ln(FRE)_i + \beta_6 \ln(NCF)_i + \beta_7 \ln(POT)_i + \beta_8 \ln(WND)_i + \beta_8 \ln(VIS)_i + \beta_8 \ln(QNH)_i + vu_i - mu_i \quad \ldots\ldots\ldots \quad 3.9$$

and

$$ln(AHP)_i = \beta_0 + \beta_1 \ln(GDP)_i + \beta_2 \ln(NOPS)_i + \beta_3 \ln(SCH)_i + \beta_4 \ln(CHA)_i + \beta_5 \ln(FRE)_i + \beta_6 \ln(NCF)_i + \beta_7 \ln(POI)_i + \beta_8 \ln(WND)_i + \beta_8 \ln(VIS)_i + \beta_8 \ln(QNH)_i + vu_i - mu_i \quad \ldots\ldots\ldots \quad 3.10$$

Where

i is the day of operation

ln is the natural logarithm (log to base e)

Various tests of null hypotheses for parameters in the production functions as well as in the inefficiency model may be performed using generalized likelihood-ratio test statistic defined by:

$$\lambda = -2[\ln\{L(H_0)\} - \ln\{L(H_1)\}] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad 3.11$$

Where;

$L(H_0)$ and $L(H_1)$ represents the value of the likelihood function under the null H_0 and the alternative H_1 hypotheses, respectively. If the null hypothesis is true, the test statistic has approximately a chi-square distribution with the degree of freedom equal to the difference between parameters involved in the null and alternative hypotheses.

3.5.2 Results of the Aircraft Stochastic Frontier Model

The parameters of the stochastic production frontier models Equations (3.9) and (3.10) are estimated using the likelihood function. The stochastic production frontier model results are presented in Table 3.6. Aircraft technical efficiency variations based on aircrafts' characteristics are summarized in Table 3.7.

Table 3.6 Aircraft departure delay stochastic model parameter estimates

Dep: proportion of departure delay	*Truncated Normal Error Term*			*Half-Normal Error Term*		
Logs of Parameters	*Estimated coefficients*	*Standard Error*	*Level of sign*	*Estimated coefficients*	*Standard Error*	*Level of sign*
(Intercept)	4.74	1.01	**	4.48	1.06	**
Prop of arrival delay	0.13	0.01	**	0.13	0.01	**
Number of operations	0.03	0.05		0.01	0.05	
Number of schedules	-0.50	0.03	**	-0.49	0.03	**
Number of charters	-0.13	0.01	**	-0.13	0.01	**
Number of freighters	0.01	0.01		0.01	0.01	
Non-commercial flts	0.01	0.01		0.01	0.01	
Persons on board	0.18	0.01	**	0.18	0.01	**
Wind speed	0.01	0.01		0.01	0.01	
Visibility	-0.17	0.05	**	-0.16	0.05	**
Queens nautical ht	0.10	0.12		0.14	0.13	
sigmaSq	0.22	0.03	**	0.08	0.01	**
Gamma	0.93	0.01	**	0.85	0.02	**
Mu	-0.92	0.21	**			
log likelihood value:	381			366		
mean aircraft departure efficiency:	0.85 (*N=1736*)			0.81 (N=1736)		

*** indicates 0.01 level of significance*

The likelihood ratio test was used to compare two models, the ordinary least squares, OLS without the inefficiency term and the Error Components Frontier, ECF with the inefficiency term. Findings indicate that the log likelihood value for OLS, 298.41, with 12 degrees of freedom is less than the value for ECF, 381 with 15 degrees of freedom. Thus, approximating the probability density function of the test statistic by a chi-square distribution with 3 degrees of freedom, the ECF model is found to be superior compared to the OLS model.

Comparison of the two stochastic frontier models in Table 3.5, the likelihood ratio test shows that the model with the ECF following the truncated normal distribution (LL=381, DF=15) is a better model compared to one with ECF that follows the half-normal probability distribution (LL=366.13; DF=14) and significant at $\alpha=0.01$ with 1 degree of freedom.

Table 3.7 Aircraft arrival delay stochastic model parameter estimates

Dep: proportion of arrival delay	*Truncated Normal Error Term*			*Half-Normal Error Term*		
Logs of parameters	*Estimated coefficients*	*Standard Error*	*Level of sign*	*Estimated coefficients*	*Standard Error*	*Level of sign*
(Intercept)	4.70	0.99	**	4.62	1.65	**
Prop of dep delay	0.42	0.03	**	0.40	0.03	**
Number of operations	-0.44	0.08	**	-0.42	0.09	**
Number of schedules	-0.42	0.05	**	-0.43	0.05	**
Number of charters	0.06	0.01	**	0.05	0.01	**
Number of frieghters	-0.06	0.01	**	-0.06	0.01	**
Non-commercial flts	0.01	0.02		0.01	0.02	
Persons on board	0.28	0.02	**	0.28	0.02	**
Wind speed	0.00	0.01		-0.00	0.01	
Visibility	-0.26	0.07	**	-0.24	0.08	**
Queen's nautical ht	0.13	0.14		0.13	0.20	
Sigma Squared	0.49	0.04	**	0.19	0.01	**
Gamma	0.92	0.01	**	0.85	0.02	**
Mu	-1.35	0.18	**			
log likelihood value:	-298			-332		
mean aircraft arrival efficiency:	0.80 (*N=1736*)			0.74 (N=1736)		

*** indicates 0.01 level of significance*

Similarly, for both of the models in Table 3.7, findings indicate that the log likelihood values for ECF with truncated normal error term and half-normal error term, -298.46; DF=15 and -332.03, DF=14 respectively were found to be greater than for their corresponding OLS models with log likelihood values -418.05; DF=12 and -418.05; DF=12 respectively. Thus, the ECF models are found to be more superior compared to their corresponding OLS models.

Furthermore, given the two stochastic frontier models in Table 3.6, the likelihood ratio test shows that the model with the ECF following the truncated normal distribution (LL=-298.46, DF=15) is a better model compared to one with ECF that follows the half-normal probability distribution (LL=-332.03; DF=14) and it is significant at $\alpha = 0.01$ with 1 degree of freedom.

However, comparing the two predicted efficiencies generated from the superior stochastic frontier models for departure and arrival proportions of delay, the Spearman's pairwise correlation test rejected the null hypothesis and concluded that the true rho is not equal to 0 (rho= - 0.0833, N=1827) as shown in Figure 3.10.

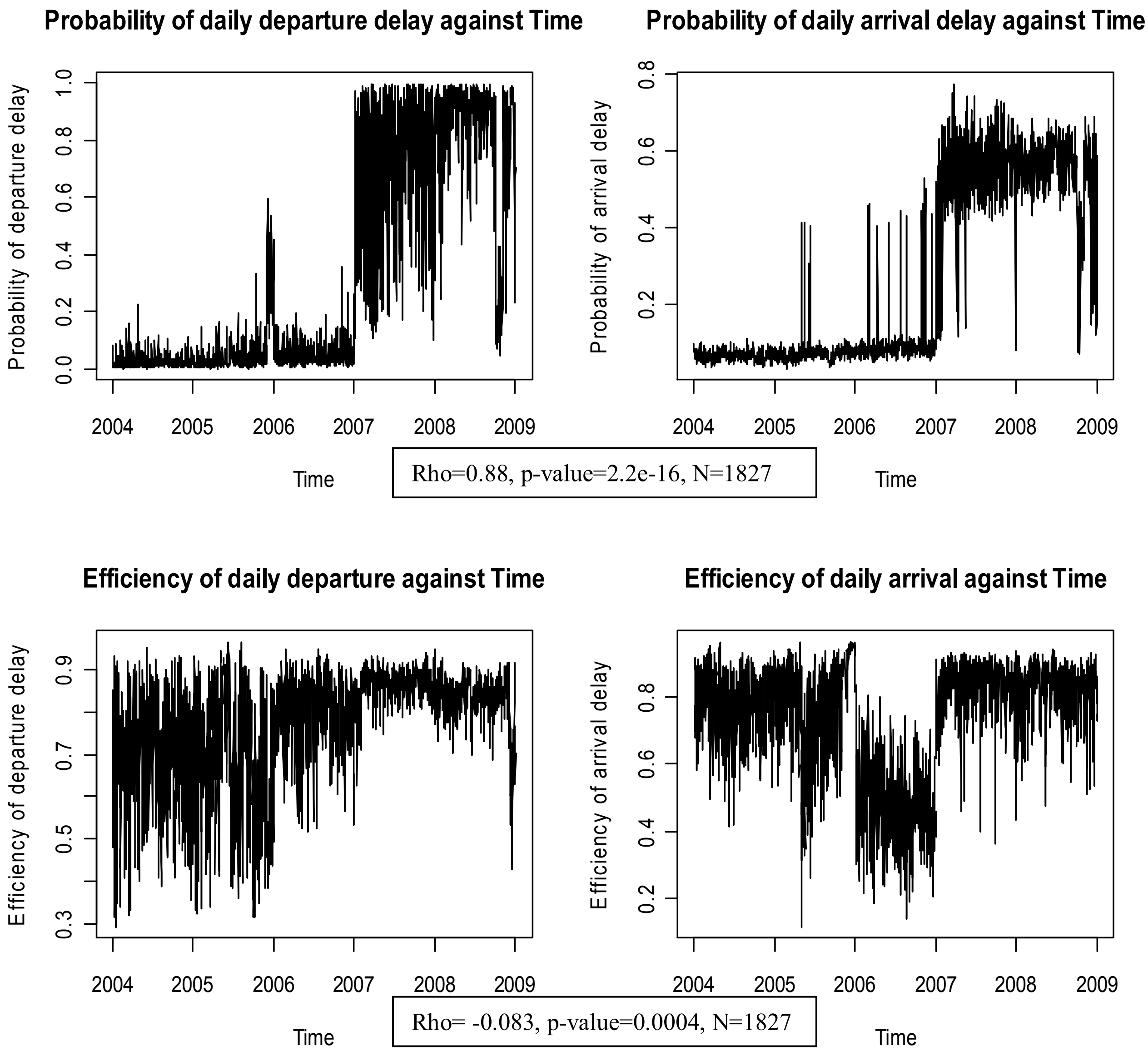

Figure 3.10 Comparison of Daily Aircraft Probability and Efficiency of departure and Arrival

Table 3.8 shows how technical efficiencies at Entebbe Internal Airport varied over the period over the study period, 2004 through 2008. It is clear that for both departures and arrivals, the efficiencies of operations were relatively high with values of over 80 percent for the period.

Table 3.8 Variation of technical efficiency for aircraft departure and arrival delay from 2004 to 2008

Year	Efficiency of departure delay	Efficiency of arrival delay
2004	0.8992	0.8590
2005	0.8992	0.7427
2006	0.8858	0.8984
2007	0.8159	0.8551
2008	0.8505	0.8783
Average	**0.8701**	**0.8467**

The average efficiency at aircraft departure, 87 percent is greater than the average efficiency at aircraft arrival, 84 percent. This indicates to the fact that since the level of control of aircraft departures is more determined and managed by the ATM at Entebbe International airport than aircraft arrivals, their arrival efficiencies are exogenously determined. Consequently, this would imply that in order to have more efficient aircraft arrivals, there is need to encourage more collaborative approach in air traffic flow management so as to operate more efficiently.

3.6 Time Series Analysis of Air Traffic Delay

In this section, an in-depth analysis of departure and arrival delay is presented to understand the characteristic trend of delay, probabilities and efficiencies over time. The trends are examined and forecasts are determined based on derived autoregressive integrated moving averages, the ARIMA models.

Analysis of the daily number of aircrafts that experienced delay at Entebbe Interntional Airport over the period 2004 through 2008 revealed a positive trend ranging from an average of 20 to about 85 aircrafts delayed every day. It was shown that there was a sharp rise in the number of aircraft delays at the beginning of the year 2007 that became a consistent over the years 2007 and 2008. One possible explanation for this sharp rise was the increased preparatory work for the Commonwealth Heads Of Government Meeting (CHOGM), that took place in November, 2007 and its effects thereafter.

3.6.1 Time Series Analysis of Delay the Airport

Based on the historic operational data for the airport, the proportions of departure and arrival delay show a positive trend over time for the study period. The implication of this is that aircraft operational data at the airport shows signs of increase and therefore, concerted efforts have to be developed to abate this. However, for purposes of this study, a forecasting system will be presented to attempt to predict delay, proportions of delay and the technical inefficiencies based on the charactersitics or behaviour of the data for this study. Figure 3.11 shows the daily delay proportions against time.

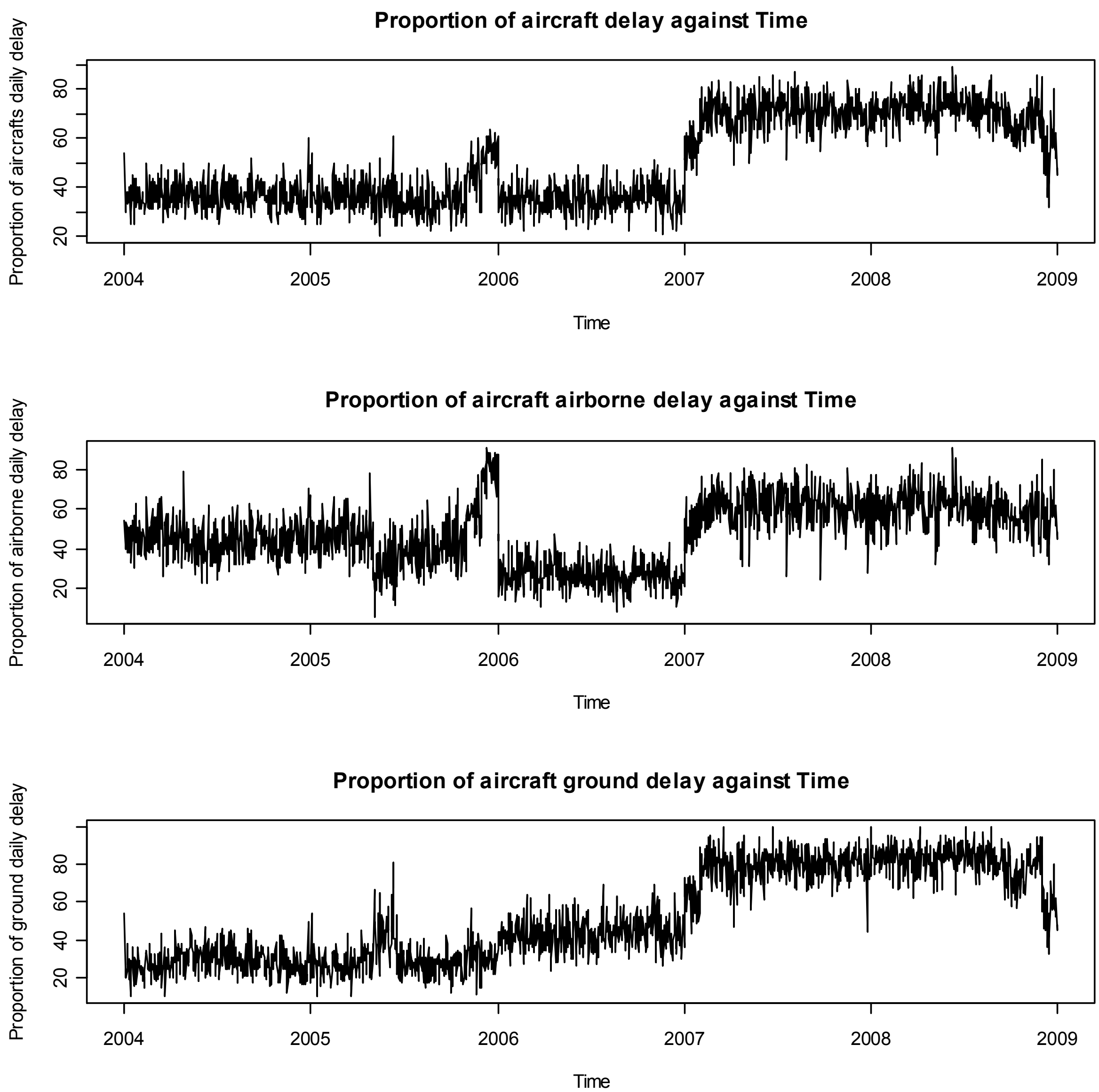

Figure 3.11 Time series plots of aircraft arrival and departure delay

3.6.2 Dynamics of Airport Delay Parameters with Time

Here, the study aimed at the graphical analysis of the dynamics of aircraft delays at Entebbe International using data for the period 2004 to 2008. The variables assessed against aircraft delay proportions here included proportion of scheduled flights, proportion of non-scheduled flights, number of operations, airport visibility and airport pressure recorded as Queens Nautical Height, QNH.

Figure 3.12 shows that the proportion of scheduled flights and the number of aircraft operations exhibited a positive trend over the time period per day. On the other hand, the proportion of non-scheduled flights over time shows a slight negative trend while airport visibility and pressure seem to show no trend over the period 2004 to 2008.

The number of aircraft operations fluctuated between 10 and 134 aircraft departures and arrivals per day. The highest recorded aircraft operation over the years was 134 aircraft arrivals and departures per day. On the other hand, the lowest aircraft operations were 10 aircraft arrivals and departures per day over the study period. Further, it is observed that operations at Entebbe International Airport were highest during the lower half of the year 2008 with an average of 87 aircrafts. The lowest of about 10 arrivals and departures was recorded in the upper half of the year 2005.

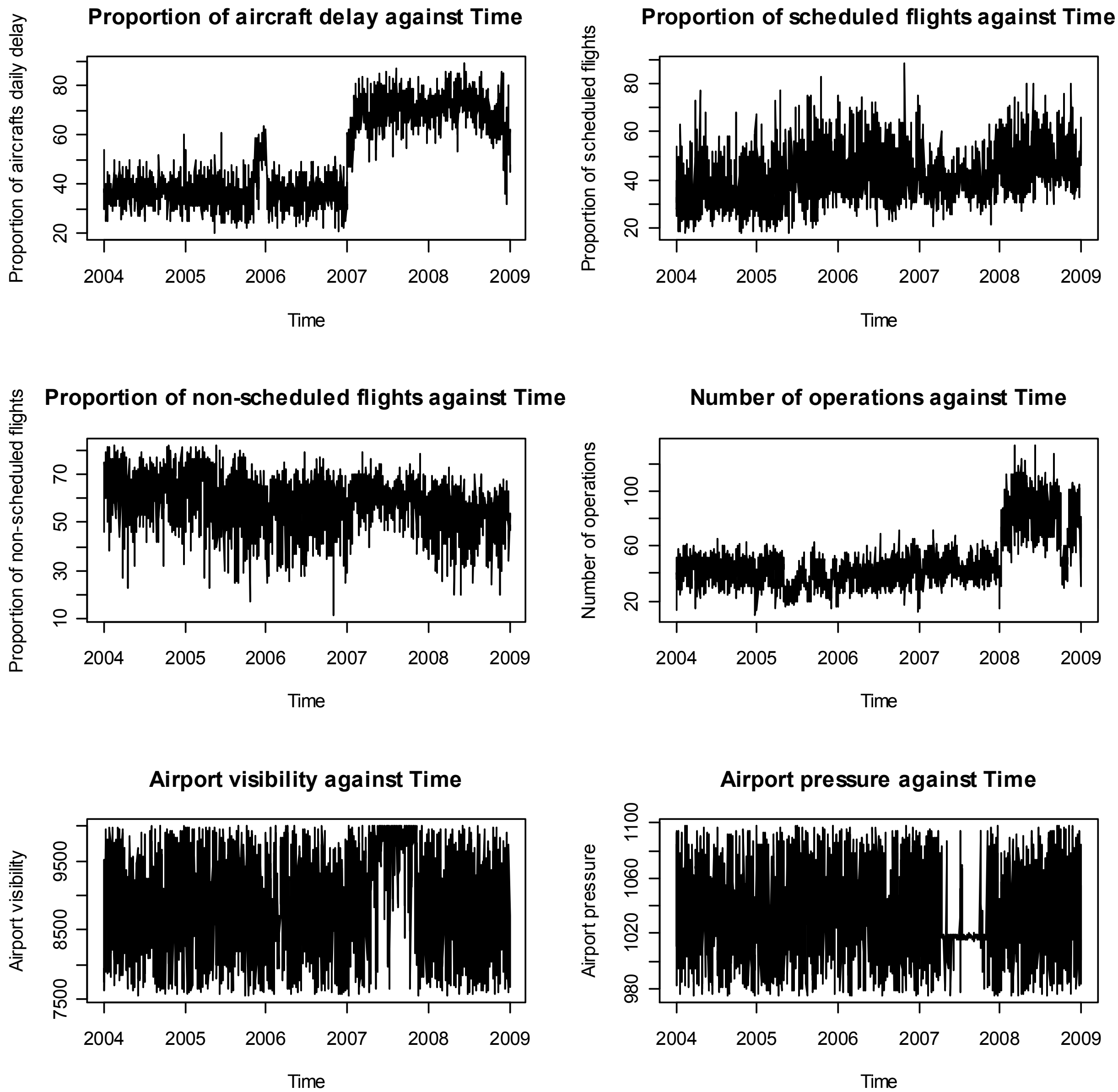

Figure 3.12 Airport delay parameters daily records over the years 2004 through 2008

The mean annual number of aircraft operations was established to follow an exponential function with the best fit of R-squared of 54 percent as indicated in Figure 3.13. The sharp rise of aircraft operations at Entebbe International Airport could be as a result of the commonwealth heads of government meeting that the country hosted in during November 2007 and also the compliancy to international civil aviation standards.

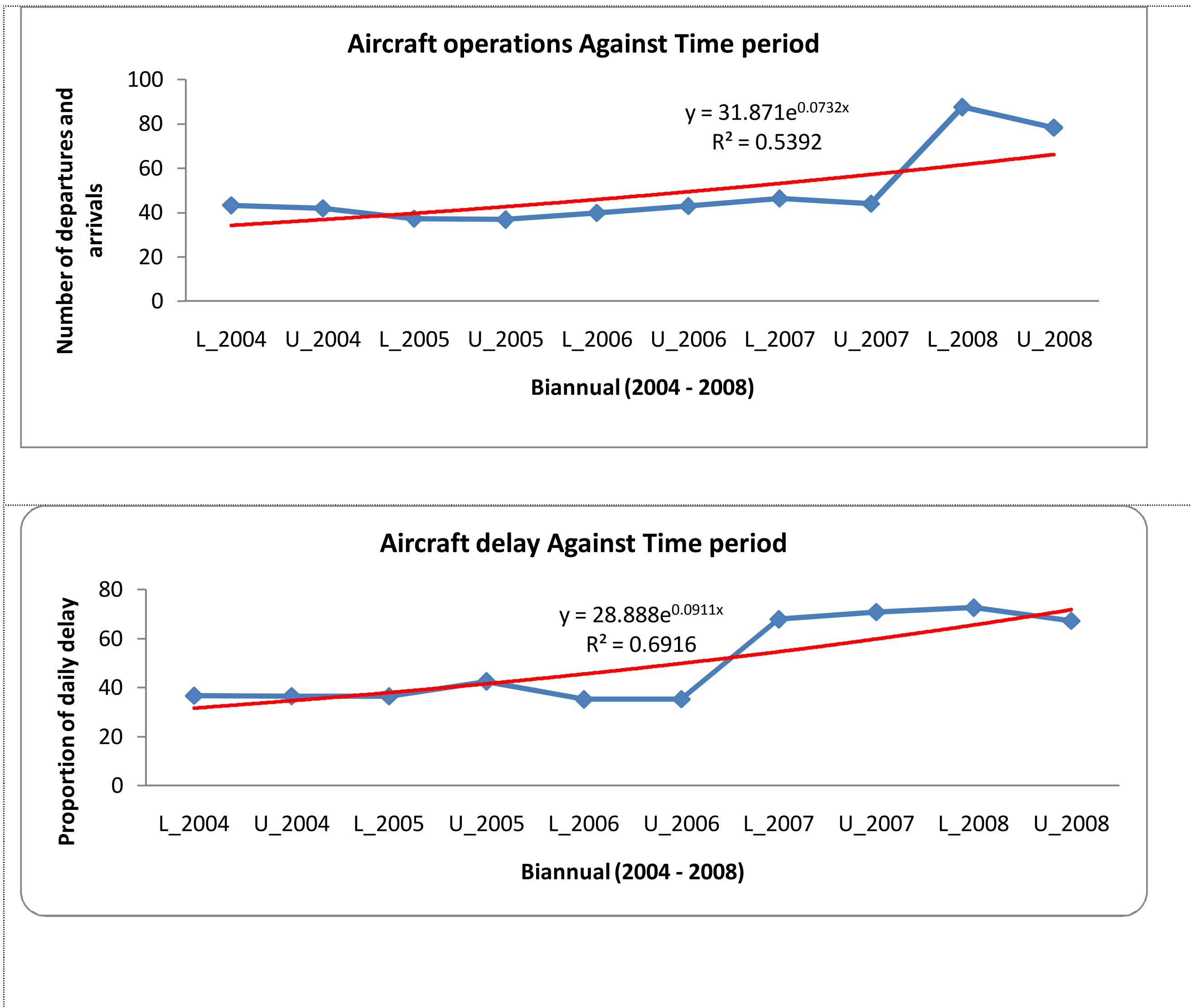

Figure 3.13 Graphs for mean biannual aircraft operations and delay proportion

Similar analyses of the proportions of aircrafts that delay either to depart or to arrive show a positive trend over the years 2004 to 2008. It is shown in Figure 3.13 that proportions of aircrafts delay at Entebbe International Airport followed an exponential function whose best fit is R-squared of about 70 Percent. Comparing the two plots, it is evident that aircraft operations are highly correlated with proportions of aircraft delays at this airport.

3.6.3 The ARIMA Stochastic Process of Aircraft Delay

The erratic movements in the time series plot as shown in Figure 3.12 suggest modelling the data using the Autoregressive Integrated Moving Average, ARIMA models. Also, with the absence of any trend or seasonality in the time series plot, an ARIMA model again seems like a logical choice.

A stochastic process is a statistical phenomenon that evolves in time according to probabilistic laws. Mathematically, it is referred to as a collection of random variables that are ordered in time and defined at a set of time points, which may be continuous or discrete.

One important class of processes where the joint distribution of $x_{t_1}, x_{t_2} \dots x_{t_k}$ is multivariate normal for all $t_1, \dots, t_k$. The multivariate normal distribution is completely characterized by its 1st and 2nd order moments and hence by μ_t and $\gamma_{(t_1,t_2)}$, and so it follows that the 2nd order stationarity implies strict stationarity for normal processes. However, μ and γ_τ may not adequately describe stationary processes which are very 'non-normal'.

Suppose that $\{Z_t\}$ is a purely random process with mean zero and variance σ_Z^2, then a process $\{X_t\}$ is said to be an autoregressive process of order p, $AR(p)$ if

$$X_t = \alpha_1 X_{t-1} + \cdots + \alpha_p X_{t-p} + Z_t \qquad \dots\dots\dots\dots \qquad 3.12$$

Where X_t is regressed on past values of X_t rather than on separate predictor variables. Examining the first order case with p=1, then the AR (1) equation, becomes

$$X_t = \alpha_1 X_{t-1} + Z_t \qquad \dots\dots\dots\dots \qquad 3.13$$

Successive substitution into the equation yields the form

$$X_t = Z_t + \alpha Z_{t-1} + \alpha^2 Z_{t-2} + \cdots \quad \text{...} \quad 3.14$$

Given that Equation 3.14 is an infinite MA process, in order to allow convergence of the sum, the value of α should be in the range of $-1 < \alpha < +1$.

The possibility that AR processes may be written in MA form and vice versa means that there is a duality between AR and MA processes which is useful for modelling aircraft delay both at departure and arrival at the airport. The difference between an autoregressive process and a moving average process is that each value in a moving average series is a weighted average of the most recent random disturbances, while each value in auto-regression is a weighted average of the recent values of the series.

Emphasis was based upon the autoregressive integrated moving averages, ARIMA modelling to time series following three phases: identification, estimation and diagnostic checking as developed by (Box & Jenkins, 1994) . The ARIMA models combine three types of processes: auto regression (AR); differencing to strip off the integration (I) of the series and moving averages (MA). All the three processes are based on the concept of random disturbances each of which with its own characteristic way of responding to random disturbances.

Time series analysis helped to explain the chronological occurrence of proportion of departure and arrival delays at Entebbe International Airport and pointed to the direction of the drift of the delay with respect to time. The trend can thus be positive, negative or non-existent, also known as stationary.

3.6.4 Results of the ARIMA Model for the Aircraft Delay

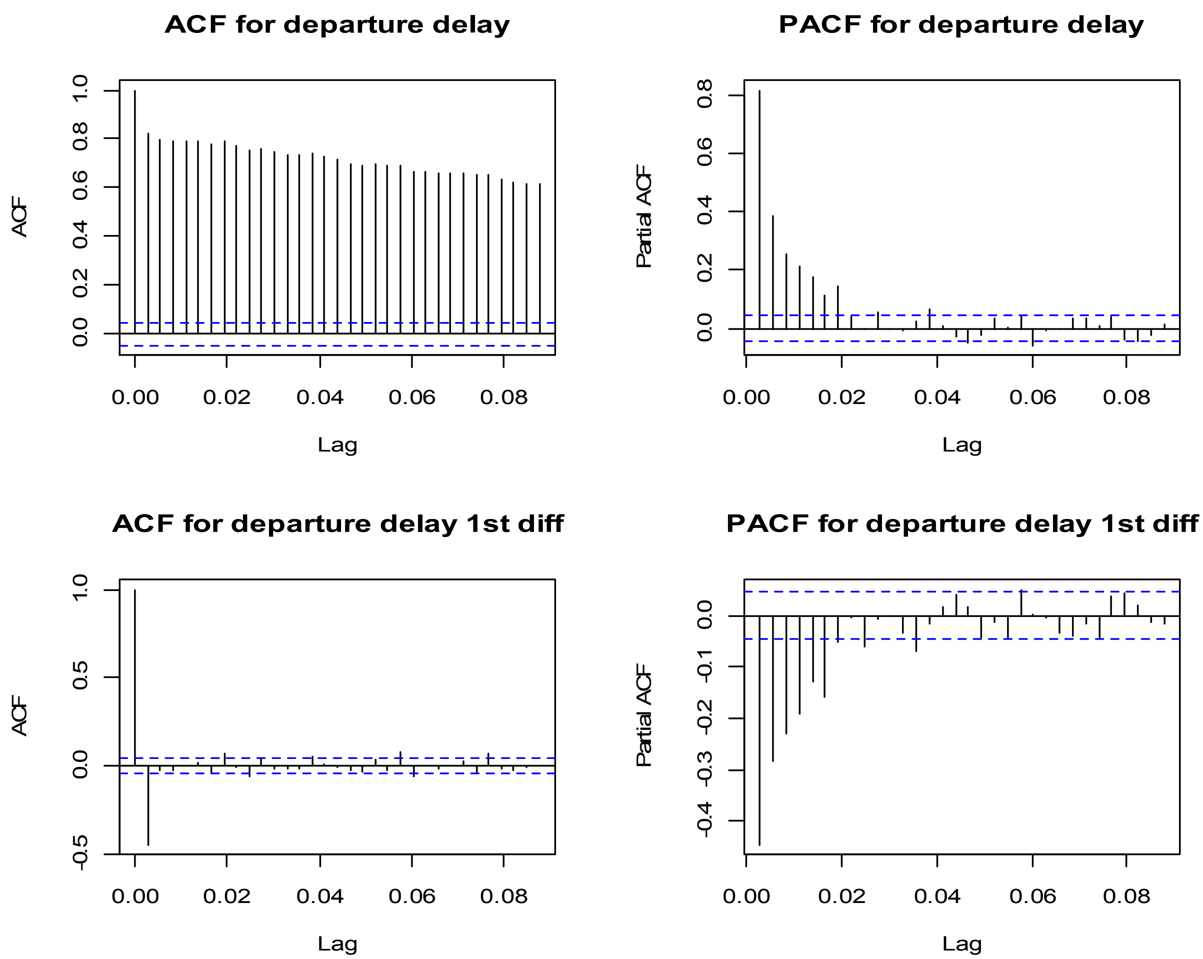

Figure: 3.14: ACF and PACF before and after first differencing

In deriving ARIMA models, a stationary mean is a necessary condition, thus differencing was done on the aircraft delay data. First differencing resulted into a seemingly stationary data over the period implying that the value of d in the ARIMA model was one because the time series varied about a fixed mean and constant variance and the dependence between successive observations do not change over time. Other test results for to obtain the order of autoregressive part p and order of moving average q of the ARIMA (p,d,q) are shown in Table 3.9.

Table 3.9: ARIMA modelling results

Fit statistic	ARIMA(1,1,0)	ARIMA(0,1,1)	ARIMA(1,1,1)	
	AR(1)	*MA(1)*	***AR(1)***	***MA(1)***
Coefficients	-0.6443	-1.0000	**-0.4478**	**-1.0000**
SE	0.0179	0.0016	**0.0210**	**0.0016**
Variance	169.7	100.16	**80.4**	
Log-likelihood	-7274.69	-6799.71	**-6596.88**	
AIC	14553	13603.43	**13199.76**	

ARIMA model was fitted to time series of proportions of aircrafts departure delay. The following model was found most suitable with standard errors of 0.0210 and 0.0016 for the AR_1 and MA_1 of the ARIMA model respectively. This model also referred to as a dynamic dependence model presupposes that the current proportions of aircraft delay at departure is a function of the previous day's proportions for departure. The estimated ARIMA model for aircraft departure is denoted as $Dd_t - Dd_{t-1} = AR\alpha_1(Dd_{t-1} - Dd_{t-2}) + MA\alpha_1(e_{t-1} - e_{t-2}) + \varepsilon_t$ where the stochastic term ε_t is the error or deviation in the proportion of flights that delay to depart on a given day. It is assumed to follow a normal distribution with mean zero and a constant variance, that is, Norm $(0, \sigma^2)$. The model above implies that the best forecast of the future aircraft departure delay is the current value since the expected value of the stochastic term is zero.

Applying the available delay data, the ARIMA (1, 1, 1) model was found most fitting because it generated the smallest Akaike Information Criteria (AIC) value of 13199 and variance of 80 with a log likelihood of -6596 for N=1827 as presented Table 3.9. Thus, the model

$Dd_t - Dd_{t-1} = 0.4478(Dd_{t-2} - Dd_{t-1}) - (e_{t-1} - e_{t-2})$ ……. 3.17

Where:

Dd_t = *proportion of aircraft departure delay on current day*

Dd_{t-1} = *proportion of aircraft departure delay on the previous day*

Or

$Dd_t = 0.5522Dd_{t-1} + 0.4478\, Dd_{t-2} - 0.0194$ ……. 3.18

Equation 3.18 presents a predictive ARIMA model for the proportion of aircraft departure delay for Entebbe International Airport. When the ARIMA prediction model was used and the proportions of departure delay compared with the original data, there were no significant differences, signifying the power of the model, see Table 3.10. The results clearly show that there is no significant difference between the proportions of departure delay and those predicted by the ARIMA (1,1,1).

Table 3.10: Paired two sample for means

Statistic	***Prop of Dep Delay***	***ARIMA(1,1,1)***
Mean	56.79129051	56.64375869
Variance	279.0547122	253.6092203
Observations	1824	1824
Pearson Correlation		0.851735784
Hypothesized Mean Difference		0
df		1823
t Stat		0.706697889
P(T<=t) one-tail		0.239922278
t Critical one-tail		1.645689912
P(T<=t) two-tail		0.479844556
t Critical two-tail		1.961266135

A plot of time series analysis diagnostics, Figure 3.15 for departure delay shows that standardized residuals almost cancel at zero as the mean, thus confirming a good fit of the ARIMA model presented. The other plots of the autoregressive cumulative function of the residuals and the p-values for the Ljung-Box statistic confirmed the ARIMA (1,1,1) model fit for the aircraft departure delays at Entebbe International Airport.

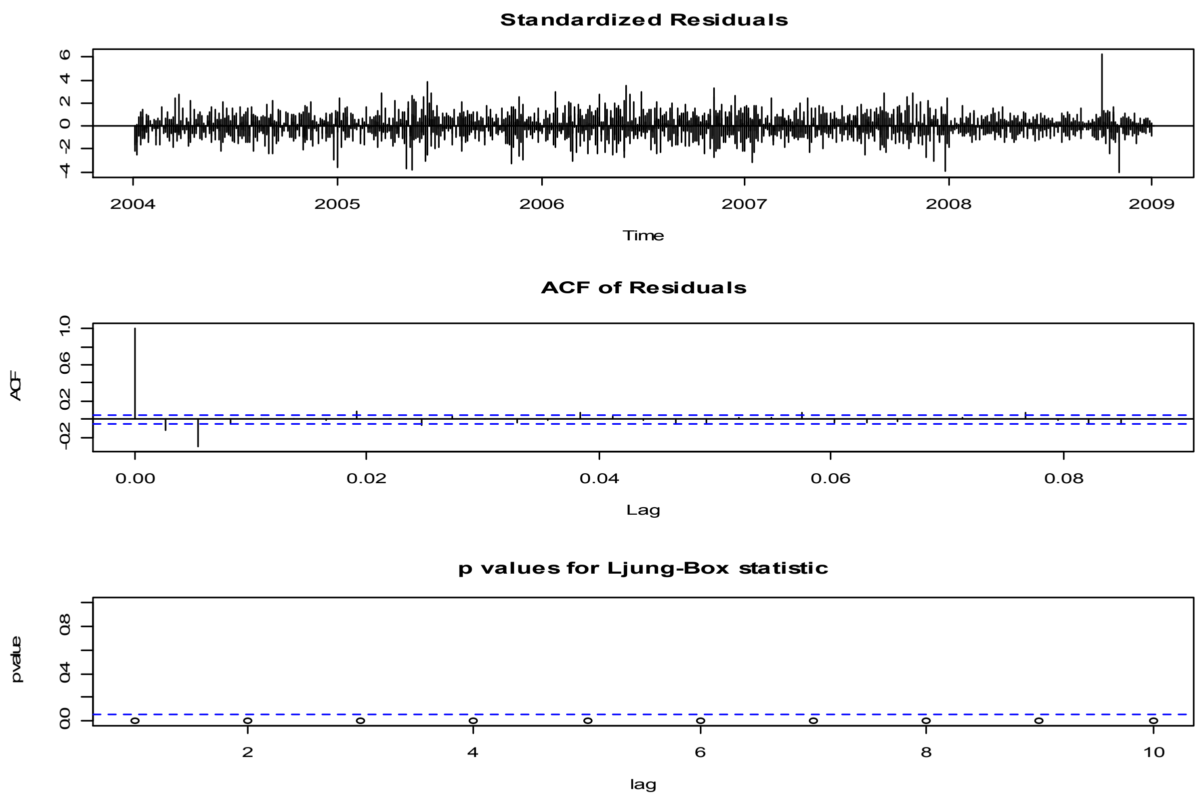

Figure 3.15 Time series diagnostics for the proportion of aircraft delay

Similar ARIMA models were developed for the aircraft arrival delay, probability of departure delay, probability of arrival delay, technical efficiency of departure and arrival of aircrafts at Entebbe International Airport. The results are summarised in Table 3.11

Table 3.11: ARIMA models for Aircraft Arrival delay, Probabilities of departure and arrival delay and Inefficiencies of at departure and arrival of aircrafts

Fit Statistic	**PropArrDelay** ARIMA(1,1,1)		**ProbDepDelay** ARIMA(1,1,1)		**ProbArrDelay** ARIMA(1,1,1)		**TIneffDep** ARIMA(1,1,1)		**TIneffArr** ARIMA(1,1,1)	
	AR_1	**MA_1**	**AR_1**	**MA_1**	**AR_1**	**MA_1**	**AR_1**	**MA_1**	**AR_1**	**MA_1**
Coeffs.	-0.5084	-1.0000	-0.4579	-1.0000	-0.5366	-1.0000	-0.4561	-1.0000	-0.509	-1.0000
SE	0.0202	0.0016	0.0208	0.0016	0.0198	0.0016	0.0218	0.0018	0.021	0.0019
Variance	96.95		0.02691		0.03122		0.008674		0.01148	
Log-Likelihood	-6767.86		704.96		569.35		1591.77		1354.82	
AIC	13541.72		-1403.91		-1132.71		-3177.53		-2703.65	

CHAPTER FOUR

STOCHASTIC OPTIMISATION MODELS

This chapter presents stochastic optimization models for air traffic management based on the derivation of the utility functions of an airport that relate to the probabilities of delay and technical efficiencies on any given day as derived from Chapter Three. Two models based on departure and arrival delays are thus derived to assess the utility levels of an airport. The third model is an aggregate of the two primary models which formulate the overall combined daily utility. A maximum utility value is then contingent upon the computed daily utilities whereby the values of the delay probability and inefficiency are derived from the interaction term. Experimental perturbations are then carried out on the models to access their sensitivities towards different values of model inputs.

4.1 Aircraft Delay Stochastic Optimisation Model

Aircraft delay stochastic optimisation models were developed based on the number of aircrafts that delay to depart and arrive respectively. It was established that total delay affects utility with a seemingly Exponential or Weibull probability density functions (pdfs). Although, none of the two distributions perfectly fitted the delay data, when the inefficiency term was introduced, the exponential probability density function emerged a better fit. It should be realised that obtaining airport utility guides air traffic flow management in not only determining the time dependant level of operations for the airport, but also acts as a strategic planning tool for the airport whose inputs and outputs are stochastic and vary with time.

4.1.1 Model Notation

The following notation is assumed in the development of stochastic optimization models. We let $\Phi = \{1,2, \dots F\}$ be a set of finite flights and $\Gamma = \{1,2, \dots T + 1\}$ to be a set of finite time periods. Given that flight $f \epsilon \Phi$ then $Dep_f \epsilon \Gamma$ and $Arr_f \epsilon \Gamma$. We let $\lambda \geq 1$ where λ is the unit cost for airborne and ground delays assumed for all flights. We then assumed Θ is a set of utility scenarios where $q \epsilon \Theta$ and P_q is the unconditional probability of occurrence of scenario $q \epsilon \Theta$. Hence, let the utility scenario be a year T_i, then the unconditional probability of the proportion of aircraft on time performance is p_{T_i}. In our case, therefore, there are five scenarios, thus $\Theta = \{T_1, T_2, T_3, T_4, T_5\}$ with probabilities $p_\Theta = \{p_{T_1}, p_{T_2}, p_{T_3}, p_{T_4}, p_{T_5}\}$

4.1.2 Decision Variables

Decision variables are important conjugates in evaluating a scenario, thereby leading to a near acceptable and reliable decision. To access whether a given aircraft delayed, we considered a given time period within which it was scheduled to either arrive or depart. Hence, in a particular time period, a flight arrived or did not arrive. Thus, the number of flights in a given time period for a given scenario can be represented as:

$$X^q_{f,t} = \begin{cases} 1 & if\ flight\ f\ is\ planned\ to\ arrive\ by\ the\ end\ of\ time\ period\ t\ under\ scenario\ q \\ 0 & \text{otherwise} \end{cases} \qquad \text{......} \quad 4.1$$

Where;

$q \epsilon \Theta$

$f \epsilon \Phi$

$t \epsilon \{Arr_f, \dots, T + 1\}$

4.1.3 Auxiliary Variables

Below are some auxiliary variables that were used in model formulation on the assumption that the system, which in this study is the airport, is empty at the beginning of the planning period and that all flights arrive by the end of period T+1.

$$Y_{f,t}^{q} = \begin{cases} X_{f,t+Arr_f-Dep_f}^{q} & if \;\; t + Arr_f - Dep_f \leq T \\ 1 & \text{otherwise} \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad 4.2$$

Where;

$q \epsilon \Theta$

$f \epsilon \Phi$

$t \epsilon \{Dep_f, \ldots, T+1\}$

W_t^q is number of aircrafts in the arrival queue at the end of time period t under scenario q

4.2 Stochastic Optimisation Models

The main assumption made here is that collaborative decisions are made between Air Traffic Control (ATC), the Airline Operational Control (AOC), and affected centres that include the originating and destination airports. The flow control options unavoidably result in either some form of departure delay or arrival delay creating two major flow control options that is, ground delay programme, GDP (here after referred to as departure delay) or air holding programme, AHP or simply the aircraft airborne delay (here after referred to as arrival delay). To understand the nature of the distributions of computed probabilities under Section 3.4, Figure 4.1 was plotted. The figure shows the near fit of the Exponential or Weibull probability density functions. However, further analysis revealed that the exponential distribution function provided a better fit for the data in this study. Thus, the resulting general utility function is given as $U(probDelay, TInefficiency) = e^{-probDelay*TInefficiency}$. It should be remembered that the utility parameters are both outputs of the models presented in Chapter Three.

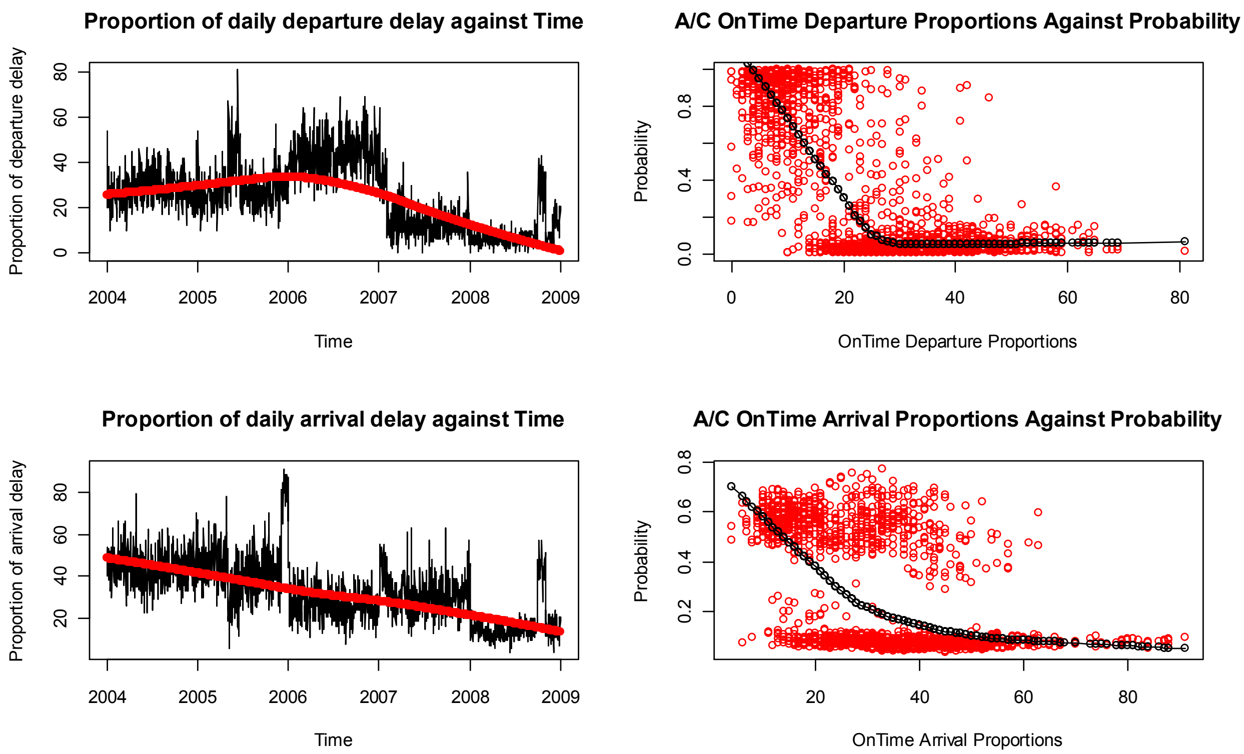

Figure 4.1 Estimating the utility function of aircrafts at the Airport

The philosophy of aircraft operations of aircrafts at Entebbe International Airport is based on a single airport with multiple arrivals and departures as summarised in Figure 4.2. On arrival at the airport, the set of flights $F = \{f_1, f_2, .., f_N\}$ are forced into a queuing system since a single runway is under use. Given the inconvenience at the airport, these flights may not land as scheduled, hence may incur some delay in air as the situation on the ground normalizes. However, the airborne delay could also have been instituted many miles away from the destination airport. Distances from the airport at which the delay is instituted may vary from a few kilometres to a maximum of the equivalence of the distance between the departure and arrival airports. Similarly, some flights on the ground may not depart because of the unbearable circumstances either at the departure airport or at the arrival airport or en-route. Among the many questions that arise is how delay decisions can be made to minimise total utility attributed to the airport. Subsequently, which proportions of aircraft delay would lead to optimum total costs as well as optimum airport utility given the available circumstance?

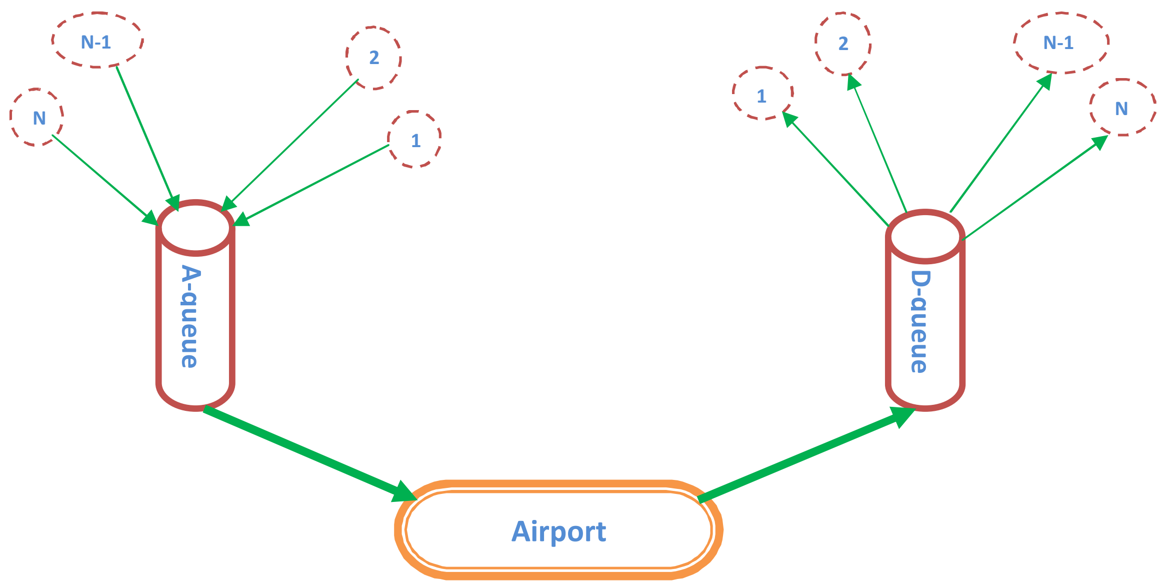

Figure 4.2 Multiple arrivals and departures of aircrafts at the Airport

Owing to weather and other related parameter uncertainties, the airport daily proportions of arrival may be affected by the probabilistic reduction of on time arrivals. Among these uncertainties are those presented in Table 3.1 of Chapter Three, besides, thunderstorms, lightening, bird hazards, VIP movements, political and social causes which are said to affect the proportions of on time aircraft departures and arrivals at Entebbe International Airport.

In the development of the models, two assumptions were made; a single airport and those flights are aggregated by scheduled arrivals and departures. The study sought to develop an objective functions which minimize the expected proportions of departure and arrival delays respectively;

Minimize {E [departure delay] and E [arrival delay]} *4.3*

Subsequently, equation 4.3 was restated using the concept of utility in order to measure efficiency of aircraft flight propagation that may have many uses among which is determination of efficiencies of airlines and even airports using derived utilities as a measure of performance.

Utility is a measure of relative satisfaction. It maps a set of alternatives onto a single number also referred to as utility. Thus, we can say *Utility (option1) ≥ Utility (option2)* if the decision maker prefers option1 to option2 or is indifferent between the two options. A rational decision maker would select the option with the highest utility. Utilities are individual, subjective and need to be obtained from the decision makers. A utility function therefore summarizes the multiple criteria involved in the decision making.

The utility function is defined as an ordinal, including both ordering and ranking concept. In this study, utility of an airport is measured by how effective aircrafts accomplish the assigned tasks in a given day. The fundamental ingredient in determining the airport's utility is the number of aircrafts that depart and arrive on time. Delays of aircrafts, however, reduce the utility associated to a particular airport where the delay is recorded. An aircraft delay is measured by computing the difference between the actual and expected flight operational time. In this study, the number of aircrafts that delayed per day was computed based on whether the scheduled time of departure or arrival was exceeded. On the other hand, total aircrafts and the number of aircrafts arriving and departing per day were also computed.

It is the duty of the airline guided by air traffic management to programme the movement of an aircraft to and from a given airport. Once the programmes are drawn by the ATM, it is the mandate of the airline to supervise its crew so that they strictly abide by the aircraft programme for the convenience and safety precautions plus smooth flow of aircrafts in the sky. Any deviation from the set programme is tantamount to an inconvenience to the other flights as well. Originally, the inconvenience is reflected in cumulative delays by aircrafts, but consequently translated into proportional financial losses. The airport's daily historical data for the years 2004 through 2008 were used to fit a suitable probability density function which subsequently determined the daily utility of aircrafts at Entebbe International Airport. The fitting of the data was done in order to characterise the arithmetic mean delay so as not to grossly underestimate it. Comparisons were made with over sixty existing probability density functions including Exponential, Normal, Weibull and Logistic probability density functions. After analysis of best fits, Exponential probability density function was found very appropriate. However, none clearly fitted the data. To determine the suitable fit, some considerations were made, including, what effect a characterisation of the delay data would have on the decision or action taken by the air traffic management. Furthermore, the distribution selected would act well as a reference distribution, have a basis in theory and empirical experience and would be used for further analysis and decision making.

Airport utility decreases with the increase in the proportion of aircrafts that delay their operations at the airport. Thus, based on Figure 4.1, the study presents the utility functions for aircrafts at departure in Equation 4.4 and at arrival Equation 4.5 respectively.

$$\mathrm{Ud_t} = [\mathrm{e}^{-(\mathrm{pd_t})*(\mathrm{Id_t})}] \quad \text{...} \qquad 4.4$$

Where;

$\mathrm{Ud_t}$ - the utility of aircrafts during departure at an airport on a given day

$\mathrm{pd_t}$ - the stochastic element that an aircraft departs on time on a given day

$\mathrm{Id_t}$ - the technical inefficiency of an airport on a given day

$$\mathrm{Ua_t} = [\mathrm{e}^{-\lambda*(\mathrm{Pa_t})*(\mathrm{Ia_t})}] \quad \text{...} \qquad 4.5$$

Where;

$\mathrm{Ua_t}$ - the utility of aircrafts during arrival at an airport on a given day

$\mathrm{Pa_t}$ - the stochastic element that an aircraft will arrive on time on a given day

$\mathrm{Ia_t}$ - the technical inefficiency of an airport on a given day

λ - the air to ground cost ratio

Thus, the output of a utility function, which are numbers in this case represent utility levels of the airport in regards to air traffic flow operations. The airport utilities derived in this study are an aggregation of a day's air traffic flow performance. Therefore, for the case of the utility functions in Equation 4.4 and Equation 4.5, the utility value at departure and arrival is a maximum when the proportion of aircrafts which experience delay at departure or arrival is zero. That is, all aircrafts depart at their scheduled times. At that point we have 100 percent aircraft flight utility. However, utility reduces as the proportions of aircraft delay increase, hence the more the delay, the less will the utility of a given airport be on a given day for either case. Data for the case study were used in the models to plot utilities against years; the plots fitted the anticipated functions as shown in Figure 4.3.

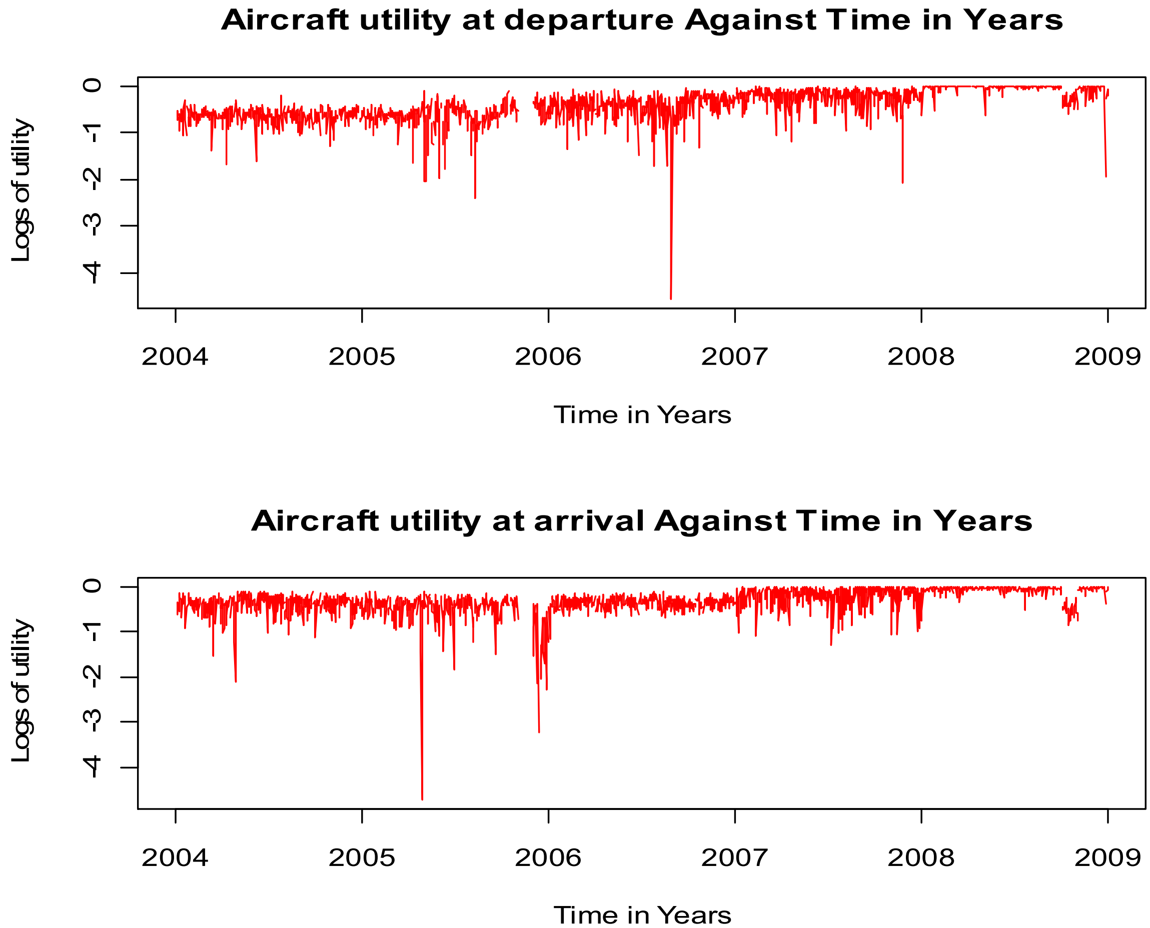

Figure 4.3 Results of the estimated utility functions for departure and arrival

To compute total utility over a period T, the summations of Equations 4.4 and 4.5 are obtained to represent the total airport utility due to air traffic flow as indicated in Equations 4.6 and 4.7 respectively. Equation 4.6 shows the total airport utility due to air traffic flow over period T for departing aircrafts, while Equation 4.7 shows the total airport utility due to air traffic flow over period T for arriving aircrafts

$$\sum_{t=1}^{T} \mathrm{Ud_t} = \sum_{t=1}^{T} [\mathrm{e}^{-(\mathrm{pd_t})*(\mathrm{Id_t})}] \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad 4.6$$

$$\sum_{t=1}^{T} \mathrm{Ua_t} = \sum_{t=1}^{T} [\mathrm{e}^{-\lambda*(\mathrm{Pa_t})*(\mathrm{Ia_t})}] \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad 4.7$$

Furthermore, if total utility is desired for a given day while considering both departures and arrivals, the total utility may be computed by taking the summation of Equations 4.6 and 4.7 to obtain total overall utility in period T as shown in Equation 4.8 and subsequently Equation 4.9.

$$\sum_{t=1}^{T} \mathrm{Ud_t} + \sum_{t=1}^{T} \mathrm{Ua_t} = \sum_{t=1}^{T} \mathrm{e}^{-(\mathrm{pd_t})*(\mathrm{Id_t})} + \sum_{t=1}^{T} \mathrm{e}^{-\lambda*(\mathrm{pa_t})*(\mathrm{Ia_t})} \quad \ldots . \quad 4.9$$

Hence, we can develop three stochastic optimisation models for maximisation of utilities at aircraft departure, aircraft arrival and combined utility at both departure and arrival over period T. Thus, to maximise the utilities over a time period;

$$\max_T \{ \mathrm{Ud_t} \} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad 4.10$$

$$\max_T \{ \mathrm{Ua_t} \} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad 4.11$$

$$\max_T \{ \mathrm{Ud_t} + \mathrm{Ua_t} \} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad 4.12$$

One important decision taken is that some flights have their arrival and departure times re-scheduled and as such delay is instituted either during aircraft arrival or at aircraft departure. Probability of occurrence of aircraft on-time operations on a certain day is computed using the logistic model post-analysis having while taking care of all the explanatory variables as indicated in Chapter Three. The stochastic optimisation models 4.10, 4.11 and 4.12 meet the following assumptions which are duly considered.

i) The number of aircrafts rescheduled is greater or equal to one and it is cumulative over a specific time period.

$\sum_{t=1}^{T} X_{it} = n_i$ 4.13

Where;

t = 1, 2... T

ii) The number of aircrafts that delay to arrive or depart is less or equal to the number scheduled under a given scenario. That is the number of aircrafts that delay at any time does not in any way exceed the number scheduled.

$\sum_{t=1}^{T} X_{it} \leq M_{qi}$ 4.14

Where;

q = 1, 2… Q

iii) Every aircraft scheduled to land actually lands

$X_{it} = \sum_{t=i}^{T} \Phi_{qit}$ 4.15

Where;

t = 1, 2… T

1 ≤ t ≤ T

q = 1, 2… Q

iv) The number of aircrafts rescheduled and actually landing is positive

$X_{it} \geq 0$ 4.16

Where;

t = 1, 2… T

1 ≤ j ≤ t

q = 1, 2… Q

Three major constraints of the stochastic optimisation models are identified;

i) The probabilities of departure and arrival delay are computed from the logistic regression model that takes into account all the necessary explanatory variables. Although the model has been tested and found reliable in predicting the conditional probabilities, the completeness of the explanatory variables is left to the researcher to determine. Thus, the product of the interaction terms is greater than zero. Conversely, the probabilities of delay at departure and arrival are greater or equal to zero, but less or equal to one.

ii) On the other hand, the technical inefficiency levels for both aircraft departure and aircraft arrivals are computed from the stochastic frontier models. These models are tested, current and also found to perform best when all the explanatory variables are included. The determination of the levels of inefficiencies is based on the error terms and their distributions. Thus, the inefficiency values at departure and arrival are greater or equal to zero and less or equal to one.

iii) However, the fact that the stochastic optimisation models depend on explanatory variables implies that they will not be applicable wherever there is no data to generate input into the model. The interaction terms in the utility function as given in the exponential functions are computed for those values occurring at the same time, t.

4.3 Stochastic Optimization Model Algorithm (SOMA)

GENERAL ALGORITHM: STOCHASTIC OPTIMIZATION MODEL ALGORITHM

// INPUTS from Manifest database

// Variables: t => day; T => max number of years q => scenarios

Step 1.1 Obtain the aircraft manifest database // Information about aircrafts

Step 1.2 Establish the day's flight schedules of aircrafts at the airport, both departures and arrivals

Step 2.0 Derive the number of flights that delay daily:

i) The number of flights that delay to depart

ii) The number of flights that delay to arrive

// INITIAL PROCESSING

Step 3.0 From the arrival data, compute the deviation of expected time of arrival (ETA) from the actual time of arrival (ATA),

Step 3.1 For each aircraft, obtain Aircraft Arrival Deviation,

$$AAD = ATA – ETA$$

Step 3.2 Let the total number of daily scheduled arrivals be TA

Step 4.0 From the departure data, compute the deviation of expected time of departure (ETD) from the actual time of departure (ATD),

Step 4.1 For each aircraft, obtain Aircraft Departure Deviation,

$$ADD = ATD – ETD$$

Step 4.2 Let the total number of daily scheduled departures be TD

// COMPUTING THE NUMBER OF AIRCRAFTS THAT DELAY DAILY

Step 5.0 Using AAD from step 3.1 above

For each day

{

If AAD > 0

Then daily total arrival aircraft delay,

$\mathrm{TAAD} = \sum_{i=1}^{t} \mathrm{AAD}_i$

Return TAAD

Else

Return 0

}

Step 6.0 Using ADD from step 4.1 above

For each day

{

If ADD > 0

Then daily total aircraft departure delay,

$\mathrm{TADD} = \sum_{i=1}^{t} \mathrm{ADD}_i$

Return TADD

Else

Return 0

}

// COMPUTING THE DAILY PROPORTION OF DEPARTURES AND ARRIVALS

Step 7.0 Obtain the proportion of the daily arrival delay

Using TAAD from step 5.0 and TA from step 3.2

For each day

{

If $t > 0$

Then daily proportion of aircraft arrival delay,

$$\text{DAAD} = \frac{\text{TAAD}}{\text{TA}}$$

Return DAAD

Else

Return 0

}

Step 7.1 Obtain the proportion of the daily departure delay

Using TAAD from step 6.0 and TA from step 4.2

For each day

{

If $t > 0$

Then daily proportion of aircraft departure delay,

$$\text{DADD} = \frac{\text{TADD}}{\text{TD}}$$

Return DADD

Else

Return 0

}

// ESTABLISH DISTRIBUTION DENSITY FUNCTION FOR THEDEPARTURE DELAY, ARRIVAL DELAY AND AIRPORT UTILITY

Step 8.0 Using the Kolmogorov Smirnov goodness of fit statistic to rank the known probability density functions to the data, it was found that the proportions of delay tended to follow the Exponential probability density functions.

Thus, the proportion of daily departure delay follows

$$\mathrm{ADD_t} \sim \mathrm{e}^{-\mathrm{DADD}}$$

Similarly, the proportion of daily arrival delay follows

$$\mathrm{AAD_t} \sim \mathrm{e}^{-\mathrm{DAAD}}$$

The combined proportions also followed the same probability density functions. Thus, the derived airport utilities followed an exponential distribution function as will be shown in subsequent sections.

// ESTABLISH THE STOCHASTIC OPTIMIZATION MODEL

Step 9.0 The airport utility will take into consideration, other stochastic variables such as the probability derived from the post-analysis of the logistic model at a level with the greatest significant number of variables and also the technical inefficiency term derived from the stochastic frontier model. Thus, for the aircraft departure, the utility function was established to follow the probability density function for the interaction term of the probability of delay at aircraft departure and the technical inefficiency term;

$$\mathrm{U(probDd, DtechInefficiency)_t} = e^{-(ProbDd_t * DtechIneffiency_t)}$$

While the utility for the aircraft arrival was similarly established to follow the probability density function for the interaction term of the probability of aircraft arrival delay and the inefficiency term at that particular time;

$\mathrm{U(probAd, AtechInefficiency)_t} = e^{-(\lambda * ProbAd_t * AtechIneffiency_t)}$

And the combined utility will constitute aggregated utilities at departure and arrival respectively, thus;

$\mathrm{U(probAd, probDd, AtechInefficiency, DtechInefficiency)_t}$

Step 9.1 Hence, the stochastic optimisation models imply maximising airport utility over a probabilistic time period T, thus;

At aircraft departure, we optimise the utility function over time period T;

$\max_T \mathrm{U(probDd, DtechInefficiency)_t}$

While at aircraft arrival, we optimise the utility function over time period T;

$\max_T \mathrm{U(probAd,\ AtechInefficiency)_t}$

The aggregated utility optimisation considers all the parameters as;

$\max_T \mathrm{U(probAd, probDd, AtechInefficiency, DtechInefficiency)_t}$

4.4 Results Obtained from the Models Using Data at Entebbe International Airport

Table 4.1 represents output of the models at departure and arrival. It is evident that aircraft utilities are lower at departure than during aircraft arrival at Entebbe International Airport. Therefore on average the utility of the airport during aircraft departures is 88 percent and 90 percent during aircraft arrivals at the airport. It is also noted that the utilities at departure and arrival of aircrafts at EIA are about the same. Hence, one would conclude that there is no significant difference in handling of aircrafts during departure and arrival at this airport.

Table 4.1: Utilities generated from the Model using 60 percent threshold level for Entebbe International Airport

Statistic	**Utility at Departure**	**Utility at Arrival**
First quartile	0.8663	0.8764
Third quartile	0.9714	0.9713
Mean Utility	**0.8838**	**0.9065**

Model flexibility enabled computations to be done on an annual basis for the study period 2004 through 2008. To compute the utility values for each year, only parameter values for the given year were applied. In both cases of airport departures and arrivals, it is observed that there was an improvement in utility over the period 2004 through 2008 probably because of a related improvement of resources, both human and otherwise at EIA. It is further confirmed that airport utility, although not significantly different at aircraft departure and arrivals, is higher at arrival than at departure, details are shown in Table 4.2. One plausible explanation would be that the weather and other phenomena en-route and at this airport are on average suitable with a few perturbations that would not severely deter arrivals of aircrafts.

Table 4.2: Airport annual utility for the period

Year	Airport Departure Utility	Airport Arrival Utility
2004	0.8932	0.9508
2005	0.8204	0.8732
2006	0.9444	0.8983
2007	0.9706	0.9871
2008	0.9878	0.9978
Average utility	**0.9233**	**0.9414**

4.5 Design of Experiments for Sensitivity Analysis of the Models

To evaluate the performance of the model, five experiments were designed to test the resilience of the stochastic optimisation models. Specific experiments are designed to attempt test the performance of the models by using different data sets. In all the experiments, the maximum utility values were generated from the model based on the data for the study and the simulated data to gauge the resilience of the models.

4.2.3.1 Design of experiment one: varying the daily probabilities to lower departures and higher arrival values

When data for Entebbe International Airport for ground and airborne delays are applied to the stochastic optimization models, its sensitivity was tested to establish how the model output varies over the years. It was also established how the changes in the model parameters would affect the ranking of utilities over the period.

Final utility values for the different years indicate the performance accrued due aircraft performance in the given year. The following algorithm was applied.

Algorithm 4.2.3.1: Simulation Experimental Design One

Step 0 Begin

Step 1 Apply the proportion of daily delay during departure at Entebbe International Airport

Step 2 Apply the proportion of daily delay during arrival at Entebbe International Airport

Step 3 Simulate lower and higher values for the probability of daily delay for aircrafts at departure and arrival. Let these values be in the range {0.1:0.4} and {0.6:0.9}

Step 4 Simulate lower and higher values for the computed probability of daily delay for aircrafts at departure and arrival. Let these values be in the range {0.1:0.4} and {0.6:0.9}

Step 5 Compare the derived utilities

Step 6 Test for differences with the normal case at Entebbe International Airport

Step 7 Do + plots

Step 8 End

Table 4.3: Utilities generated using simulated probabilities

Statistic	Utility at Departure with lower probability values	Utility at Arrival with lower probability values
First quartile	0.9799	0.9663
Third quartile	0.9919	0.9842
Mean Utility	**0.9814**	**0.9715**
	higher probability values	**higher probability values**
First quartile	0.8854	0.8140
Third quartile	0.9521	0.9090
Mean Utility	**0.8985**	**0.8457**

Table 4.3 shows that lower probabilities of delay at departure and arrival of aircrafts are inversely related to airport utilities. Conversely, the airport's utility will be high when aircrafts' delay probabilities at departure and arrival during a specific time interval are low. Given the scenario in Algorithm 4.2.3.1, the performance of the airport over the study period is as shown Figure 4.4.

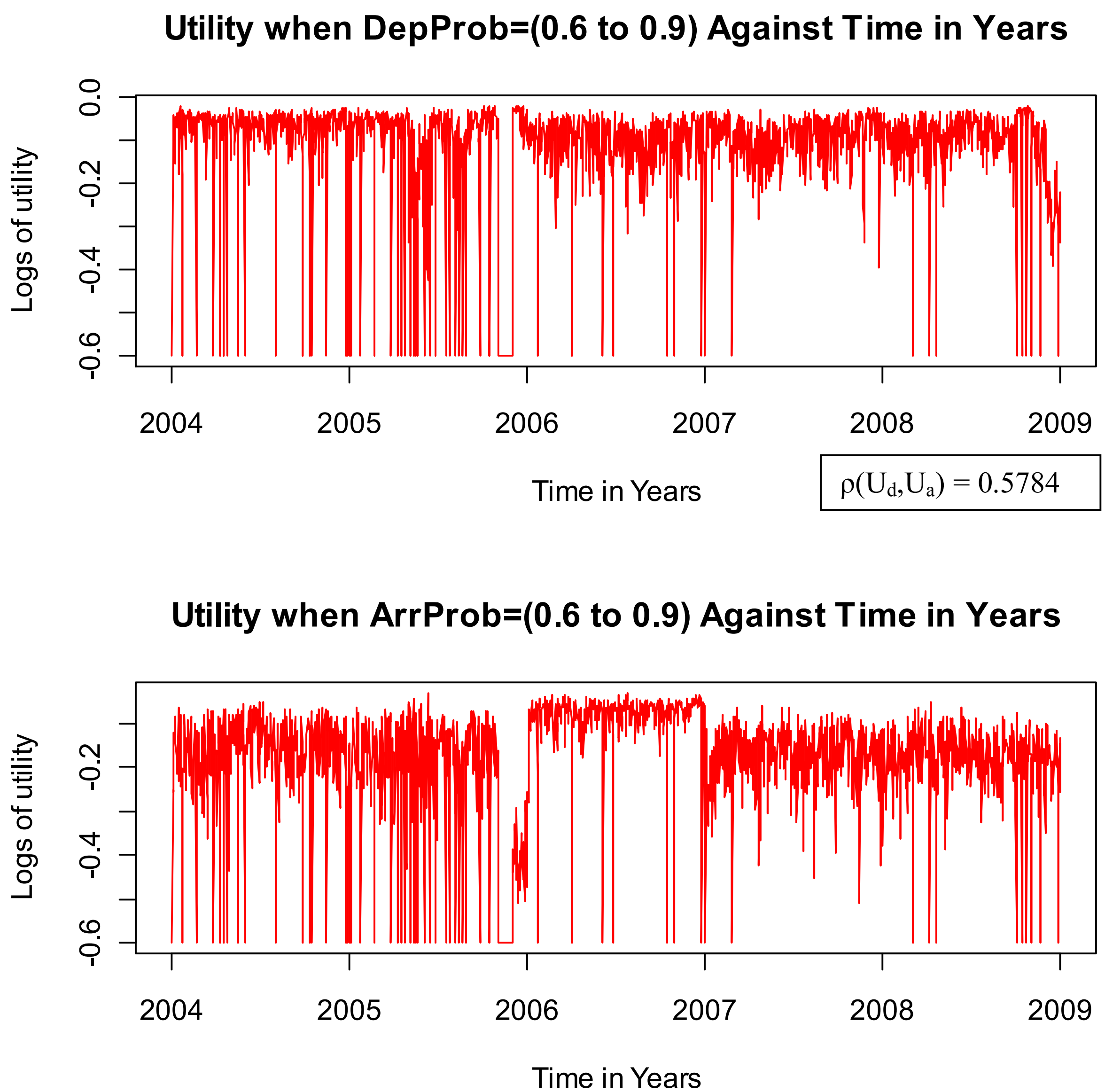

Figure 4.4: ***Aircraft Utility for departure and arrival with high probability of delay***

4.2.3.2 Design of experiment two: varying the daily inefficiency scores to lower and higher values for both aircraft departures and arrivals

When data for Entebbe International Airport for ground and arrival delays are applied to the stochastic optimization models, its sensitivity was tested to establish how the model output varied over the years. It also established how the changes in the model parameters would affect the ranking of utilities over the period.

Final utility values for the different years indicate the performance accrued due aircraft performance in the given period of time. The following algorithm was applied.

Algorithm 4.2.3.2: Simulation Experimental Design Two

Step 0 Begin

Step 1 Apply the proportion of daily delay during departure at Entebbe International Airport

Step 2 Apply the proportion of daily delay during arrival at Entebbe International Airport

Step 3 Simulate lower and higher values of airport efficiency at aircraft departure

Let these values be in the range {0.1:0.4} and {0.6:0.9}

Step 4 Simulate lower and higher values of airport efficiency at aircraft arrival

Let these values be in the range {0.1:0.4} and {0.6:0.9}

Step 5 Compare the derived utilities

Step 6 Test for differences

Step 7 Do + plots

Step 8 End

Table 4.4: Utilities generated using simulated inefficiency data

Statistic	Utility at Departure with lower efficiency values	Utility at Arrival with lower efficiency values
First quartile	0.4737	0.6080
Third quartile	0.8543	0.8897
Mean Utility	**0.6687**	**0.7378**
	higher efficiency values	**higher efficiency values**
First quartile	0.7174	0.8016
Third quartile	0.9324	0.9494
Mean Utility	**0.8267**	**0.8687**

When the airport operates more efficiently, its overall average utilities are also established to be higher. The efficiency here means abiding by the scheduled times of operations. It should be noted that sometimes, the utility level is determined by factors beyond management of the air traffic controllers. Whereas they would wish to have 100 percent utility performance at the airport, factors such as suitability of weather at the departure airports, during airborne and even at the airport itself may not be suitable for aircrafts to land or to takeoff.

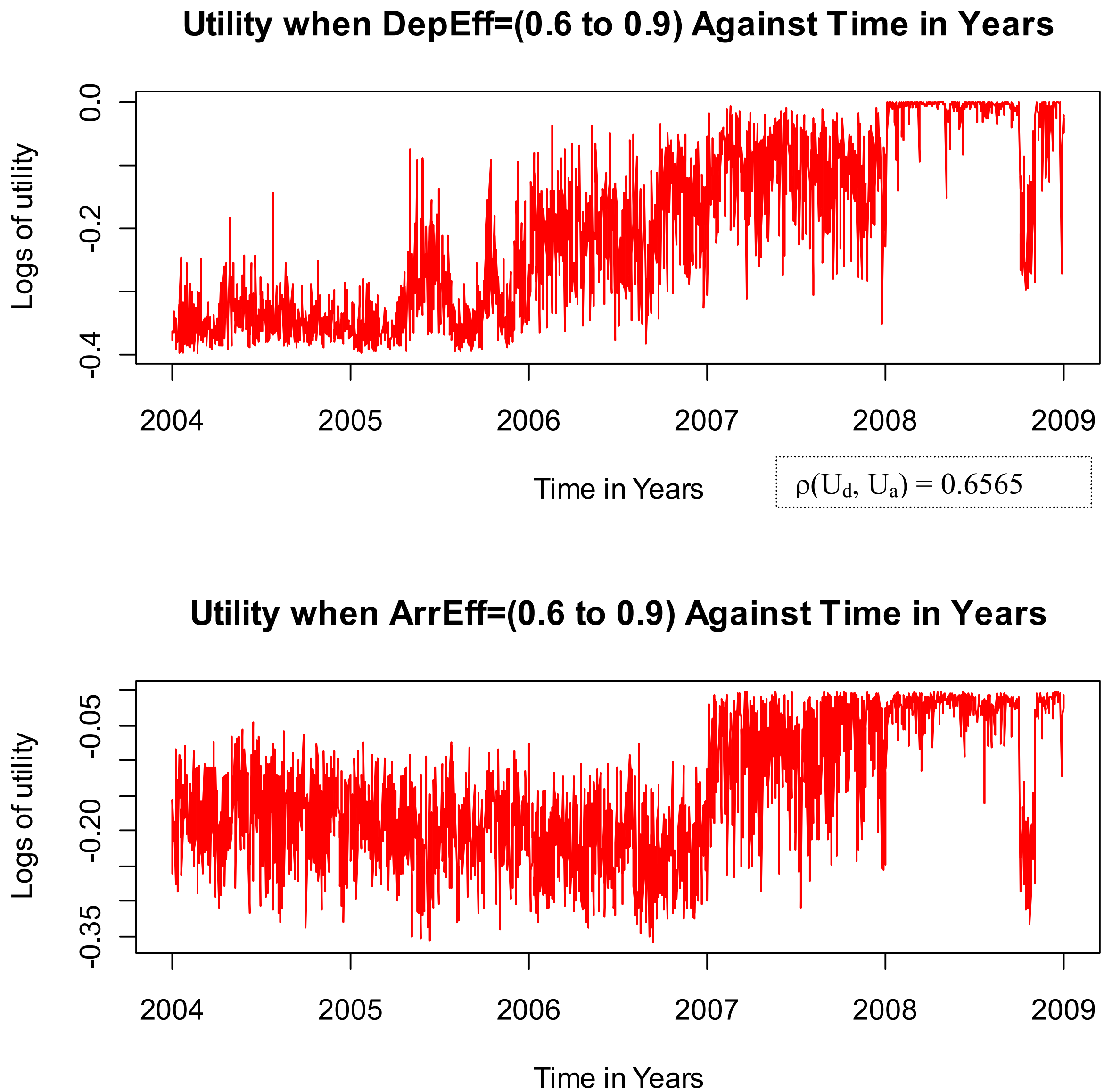

Figure 4.5: Airport Utility with high inefficiency for both departures and arrivals of aircrafts

4.2.3.3 Design of experiment three: varying the cost ratios between 1.0 and 2.0 while using EIA arrival efficiency and higher values for aircraft arrivals efficiency

When data for Entebbe International Airport for ground and arrival delays are applied to the stochastic optimization models, its sensitivity was also tested to establish how the model output varied over the years. It also established how the changes in the model parameters would affect the ranking of utilities over the period.

Final utility values for the different years indicate the performance accrued due aircraft performance in the given period of time. The following algorithm was applied.

Algorithm 4.2.3.3: ***Simulation Experimental Design Three***

Step 0 Begin

Step 1 Apply the proportion of daily delay during arrival at Entebbe International Airport

Step 2 Use data for Entebbe International Airport

Step 3 Simulate high values of airport efficiency during aircraft arrival.

Let the values be in the range {0.6:0.9}

Step 4 Simulate values of the cost ratio in the range {1.0: 2.0, 0.1}

Step 5 Compare the derived utilities

Step 6 Do + plots

Step 7 End

Table 4.6: Utilities generated using simulated air to ground cost ratio using data for EIA and when the efficiency level is high

	Entebbe International Airport arrival efficiency data	**Simulated arrival efficiency data {0.6:0.9, 0.1}**
Lambda *(Air to ground cost ratio)*	Mean Utility	Mean Utility
1.0	0.9065	0.8687
1.1	0.8982	0.8569
1.2	0.8901	0.8455
1.3	0.8821	0.8342
1.4	0.8743	0.8232
1.5	0.8667	0.8124
1.6	0.8592	0.8018
1.7	0.8518	0.7914
1.8	0.8446	0.7812
1.9	0.8375	0.7713
2.0	0.8306	0.7615

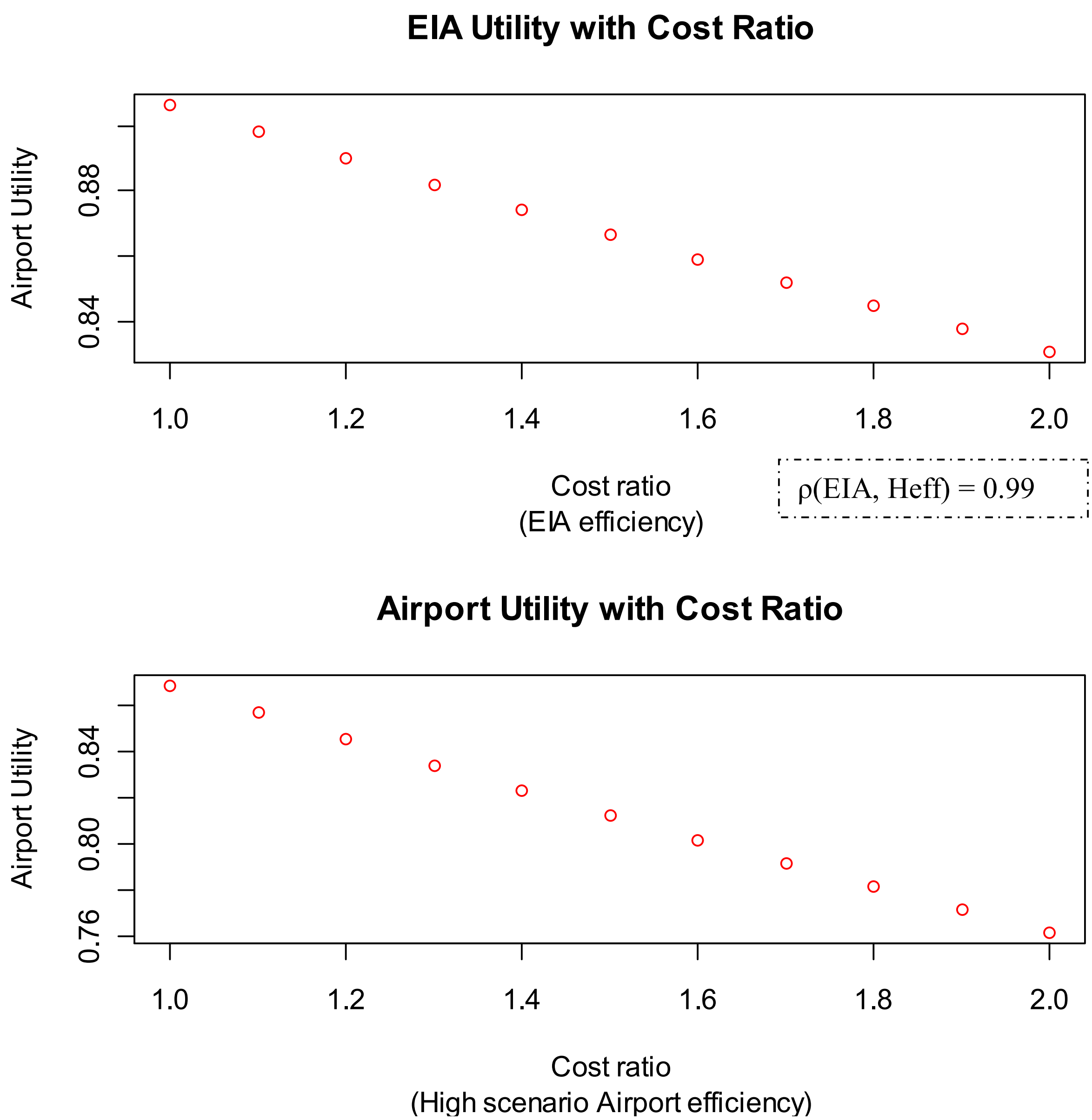

Figure 4.6: ***Entebbe International Airport Utility and a simulated Airport Utility with high efficiency levels for aircraft arrivals at varying cost ratios***

CHAPTER FIVE
DISCUSSIONS OF THE AIR TRAFFIC FLOW MODELS

In this chapter, a discussion of the findings is made. The discussion is premised on the results of the models based on the study data and some data simulations. Firstly, the discussion is focussed on the statistical models for air traffic flow management. The statistical models include logistic models, stochastic frontier models and the ARIMA (p, d, q) models. Further discussions are derived from the stochastic optimisation models as presented in Chapter Four and the models' sensitivity analysis. The significance of stochastic against deterministic approach is also explored in an attempt to confirm that the best feasible future strategies of air traffic flow management. Lastly, a discussion about decision making in the management of air traffic flow, management information systems, and air traffic flow efficiency computations is presented.

6.2 Statistical Models for Air Traffic Flow Management

Logistic model dynamics for aircraft departure and arrival delays show that more explanatory variables, eight in number are significant for explaining the proportion of aircraft delay at departure. Only five explanatory variables were tested significant in explaining the proportion of aircraft arrival delay at 0.05 and 0.01 levels of significance. At these levels, the AIC for departure and arrival delay determinants were 731.5 and 1732.6 respectively. This confirms the need to examine other factors as well if one is to understand the causes of aircraft departure and arrival delays at any airport during aircraft departure and arrival respectively. The possible factors to consider are those at the departure or arrival airports for aircrafts arriving and departing respectively and the suitability of en-route factors. However, in both cases of aircraft departure and arrivals, it was established that the non-scheduled type of flights have an effect on the timeliness of aircraft departures and arrivals as demonstrated in Table 3.2.

Thus, the philosophy behind these findings is that controlling the non-scheduled type of flights improves the timeliness of aircraft departures and arrivals. This philosophy has been found to hold true as shown in Table 3.2, where the number of chartered flights, number of freighters and the number of other non-commercial flights were significantly explaining the proportions of departure delay. Similarly, the number of freighters and other non-commercial flights significantly explained the proportions of arrival delay. The extreme solution would be to eliminate the non-scheduled type of flights, but this may not apply since, there is a growing demand for chartered flights, freighters, and non-scheduled flights. The optimal solution would then be to submit all non-scheduled flight's programmes in sufficiently ample time to warrant that their schedules do not interfere with other scheduled flights.

Analysis of the probabilities of delay at different threshold levels of delay revealed a seemingly obvious outcome that raising the threshold level generates lower values of the probabilities of delay for either departure or arrival. The logistic model would not perform well with very low threshold levels below a 50 percent mark because at those levels there were fewer counts of delay occurrences. Thus for this study, a threshold yielding more number of explanatory variables in the model was plausible and this occurred at a 60 percent delay threshold level for both aircraft departures and arrivals respectively. Therefore, considering data over the study period, at 60 percent threshold level, the probabilities of aircraft departure delay has been reducing over the time period 2004 through 2008. This implies that the air traffic flow management division at EIA has been empowered to sustainably combat aircraft departure delays. Some of the measures mentioned during their interaction with the researcher included the installation of the radar system and adoption of the automated aircraft plan scheduling system. A similar observation and explanation holds for the variation of arrival delay probabilities for the delay threshold level of 60 percent as shown in Figure 3.6.

When probabilities are computed separately for each year over the period under study, a similar negative trend was established for both departure and arrival delays. Interestingly, treating each year separately confirmed the same trend over the period with decreasing departure and arrival delays as shown in Table 3.5. It is also clear that EIA benefitted from CHOGM preparations by attracting some investments to refurbish the only international airport in the country.

Stochastic frontier models in this study revealed that visibility plays a vital role in determining aircraft departure and arrival delays. The two frontier models established a proxy to the measurement of efficiency of air traffic flow of 81 and 74 percent for aircraft departure and arrival respectively whose error terms are estimated to follow the half-normal that provided better AIC test values. The estimates presented in Tables 3.6 and Table 3.7 used time invariant, hence bearing the coefficient of zero. When efficiencies were disaggregated over time, it was established that they fluctuated about 80 percent for both departures and arrivals. Thus, one would conclude that timeliness at EIA is at an average of 80 percent resulting into an average inefficiency of 20 percent as shown in Table 3.8. This could be attributed to factors such as less automation and also the fact that ATM decisions are not based on sufficiently provided statistical information, a basis which guaranteed this study to improve aircraft operation timeliness.

Time series analysis established that although there is no trend of airport visibility and pressure, these parameters are significant for air traffic management to take appropriate decisions for air traffic flow in and out of the Entebbe International Airport. The other parameters showed some trend as in Figure 3.12. The ARIMA (p, d, q) model was found suitable for forecasting aircraft proportions of departure and arrival delays and established to follow ARIMA (1, 1, 1) for all cases as shown in Table 3.9 and Table 3.10. The correlation between the observed and the forecast values for all cases forecast by the ARIMA (1, 1, 1) were all positive and strong, signifying a reliable fit for the time series.

6.2 Air Traffic Flow Management Stochastic Optimization Models

The stochastic optimisation models presented aim at pointing towards possible means and ways of optimising the utility for an airport. The models applied the approach for utility of an airport. Here, the study established that utility of an airport follows some distribution function similar the exponential density functions with the interaction term consisting of the probability of delay and the inefficiency level. It should be remembered that the probabilities of delay are a by-product of the logistic model and values are obtained on a daily basis over a period of five years. Similarly, the airport inefficiency terms are computed from the stochastic frontier model and values obtained on a daily basis for the scope of study period. These pre-stochastic optimisation model computations are derived for both aircraft departures and arrivals respectively. Hence, the two models are derived from aircraft departure and arrival. A close examination of the utility functions reveals that a unit increase in delay decreases the airport's utility level. The models use utility functions and the theory of scenarios that apply time-dependence to a set $\{T_1, T_2.., T_Q\}$ whose probabilities are $\{T_{P1}, T_{P2} ... T_{PQ}\}$ respectively. In order to obtain an optimal utility, we compute the maximum utility in a set of utilities over some time period that represents a scenario. Time period determine the necessary variation in airport utilities because even the stochastic determinants of aircraft delay vary over time. We then find the values from the interaction term that maximise the airport utility.

However, it should be noted that the effect of airport utility by the interaction term of probability of aircraft delays and airport inefficiency vary between departure and arrival by the ratio of arrival delay costs to departure delay costs. These costs vary based on the scenario and both practice and theory suggest that airborne delay costs are usually more than ground delay; hence the relationship $\lambda = \frac{C_a}{C_g} \geq 1$ is used in the models to enhance their applicability. The modelling approach emphasizes the need to have minimal aircraft delays so as to increase airport utility. The model used the approach of optimisation of aircraft utility which in turn relies of the magnitude of the interaction between probability of delay and inefficiency level, implying that when the interaction term is zero units then the airport utilities would be at maximum 100 percent because all aircrafts will be landing and departing on time as expected. Conversely, when the interaction term is nearer one (unity), the airport utility would be at the least minimum level of about 36 percent. The study assumed that other explanatory factors than aircraft delays are assumed to contribute about 36 percent towards the airport utility. The approach to stochastic optimisation presented in this study plays many air traffic flow management roles such as providing information for reliable air traffic flow management, providing a benchmark for strategic planning for air traffic flow management and presents as a reliable tool for monitoring the performance of different aircrafts within an airline, airlines within an airport and airports within a region. If applied, these models can go a long way in improving the efficiency of air traffic flow management in the aviation industry.

6.2 Decision making and Air traffic Flow Management

Decision making is a key ingredient in any management process. A decision taken now regardless of its magnitude is much better than a decision taken moments later for it saves lives. A decision taken without sufficient consultation from those concerned to provide necessary information in a good time, within the right time intervals leaves the decision maker as a blame bearer for the repercussions thereafter. In this era of ICT, it is very easy to believe without question that automation of systems is the only sure way by which management of information systems should be operated. It is imperative to stretch one more mile and see the relevance of human intervention through both evidence-based and simulated models as the ones developed in this study. This helps answer one of the often ignored, but important management question of whether management should sit back and relax since they have automated management systems like management information systems that give managers the information they need to make routine and operational decisions. This study showed that human intervention is paramount at all levels of decision making; it is such models that result into automated systems, but the human input should precede the automation process whose performance require detailed testing to guarantee system accuracy and reliability.

6.2 Implications of Air Traffic Flow Management Decision

Air traffic flow management is crucial not only in ensuring efficiency in aviation business management productivity of a country, but also directly concerns people's lives and well-being. A number of lives are affected due to air traffic not well-informed decisions varying from passengers on board; the crew and people on the ground pursuing their daily activities in say trading centres, cities, offices, homes, educational institutions and even in gardens practising agriculture. Such worst case scenarios would be avoided if appropriate decisions are taken by applying more customised systems to inform pilots and air traffic flow managers.

A case pointed out on the 8th October, 2001 at Linate airport in Milan, Italy, whereby an MD87 SAS airplane with 110 crew members and passengers on board collided on the ground with a Cessna Citation II jet with 2 pilots and 2 passengers Lunetta P *et al.* (2003) . The plane caught fire after having crashed into an airport baggage hangar causing death of 118 victims belonging to nine nationalities including four other victims among the ground staff.

A fatal plane accident that involved a Cessna 206 small aircraft in Malawi killed several Britons on the 16th June, 2007 where, the reported main cause was poor weather. A similar cause resulted into the loss in May, 2007 of a Kenya Airways Boeing 737 over Cameroon, in which 114 lives, 5 of them British citizens were lost Irwin (2009) . Some statistics pertaining Africa show that air travel in Africa carries above average risks. While only about 4 percent of the world's air traffic pass over Africa, since the year 2001, over 17 percent of the world's fatal air crashes have occurred here in Africa. This is obviously a cause of great concern and while it is important to recognize that even in Africa, air transport is still a relatively safer form of transport, more work through research needs to be done to improve the safety of air travel.

The African and Indian Ocean Islands Safety Enhancement Team (ASET) based in Nairobi, Kenya, to coordinate air safety matters amid growing concerns on air safety in the continent was launched, Mburu (2004) . ASET's objective is to help Africa achieve international air safety levels and hope to reduce the continents' civil aviation accidents by half by the year 2010.

6.2 Air Traffic Management Information Systems

Many information systems do exist, among them are, decision support systems (DSS) that managers use in semi-structured and unstructured situations to analyse information relevant for a particular decision like should an aircraft be delayed on ground now at Entebbe International airport because of unfavourable weather conditions at say Heathrow International airport or otherwise. A DSS is designed normally to complement the decision style of management, hence when the decision style of management is poor, even the DSS will inherit the poor style. Analysis of operations of DSS reveals very interesting findings in regards to modelling. The components of a DSS include: data management to organize relevant internal and external information into a database. Model management is used to support the design and choice phases of decision making. Dialog management is the user interface that allows the manager to interact with and use the DSS easily and effectively. And the main contribution of this study falls under model management.

Aviation Management Information System (AMIS)[5] is a very powerful integrated computer system for managing the technical operations activities of an airline, or aircraft fleet operator. The system is licensed worldwide to large and small companies operating many types of fixed and rotary-wing aircraft.

AMIS was designed from its very beginning in 1980 as a professional aviation technical operations management system. Since then the system has undergone many improvements based on direct customer, regulatory and industry input. The system is based upon open systems technology and runs on microcomputers to mainframes under the Unix / Linux Operating System and various Relational Database Management Systems. Because of its architecture, AMIS can be operated 24 hours a day / 7 days a week with no downtime at all. There are no software limits imposed by the system which is parameter-driven and very user-friendly. Although, AMIS-2008 represents the latest, most powerful and user-friendly version of the system, it does not provide computations for probability of aircraft delay, airport technical efficiencies and subsequently, the airport utility performance level.

The other system popularly used is the airline management information system, AMIS[6] is a completely customized and versatile application developed for Airlines to manage their entire activities. This system covers all aspects of airline's requirements in modular structure and

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[5] The aviation management information system is developed by the Transportation Systems Consulting Corporation, whose website http://www.tsc-corp.com/amis.htm was accessed on the 25th October, 2010

[6] The airline management information system was developed by Computer Advance System Trading House Pvt. Ltd. Their website is http://www.softscout.com/software/Aviation-and-Aerospace/Airline-Management/Airlines-Management-Information-System.html accessed on the 25th October, 2010.

effectively creates a paper-less office. It consists of various modules, such as, Finance & accounting; Reservation & ticketing; Inventory & procurement; Flight operation & engineering; Personnel & payroll and Marketing & statistics. However, it does not track the timeliness of the airlines' aircraft timeliness based on the probability of aircraft delay, their efficiencies and subsequently, the aircraft utility performance levels.

Therefore, a stochastic optimisation system that applies the necessary operational data from available sources such as meteorological briefing office and aviation manifest data, as one whose prototype is developed and presented in this Thesis is worthy advancing. The prototype system is capable of using inputs from the logistic and stochastic frontier models and using them to optimise the airport utility for any given set of time periods. It is therefore possible to rank the performance of airports within a region, airlines at an airport or even individual aircrafts within the airline.

6.2 Air Traffic Flow Management Contribution to National Development

Millennium development goal number eight emphasizes to a global partnership for development and focuses on the following important issues of building meaningful partnerships between the industrialized and developing countries through larger and better development assistance. The development of an open and rule-based trading system and development of a comprehensive solution to the debt issue. The goal furthermore, suggests that special attention should be given to LDCs, SIDs and landlocked countries such as Uganda. This goal cannot be achieved by the prescribed year of 2015 if appropriate measures in air traffic flow management system have not been enhanced with appropriate results and models as those presented in this thesis. Efficiency of air traffic flow management is a central factor in the achievement of not only MDG eight, but all other MDGs which are logically interrelated. Therefore, in the pursuit of MDGs, developing countries should prioritize air traffic flow management systems in their respective countries so that goods and services are transported on time. Such goods and services cover a bigger spectrum that include, but not limited to improved seeds to combat hunger and poverty, improved environmental sustainability technologies, improved drugs and technologies to combat diseases such as HIV/AIDS, improved maternal and child care technologies and generally affordable agricultural modernization technologies.

CHAPTER SIX
CONCLUSIONS AND RECOMMENDATIONS

This chapter draws conclusions based on the findings of the study from which recommendations in relationship to air traffic management and additional knowledge gaps are made.

5.1 Conclusions

This study made fundamental contributions towards air traffic flow management problem by firstly developing evidence based statistical models. The development of these models was based on the aggregated daily historical data for the period 2004 through 2008. The main purpose of data modelling was to derive information that would subsequently aid air traffic flow management to develop appropriate strategic decisions that enable efficient air traffic flow based on the a number of significant explanatory parameters. The models are subsequently used as a reference tool for computations of probability of aircraft delays and measurement of airport operations' efficiency at varying time intervals. Secondly, the stochastic optimization models developed are a fundamental tool towards efficient use of aircrafts, airport space and time resources. The three utility models are based on the interaction terms between the derived probabilities of delay and airport inefficiency scores. Two stochastic optimisation models measure airport utility at aircraft departure and arrival, while the third model is an aggregate of utility at departure and arrival. In the stochastic optimisation models presented, it is evident that the maximum utility of an airport for a given time period, will have a better interaction mix of probability of delay and airport inefficiency value. One may go deeper to establish these values and also the values of the explanatory parameters that resulted into the maximum utility for the airport over scenarios corresponding to time periods. Subsequently, a scenario where there are no delays at all, that is, one with a delay of zero and inefficiency of zero, is found to yield the maximum utility of 100 percent for the airport assuming all other factors a constant. Such a scenario would imply well-organised and coordinated air traffic management team coupled with good weather. Furthermore, it is suggested from the model analysis that if a delay is inevitable, it is better to have it before aircraft departure than in air before arrival because of high risks and cost implications.

Current Air Traffic Management in Uganda

Air traffic flow in Uganda is managed by the Department of Air Traffic Management (DATM), under the Directorate of Air Navigation Services (DANS) of the Civil Aviation Authority (CAA). The main functions of the DATM are to: 1) prevent collision between aircraft both in flight and on the maneuvering area; 2) prevent obstructions on the maneuvering area; 3) expedite and maintain an orderly flow of air traffic; 4) provide advice and information useful for the safe and efficient conduct of flights; 5) notify appropriate organisations regarding aircraft in need of search and rescue aid and assist such organisations as required. However, it is observed that the smooth flow of air traffic in Uganda is also influenced by exogenous factors mostly determined by conditions of airports where departing aircrafts are destined. The exogenous factors are categorized as environmental and aviation related.

Environmental factors

Weather phenomena like rain and thunderstorms act to reduce the visibility at Entebbe International Airport (EIA). The Department of Meteorology is mandated to provide timely weather information to the CAA to facilitate aircraft flow management and informed decisions in planning aircraft movement by the DATM. The other environmental factor is the bird hazard;

besides, the local and migratory tendency of bird species, there are other bird attractions reported at EIA including; fishing, garbage, sand excavations, gardening, human settlements and other natural attractions like anthills, tall trees and bushes. However, to abate bird hazard phenomenon, a number of measures have been taken that include; formation of the Bird Hazard Control Unit (BHCU), Environment Management, Community-Based Activities, Bird Scare Methods, Foot Patrols, Pyrotechnics and Runway Inspections. Due to these measures, the prevalence rate of bird strikes has drastically reduced at the airport. It is, however, estimated that Airline companies could lose up to $10 million in replacement of a single aircraft engine due to destruction by birds. In worse cases, there could be total loss of an aircraft, its passengers and or cargo.

Aviation factors

Aviation factors refer to the airport capacity, facilities, quantity and quality of services provided, including the human resource capacity at the airport to the satisfaction of aviation passengers and cargo. Uganda has Bilateral Air Service Agreements with over thirty three countries. Sixteen international Airlines have scheduled operations to and from Entebbe International Airport which serve 14 destinations. The airport also offers hub and spoke operations especially in the Great Lakes region and connections to the rest of the world. There is currently one runway 17/35 at EIA whose capacity seems to be constrained due to the increasing aircraft operations.

Air Traffic Management Implications

This thesis has implications for management of air traffic flow at Entebbe International Airport. Lessons from it might have wider implications in other airports with a similar context. As a result of lack of timely information and tools to facilitate management of air traffic flow management at the Airport, Civil Aviation Authority could promote the development of customised tools that generate information to assist in air traffic flow management. They should take advantage of the skills and knowledge that exist to develop more appropriate statistical tools based on the local challenges faced at the airport. Such efforts could then be customised and automated to manage information about the inevitable aircraft delays.

The advantages that accrue from efficient air traffic flow cannot be understated. Uganda's profile as a landlocked country renders air transport a strategic importance to the nation as it guarantees an alternative gateway to the rest of the world. As it is expected, relative to other transport means, air transport provides the most efficient and quickest transport means to and from the country. The dependency of the country's economy to agriculture means that perishable exports require reaching their destinations much quicker, thus any aircraft delay may lead to loss of income. Therefore, the development of a safe, efficient and reliable air transport industry should be among government's priority programmes.

Theoretical Implications

A review of literature identified a research gap in air traffic flow management aimed at improving air traffic flow management at airports especially in developing countries. A number of scholars have carried out research on air traffic flow management for developed countries. A few researchers have dealt with air traffic flow management problem in developing countries.

Little research on improving air traffic flow management especially by focussing on air traffic delays in developing countries was identified. No research examined air traffic flow management to provide a tool for air traffic delays management was identified for the Africa region. None could be found that looked at stochastic analysis of air traffic delays, hence stochastic optimisation modelling with a wide definition used in this research.

One of the important contributions of this thesis is the bringing together of existing knowledge from different disciplines to address the issue of inefficient air traffic flow management, a problem affecting many airports in developing countries. The thesis argues that while it is challenging, historical data would be used to generate necessary and timely statistics for use by the air traffic management to make informed decisions. This would go a long way in reducing the otherwise would be avoided air traffic delays, thus leading to a sustainable efficient flow of air traffic. In addition to this, the thesis contributed to the knowledge gap between theory of maximisation of aircraft utility that relates to the interaction between probability of delay and the airport inefficient performance level. Minimisation of air traffic delays will subsequently be achieved when statistical tools are used to inform air traffic management through development of algorithms and graphical user interfaces for the stochastic optimisation models. Many air traffic managers, though sometimes would notice and record air traffic delays at Entebbe International Airport, they would neither quantify it nor trace for any existing trend. No research that looked at the proportions of daily air traffic delays was identified. Most research about the subject identified for developed countries especially in the United States of America analysed aircraft delay based upon the duration of delay in minutes. The advantage that accrued from deriving the airport utility based on the interaction term is an improvement of the time complexity. The models developed in this research take much smaller time to compute than cases where the delay is recorded in minutes would take. This research adds to the theory of algorithm design and analysis that considers time complexity as a more serious factor to consider than space complexity.

Final Reflections

Research in the area of air traffic flow management in Uganda is substantially lacking. There exists no literature published for studies done about air traffic flow management in Uganda. However, many countries develop because of the advancement of localised management tools and models that enhance decision making processes. More specifically, timely aircraft operations at departure and arrival leads to efficient air traffic flow management which subsequently contributes to sustainable economic development. This can be achieved when there is timeliness in handling of both cargo and passenger departures and arrivals.

6.2 Recommendations

This section presents recommendations categorised into application of stochastic optimisation models in air traffic flow management and areas of further research.

Application of Stochastic Optimisation Models in Air Traffic Flow Management

The study recommends appropriate use of the tools developed and presented in this study. It also encourages air traffic management to facilitate implementation of the models and knowledge obtained from this research. The models are well-developed, tested and ready for implementation with the permission of the civil aviation authority. Sensitization of air traffic management about the need to support evidence-based research and development of more appropriate and helpful tools to facilitate efficient management of air traffic flow in Uganda is highly encouraged. Furthermore, appropriate policies can be developed based on the information derived from the models presented in this thesis.

The Civil Aviation Authorities needs to empower and facilitate their Statistics Departments to collect data about Aircraft timeliness by type of aircraft, aircraft make, Airline and other parameters so as to monitor air traffic efficiency at Entebbe International Airport. Subsequently, the data may be sent into a repository managed by the Bureaux of Statistics and any analysis made to be published and disseminated through Academic Journals and other electronic media such as the Internet.

Policy implications on air traffic management

To achieve any set objective, there must exist a policy. Therefore, if governments tasked the aviation industry to work towards an improved vision for safe, secure, efficient and liberalized industry that is environmentally responsible, then the future would be very bright Bisignani (2008) . To achieve a better overall efficiency of air traffic, higher safety standards and better use of airspace capacity in the region and the African continent at large, individual countries must have appropriate air traffic management policies. The following reasons are significant in illuminating the need to have a better ATM policy whose overall goal should be to improve existing air transport system.

i) The growing daily proportions of delays
ii) Steady rise in air travel in the country and region
iii) Shrinking airport capacity in terms of runways
iv) Fragmentation of African airspace
v) Use for military purpose of the airspace in terms of peacekeeping.

The ATM policy should be driven by the need to establish higher safety standards, better overall efficiency of air transport and better use of airspace capacity.

However, to improve air traffic management, the research recommends an assessment of the factors that may shape the environment for modernisation of air traffic management and among them are the following.

a) Political imperative is required towards air traffic management in order to command consistent attention from the legislation and the government. The Civil Aviation Authority (CAA) initiative to develop a new national air transportation plan and recent parliamentary legislation are encouraging and have provided new thrust and direction, but it remains to be seen if this can be implemented.

b) The consistent legacy of technological problems requires huge investments. Globally, the last decade has seen many false starts in deploying new technologies for ATM. This has consumed resources and created a hesitation to invest.

c) There is the famous budget constraint especially in the developing countries. A new ATM system could yield large savings for the economy, but massive government investment in a system where the payoff could be delayed for a decade or more is unlikely given the budget problems the countries on the African continent are faced with. Nor are the airlines in a situation where they could fund large-scale change in air traffic management.

d) There is lack of sufficient consultative culture with the engineering professionals. The CAA and the aerospace community may have a reservoir of talent and expertise, but there are insufficient links to policymaking or to the political leadership especially in the developing countries. ATM is a complex subject. This can limit the ATM community's effectiveness in influencing policy and decision making.

Suggestions for accelerating national modernisation of ATM include.

1. The civil aviation authority needs to develop a new ATM plan. It must create a broad vision for the future and focus on action. This means identifying relevant existing programs, allocating resources as needed to new research and programs, establishing processes within the CAA and other supporting agencies, and creating a coherent, integrated approach to change.
2. Robust consultation on modernization with foreign ATM authorities at the political and technical level (Europe, USA and perhaps in Asia) to ensure international coordination must become a primary CAA mission. These processes must facilitate ATM transformation and become a core component of the CAA's work. The joint planning effort will require the development of new formal processes for coordination, for example through new bilateral agreements at the political level, with corresponding coordination at the technical level.
3. There is need for a presidential decision to endorse ATM transformation as a national priority, identify goals and timelines, and designate a State House entity specifically responsible for coordinating action on ATM among all involved agencies (CAA, Air Force, and the Ministries of Defense, Works and Transport, Investment Authority, Trade and Industry and Water and Environment). The CAA, unequalled in its technical expertise, should not be asked to shoulder interagency policy and political tasks for which it was not designed.
4. Despite the larger budgetary challenges the country has always faced partly due to the fact that it is a developing country, once program requirements are established under the ATM planning effort, new mechanisms for funding the modernization of air traffic

management should be found to allow a substantial increase. The first step is to fund the developmental and planning effort. The parliamentary committees of jurisdiction, which play a central role in providing continued oversight and encouragement for modernization, should consider whether additional legislation could help achieve this.

5. The CAA needs to reorganize itself so as to emphasize customer service. This is good, but the CAA also needs to reorganize to make transformation of ATM a core organizational mission. This will require a long-term strategy endorsed by senior management at the CAA and Ministry of Works and Transport, as well as coordination with foreign ATM authorities. In approaching this problem, the CAA can draw on the experiences of the Ministry of Defense in transformation since modernisation of the army primarily implies modernisation of ATM.

6.3 Further Research

There is need to pursue further research in the area of air traffic flow management using methodologies such as stochastic modelling, systems analysis and subsequently object oriented software development for the airports on the African continent so as to create a friendlier interface for promotion and use of the models such as the one presented in the study.

Further research need to be carried out to fill the pending gaps that have not been covered in this study such as a comparative analysis of the performance of international airports in the African region that would lead to the development of compromised multi-airport stochastic optimization models. The area of interest would be a study towards disaggregation of airport or aircraft timeliness performance based on the category of departure and arrival airports. This would require more research to the application of dynamic stochastic optimization models that would employ the Bayesian theory to model both en-route and departure aircraft delays in a multi-airport environment.

Furthermore, research need to be done to integrate R statistical language at the backend and C# computer programming language at the frontend to present the graphical user interface while presenting stochastic optimisation models.

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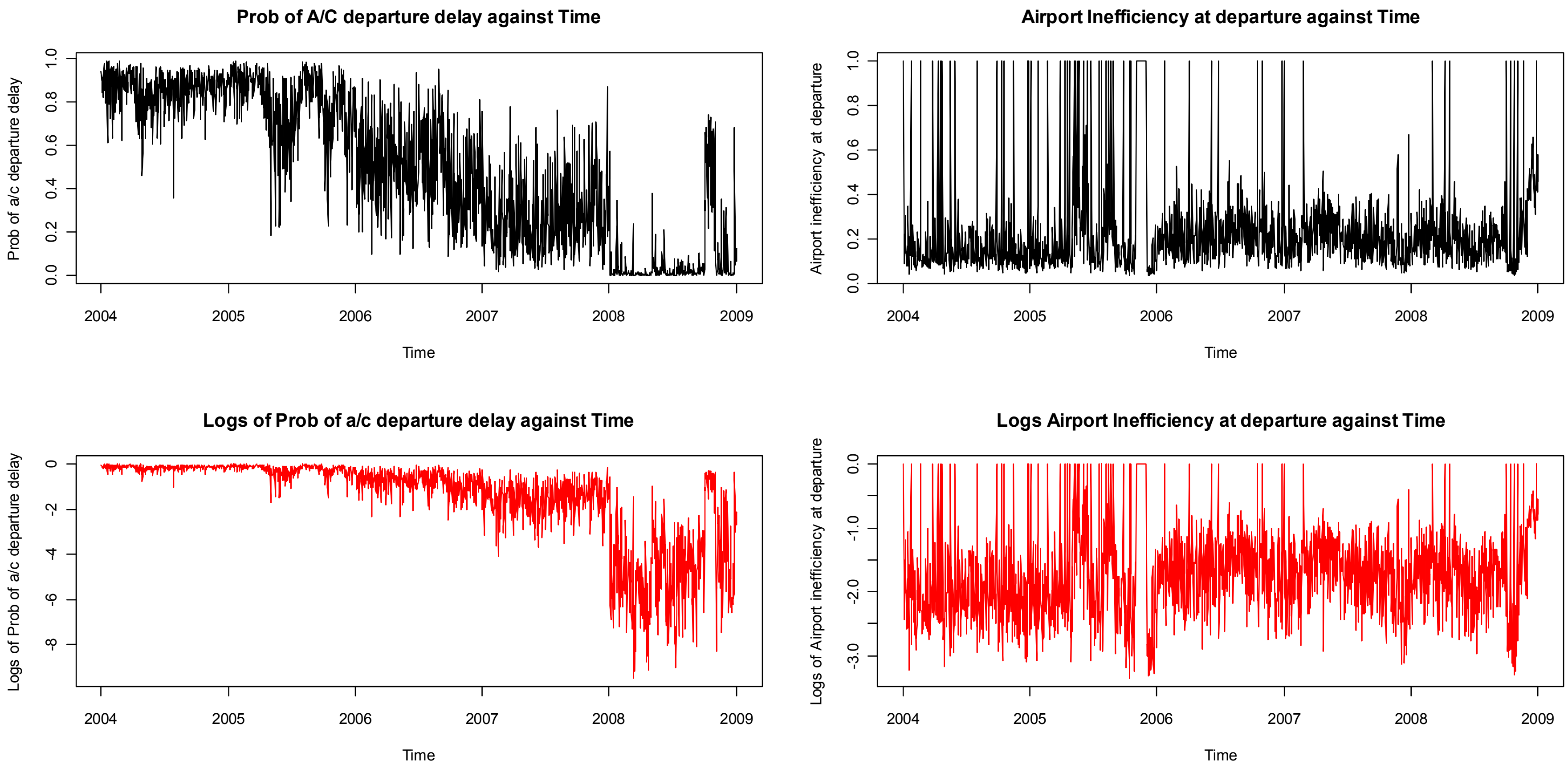
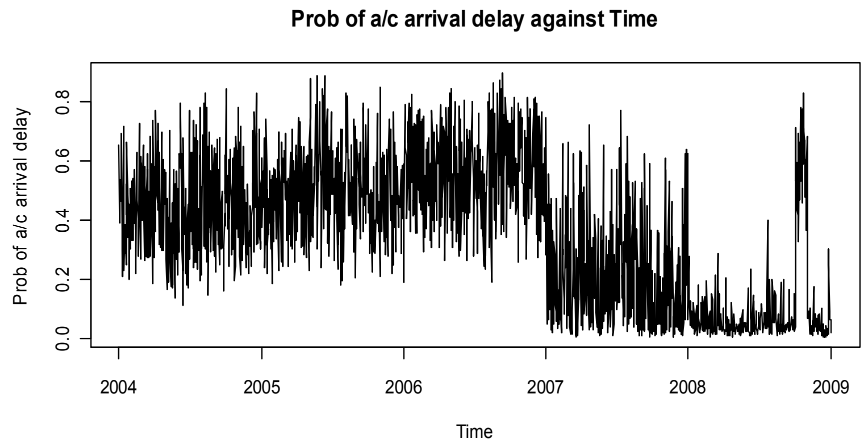
APPENDICES

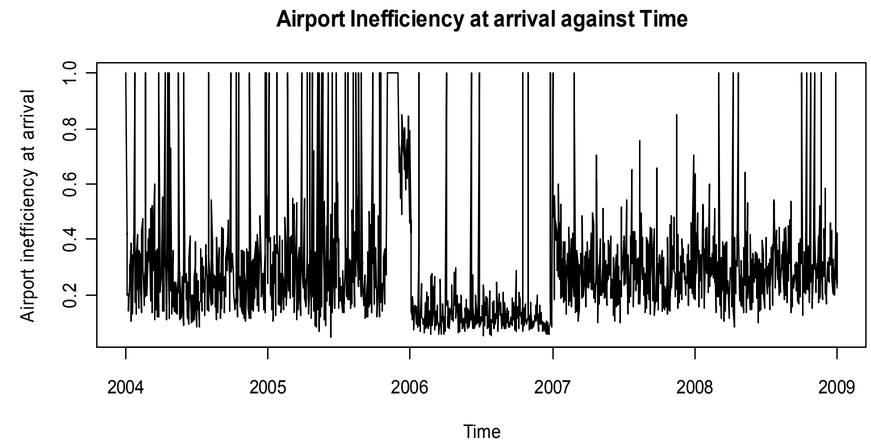
Appendix A: Probability of Aircraft Departure Delay and Airport Inefficiency against Time

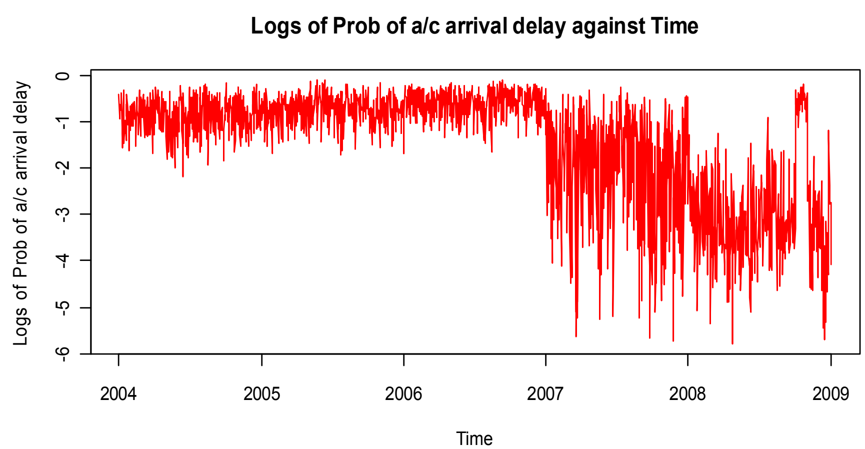


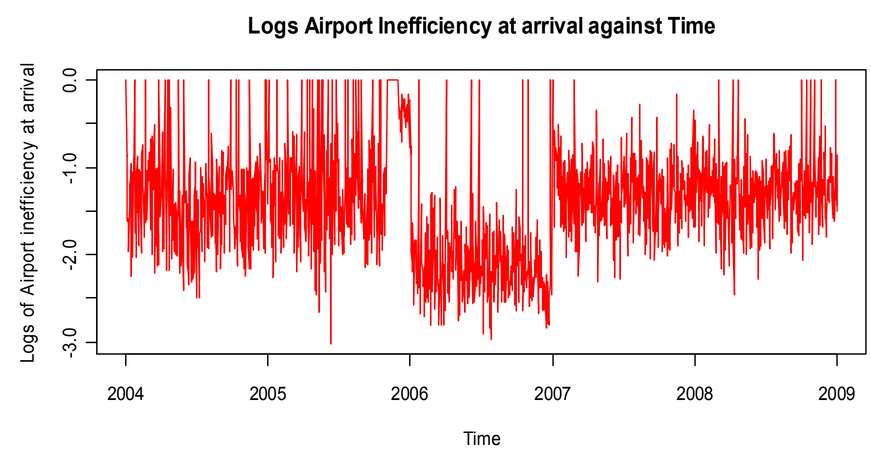
Source: Wesonga (2010), PhD Research Study

Appendix B: Probability of Aircraft Arrival Delay and Airport Inefficiency against Time









Source: Wesonga (2010), PhD Research Study

Appendix C: R Objects for the Stochastic Optimisation Model

Object	**Description**
"ahp"	Air holding program
"ArrDelay"	Arrival Delay
"ArrDelayU"	Arrival Delay Utility
"DepDelay"	Departure Delay
"DepDelayU"	Departure Delay Utility
"E2MaximumFinUtilityH"	Experiment two maximum final utility higher probabilities
"E2MaximumFinUtilityL"	Experiment two maximum final utility lower probabilities
"fct"	Function
"FinUtilities"	Final utilities
"FinUtility"	Final utility
"gdp"	Ground delay programme
"lambda"	Lambda
"MaximumFinUtility"	Maximum final utility
"Ontime"	On time
"OntimeProp"	On time proportions
"phd"	Degree of philosophy
"ProbUtilities"	Probability of utilities
"ScenarioProb"	Scenario probability
"sumUtility"	Sum of utility
"Utility"	Utility
"varArrDelay"	Variance of arrival delay
"varDepDelay"	Variance of departure delay
"varOntimeProp"	Variance of on time proportions

Appendix D: R Code for the Stochastic Optimisation Model

```
# Stochastic Optimisation Models for Air Traffic Management
# By Wesonga Ronald, PhD. Statistics Researcher

# Supervisors:
# Professor Jehopio Peter
# Professor Xavier  Mugisha
# Professor Venancius Baryamureeba

# Chair              - Agnes Ssekiboobo (Mrs.)
# Academic Registrar - Tom Otim

# Defence opponent   - Professor Fabian Nabugoomu

# Panelists:
# Professor Livingstone Luboobi
# Professor Leonard Atuhaire
# Professor Makumbi Tom Nyanzi
# Professor Bruno Ocaya
# Professor Ngubiri Johhn
# Professor Ntozi James
# Professor Juma Kasozi

# chapter Three - statistical models for air traffic flow management
# chapter Four  - stochastic optimisation models for air traffic flow management


setwd("C:/Users/Wesonga/Documents/Dacer/phd/data/AGG/R")
getwd()

# read.csv("rdataset.csv",header=TRUE) # if only reading is  necessary
phd <- read.csv("rdataset.csv",header=TRUE)
edit(phd)
dim(phd)

# preliminary analysis and tests

shapiro.test(phd$gdpdrate)
shapiro.test(phd$ahpdrate)
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29. # par(mfrow=c(2,1))
30. # qqnorm(phd$gdpdrate)
31. # qqnorm(phd$ahpdrate)      # Noramlity check
32. # stripchart(phd$ahpdrate)  # Continuity of data

33. linest <- lm(phd$ahpdrate ~ phd$gdpdrate)
34. plot(phd$ahpdrate ~ phd$gdpdrate, pch=16, main = "plot of departure delay against arrival
    delay proportions", sub="at Entebbe international Airport")
35. abline(linest, col="RED")

36. t.test(phd$gdpdrate, phd$ahpdrate)
37. mean(phd$gdpdrate) - mean(phd$ahpdrate)

38. par(mfrow=c(1,2))

39. hist(log(phd$gdpdrate), seq(2, 5.0, 0.5), prob=TRUE, main="Density against Logs of
    Proportions of Departure Delay", xlab="Logs of A/C Proportions of Departure Delay")
40. lines(density(log(phd$gdpdrate), bw=0.5))
41. rug(log(phd$gdpdrate))

42. hist(log(phd$ahpdrate), seq(2, 5.0, 0.5), prob=TRUE, main="Density against Logs of
    Proportions of Arrival Delay", xlab="Logs of A/C Proportions of Arrival Delay")
43. lines(density(log(phd$ahpdrate), bw=0.5))
44. rug(log(phd$ahpdrate))


45. par(mfrow=c(3,2))
46. plot(phd$gdpdrate ~ phd$numops +phd$sch_prop +phd$non_sch_prop +phd$POBout
    +phd$visiblty+phd$qnh)

47. # subsetting data by year

48. year2004 <- subset(phd, phd$year == 2004)
49. year2005 <- subset(phd, phd$year == 2005)
50. year2006 <- subset(phd, phd$year == 2006)
51. year2007 <- subset(phd, phd$year == 2007)
52. year2008 <- subset(phd, phd$year == 2008)
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```
53. # DEPARTURE DELAY ANALYSIS
54. # using dummies of departure delay as a binary dependent variable
55. phddepdelay <- glm(phd$gdpfifty ~
    phd$ahpfifty+phd$ahpdelay+phd$numops+phd$shedules+phd$charters+phd$freiters+phd
    $NCF+phd$POBout+phd$windsped+phd$visiblty+phd$qnh,family="binomial",data=phd)
56. search<-step(phddepdelay)
57. summary(search)
58. probdepdelay <- predict(phddepdelay, type = "response")
59. summary(probdepdelay)

60. #monthly analysis at 50 percent threshold
61. phddepfifty <- glm(phd$gdpfifty ~
    phd$ahpfifty+phd$ahpdelay+phd$numops+phd$shedules+phd$charters+phd$freiters+phd
    $NCF+phd$POBout+phd$windsped+phd$visiblty+phd$qnh,family="binomial",data=phd)
62. searchfifty<-step(phddepfifty)
63. summary(searchfifty)
64. probdepfifty <- predict(phddepfifty, type = "response")
65. summary(probdepfifty)


66. phd.dep.propfifty<- ts(phd$gdpdrate,start=c(2004,1),frequency=365)
67. phd.dep.probfifty<- ts(probdepfifty,start=c(2004,1),frequency=365)

68. par(mfrow=c(2,2))
69. plot (phd.dep.propfifty, main = "Proportion of aircraft departure delay against Time",ylab =
    "Proportion of aircrafts monthly arrival delay")
70. plot (phd.dep.probfifty, main = "Probability of aircraft departure delay (50% threshold)
    against Time",ylab = "Estimated probability of departure delay")
71. t.test(probdepfifty, phd$gdpdrate)
72. var.test(probdepfifty,phd$gdpdrate)
73. prop.test(probdepfifty, phd$gdpdrate)
74. prop.trend.test(probdepfifty,phd$gdpdrate)


75. #monthly analysis at 60 percent threshold
76. phddepsixty <- glm(phd$gdpsixty ~
    phd$ahpsixty+phd$ahpdelay+phd$numops+phd$shedules+phd$charters+phd$freiters+phd
    $NCF+phd$POBout+phd$windsped+phd$visiblty+phd$qnh,family="binomial",data=phd)
77. searchsixty<-step(phddepsixty)
78. summary(searchsixty)
```

79. probdepsixty <- predict(phddepsixty, type = "response")
80. summary(probdepsixty)

81. phd$probdepsixty <- predict(phddepsixty, type = "response", asInData = TRUE)
82. mean(phd$probdepsixty)
83. summary(phd$probdepsixty)

84. phd.dep.propsixty<- ts(phd$gdpdrate,start=c(2004,1),frequency=365)
85. phd.dep.probsixty<- ts(phd$probdepsixty,start=c(2004,1),frequency=365)

86. par(mfrow=c(2,1))
87. plot (phd.dep.propsixty, main = "Proportion of aircraft departure delay against Time",ylab = "Proportion of aircrafts monthly arrival delay")
88. plot (phd.dep.probsixty, main = "Probability of aircraft departure delay (60% threshold) against Time",ylab = "Probability of departure delay")

89. # ARIMA models Analysis of departure delay
90. phd.dep.probsxty <- diff(phd.dep.probsixty,1,1)
91. plot(phd.dep.probsxty)

92. par(mfrow=c(2,2))
93. acf(phd.dep.probsixty, lag.max = NULL,main="ACF for prob of departure delay", type = c("correlation", "covariance", "partial"), plot = TRUE, na.action = na.fail, demean = TRUE)
94. pacf(phd.dep.probsixty, lag.max = NULL,main="PACF for prob of departure delay", plot = TRUE, na.action = na.fail)

95. acf(phd.dep.probsxty, lag.max = NULL,main="ACF for prob of departure delay 1st diff", type = c("correlation", "covariance", "partial"), plot = TRUE, na.action = na.fail, demean = TRUE)
96. pacf(phd.dep.probsxty, lag.max = NULL,main="PACF for prob of departure delay 1st diff", plot = TRUE, na.action = na.fail)

97. fit1<-arima(phd.dep.probsxty,c(1,1,1))
98. fit2<-arima(phd.dep.probsxty,c(0,1,1))
99. fit3<-arima(phd.dep.probsxty,c(1,0,1))
100. fit4<-arima(phd.dep.probsxty,c(1,1,0))

101. fit1
102. fit2

```
103.	fit3
104.	fit4

105.	tsdiag(fit1)
106.	tsdiag(fit2)
107.	tsdiag(fit3)


108.	# disaggregation by year

109.	year2008depsixty <- glm(year2008$gdpsixty ~ year2008$ahpsixty+year2008$ahpdelay+year2008$numops+year2008$shedules+year2008$charters+year2008$freiters+year2008$NCF+year2008$POBout+year2008$windsped+year2008$visiblty+year2008$qnh,family="binomial",data=year2008)
110.	searchyear2008sixty<-step(year2008depsixty)
111.	summary(searchyear2008sixty)

112.	year2008$probdepsixty <- predict(year2008depsixty, type = "response", asInData = TRUE)
113.	summary(year2008$probdepsixty)

114.	year2008.dep.propsixty<- ts(year2008$gdpdrate,start=c(2008,1),frequency=366)
115.	year2008.dep.probsixty<- ts(year2008$probdepsixty,start=c(2008,1),frequency=366)

116.	# par(mfrow=c(5,1))
117.	plot (year2008.dep.propsixty, main = "Proportion of aircraft departure delay against Time",ylab = "Proportion of aircrafts monthly arrival delay")
118.	plot (year2008.dep.probsixty, main = "departure delay probability(60% threshold) for 2008",ylab = "departure delay prob")



119.	#monthly analysis at 70 percent threshold
120.	phddepseventy <- glm(phd$gdpseventy ~ phd$ahpseventy+phd$ahpdelay+phd$numops+phd$shedules+phd$charters+phd$freiters+phd$NCF+phd$POBout+phd$windsped+phd$visiblty+phd$qnh,family="binomial",data=phd)
121.	searchseventy<-step(phddepseventy)
122.	summary(searchseventy)
123.	probdepseventy <- predict(phddepseventy, type = "response")
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124.    summary(probdepseventy)

125.    phd$probdepseventy <- predict(phddepseventy, type = "response", asInData = TRUE)


126.    phd.dep.propseventy<- ts(phd$gdpdrate,start=c(2004,1),frequency=365)
127.    phd.dep.probseventy<- ts(probdepseventy,start=c(2004,1),frequency=365)

128.    par(mfrow=c(1,2))
129.    plot (phd.dep.propseventy, main = "Proportion of aircraft departure delay against
    Time",ylab = "Proportion of aircrafts monthly arrival delay")
130.    plot (phd.dep.probseventy, main = "Probability of aircraft departure delay (70%
    threshold) against Time",ylab = "Estimated probability of departure delay")

131.    #monthly analysis at 80 percent threshold
132.    phddepeighty <- glm(phd$gdpeighty ~
    phd$ahpeighty+phd$ahpdelay+phd$numops+phd$shedules+phd$charters+phd$freiters+ph
    d$NCF+phd$POBout+phd$windsped+phd$visiblty+phd$qnh,family="binomial",data=phd)
133.    searcheighty<-step(phddepeighty)
134.    summary(searcheighty)
135.    probdepeighty <- predict(phddepeighty, type = "response")
136.    summary(probdepeighty)


137.    phd.dep.propeighty<- ts(phd$gdpdrate,start=c(2004,1),frequency=365)
138.    phd.dep.probeighty<- ts(probdepeighty,start=c(2004,1),frequency=365)

139.    par(mfrow=c(1,2))
140.    plot (phd.dep.propeighty, main = "Proportion of aircraft departure delay against
    Time",ylab = "Proportion of aircrafts monthly arrival delay")
141.    plot (phd.dep.probeighty, main = "Probability of aircraft departure delay (80%
    threshold) against Time",ylab = "Estimated probability of departure delay")


142.    # ARRIVAL DELAY ANALYSIS
143.    # using dummies of arrival delay as a binary dependent variable

144.    phdarrdelay <- glm(phd$ahpfifty ~
    phd$gdpfifty+phd$gdpdelay+phd$numops+phd$shedules+phd$charters+phd$freiters+phd
    $NCF+phd$POBin+phd$windsped+phd$visiblty+phd$qnh,family="binomial", data=phd)
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145. search<-step(phdarrdelay)
146. summary(search)
147. probarrdelay <- predict(phdarrdelay, type = "response")
148. summary(probarrdelay)

149. # at threshold delay = 60
150. # sample(phd$ahpdummy[phd$monthly==60])  => sample approach

151. # phdarrdelayforty <- glm(sample(phd$ahpforty[phd$monthly==60]) ~ sample(phd$gdpforty[phd$monthly==60])+sample(phd$gdpdelay[phd$monthly==60])+sample(phd$numops[phd$monthly==60])+sample(phd$shedules[phd$monthly==60])+sample(phd$charters[phd$monthly==60])+sample(phd$freiters[phd$monthly==60])+sample(phd$NCF[phd$monthly==60])+sample(phd$POBout[phd$monthly==60])+sample(phd$windsped[phd$monthly==60])+sample(phd$visiblty[phd$monthly==60])+sample(phd$qnh[phd$monthly==60]),family="binomial", data=phd)
152. # search<-step(phdarrdelayforty)
153. # summary(search)
154. # probarrdelayforty <- predict(phdarrdelayforty, type = "response")
155. # mean(probarrdelayforty)


156. #monthly analysis at 50 percent threshold
157. phdarrfifty <- glm(phd$ahpfifty ~ phd$gdpfifty+phd$gdpdelay+phd$numops+phd$shedules+phd$charters+phd$freiters+phd$NCF+phd$POBin+phd$windsped+phd$visiblty+phd$qnh,family="binomial",data=phd)
158. searcharrfifty<-step(phdarrfifty)
159. summary(searcharrfifty)
160. probarrfifty <- predict(phdarrfifty, type = "response")
161. summary(probarrfifty)


162. phd.arr.propfifty<- ts(phd$ahpdrate,start=c(2004,1),frequency=365)
163. phd.arr.probfifty<- ts(probarrfifty,start=c(2004,1),frequency=365)

164. par(mfrow=c(2,2))
165. plot (phd.arr.propfifty, main = "Proportion of aircraft arrival delay against Time",ylab = "Proportion of aircrafts monthly arrival delay")
166. plot (phd.arr.probfifty, main = "Probability of aircraft arrival delay (50% threshold) against Time",ylab = "Estimated probability of arrival delay")
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```
167. #monthly analysis at 60 percent threshold

168. phdarrsixty <- glm(phd$ahpsixty ~ phd$gdpsixty+phd$gdpdelay+phd$numops+phd$shedules+phd$charters+phd$freiters+phd$NCF+phd$POBin+phd$windsped+phd$visiblty+phd$qnh,family="binomial",data=phd)
169. searcharrsixty<-step(phdarrsixty)
170. summary(searcharrsixty)
171. probarrsixty <- predict(phdarrsixty, type = "response")
172. summary(probarrsixty)

173. phd$probarrsixty <- predict(phdarrsixty, type = "response", asInData = TRUE)
174. mean(phd$probarrsixty)
175. summary(phd$probarrsixty)

176. phd.arr.propsixty<- ts(phd$ahpdrate,start=c(2004,1),frequency=365)
177. phd.arr.probsixty<- ts(phd$probarrsixty,start=c(2004,1),frequency=365)

178. par(mfrow=c(2,1))
179. plot (phd.arr.propsixty, main = "Proportion of aircraft arrival delay against Time",ylab = "Proportion of aircrafts monthly arrival delay")
180. plot (phd.arr.probsixty, main = "Probability of aircraft arrival delay (60% threshold) against Time",ylab = "Probability of arrival delay")

181. # ARIMA models Analysis of arrival delay

182. phd.arr.probsxty <- diff(phd.arr.probsixty,5,5)
183. plot(phd.arr.probsxty)

184. par(mfrow=c(2,2))
185. acf(phd.arr.probsixty, lag.max = NULL,main="ACF for prob arrival delay", type = c("correlation", "covariance", "partial"), plot = TRUE, na.action = na.fail, demean = TRUE)
186. pacf(phd.arr.probsixty, lag.max = NULL,main="PACF for prob of arrival delay", plot = TRUE, na.action = na.fail)

187. acf(phd.arr.probsxty, lag.max = NULL,main="ACF for arrival delay prob 1st diff", type = c("correlation", "covariance", "partial"), plot = TRUE, na.action = na.fail, demean = TRUE)
188. pacf(phd.arr.probsxty, lag.max = NULL,main="PACF for arrival delay prob 1st diff", plot = TRUE, na.action = na.fail)
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```
189. fit1<-arima(phd.arr.probsxty,c(1,1,1))
190. fit2<-arima(phd.arr.probsxty,c(0,1,1))
191. fit3<-arima(phd.arr.probsxty,c(1,0,1))
192. fit4<-arima(phd.arr.probsxty,c(1,1,0))

193. fit1
194. fit2
195. fit3
196. fit4

197. tsdiag(fit1)
198. tsdiag(fit2)
199. tsdiag(fit3)

200. # ARRival disaggregation by year

201. year2004arrsixty <- glm(year2004$ahpsixty ~
     year2004$gdpsixty+year2004$gdpdelay+year2004$numops+year2004$shedules+year2004
     $charters+year2004$freiters+year2004$NCF+year2004$POBin+year2004$windsped+year
     2004$visiblty+year2004$qnh,family="binomial",data=year2004)
202. searchyear2004sixty<-step(year2004arrsixty)
203. summary(searchyear2004sixty)

204. year2004$probarrsixty <- predict(year2004arrsixty, type = "response", asInData =
     TRUE)
205. summary(year2004$probarrsixty)


206. #monthly analysis at 70 percent threshold

207. phdarrseventy <- glm(phd$ahpseventy ~
     phd$gdpseventy+phd$gdpdelay+phd$numops+phd$shedules+phd$charters+phd$freiters+p
     hd$NCF+phd$POBin+phd$windsped+phd$visiblty+phd$qnh,family="binomial",data=phd)
208. searcharrseventy<-step(phdarrseventy)
209. summary(searcharrseventy)
210. probarrseventy <- predict(phdarrseventy, type = "response")
211. summary(probarrseventy)
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212. phd.arr.propseventy<- ts(phd$ahpdrate,start=c(2004,1),frequency=365)
213. phd.arr.probseventy<- ts(probarrseventy,start=c(2004,1),frequency=365)

214. par(mfrow=c(1,2))
215. plot (phd.arr.propseventy, main = "Proportion of aircraft arrival delay against Time",ylab = "Proportion of aircrafts monthly arrival delay")
216. plot (phd.arr.probseventy, main = "Probability of aircraft arrival delay (80% threshold) against Time",ylab = "Estimated probability of arrival delay")

217. # monthly analysis at 80 percent threshold

218. phdarreighty <- glm(phd$ahpeighty ~ phd$gdpeighty+phd$gdpdelay+phd$numops+phd$shedules+phd$charters+phd$freiters+phd$NCF+phd$POBin+phd$windsped+phd$visiblty+phd$qnh,family="binomial",data=phd)
219. searcharreighty<-step(phdarreighty)
220. summary(searcharreighty)
221. probarreighty <- predict(phdarreighty, type = "response")
222. summary(probarreighty)


223. phd.arr.propeighty<- ts(phd$ahpdrate,start=c(2004,1),frequency=365)
224. phd.arr.probeighty<- ts(probarreighty,start=c(2004,1),frequency=365)

225. par(mfrow=c(1,2))
226. plot (phd.arr.propeighty, main = "Proportion of aircraft arrival delay against Time",ylab = "Proportion of aircrafts monthly arrival delay")
227. plot (phd.arr.probeighty, main = "Probability of aircraft arrival delay (50 percent) against Time",ylab = "Estimated probability of arrival delay")


228. # STOCHASTIC FRONTIER MODELING

229. # departure delay analysis

230. # Error Components Frontier (Battese & Coelli 1992), with time effect

231. library(frontier)

232. phddepstochasticTime <- sfa(log(phd$gdpdrate) ~ log(phd$ahpdrate)+log(phd$numops)+log(phd$shedules)+log(phd$charters)+log(phd$freit
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ers)+log(phd$NCF)+log(phd$POBout)+log(phd$windsped)+log(phd$visiblty)+log(phd$qnh),truncNorm = TRUE, timeEffect = TRUE, data=phd)

# Error Components Frontier (Battese & Coelli 1992), no time effect
phddepstochasticF <- sfa(log(phd$gdpdrate) ~ log(phd$ahpdrate)+log(phd$numops)+log(phd$shedules)+log(phd$charters)+log(phd$freiters)+log(phd$NCF)+log(phd$POBout)+log(phd$windsped)+log(phd$visiblty)+log(phd$qnh),truncNorm = FALSE, timeEffect = TRUE,data=phd)
phddepstochasticT <- sfa(log(phd$gdpdrate) ~ log(phd$ahpdrate)+log(phd$numops)+log(phd$shedules)+log(phd$charters)+log(phd$freiters)+log(phd$NCF)+log(phd$POBout)+log(phd$windsped)+log(phd$visiblty)+log(phd$qnh),truncNorm = TRUE, timeEffect = FALSE,data=phd)
summary(phddepstochasticT)
coef(summary(phddepstochasticT),which="ols")
coef(summary(phddepstochasticT),which="grid")
coef(summary(phddepstochasticT),which="mle")

phd$depstochastic <- efficiencies(phddepstochasticT, asInData = TRUE)
phd$depstochastic[is.na(phd$depstochastic)] <- 0
# replace(phd$depstochastic, NA, 0)
phd$depstochastic
summary(phd$depstochastic)
mean(phd$depstochastic)

# ALternatively returning efficiency estimates
residuals( phddepstochastic )
phd$residuals <- residuals( phddepstochastic, asInData = TRUE )

# compare the model to a corresponding model without inefficiency
lrtest( phddepstochasticF, phddepstochasticT )
lrtest( phddepstochasticT )
# Extract the covariance matrix of the maximum likelihood coefficients of a stochastic frontier model
vcov(phddepstochastic)

# ARIMA models Analysis of departure delay technical inefficiency

phd.dep.stochastic<- ts((1-phd$depstochastic),start=c(2004,1),frequency=365)

phd.dep.stocfront <- diff((1-phd.dep.stochastic),1,1)
```

```
257. plot(phd.dep.stocfront)

258. par(mfrow=c(2,2))
259. acf(phd.dep.stocfront, lag.max = NULL,main="ACF for departure TInneffiency", type = c("correlation", "covariance", "partial"), plot = TRUE, na.action = na.fail, demean = TRUE)
260. pacf(phd.dep.stocfront, lag.max = NULL,main="PACF for departure TInnefficiency", plot = TRUE, na.action = na.fail)

261. acf(phd.dep.stocfront, lag.max = NULL,main="ACF for departure TInneffiency", type = c("correlation", "covariance", "partial"), plot = TRUE, na.action = na.fail, demean = TRUE)
262. pacf(phd.dep.stocfront, lag.max = NULL,main="PACF for departure TInneffiency", plot = TRUE, na.action = na.fail)

263. fit1<-arima(phd.dep.stocfront,c(1,1,1))
264. fit2<-arima(phd.dep.stocfront,c(0,1,1))
265. fit3<-arima(phd.dep.stocfront,c(1,0,1))
266. fit4<-arima(phd.dep.stocfront,c(1,1,0))

267. fit1
268. fit2
269. fit3
270. fit4

271. tsdiag(fit1)
272. tsdiag(fit2)
273. tsdiag(fit3)

274. # disaggregated by year

275. year2008depstochasticT <- sfa(log(year2008$gdpdrate) ~ log(year2008$ahpdrate)+log(year2008$numops)+log(year2008$shedules)+log(year2008$charters)+log(year2008$freiters)+log(year2008$NCF)+log(year2008$POBout)+log(year2008$windsped)+log(year2008$visiblty)+log(year2008$qnh),truncNorm = FALSE, timeEffect = FALSE,data=year2008)
276. year2008$depstochastic <- efficiencies(year2008depstochasticT, asInData = TRUE)
277. year2008$depstochastic[is.na(year2008$depstochastic)] <- 0
278. summary(year2008$depstochastic)
```

```
year  <- c(2004, 2005, 2006, 2007, 2008)
depTE <- c(0.8992, 0.8992, 0.8858, 0.8159, 0.8505)
arrTE <- c(0.8590, 0.7427, 0.8984, 0.8551, 0.8783)
t.test(depTE, arrTE)
plot(depTE~arrTE+year, col = "RED")

# arrival delay analysis

# Error Components Frontier (Battese & Coelli 1992), with time effect
phdarrstochasticTime <- sfa(log(phd$ahpdrate) ~ log(phd$gdpdrate)+log(phd$numops)+log(phd$shedules)+log(phd$charters)+log(phd$freiters)+log(phd$NCF)+log(phd$POBin)+log(phd$windsped)+log(phd$visiblty)+log(phd$qnh),truncNorm = TRUE, timeEffect = TRUE, data=phd)

# Error Components Frontier (Battese & Coelli 1992), no time effect
phdarrstochasticF <- sfa(log(phd$ahpdrate) ~ log(phd$gdpdrate)+log(phd$numops)+log(phd$shedules)+log(phd$charters)+log(phd$freiters)+log(phd$NCF)+log(phd$POBin)+log(phd$windsped)+log(phd$visiblty)+log(phd$qnh),truncNorm = FALSE, timeEffect = TRUE,data=phd)
phdarrstochasticT <- sfa(log(phd$ahpdrate) ~ log(phd$gdpdrate)+log(phd$numops)+log(phd$shedules)+log(phd$charters)+log(phd$freiters)+log(phd$NCF)+log(phd$POBin)+log(phd$windsped)+log(phd$visiblty)+log(phd$qnh),truncNorm = FALSE, timeEffect = FALSE,data=phd)
summary(phdarrstochasticT)
coef(summary(phdarrstochasticT),which="ols")
coef(summary(phdarrstochasticT),which="grid")
coef(summary(phdarrstochasticT),which="mle")

phd$arrstochastic <- efficiencies(phdarrstochasticT, asInData = TRUE)
phd$arrstochastic[is.na(phd$arrstochastic)] <- 0
summary(phd$arrstochastic)
mean(phd$arrstochastic)


plot(phd$arrstochastic)

# ALternatively returning efficiency estimates
residuals( phdarrstochastic )
phd$arrresiduals <- residuals( phdarrstochastic, asInData = TRUE )
plot(phd$arrresiduals)
```

303. # compare the model to a corresponding model without inefficiency
304. lrtest(phdarrstochasticF, phdarrstochasticT)
305. lrtest(phdarrstochasticT)

306. # Extract the covariance matrix of the maximum likelihood coefficients of a stochastic frontier model
307. vcov(phdarrstochasticT)

308. # ARIMA models Analysis of arrival delay technical inefficiency

309. phd.arr.stochastic<- ts((1-phd$arrstochastic),start=c(2004,1),frequency=365)

310. phd.arr.stocfront <- diff((1-phd.arr.stochastic),1,1)
311. plot(phd.arr.stocfront)

312. par(mfrow=c(2,2))
313. acf(phd.arr.stocfront, lag.max = NULL,main="ACF for departure TInneffiency", type = c("correlation", "covariance", "partial"), plot = TRUE, na.action = na.fail, demean = TRUE)
314. pacf(phd.arr.stocfront, lag.max = NULL,main="PACF for departure TInnefficiency", plot = TRUE, na.action = na.fail)

315. acf(phd.arr.stocfront, lag.max = NULL,main="ACF for departure TInneffiency", type = c("correlation", "covariance", "partial"), plot = TRUE, na.action = na.fail, demean = TRUE)
316. pacf(phd.arr.stocfront, lag.max = NULL,main="PACF for departure TInneffiency", plot = TRUE, na.action = na.fail)

317. fit1<-arima(phd.arr.stocfront,c(1,1,1))
318. fit2<-arima(phd.arr.stocfront,c(0,1,1))
319. fit3<-arima(phd.arr.stocfront,c(1,0,1))
320. fit4<-arima(phd.arr.stocfront,c(1,1,0))

321. fit1
322. fit2
323. fit3
324. fit4

```
325. tsdiag(fit1)
326. tsdiag(fit2)
327. tsdiag(fit3)
328. tsdiag(fit4)

329. # disaggregated by year

330. year2004arrstochasticT <- sfa(log(year2004$ahpdrate) ~ log(year2004$gdpdrate)+log(year2004$numops)+log(year2004$shedules)+log(year2004$charters)+log(year2004$freiters)+log(year2004$NCF)+log(year2004$POBin)+log(year2004$windsped)+log(year2004$visiblty)+log(year2004$qnh),truncNorm = TRUE, timeEffect = TRUE,data=year2004)
331. year2004$arrstochastic <- efficiencies(year2004arrstochasticT, asInData = TRUE)
332. year2004$arrstochastic[is.na(year2004$arrstochastic)] <- 0
333. summary(year2004$arrstochastic)


334. # Plots

335. phd.prob.departure<- ts(phd$probdepseventy,start=c(2004,1),frequency=365)
336. phd.prob.arrival<- ts(phd$probarrsixty,start=c(2004,1),frequency=365)
337. phd.eff.departure<- ts(phd$depstochastic,start=c(2004,1),frequency=365)
338. phd.eff.arrival<- ts(phd$arrstochastic,start=c(2004,1),frequency=365)

339. par(mfrow=c(2,2))
340. plot (phd.prob.departure, main = "Probability of daily departure delay against Time",ylab = "Probability of departure delay")
341. plot (phd.prob.arrival, main = "Probability of daily arrival delay against Time",ylab = "Probability of arrival delay")
342. plot (phd.eff.departure, main = "Efficiency of daily departure against Time",ylab = "Efficiency of departure delay")
343. plot (phd.eff.arrival, main = "Efficiency of daily arrival against Time",ylab = "Efficiency of arrival delay")


344. # correlations and  tests between the predicted efficiencies
345. cor(phd$depstochastic,phd$arrstochastic, use="pairwise", method="pearson")
346. cor.test(phd$depstochastic,phd$arrstochastic, method="spearman", alternative="two.sided")
```

```
347.	# correlations and  tests between the predicted efficiencies and probabilities
348.	cor(phd$probdepseventy,phd$probarrsixty,phd$depstochastic,phd$arrstochastic, use="pairwise", method="pearson")
349.	cor.test(phd$depstochastic,phd$arrstochastic, method="spearman", alternative="two.sided")

350.	attach(warpbreaks)
351.	by(warpbreaks[, 1], phd$year, mean(phd$probdepseventy))

352.	table( phd$year, phd$probdepseventy)


353.	## UTILITY DERIVATION

354.	phd.dep.ontime <- ts(phd$gdptrate,start=c(2004,1),frequency=365)
355.	phd.arr.ontime <- ts(phd$ahptate,start=c(2004,1),frequency=365)
356.	phd.dep.probseventy <- ts(phd$probdepseventy,start=c(2004,1),frequency=365)
357.	phd.arr.probsixty <- ts(phd$probarrsixty,start=c(2004,1),frequency=365)


358.	par(mfrow=c(2,2))
359.	plot (phd.dep.ontime, main = "Proportion of daily departure delay against Time",ylab = "Proportion of departure delay")
360.	lines(lowess(phd.dep.ontime), type="o", col = "red",)
361.	plot (phd$gdptrate, phd.dep.probseventy, col = "red", main="A/C OnTime Departure Proportions Against Probability", xlab="OnTime Departure Proportions", ylab="Probability")
362.	lines(lowess(phd$gdptrate,phd.dep.probseventy), type="o")
363.	plot (phd.arr.ontime, main = "Proportion of daily arrival delay against Time",ylab = "Proportion of arrival delay")
364.	lines(lowess(phd.arr.ontime), type="o", col = "red",)
365.	plot (phd$ahptate, phd.arr.probsixty, col = "red", main="A/C OnTime Arrival Proportions Against Probability", xlab="OnTime Arrival Proportions", ylab="Probability")
366.	lines(lowess(phd$ahptate,phd.arr.probsixty), type="o")


367.	## par(mfrow=c(2,1))
368.	## plot (phd$gdptrate, main = "Proportion of daily departure delay against Time",ylab = "Proportion of departure delay")
```

```
## plot (phd$ahptate, main = "Proportion of daily arrival delay against Time",ylab = "Proportion of arrival delay")

## ONTIME ASSESSment
# Departure log leads to normalisation producing half-normal
hist(log(phd$gdptrate), seq(0, 5, 1), prob=TRUE, main="Density against Proportion of OnTime A/C Departures", xlab="Log of Aircraft ontime arrival proportion")
lines(density(log(phd$gdptrate), bw=1))
rug(log(phd$gdptrate))

# Arrival log leads to normalisation
hist(log(phd$ahptate), seq(0, 5, 1), prob=TRUE, main="Density against Proportion of OnTime A/C Departures", xlab="Log of Aircraft ontime arrival proportion")
lines(density(log(phd$ahptate), bw=1))
rug(log(phd$ahptate))

## DElay ASSESSment
# Departure log leads to normalisation producing half-normal
hist(log(phd$gdpdrate), seq(0, 5, 1), prob=TRUE, main="Density against Proportion of OnTime A/C Departures", xlab="Log of Aircraft ontime arrival proportion")
lines(density(log(phd$gdpdrate), bw=1))
rug(log(phd$gdpdrate))

# Arrival log leads to normalisation
hist(log(phd$ahpdrate), seq(0, 5, 1), prob=TRUE, main="Density against Proportion of OnTime A/C Departures", xlab="Log of Aircraft ontime arrival proportion")
lines(density(log(phd$ahpdrate), bw=1))
rug(log(phd$ahpdrate))

## Distributions

#gdpontimeprop <- phd$gdptrate/100
#expgdpontime <- 1-(exp(-gdpontimeprop/mean(gdpontimeprop)))
#Utilitygdpontime <- (gdpontimeprop + phd$depstochastic)^ phd$probdepseventy

#t.test(gdpontimeprop, expgdpontime)
#plot(gdpontimeprop, expgdpontime)
#lines(lowess(gdpontimeprop, expgdpontime), type="o", col="RED")

#t.test(gdpontimeprop, Utilitygdpontime)
```

```
#plot(gdpontimeprop, Utilitygdpontime)
#lines(lowess(gdpontimeprop, Utilitygdpontime), type="o", col="RED")

#plot((rexp(1827, rate=0.8)/0.8))

# Departure utility

dailydeputility <- exp(-meaninteractioninverse*(phd$probdepsixty)*(1-phd$depstochastic))
averagedailydeputility <- summary(dailydeputility)
averagedailydeputility

par(mfrow=c(2,1))
phd.dep.utility <- ts(dailydeputility,start=c(2004,1),frequency=365)
plot(phd.dep.utility,col = "red", main="Aircraft utility affected by departure delay Against Time in Years", xlab="Time in Years", ylab="Logs of utility")
plot(log(phd.dep.utility),col = "red", main="Aircraft utility at departure Against Time in Years", xlab="Time in Years", ylab="Logs of utility")

# Annualised Departure utility

dailydeputility2008 <- exp((-(year2008$probdepsixty)*(1-year2008$depstochastic)))
averagedailydeputility2008 <- summary(dailydeputility2008)
averagedailydeputility2008

par(mfrow=c(2,1))
phd.dep.utility <- ts(dailydeputility,start=c(2004,1),frequency=365)
plot(phd.dep.utility,col = "red", main="Aircraft utility affected by departure delay Against Time in Years", xlab="Time in Years", ylab="Logs of utility")
plot(log(phd.dep.utility),col = "red", main="Aircraft utility at departure Against Time in Years", xlab="Time in Years", ylab="Logs of utility")



# Arrival utility
lambda = 1.0
dailyarrutility <- exp(-(lambda*(phd$probarrsixty))*(1-phd$arrstochastic))
averagedailyarrutility <- summary(dailyarrutility)
averagedailyarrutility
```

```
#Annualised Arrival Utilities when lambda =1

lambda = 1
dailyarrutility2004 <- exp(-(lambda*(year2004$probarrsixty))*(1-year2004$arrstochastic))
averagedailyarrutility2004 <- summary(dailyarrutility2004)
averagedailyarrutility2004


phd.arr.utility <- ts(dailyarrutility,start=c(2004,1),frequency=365)
plot(phd.arr.utility,col = "red", main="Aircraft utility affected by arrival delay Against Time in Years", xlab="Time in Years", ylab="Logs of utility")
plot(log(phd.arr.utility),col = "red", main="Aircraft utility at arrival Against Time in Years", xlab="Time in Years", ylab="Logs of utility")


# Experimental simulations ONE
phd$probdepsixty <- sample(0.6:0.9,1827,rep=T)

dailydeputility <- exp(-(phd$probdepsixty)*(1-phd$depstochastic))
averagedailydeputility <- summary(dailydeputility)
averagedailydeputility

par(mfrow=c(2,1))
phd.dep.utility <- ts(dailydeputility,start=c(2004,1),frequency=365)
plot(log(phd.dep.utility),col = "red", main="Utility when DepProb=(0.6 to 0.9) Against Time in Years", xlab="Time in Years", ylab="Logs of utility")


# Arrival utility
phd$probarrsixty <- sample(0.6:0.9,1827,rep=T)

lambda = 1
dailyarrutility <- exp(-(lambda*(phd$probarrsixty)*(1-phd$arrstochastic)))
averagedailyarrutility <- summary(dailyarrutility)
averagedailyarrutility

phd.arr.utility <- ts(dailyarrutility,start=c(2004,1),frequency=365)
```

```
plot(log(phd.arr.utility),col = "red", main="Utility when ArrProb=(0.6 to 0.9) Against Time in Years", xlab="Time in Years", ylab="Logs of utility")

cor(phd.dep.utility, phd.arr.utility)
cor(dailydeputility,dailyarrutility )


# Experimental simulations TWO
phd$depstochastic <- sample(0.6:0.9,1827,rep=T)

dailydeputility <- exp((-(phd$probdepsixty)*(1-phd$depstochastic)))
averagedailydeputility <- summary(dailydeputility)
averagedailydeputility

par(mfrow=c(2,1))
phd.dep.utility <- ts(dailydeputility,start=c(2004,1),frequency=365)
plot(log(phd.dep.utility),col = "red", main="Utility when DepEff=(0.6 to 0.9) Against Time in Years", xlab="Time in Years", ylab="Logs of utility")


# Arrival utility
phd$arrstochastic <- sample(0.6:0.9,1827,rep=T)

lambda = 2.0
dailyarrutility <- exp(-(lambda*(phd$probarrsixty)*(1-phd$arrstochastic)))
averagedailyarrutility <- summary(dailyarrutility)
averagedailyarrutility

phd.arr.utility <- ts(dailyarrutility,start=c(2004,1),frequency=365)
plot(log(phd.arr.utility),col = "red", main="Utility when ArrEff=(0.6 to 0.9) Against Time in Years", xlab="Time in Years", ylab="Logs of utility")
cor(phd.dep.utility,phd.arr.utility)

# Experimental simulations THREE
phd$depstochastic <- sample(0.6:0.9,1827,rep=T)

dailydeputility <- exp((-(phd$probdepsixty)*(1-phd$depstochastic)))
averagedailydeputility <- summary(dailydeputility)
averagedailydeputility
```

```
par(mfrow=c(2,1))
phd.dep.utility <- ts(dailydeputility,start=c(2004,1),frequency=365)
plot(log(phd.dep.utility),col = "red", main="Utility when DepIneff=(0.6 to 0.9) Against Time in Years", xlab="Time in Years", ylab="Logs of utility")


# Arrival utility
phd$arrstochastic <- sample(0.6:0.9,1827,rep=T)

lambda = 2.0
dailyarrutility <- exp(-(lambda*(phd$probarrsixty)*(1-phd$arrstochastic)))
averagedailyarrutility <- summary(dailyarrutility)
averagedailyarrutility

phd.arr.utility <- ts(dailyarrutility,start=c(2004,1),frequency=365)
plot(log(phd.arr.utility),col = "red", main="Utility when ArrIneff=(0.6 to 0.9) Against Time in Years", xlab="Time in Years", ylab="Logs of utility")


# Experimental simulations FOUR

# Arrival utility

phd$arrstochastic <- sample(0.1:0.4,1827,rep=T)

lambda <- 1.1
dailyarrutility <- exp(-(lambda*(phd$probarrsixty)*(1-phd$arrstochastic)))
averagedailyarrutility <- summary(dailyarrutility)
averagedailyarrutility

# some plots

lambda <- c(1.0,1.1,1.2,1.3,1.4,1.5,1.6,1.7,1.8,1.9,2.0)
utilityEIA <- c(0.9065,0.8982,0.8901,0.8821,0.8743,0.8667,0.8592,0.8518,0.8446,0.8375,0.8306)
utilityHigheff <- c(0.8687,0.8569,0.8455,0.8342,0.8232,0.8124,0.8018,0.7914,0.7812,0.7713,0.7615)

UtilityLinestLe <- lm(utilityEIA~lambda)
UtilityLinestHe <- lm(utilityHigheff~lambda)
```

492. cor(utilityEIA,utilityHigheff)   # Establishing the correlation

493. par(mfrow=c(2,1))

494. plot(lambda, utilityEIA, main="EIA Utility with Cost Ratio",col="red", sub="(EIA efficiency)",xlab="Cost ratio", ylab="Airport Utility")

495. #abline(E42MaxUtilityLineL)

496. plot(lambda,utilityHigheff, main="Airport Utility with Cost Ratio",col="red", sub="(High scenario Airport efficiency)", xlab="Cost ratio", ylab="Airport Utility")

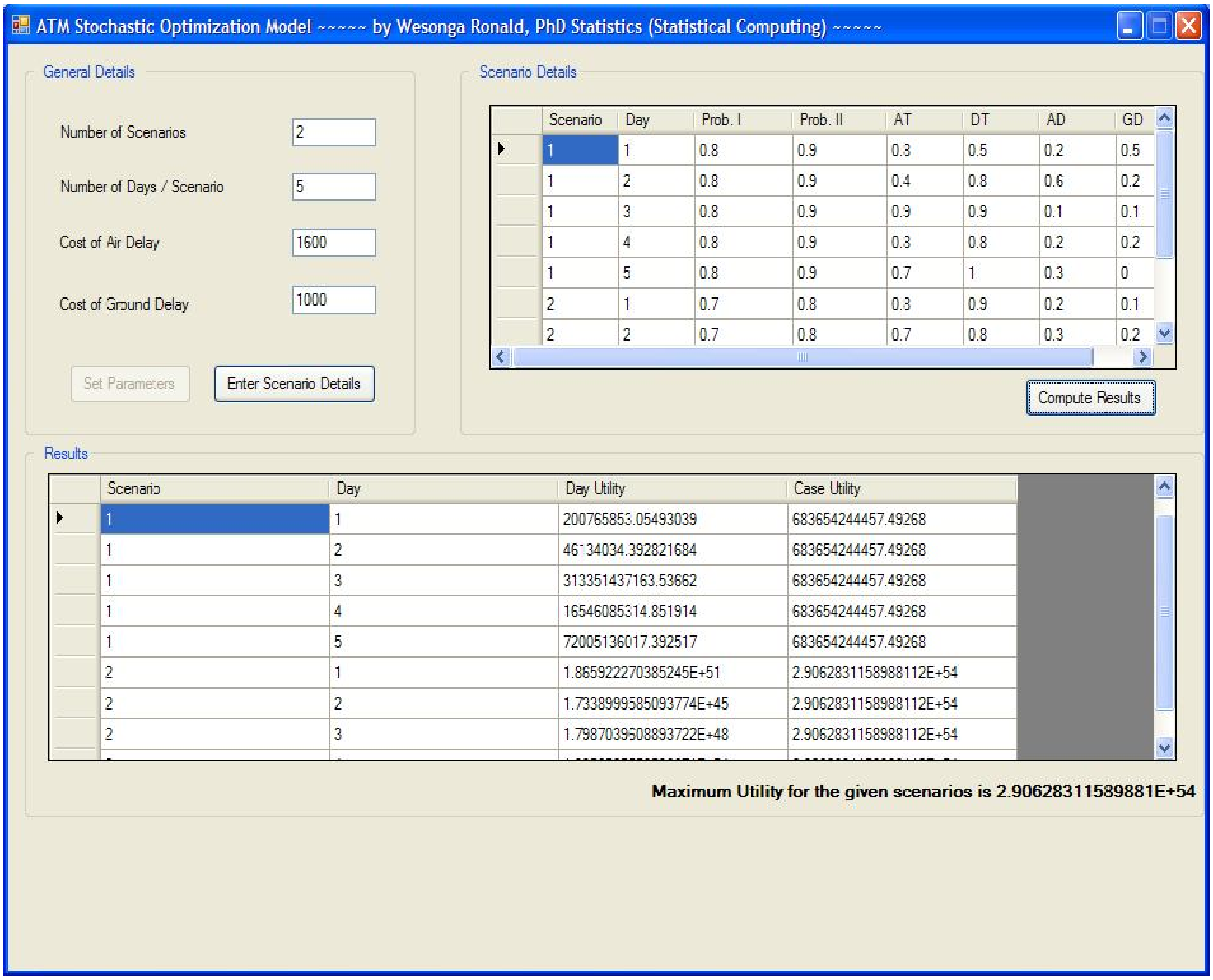
497. #abline(E42MaxUtilityLineH)

498. t.test(utilityLowIneff,utilityHighIneff) # H0: E1MaximumFinUtilityL = E1MaximumFinUtilityH

499.

500. var.test(utilityLowIneff,utilityHighIneff) # H0: var(E1MaximumFinUtilityL) / var(E1MaximumFinUtilityH) =1

Appendix E: User-Interface for the Stochastic Optimisation Model



Appendix F: Code in C# for the Stochastic Optimisation Model

```
using System;
using System.Collections.Generic;
using System.Text;
using System.Collections;

namespace UtilityOptimization.Service
{
    public class Scenario
    {
        public int ScenarioNumber { get; set; }
        public float ScenarioProbability1 { get; set; }
        public float ScenarioProbability2 { get; set; }
        public IList<DayDetail> DayDetails { get; set; }
        public double VarianceAD { get; set; }
        public double VarianceGD { get; set; }
        public double VarianceATDT { get; set; }
        public double ScenarioUtility { get; set; }

        private IList<float> ads;
        private IList<float> gds;
        private IList<float> ats;
        private IList<float> dts;

        public Scenario()
        {
            ads = new List<float>();
            gds = new List<float>();
            ats = new List<float>();
            dts = new List<float>();
        }

        private double ComputeSumOfVariables(IList<float> variables)
        {
            double sum = 0.0;
            foreach (float variable in variables)
            {
                sum += variable;
            }
            return sum;
        }

        private double ComputeAverageOfVariables(IList<float> variables)
        {
            return ComputeSumOfVariables(variables) / variables.Count;
        }

        public double ComputeVarianceOfVariables(IList<float> variables)
        {
            double sumofsquares = 0.0;
            double average = ComputeAverageOfVariables(variables);
            foreach (float variable in variables)
            {
                sumofsquares += Math.Pow(variable - average, 2);
            }
```

```
            return sumofsquares / (variables.Count - 1);
        }

        public double ComputeCovarianceOfVariables(IList<float> variables1,
IList<float> variables2)
        {
            if (variables1.Count != variables2.Count)
                throw new Exception("Variables should have the same number of
elements");
            else
            {
                double sum = 0.0;
                double variables1average =
ComputeAverageOfVariables(variables1);
                double variables2average =
ComputeAverageOfVariables(variables2);

                for (int i = 0; i < variables1.Count; i++)
                {
                    sum += (variables1[i] - variables1average) *
(variables2[i] - variables2average);
                }
                return sum / variables1.Count;
            }
        }

        public void ComputeVarianceAD()
        {
            foreach (DayDetail day in DayDetails)
                ads.Add(day.AD);
            VarianceAD = ComputeVarianceOfVariables(ads);
        }

        public void ComputeVarianceGD()
        {
            foreach (DayDetail day in DayDetails)
                gds.Add(day.GD);
            VarianceGD = ComputeVarianceOfVariables(gds);
        }

        public void ComputeVarianceATDT()
        {
            foreach (DayDetail day in DayDetails)
                ats.Add(day.AT);
            foreach (DayDetail day in DayDetails)
                dts.Add(day.DT);
            VarianceATDT = (ComputeVarianceOfVariables(ats) +
ComputeVarianceOfVariables(dts) + (2 * ComputeCovarianceOfVariables(ats,
dts)));
        }

        public double ComputeDayUtility(DayDetail day, int cg, int ca)
        {
            double util1 = Math.Exp((day.AT + day.DT) / VarianceATDT);
            double util2 = Math.Exp(-((cg/ca)*(day.AD/VarianceAD)));
            double util3 = Math.Exp(-(day.GD / VarianceGD));
            return (util1 - util2 - util3);
```

```
        }

        public double ComputeScenarioUtility(int cg, int ca)
        {
            double totalDayUtility = 0.0;

            foreach (DayDetail day in DayDetails)
            {
                totalDayUtility += ComputeDayUtility(day, cg, ca);
            }
            return ((ScenarioProbability1 * totalDayUtility) +
(ScenarioProbability2 * totalDayUtility));
        }

    }
}
```

```
using System;

namespace UtilityOptimization.Service
{
    public class DayDetail
    {
        public int DayNumber { get; set; }
        public float AT { get; set; }
        public float DT { get; set; }
        public float AD { get; set; }
        public float GD { get; set; }

        public DayDetail(int no, float at, float dt)
        {
            DayNumber = no;
            AT = at;
            DT = dt;
            AD = (float)Math.Round((1 - at),2);
            GD = (float)Math.Round((1 - dt),2);
        }
    }
}
```

```
using System;
using System.Collections.Generic;

namespace UtilityOptimization.Service
{
    public class Utility
    {
        public int NumberOfScenarios { get; set; }
        public int NumberOfDaysPerScenario { get; set; }
        public int CostOfAirDelay { get; set; }
        public int CostOfGroundDelay { get; set; }
        public IList<Scenario> Scenarios { get; set; }
    }
}
```

```
using System;
using System.Collections.Generic;
using System.Linq;
using System.Windows.Forms;

namespace UtilityOptimization
{
    static class Program
    {
        /// <summary>
        /// The main entry point for the application.
        /// </summary>
        [STAThread]
        static void Main()
        {
            Application.EnableVisualStyles();
            Application.SetCompatibleTextRenderingDefault(false);
            frmUtilityOptimisation utilityOptimisation = new
frmUtilityOptimisation();
            Application.Run(utilityOptimisation);
        }
    }
}
```

```
namespace UtilityOptimization
{
    partial class frmScenarioDetails
    {
        /// <summary>
        /// Required designer variable.
        /// </summary>
        private System.ComponentModel.IContainer components = null;

        /// <summary>
        /// Clean up any resources being used.
        /// </summary>
        /// <param name="disposing">true if managed resources should be
disposed; otherwise, false.</param>
        protected override void Dispose(bool disposing)
        {
            if (disposing && (components != null))
            {
                components.Dispose();
            }
            base.Dispose(disposing);
        }

        #region Windows Form Designer generated code

        /// <summary>
        /// Required method for Designer support - do not modify
        /// the contents of this method with the code editor.
        /// </summary>
        private void InitializeComponent()
        {
            this.groupBox2 = new System.Windows.Forms.GroupBox();
            this.btnSaveScenarioDetails = new System.Windows.Forms.Button();
            this.btnAddDayDetails = new System.Windows.Forms.Button();
            this.txtScenarioProbability2 = new
System.Windows.Forms.TextBox();
            this.label3 = new System.Windows.Forms.Label();
            this.txtScenarioProbability1 = new
System.Windows.Forms.TextBox();
            this.label1 = new System.Windows.Forms.Label();
            this.dgvScenarioDetails = new
System.Windows.Forms.DataGridView();
            this.groupBox2.SuspendLayout();

((System.ComponentModel.ISupportInitialize)(this.dgvScenarioDetails)).BeginIn
it();
            this.SuspendLayout();
            //
            // groupBox2
            //
            this.groupBox2.Controls.Add(this.btnSaveScenarioDetails);
            this.groupBox2.Controls.Add(this.btnAddDayDetails);
            this.groupBox2.Controls.Add(this.txtScenarioProbability2);
            this.groupBox2.Controls.Add(this.label3);
            this.groupBox2.Controls.Add(this.txtScenarioProbability1);
            this.groupBox2.Controls.Add(this.label1);
            this.groupBox2.Controls.Add(this.dgvScenarioDetails);
```

```
            this.groupBox2.Font = new System.Drawing.Font("Microsoft Sans
Serif", 9F, System.Drawing.FontStyle.Bold, System.Drawing.GraphicsUnit.Point,
((byte)(0)));
            this.groupBox2.Location = new System.Drawing.Point(12, 23);
            this.groupBox2.Name = "groupBox2";
            this.groupBox2.Size = new System.Drawing.Size(512, 377);
            this.groupBox2.TabIndex = 1;
            this.groupBox2.TabStop = false;
            this.groupBox2.Text = "  Scenario Details  ";
            //
            // btnSaveScenarioDetails
            //
            this.btnSaveScenarioDetails.DialogResult =
System.Windows.Forms.DialogResult.OK;
            this.btnSaveScenarioDetails.Enabled = false;
            this.btnSaveScenarioDetails.Font = new
System.Drawing.Font("Microsoft Sans Serif", 8.25F,
System.Drawing.FontStyle.Regular, System.Drawing.GraphicsUnit.Point,
((byte)(0)));
            this.btnSaveScenarioDetails.Location = new
System.Drawing.Point(352, 329);
            this.btnSaveScenarioDetails.Name = "btnSaveScenarioDetails";
            this.btnSaveScenarioDetails.Size = new System.Drawing.Size(132,
32);
            this.btnSaveScenarioDetails.TabIndex = 4;
            this.btnSaveScenarioDetails.Text = "&Save Scenario Details";
            this.btnSaveScenarioDetails.UseVisualStyleBackColor = true;
            this.btnSaveScenarioDetails.Click += new
System.EventHandler(this.btnSaveScenarioDetails_Click);
            //
            // btnAddDayDetails
            //
            this.btnAddDayDetails.Font = new System.Drawing.Font("Microsoft
Sans Serif", 8.25F, System.Drawing.FontStyle.Regular,
System.Drawing.GraphicsUnit.Point, ((byte)(0)));
            this.btnAddDayDetails.Location = new System.Drawing.Point(214,
329);
            this.btnAddDayDetails.Name = "btnAddDayDetails";
            this.btnAddDayDetails.Size = new System.Drawing.Size(132, 32);
            this.btnAddDayDetails.TabIndex = 3;
            this.btnAddDayDetails.Text = "&Add Day Details";
            this.btnAddDayDetails.UseVisualStyleBackColor = true;
            this.btnAddDayDetails.Click += new
System.EventHandler(this.btnAddDayDetails_Click);
            //
            // txtScenarioProbability2
            //
            this.txtScenarioProbability2.Font = new
System.Drawing.Font("Microsoft Sans Serif", 8.25F,
System.Drawing.FontStyle.Regular, System.Drawing.GraphicsUnit.Point,
((byte)(0)));
            this.txtScenarioProbability2.Location = new
System.Drawing.Point(414, 31);
            this.txtScenarioProbability2.Name = "txtScenarioProbability2";
            this.txtScenarioProbability2.Size = new System.Drawing.Size(70,
20);
            this.txtScenarioProbability2.TabIndex = 2;
```

```
            //
            // label3
            //
            this.label3.AutoSize = true;
            this.label3.Font = new System.Drawing.Font("Microsoft Sans
Serif", 8.25F, System.Drawing.FontStyle.Regular,
System.Drawing.GraphicsUnit.Point, ((byte)(0)));
            this.label3.Location = new System.Drawing.Point(271, 34);
            this.label3.Name = "label3";
            this.label3.Size = new System.Drawing.Size(109, 13);
            this.label3.TabIndex = 18;
            this.label3.Text = "Scenario Probability 2";
            //
            // txtScenarioProbability1
            //
            this.txtScenarioProbability1.Font = new
System.Drawing.Font("Microsoft Sans Serif", 8.25F,
System.Drawing.FontStyle.Regular, System.Drawing.GraphicsUnit.Point,
((byte)(0)));
            this.txtScenarioProbability1.Location = new
System.Drawing.Point(163, 34);
            this.txtScenarioProbability1.Name = "txtScenarioProbability1";
            this.txtScenarioProbability1.Size = new System.Drawing.Size(70,
20);
            this.txtScenarioProbability1.TabIndex = 1;
            //
            // label1
            //
            this.label1.AutoSize = true;
            this.label1.Font = new System.Drawing.Font("Microsoft Sans
Serif", 8.25F, System.Drawing.FontStyle.Regular,
System.Drawing.GraphicsUnit.Point, ((byte)(0)));
            this.label1.Location = new System.Drawing.Point(17, 37);
            this.label1.Name = "label1";
            this.label1.Size = new System.Drawing.Size(109, 13);
            this.label1.TabIndex = 16;
            this.label1.Text = "Scenario Probability 1";
            //
            // dgvScenarioDetails
            //
            this.dgvScenarioDetails.AllowUserToAddRows = false;
            this.dgvScenarioDetails.AllowUserToDeleteRows = false;
            this.dgvScenarioDetails.AllowUserToResizeColumns = false;
            this.dgvScenarioDetails.AllowUserToResizeRows = false;
            this.dgvScenarioDetails.ColumnHeadersHeightSizeMode =
System.Windows.Forms.DataGridViewColumnHeadersHeightSizeMode.AutoSize;
            this.dgvScenarioDetails.Location = new System.Drawing.Point(20,
68);
            this.dgvScenarioDetails.Name = "dgvScenarioDetails";
            this.dgvScenarioDetails.ReadOnly = true;
            this.dgvScenarioDetails.RowHeadersWidthSizeMode =
System.Windows.Forms.DataGridViewRowHeadersWidthSizeMode.DisableResizing;
            this.dgvScenarioDetails.Size = new System.Drawing.Size(464, 244);
            this.dgvScenarioDetails.TabIndex = 0;
            //
            // frmScenarioDetails
            //
```

```
            this.AutoScaleDimensions = new System.Drawing.SizeF(6F, 13F);
            this.AutoScaleMode = System.Windows.Forms.AutoScaleMode.Font;
            this.ClientSize = new System.Drawing.Size(534, 420);
            this.Controls.Add(this.groupBox2);
            this.FormBorderStyle =
System.Windows.Forms.FormBorderStyle.FixedDialog;
            this.MaximizeBox = false;
            this.MinimizeBox = false;
            this.Name = "frmScenarioDetails";
            this.StartPosition =
System.Windows.Forms.FormStartPosition.CenterScreen;
            this.Text = "Enter Scenario";
            this.Load += new
System.EventHandler(this.UtilityOptimization_Load);
            this.groupBox2.ResumeLayout(false);
            this.groupBox2.PerformLayout();

((System.ComponentModel.ISupportInitialize)(this.dgvScenarioDetails)).EndInit
();
            this.ResumeLayout(false);

        }

        #endregion

        private System.Windows.Forms.GroupBox groupBox2;
        private System.Windows.Forms.Button btnAddDayDetails;
        private System.Windows.Forms.TextBox txtScenarioProbability2;
        private System.Windows.Forms.Label label3;
        private System.Windows.Forms.TextBox txtScenarioProbability1;
        private System.Windows.Forms.Label label1;
        private System.Windows.Forms.Button btnSaveScenarioDetails;
        private System.Windows.Forms.DataGridView dgvScenarioDetails;
    }
}
```

```
namespace UtilityOptimization
{
    partial class frmUtilityOptimisation
    {
        /// <summary>
        /// Required designer variable.
        /// </summary>
        private System.ComponentModel.IContainer components = null;

        /// <summary>
        /// Clean up any resources being used.
        /// </summary>
        /// <param name="disposing">true if managed resources should be
disposed; otherwise, false.</param>
        protected override void Dispose(bool disposing)
        {
            if (disposing && (components != null))
            {
                components.Dispose();
            }
            base.Dispose(disposing);
        }

        #region Windows Form Designer generated code

        /// <summary>
        /// Required method for Designer support - do not modify
        /// the contents of this method with the code editor.
        /// </summary>
        private void InitializeComponent()
        {
            this.groupBox1 = new System.Windows.Forms.GroupBox();
            this.btnEnterScenarioDetails = new System.Windows.Forms.Button();
            this.btnSetParameters = new System.Windows.Forms.Button();
            this.txtCostOfGroundDelay = new System.Windows.Forms.TextBox();
            this.label4 = new System.Windows.Forms.Label();
            this.txtNumberOfScenarios = new System.Windows.Forms.TextBox();
            this.txtNumberOfDaysPerScenario = new
System.Windows.Forms.TextBox();
            this.txtCostOfAirDelay = new System.Windows.Forms.TextBox();
            this.label3 = new System.Windows.Forms.Label();
            this.label2 = new System.Windows.Forms.Label();
            this.label1 = new System.Windows.Forms.Label();
            this.groupBox2 = new System.Windows.Forms.GroupBox();
            this.btnComputeResults = new System.Windows.Forms.Button();
            this.dgvScenarioDetails = new
System.Windows.Forms.DataGridView();
            this.groupBox3 = new System.Windows.Forms.GroupBox();
            this.lblMaxScenario = new System.Windows.Forms.Label();
            this.dgvResults = new System.Windows.Forms.DataGridView();
            this.groupBox1.SuspendLayout();
            this.groupBox2.SuspendLayout();

((System.ComponentModel.ISupportInitialize)(this.dgvScenarioDetails)).BeginIn
it();
            this.groupBox3.SuspendLayout();
```

```
((System.ComponentModel.ISupportInitialize)(this.dgvResults)).BeginInit();
            this.SuspendLayout();
            //
            // groupBox1
            //
            this.groupBox1.Controls.Add(this.btnEnterScenarioDetails);
            this.groupBox1.Controls.Add(this.btnSetParameters);
            this.groupBox1.Controls.Add(this.txtCostOfGroundDelay);
            this.groupBox1.Controls.Add(this.label4);
            this.groupBox1.Controls.Add(this.txtNumberOfScenarios);
            this.groupBox1.Controls.Add(this.txtNumberOfDaysPerScenario);
            this.groupBox1.Controls.Add(this.txtCostOfAirDelay);
            this.groupBox1.Controls.Add(this.label3);
            this.groupBox1.Controls.Add(this.label2);
            this.groupBox1.Controls.Add(this.label1);
            this.groupBox1.Location = new System.Drawing.Point(13, 13);
            this.groupBox1.Name = "groupBox1";
            this.groupBox1.Size = new System.Drawing.Size(307, 267);
            this.groupBox1.TabIndex = 0;
            this.groupBox1.TabStop = false;
            this.groupBox1.Text = "  General Details  ";
            //
            // btnEnterScenarioDetails
            //
            this.btnEnterScenarioDetails.Enabled = false;
            this.btnEnterScenarioDetails.Location = new
System.Drawing.Point(148, 216);
            this.btnEnterScenarioDetails.Name = "btnEnterScenarioDetails";
            this.btnEnterScenarioDetails.Size = new System.Drawing.Size(128,
28);
            this.btnEnterScenarioDetails.TabIndex = 6;
            this.btnEnterScenarioDetails.Text = "&Enter Scenario Details";
            this.btnEnterScenarioDetails.UseVisualStyleBackColor = true;
            this.btnEnterScenarioDetails.Click += new
System.EventHandler(this.btnEnterScenarioDetails_Click);
            //
            // btnSetParameters
            //
            this.btnSetParameters.Location = new System.Drawing.Point(35,
216);
            this.btnSetParameters.Name = "btnSetParameters";
            this.btnSetParameters.Size = new System.Drawing.Size(96, 28);
            this.btnSetParameters.TabIndex = 5;
            this.btnSetParameters.Text = "&Set Parameters";
            this.btnSetParameters.UseVisualStyleBackColor = true;
            this.btnSetParameters.Click += new
System.EventHandler(this.btnSetParameters_Click);
            //
            // txtCostOfGroundDelay
            //
            this.txtCostOfGroundDelay.Location = new
System.Drawing.Point(210, 160);
            this.txtCostOfGroundDelay.Name = "txtCostOfGroundDelay";
            this.txtCostOfGroundDelay.Size = new System.Drawing.Size(66, 20);
            this.txtCostOfGroundDelay.TabIndex = 4;
            //
```

```
            // label4
            //
            this.label4.AutoSize = true;
            this.label4.Location = new System.Drawing.Point(25, 166);
            this.label4.Name = "label4";
            this.label4.Size = new System.Drawing.Size(108, 13);
            this.label4.TabIndex = 6;
            this.label4.Text = "Cost of Ground Delay";
            //
            // txtNumberOfScenarios
            //
            this.txtNumberOfScenarios.Location = new
System.Drawing.Point(210, 40);
            this.txtNumberOfScenarios.Name = "txtNumberOfScenarios";
            this.txtNumberOfScenarios.Size = new System.Drawing.Size(66, 20);
            this.txtNumberOfScenarios.TabIndex = 1;
            //
            // txtNumberOfDaysPerScenario
            //
            this.txtNumberOfDaysPerScenario.Location = new
System.Drawing.Point(210, 79);
            this.txtNumberOfDaysPerScenario.Name =
"txtNumberOfDaysPerScenario";
            this.txtNumberOfDaysPerScenario.Size = new
System.Drawing.Size(66, 20);
            this.txtNumberOfDaysPerScenario.TabIndex = 2;
            //
            // txtCostOfAirDelay
            //
            this.txtCostOfAirDelay.Location = new System.Drawing.Point(210,
119);
            this.txtCostOfAirDelay.Name = "txtCostOfAirDelay";
            this.txtCostOfAirDelay.Size = new System.Drawing.Size(66, 20);
            this.txtCostOfAirDelay.TabIndex = 3;
            //
            // label3
            //
            this.label3.AutoSize = true;
            this.label3.Location = new System.Drawing.Point(25, 122);
            this.label3.Name = "label3";
            this.label3.Size = new System.Drawing.Size(85, 13);
            this.label3.TabIndex = 2;
            this.label3.Text = "Cost of Air Delay";
            //
            // label2
            //
            this.label2.AutoSize = true;
            this.label2.Location = new System.Drawing.Point(25, 82);
            this.label2.Name = "label2";
            this.label2.Size = new System.Drawing.Size(136, 13);
            this.label2.TabIndex = 1;
            this.label2.Text = "Number of Days / Scenario";
            //
            // label1
            //
            this.label1.AutoSize = true;
            this.label1.Location = new System.Drawing.Point(25, 43);
```

```
            this.label1.Name = "label1";
            this.label1.Size = new System.Drawing.Size(106, 13);
            this.label1.TabIndex = 0;
            this.label1.Text = "Number of Scenarios";
            //
            // groupBox2
            //
            this.groupBox2.Controls.Add(this.btnComputeResults);
            this.groupBox2.Controls.Add(this.dgvScenarioDetails);
            this.groupBox2.Location = new System.Drawing.Point(355, 13);
            this.groupBox2.Name = "groupBox2";
            this.groupBox2.Size = new System.Drawing.Size(585, 267);
            this.groupBox2.TabIndex = 1;
            this.groupBox2.TabStop = false;
            this.groupBox2.Text = "  Scenario Details";
            //
            // btnComputeResults
            //
            this.btnComputeResults.Enabled = false;
            this.btnComputeResults.Location = new System.Drawing.Point(444,
226);
            this.btnComputeResults.Name = "btnComputeResults";
            this.btnComputeResults.Size = new System.Drawing.Size(104, 28);
            this.btnComputeResults.TabIndex = 1;
            this.btnComputeResults.Text = "&Compute Results";
            this.btnComputeResults.UseVisualStyleBackColor = true;
            this.btnComputeResults.Click += new
System.EventHandler(this.btnComputeResults_Click);
            //
            // dgvScenarioDetails
            //
            this.dgvScenarioDetails.AllowUserToAddRows = false;
            this.dgvScenarioDetails.AllowUserToDeleteRows = false;
            this.dgvScenarioDetails.ColumnHeadersHeightSizeMode =
System.Windows.Forms.DataGridViewColumnHeadersHeightSizeMode.AutoSize;
            this.dgvScenarioDetails.Location = new System.Drawing.Point(23,
30);
            this.dgvScenarioDetails.Name = "dgvScenarioDetails";
            this.dgvScenarioDetails.ReadOnly = true;
            this.dgvScenarioDetails.Size = new System.Drawing.Size(540, 190);
            this.dgvScenarioDetails.TabIndex = 0;
            //
            // groupBox3
            //
            this.groupBox3.Controls.Add(this.lblMaxScenario);
            this.groupBox3.Controls.Add(this.dgvResults);
            this.groupBox3.Location = new System.Drawing.Point(13, 286);
            this.groupBox3.Name = "groupBox3";
            this.groupBox3.Size = new System.Drawing.Size(927, 267);
            this.groupBox3.TabIndex = 2;
            this.groupBox3.TabStop = false;
            this.groupBox3.Text = "  Results";
            //
            // lblMaxScenario
            //
            this.lblMaxScenario.AutoSize = true;
```

```
            this.lblMaxScenario.Font = new System.Drawing.Font("Microsoft
Sans Serif", 9F, System.Drawing.FontStyle.Bold,
System.Drawing.GraphicsUnit.Point, ((byte)(0)));
            this.lblMaxScenario.Location = new System.Drawing.Point(489,
240);
            this.lblMaxScenario.Name = "lblMaxScenario";
            this.lblMaxScenario.Size = new System.Drawing.Size(271, 15);
            this.lblMaxScenario.TabIndex = 1;
            this.lblMaxScenario.Text = "Maximum Utility for the given
scenarios is ";
            //
            // dgvResults
            //
            this.dgvResults.AllowUserToAddRows = false;
            this.dgvResults.AllowUserToDeleteRows = false;
            this.dgvResults.ColumnHeadersHeightSizeMode =
System.Windows.Forms.DataGridViewColumnHeadersHeightSizeMode.AutoSize;
            this.dgvResults.Location = new System.Drawing.Point(18, 21);
            this.dgvResults.Name = "dgvResults";
            this.dgvResults.ReadOnly = true;
            this.dgvResults.Size = new System.Drawing.Size(887, 206);
            this.dgvResults.TabIndex = 0;
            //
            // frmUtilityOptimisation
            //
            this.AutoScaleDimensions = new System.Drawing.SizeF(6F, 13F);
            this.AutoScaleMode = System.Windows.Forms.AutoScaleMode.Font;
            this.ClientSize = new System.Drawing.Size(968, 566);
            this.Controls.Add(this.groupBox3);
            this.Controls.Add(this.groupBox2);
            this.Controls.Add(this.groupBox1);
            this.MaximizeBox = false;
            this.Name = "frmUtilityOptimisation";
            this.StartPosition =
System.Windows.Forms.FormStartPosition.CenterScreen;
            this.Text = "ATM Stochastic Optimization Model ~~~~~ by Wesonga
Ronald, PhD Statistics (Statistical Computing) ~~~~~";
            this.Load += new
System.EventHandler(this.frmUtilityOptimisation_Load);
            this.groupBox1.ResumeLayout(false);
            this.groupBox1.PerformLayout();
            this.groupBox2.ResumeLayout(false);

((System.ComponentModel.ISupportInitialize)(this.dgvScenarioDetails)).EndInit
();
            this.groupBox3.ResumeLayout(false);
            this.groupBox3.PerformLayout();

((System.ComponentModel.ISupportInitialize)(this.dgvResults)).EndInit();
            this.ResumeLayout(false);

        }

        #endregion

        private System.Windows.Forms.GroupBox groupBox1;
        private System.Windows.Forms.TextBox txtNumberOfScenarios;
```

```
    private System.Windows.Forms.TextBox txtNumberOfDaysPerScenario;
    private System.Windows.Forms.TextBox txtCostOfAirDelay;
    private System.Windows.Forms.Label label3;
    private System.Windows.Forms.Label label2;
    private System.Windows.Forms.Label label1;
    private System.Windows.Forms.TextBox txtCostOfGroundDelay;
    private System.Windows.Forms.Label label4;
    private System.Windows.Forms.Button btnEnterScenarioDetails;
    private System.Windows.Forms.Button btnSetParameters;
    private System.Windows.Forms.GroupBox groupBox2;
    public System.Windows.Forms.DataGridView dgvScenarioDetails;
    private System.Windows.Forms.Button btnComputeResults;
    private System.Windows.Forms.GroupBox groupBox3;
    private System.Windows.Forms.DataGridView dgvResults;
    private System.Windows.Forms.Label lblMaxScenario;
 }
}
```