QUEUEING MODELLING OF AIR TRANSPORT SYSTEM PASSENGERS' A CASE STUDY OF NNAMDI AZIKIWE INTERNATIONAL AIRPORT, ABUJA

The airline industry in most countries is strategic to economic development as it ensures safe and timely travelling and encourages business activities while generating employment opportunities. The Nigerian air transport industry system faces a lot of challenges due to unwanted waiting lines or delay of passengers who are eager to meet up for appointments or in preference to road transport systems. These problems include many passengers queuing for boarding, departure with different arrival rates. This project developed a queuing model as part solution to the problem. The Nnamdi Azikiwe International Airport (NAIA) Abuja was used as a case study to model a solution to this general problem. Arik Airline Limited, British Airways, Ethiopian Airline and Aero Contractors were the companies used for the study. The waiting modelling involved the use of Birth and Death Rate (BDR) and Multi-Server (MS) Models, which are the most commonly, used models to solve this type of problems. Data was collected from the companies to validate the result of the models. The results showed that in order to meet the current demand of passengers in NAIA, Abuja it is required that each airline to operate with minimum of five (5) aircrafts for daily service to cope with the average demand of 21863 passengers per month on their present routes. Service factors of 0.5 (utilisation factor of 0.4, 0.6 and 0.9) at 5% significance level were used for both BDR and MS model. The model when applied showed that the system became more reliable and efficient with minimal delay of service in all sectors considered in this work. However, BDR and MS models should be applied to other airports in Nigeria to minimise delay while the relevant authorities should monitor the recording of passenger patronage in Nigerian airports.

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background of the study

Africa is yet to be industrialised and this affect its contribution in global market especially in air transport sector "with less than 3.7 percent" in the recent (Bofinger, 2009). This value was found primarily in intercontinental traffic, in certain regions and countries, domestic traffic, such as in Nigeria. Market forecasts for the airline industry are difficult to make because of fluctuating fuel prices and the global economic crisis.

Queuing which always takes place in the form of lining up, is rarely anyone's favourite activity. It is the cornerstone of efficiency and organisational ability for most service industry especially in the airline industry. At any given moment, there may be more people or cases needing service, help or attention the industry can handle. Queues help workers and managers track, prioritise and ensure the delivery of services and transactions. Queuing modelling has helped in tracking customers' services and needs through customer service departments by creating virtual queues, assigning people needing service case numbers and priority statuses. Queuing modelling helps for assessing air industry responses to passengers needs. It helps technicians and specialists stay on top of all the situations and cases before them. For instance, a company's information technology help desk may serve hundreds and even thousands of employees using personal computers, mobile devices and proprietary devices. This requires a detailed and comprehensive tracking system to help managers efficiently allocate their team members' time and expertise. It has been used for managing businesses through the use of mathematical models and formulas to determine the best way of serving the greatest number of customer based on staffing resources. In retail businesses outlet, the volume of transactions is extremely important in maximising revenues and profitability. Thus, lines and queues are critical and important in servicing industry. This is the reason why supermarkets typically operate on multiple lines using several check stands, while banks and airlines usually use long queues that lead to delay. Queueing of passengers in Nnamdi Azikiwe International Airport (NAIA) causes delays due to irregularities in service processes. According to Mehri, H., Djemel, T., and Kammoun, H.(2009), there are three basic components of a queuing process which are arrivals, service facilities, and the actual waiting line. Arrival is an input source that generates arrivals or passengers for NAIA, Abuja system. It is important to consider the size of the calling population as infinite because the passengers arrive into the system at different rates. Hence the pattern of arrivals of the queueing system in the study would be first come first served (FCFS).

Therefore, in order to minimise delay of passenger and also to ensure improved performance in the system, the queueing data of the NAIA, Abuja were collected and modelled using both Birth and Death Rate (BDR) and Multi-Server (MS) approach.

1.2 Problem statement

Road safety factors have contributed to better responses of air transport systems in Nigeria due to bad road network, inadequate driver training and predominance of non-motorised traffic and pedestrian. These problems have increased much more passenger queuing for airline transport system which helps in turn to aid their business transaction, ease their journey, meeting up with their promising deadlines. As a result, Nigeria air transport industry system faces a lot of waiting time or delay of passengers who are ready to meet up for business or in preference for life safety to road transport systems. The air industry in Nigeria faces problems of many passengers queuing for boarding, departure with different arrival rate especially in Nnamdi Azikiwe International Airport (NAIA) the only airport facility in the nation's capital city, Abuja.

Queuing in NAIA, Abuja has become much more complex to solve manually due to the pattern and irregularities in the arrival or service processes. The airport has less capacity to serve all arrivals and departures promptly resulting into randomness that results to some waiting. Waiting or queuing could be eliminated if the irregularity could be taken care of, without increasing overall service capacity or diminishing the overall flow of arriving passenger. Waiting is therefore a consequence of irregularity in the airport.

NAIA, Abuja faces problem of waiting line or queuing in its system such as cargo and ticket clearance, departure and arrival rate. The average number of travellers in the system tends to be uncontrollable. The possible prediction of various numbers of passengers in the system is necessary for minimising the waiting line called queuing. Number of delay of passenger waiting for departure would be minimised and therefore the industry service will improve as well. As part of a solution to this complex problem that frustrate travellers on arrivals through the airport. This study is designed to develop a queuing model to facilitate prediction and processing of travellers on arrivals for effectiveness.

1.3 Aim of study

The study is aimed at minimising waiting lines of air transport services system in Nnamdi Azikiwe International Airport (NAIA) Abuja, in order to reduce delay in departure rate of passenger boarding by the air system, so as to predict performance of service level that would bring improvement of traffic flow management into the system.

1.4 Objectives of study

The objectives of the study include the followings:

a) Predicting the arrival and departure rate of passengers in the system
b) Predicting the expected number of passenger in the system and the system's service level of performance
c) Development of a queuing model to harmonise the passenger arrival rate, departure rate with the capacity of the handling facilities of the airport and expected passengers population in the system at a period for improved service.
d) Validation of the models with test data obtained from selected airlines that use the NAIA, Abuja to ascertain the performance of the model

1.5 Significance of the study

The main significance of the project when completed includes the following:

a) It will reduce airline operators' inefficiency in NAIA Abuja, which is essential for managing queuing practices.
b) The different models of queuing based on Birth and Death Rate (BDR) and Multi-Server (MS) models would reduce the delay in the system and improve operation economics.
c) The use of the model will give better outcome and maximum efficiency for managing available resources as it would significantly shorten the waiting periods of passengers, the number of waiting points and servers.
d) Successful application of the model at NAIA, Abuja would prompt the application of the models to other airports in Nigeria that have similar problems for better service.

e) It would reduce delay in services, quicken departures, and eliminate airport congestions with the attendant benefits of improved security especially in respect to terrorists that may be hanging around waiting passenger to execute their plans and other negative vices that occur in most airports of the world.

1.6 Scope of the study

The study focuses on modelling of waiting line of passengers boarding by air in NAIA, Abuja. It will entail the application of Birth and Death Rate (BDR) and Multi-Server (MS) models. The method is used for predicting performance level of the system because it helps in minimising delay of service. The study will use experimental data from the services company within (NAIA) Abuja such as number of passengers in the system and ticket fares. It will be based on required variables like the waiting line model of this system are number of passengers. The study result if successful may be extended to solve similar problems in other Nigerian airports.

1.7 Limitation

The study is limited to air transport systems in NAIA, Abuja to enable a handy and precise collection of data and analysis. It will involve predicting of waiting line of airline passengers in Abuja and departure rate of the passenger. Consequently, the performance service level of the airline in NAIA, Abuja will be predetermined using queueing modelling analysis and Chi-square distributional assumption based on empirical industrial data of past records and observations. The delimiting factor that affected effectiveness of the study was lack of full co-operation of some of the industry staff in giving the correct past data of their operations due to unavailability of such data for the purposes of tax evasion. The sampling data for passengers would be collected from NAIA, Abuja. The study would select two international and two domestic airline servicing companies as representatives of the entire system.

1.8 Research methodology

In the study, a quantitative approach was adopted. Therefore existing passenger's data in the system were collected for analysis. The source of information and data for the study was mostly through questionnaire on sampled groups, companies and passengers. The collected data were analysed using queuing modelling for determining the waiting lines of the passengers. An appropriate queuing model will be developed based on the data and information available to handle the peculiar situation at NAIA, Abuja.

1.9 Definition of terminologies

NAIA, Abuja: Nnamdi Azikiwe International Airport (NAIA)

Queue length: The total number of passengers in the air system

Arrival rate: Number of passengers coming into NAIA for airline services per time

Departure rate: Number of passengers being served per unit time

Queuing Modelling: Analysis of arrival and departure rate of the passengers in the system

First come first served: The servicing rate of the system in accordance to arriving rate

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Preamble

Nnamdi Azikiwe International Airport in the Federal Capital Territory of Abuja, Nigeria is a public airport operated by the Federal Airport Authority of Nigeria and managed by the Abuja gateway Consortium. It is located forty kilometres from the city centre of Abuja and is the main airport servicing the Nigerian capital city. It was named after Nigeria's first president Dr Nnamdi Azikiwe as a mark of honour to the national hero. It consists of international and domestic terminals. Both terminals share the same facilities like runway and control tower. NAIA has over fourteen airlines on both domestic and international routes. The major domestic airline operators that use the airport include Aero Contractors, Arik Air Limited, Dana Airways and Medview Airline. The operators on international flight services include Air France, British Airways, Ethiopian Airline, KLM, Lufthansa and Egypt Air. The airport also operates cargo flight services that are provided by several domestic and international airlines. In 2012, NAIA airlifted over three million passengers from the airport. It is the second busiest airport in Nigeria after Murtala Muhammed Airport, Lagos.

According to Bofinger (2009), in 2008 the price of crude oil rose to $150 per barrel, which caused significant damage to airline industry. Since then prices have declined by nearly two-thirds, but as the industry recovers from the oil shock it faces declining demand due to the global recession. The air transport market in Sub-Saharan Africa presents a strong dichotomy. In Southern and Eastern Africa the market is growing through promising signs; air traffic is on the rise, the number of routes and the size of aircraft are being adapted to the market, and a number of large carriers are viable and expanding overall connectivity has been declining. As oil prices rise, the role of air transportation will be looked at even more critically. Africa is a poor continent, and some countries face the potential of further isolation as the cost of flying increases. Infrastructure is not at the heart of the sector's problems. The number of airports is stable, and there are enough runways to handle traffic. What is required is better scheduling and relatively modest investment in parallel taxiways and some terminal facilities. Safety continues to be a problem, however, while aircraft are generally safe, pilot capabilities and safety administration are lacking and air traffic control facilities are poor. Although revenues from airports and air traffic are probably high enough to finance the necessary improvements, the sector has failed to capture them. Identifying and solving transportation problems is one of the chief tasks confronting governments in developing countries like Nigeria. Despite large expenditures on urban transport systems, the current transportation problems in developing nations continue to worsen because of bad planning, lack of good governance, and corruption Masood, M.T., Khan, A., and Naqvi, H.A 2011).

Solving air transport systems problems requires efficient planning of the system. Therefore planning of passengers' departure and arrival timings in Nigeria airline systems is a technique that would solve waiting line problem. According to Mehri, et al. (2009), the study of waiting lines, called queuing theory, involves the use of quantitative analysis techniques. Waiting lines occurs in places such as grocery stores, gasoline station and bank. Queues is a waiting line in form of machines waiting to be repaired, trucks in line to be unloaded, or airplanes lined up on a runway waiting for permission to take off (Altiok, 1997). Queuing models have found widespread use in the analysis of service facilities, industrial systems, production and many other situations where congestion or competition for scarce resources may occur. According to Masood, et al. (2011), exchanging of goods and persons as well as the personal right of freedom both are values and benefits for growing developing country. Therefore, transport and mobility are constitutional elements of cities which need to be organized in a sustainable manner. Transportation network is vital importance to development of any nation and affects all sectors through economic linkages. It ensures safe and timely travel and it encourages business activities and cuts down transportation costs and risks while granting produce access to markets for their goods. A reliable transportation network also provides swift access to labour force and hence generates employment opportunities.

In Nigeria there is poor transportation network which has contributed to decline of economic growth in recent years. Some business men, travellers, labour, industrialist etc in Nigeria prefer to join air transport system to aid their business transaction because of poor road network. As a result, commercial air transportation witnessed some substantial developments in recent pasts. One of such development is the increase in the number of operators and participants in the industry (Ogwude, 1986). Nigeria air service industry had one airline before 1983; three from 1983 to 1988; nine from 1989 to 1995 and fifteen from 1995 to 2010 Ukpere, W.I., Stephens, M.S., Ikeogu, C.C., Ibe, C.C., and Akpan, E.O.P., (2012)

2.2 Problem facing transportation systems in Nigeria

According to Odufuwa, B.O., Ademiluyi, I.A., and Adedeji, O.H. (2008), rapid urbanization and increasing rate of poverty are among the greatest challenges facing developing countries before and in the new millennium. This is obvious from the alarming rate of urban population growth, particularly in Nigeria. Indeed, for more than 50years, the progressive population drift to urban centres in Nigeria have not been matched by corresponding upgrade in infrastructural facilities. In other words, the implication of urban population growth on the economy of developing countries has been described as stagnant and unrewarding. Public infrastructure and social services have over the years been overstretched, while the process of urban development and infrastructural overhaul has been insignificant in most cities. In recent times, transportation infrastructure is often viewed by national policy makers as a second tier investment priority, pitted against more immediate, socially oriented poverty reduction programmes. In the face of fiscal pressures, spending on the maintenance of transport infrastructure, let alone on the building of new infrastructure, is often the first to be postponed, if not forgone. The effect of population explosion on the urban areas is inadequacy of transport provision that would have made it easy for people to always visit their homes and make business contacts. It is a common sight to see urban dwellers travel in over-crowded public transport vehicles, with extremely poor services and unhealthy travel environment. In many Nigerian cities, transport situation has reached a crisis point; the consequence of several years of neglect by successive administrations.

Hence, there is nothing novel in stating that transportation in Nigeria is grossly inadequate (Oyesiku, 2002 and Odufuwa, 2003). Over three quarters of the households in most Nigerian cities earn income below poverty lines (Osinubi, 2003 and Oyesiku, 2004). This has affected the rate of procurement of new vehicles, and it is obvious that this trend coupled with the inevitable declining level of existing purchasing power has taken its toll on the mobility needs of Nigerians. In the last few decades, most people in urban areas have depended heavily on non-motorized means. Few of the populace has access to private motorized means; either for unavailability of spear parts or because of its prohibitive price of moving around.

In other words, poor quality, unaffordable, unsafe and grossly uncomfortable means of mobility in Nigerian cities pose great threat to the people. Given the acute shortfall in transportation supply, private vehicle ownership is still very low; while, public transport has become more common and transport externalities have become endemic. The impact of this distressed sector on the economy of the ensuing crisis is severe, with the urban poor suffering more than any other group. The growing transport paucity has had a debilitating effect on the lives of the people and it has continued to trap and push its catchments towards poorer livelihoods.

2.3 Waiting line in air transport system

Airports are nowadays multimodal, multi-service platforms, with intense non-aeronautical activities that cover several different industrial, economical and social aspects. Taxi services are a fundamental piece of the transportation diversity that airport requires, in order to become attractive and efficient. This transportation service gains special relevance when coupled to existing high-demand nodes like hospitals, monuments, shopping areas, hotels, or airports. Its "service profile" is highly compatible to the traditionally higher willingness to pay of passengers with trip urgency and high comfort needs or economic power, such as hospital patients, shoppers, businessmen or tourists.

A queue is a waiting line (like customers waiting at a supermarket checkout counter); queueing theory is the mathematical theory of waiting lines. More generally, queueing theory is concerned with the mathematical modeling and analysis of systems that provide service to random demands especially in airport transport system. A queuing model is an abstract description of such a system. Typically, a queuing model represents the following:

a) The system's physical configuration, by specifying the number and arrangement of the servers, which provide service to the customers
b) The stochastic (that is, probabilistic or statistical) nature of the demands, by specifying the variability in the arrival process and in the service process. For example, in the context of computer communications, a communications channel might be a server and the messages the customers; the (random) times at which messages request the use of the would be the arrival process, and the (random) lengths of service time that the messages hold the channel while being transmitted would constitute the service process. Another example is a computer system where a programmer (customer) sitting at a terminal requests access to a CPU (server) for the processing of a transaction; both the arrival time of the request for access and the amount of processing time requested are random .

2.4 Queueing modelling of other airline system

According to Subramanian (2007), three performance metrics for the National Airspace System (NAS) could be modelled depending on aggregate econometric models for flight delays, flight cancellation probabilities and passenger delays especially in United States. Flight delays can be attributed to queuing effects within the air transportation network. As delays in air transportation system worsen, more and more people switch to another mode of transportation.

The steady rise in demand for air transportation has demonstrated the need for improved air traffic flow management. One of the metrics that has been used to assess the performance of NAS is the actual aggregate delay. Flight delays, in many cases, are caused by the application of Traffic Flow Management (TFM) initiatives in response to weather conditions and excessive traffic volume. TFM initiatives such as ground stops, ground delay programs, rerouting, airborne holding, and miles-in-trail restrictions, are actions that are needed to control the air traffic demand to mitigate the demand-capacity imbalances due to the reduction in capacity. Consequently, TFM initiatives result in NAS delays. Of all the causes, weather has been identified as the most important causative factor for NAS delays.

Therefore, to guide flow control decisions during the day of operations, and for post operations analysis, it is useful to create a baseline for NAS performance and establish a model that characterizes the relation between weather and NAS delays. Hence given the demand and expected weather, the model can be used to predict the expected aggregate delay. Flight cancellation probability is defined as the probability that a flight scheduled will be cancelled. Airlines usually cancel flights scheduling when they experience non-availability problems related to crew, maintenance and security personnel, Air Traffic Control (ATC) problems like runway breakdowns etc, and weather related problems that reduce the airport capacity. Before cancelling a flight, the airlines would weigh the economics like fuel costs saving for the cancelled flight against the cost incurred due to passenger delays and loss of goodwill to guide in telling decision as whether to cancel a flight or not. In most cases, decisions related to cancellations are affected by circumstances beyond the control of airlines for instance weather problems and reduction of airport capacities.

In some cases, airlines might face an operational problem that forces the cancellation of a particular flight. However, many times airlines can exercise some control over which flights are cancelled and the number of flights to be cancelled after considering economic trade-offs.

The airlines have the responsibility to provide their updated flight plans to the ATC system so that airport resources can be better used in lieu of flight cancellations. Since flight cancellations mean a significant loss to the airlines, it becomes of paramount significance to model them accurately.

Flights delayed or cancelled adversely affect the passengers. Loss of productivity (or Passenger Time Value) represents valuation of the loss of passenger time value contributed to Nigeria economy due to bad quality of service. Passenger delay is the actual delay passengers experience by disruption in aviation activities, including both flight delay and cancellations.

Delay and cancellation are essentially the same from the passenger perspective. They both impose delays to travel time. Generally, cancellations generate extremely high passenger delays. In order to estimate passenger delay, transformations must be applied to convert the number of cancellations into delay of relocated passengers on the cancelled flights. Thus the total passenger delay includes not only delays obtained from delayed flights but also delays induced by cancellations (Subramanian, 2007).

2.5 Queueing theory

According to Salvendy (2001), queueing theory was first known in early 1900s with the work of A. K. Erlang of the Copenhagen Telephone Company, who derived several important formulae for teletraffic engineering that today, bear his name. The range of applications has grown to include not only telecommunications and computer science, but also manufacturing, air traffic control, military logistics, design of theme parks, and many other areas that involve service systems whose demands are random. Queueing theory is considered to be one of the standard methodologies (together with linear programming, simulation, etc.) of operations research and management science, and is standard fare in academic programs in industrial engineering, manufacturing engineering, etc., as well as in programs in telecommunications, computer engineering, and computer science. But, despite its apparent simplicity (customers arrive, request service, and leave or wait until they get it), the subject is one of some depth and subtlety.

2.6 Applications of queuing theory

According to Dombacher (2010), queueing theory allows for calculation of a broad spectrum of applications. These include:

a) In manufacturing systems: raw materials are transported from station to station using a conveyor belt. With each station having performed its task, the item is allowed to proceed to the next station. If processing times at all stations are equal and the conveyor belt is filled in the same frequency as items proceed from one station to the other, no waiting can occur, as the assembly line works in synchronous mode. In asynchronous mode, queueing for stations might occur and clearly has an impact on overall performance

b) Computer systems that perform real time or high speed operations are often subject to bad performance due to a single bottleneck device such as CPU, disk drive, graphics card, communication ports or bus system. By the use of analytical models the bottleneck device may be detected and as a consequence upgraded. By nature of the protocols used in computer networks, delays occur due to congestion of the transport network. These delays may be seen as waiting time until the media becomes free again thus allowing for calculation of throughput, overall delay and other performance values.

c) Teletraffic engineering deals with the availability of stations, trunks and interconnection lines. Although these systems are characterized by blocking more than by delay, they still belong to the world of queueing systems. With the introduction of new media in teletraffic engineering, the delay paradigm becomes more important again.

d) Workforce management is concerned about the most efficient allocation of personnel. The application of queueing theory in workforce management is most visible in call centres, where agents have to be allocated according to the call load. Relying on other techniques such as forecasting, queueing theory may be seen just as another brick in the wall in a wide range of solution methods to be applied to solve problems appearing in workforce management.

2.7 Fundamental approach of modelling

According to Salvendy (2001), the process of modeling involves the following steps:

a) Identifying the issues to be addressed: Ascertain the needs of user. What decisions are the models required to support? These can range from the very specific, such as how large a specific storage location should be, to the somewhat vague, such as whether it is possible to identify when a particular way of operating the system is optimal.

b) Learning about the system*:* Identify the components of the system, such as people, machines, material handling, storage data collection and control system. Determine the characteristics of jobs or customers and the target volumes, quality, and cost. This step can involve close contact with the system designers and a review of any existing models to identify their capability and their shortcomings.

c) Choosing a modeling approach*:* Various types of modeling approaches can be used, ranging from formal mathematical models through computer simulations to the development of a ‘‘toy’’ system in which toy parts or people physically move from one toy machine to another. The choice of modeling approach is determined by the time and cost budget for model development and the anticipated way in which the model will be used.

d) Developing and testing the model: This step requires obtaining data on parameters of the model, and often the lack of desirable data forces the model to be substantially simplified.

e) Developing a model interface for the user: If the model is to be of value in making decisions, it has to be provided with some interface so that it can be used by managers. This requires the modeler either to embody the model in a decision support system or to present the model and its implications in a way that managers can understand.

f) Verifying and validating the model: The model has to be checked to see that it is a reasonably correct representation of the reality it seeks to represent. Verification is the process of ensuring that the model results are correct for the assumptions made in developing the model. Validation is the process of ensuring that the model is an accurate representation of the real system. This may also involve convincing the user that the model is adequate for the decision he or she requires it to support.

g) Experimenting with the model: This requires exploring the impact of changes in model parameters and developing understanding of the factors influencing performance of the system so that the manager can be confident in the decisions made using the model.

h) Presenting the results: Using the model, manager should come up with a recommended course of action. This recommendation may have to be presented to higher-level management and the role of the model in aiding the decision explained. Alternatively, the model and the results of its use will be presented in a report or paper that, apart from describing the model itself, should explain what the model can do, what it cannot do, and how accurate are they.

2.7.1 Types of modelling

For systems processing discrete jobs or customers, there are three types of models in common use as briefly discussed (Salvendy, 2001; Viswanadhan and Narahari, 1992; Yin and Zang, 1996) as briefly discussed below:

a) Physical models: It represent the real system by another physical system, in which jobs or customers move from one machine or service center to another and the machines or service centers perform processing operations on the jobs or customers. The major difference to the real system is that the model uses a different dimensional scale, so a large system will occupy a table top. Physical models can use toy-sized components, but they can be provided with a control system that employs the same logic as the real system. Physical models are excellent as a means of educating management and workers about the control of the system, but they do not lend themselves for assessing the long-run behavior of the system, as it is difficult to represent the statistical properties of events such as machine

b) Simulation models: These represent the events that could occur as a system operates by a sequence of steps in a computer program. This means that the logical relationships that exist between events can be described in detail. The probabilistic nature of many events, such as machine failure, can be represented by sampling from a distribution representing the pattern of occurrence of the event, for example, the distribution of the time between machine failures. Thus, in order to represent the typical behavior of the system, it is necessary to run the simulation model for a sufficiently long time that all events can occur at reasonable number of times. Simulation models can be provided with an interactive graphic display to demonstrate the movement of jobs or customers. This can be of great value in communicating the assumptions of the model to engineers and others.

c) Analytical models: this describes the system using mathematical or symbolic relationships. These are then used to derive a formula or define an algorithm or computational procedure by which the performance measures of the system can be calculated. Analytical models can also be used to demonstrate properties of various operating rules and control strategies. Sometimes it is not possible, within a reasonable amount of computer time or space, to obtain the performance measure from the relationships describing the system without making further assumptions that modify these relationships. The resulting model is thus approximate rather than exact. Testing the approximation may then require a simulation model, so approximate models are useful only if they are easy to use and can provide insight into what determines the system behaviour.

2.7.2 Queueing modelling

Queueing model may be stochastic model which focus on waiting. Models of waiting are called queuing systems, or simply queues (Asmussen, 1987; Bramson, 1994; Buzacott and Shanthikumar, 1993). A queueing system may be divided loosely into three subsystems:

a) The arrival process,

b) The waiting area

c) The service system.

Each of these subsystems can operate in a variety of ways. The following are some of the more common possibilities. The arrival process specifies a sequence of jobs or batches of jobs and the times at which they enter the system. The arrival times may constitute a Poisson process or a renewal process, for example. The jobs may be indistinguishable from one another, or they may be of several classes, to be treated differently in the waiting or service area.

The waiting area may be managed in various ways. Jobs may be ordered according to time of arrival, the most recent arrival being the first to be served (first-in-first-out, or FIFO). This is the most common discipline used in serving people because of the sense of fairness it engenders. To give some simple alternatives, jobs may be served in random order (SIRO) or last-in-first-out (LIFO). Under the processor sharing (PS) discipline, all jobs present share the server's attention equally. Jobs may also be served according to priorities determined based on job class or service needs. Preemption, in which an arriving high-priority job ejects has a low-priority job from service, may or may not be allowed.

The service system is where jobs receive what they have waited for. There may be one or many servers, and the servers may be subject to breakdowns. Jobs may be served singly or in batches, and service times may depend on job class. Queueing models are particularly useful for determining the following performance measures of a service system (Daley, et al. 1992; Gershwin, 1994; Jackson, 1963):

a) Capacity or throughput: This is the maximum rate at which the system can accept jobs or customers over some long time interval. Throughput is usually measured in jobs or customers per hour (or some other suitable time interval). Individual components of the system will, of course, have a higher short-term capacity than throughput, but over the long run they will lose capacity because of machine breakdowns or worker absences. Capacity will also be lost because of interaction between the different parts of the system.

b) Flow Time or Lead Time: The flow time, sometimes called the lead time in manufacturing, is the time from when a job or customer arrives at the system until the job or customer departs the system. It will be greater than the actual processing time because jobs are held in inventory buffers and customers wait in queues. Queueing models usually focus on determining the average flow time, but it is usually also possible to determine the variance and higher moments.

c) Inventories and queue lengths: It is often important to know where inventories and queues are distributed through the system. The average total flow time and the average total queue length are connected by Little's law (Jackson, 1963) as stated in equation 2.1

$$\bar{l} = \lambda \bar{w} \tag{2.1}$$

Where;

$\bar{l}$ = Queue length (m)

$\bar{w}$ = Average flow time (s)

λ = Average rate at which jobs or customers flow through the system (m/s)

Given either queue length or flow time, the other performance measure can be readily determined from equation (2.1) above.

d) Service level: The service level can be measured in a variety of different ways, such as the fraction of demands met immediately or the average time to fulfill a customer demand. Service level is a particularly important performance measure when finished product inventories are kept and it is necessary to trade off the inventory investment with the penalties of delay in meeting customer demand. Then, the mathematical analysis of the model would yield formulas that presumably relate the physical and stochastic parameters to certain performance measures, such as average waiting time, server utilization, throughput, probability of buffer overflow. The art of applied queuing theory is to construct a model that is simple enough so that it yields mathematical analysis, yet contains sufficient detail so that its performance measures reflect the behavior of the real system like air transport system.

2.8 Application of queueing models

Queueing models are particularly useful in designing and improving upon system performance. In particular, they are of great value for addressing the following issues (Salvendy, 2001):

a) Investigating alternative configurations: There are usually alternative ways of allocating tasks to machines or people, and each alternative will result in different pattern of work flow. Queueing models are particularly valuable in rapidly exploring a wide range of alternatives and seeing how system performance is modified.

b) Exploring the impact of parameters set by management: Typically, management have to choose values for such parameters as inventory buffer capacities, the number of kanbans, or base stock levels. Queueing models enable their impact on performance measures such as throughput or service level to be found. If costs are available, then it is possible to determine the values that optimize performance.

c) Comparing alternative scheduling and work-allocation rules: Queueing models can be used to compare different scheduling rules. They can also be used to explore the way in which performance is changed as more information about jobs or customers is acquired and that information used to modify the routing and allocation of jobs or customers to machines or servers.

d) Understanding the impact of variability: Typically, less variability improves performance. But since reducing variability can be costly, it is desirable to know by how much performance is improved. Variability reduction is typically the aim of quality management efforts, and queuing models can help focus that effort.

2.9 Optimisation of queuing modelling

According to Mukherjee, et al. (2007), classical approaches to estimating delays is to consider delay of a entity as a random variable that is a function of any other random phenomena including arrival and service processes. In the air transportation context, while delay is certainly highly stochastic, the airlines can exercise substantial control over the amount of delay and its distribution among flights by judiciously substituting flights among allocated slots and by canceling key flights. The degree of control exercised by airlines has been improved on substantially with the implementation of Collaborative Decision Making (CDM) procedures in the United States (Wambsganss, 1996 and Vossen and Ball, 2006). However, overall system performance should be measured both in terms of flight delays and flight cancellation rates.

In fact, research has shown that passenger delays are very substantially impacted by flight cancellation rates so that ignoring these can greatly misrepresent system performance. For these reasons it is important to estimate both flight delays and cancellation rates. At the same time, it becomes evident that cancellation rates, while motivated by random phenomena, are the result of human control actions. Mukherjee, et al. (2007), discussed other queueing modeling implication as follows.

2.9.1 Long-term averages and capacity scenarios

The ultimate goal was to estimate long time average flight delays and cancellation rate. As such our model could not assume one set of airport conditions that might occur on a particular day. Liu, Hansen and Mukherjee (2006) employed a set of capacity scenarios and each scenario specified hourly airport acceptance rate (arrival capacities) and acceptance varies with weather conditions in most U.S. airports. According to Mukherjee, et al. (2007), delay estimates for each scenario could be modelled and can be combined to produce long-term average using the association scenario probabilities.

2.9.2 Estimation of delay

According to Hansen, et al. (2009), air traffic system faces a major transformation in the coming years. Transformation in air traffic management may include the use of four dimensional trajectories (4DT), with time being the fourth dimension. This will enable the accurate prediction of aircraft position within a given time horizon and therefore the reduction of separations standards between aircraft. Trajectory based operations are expected to reduce excess separation resulting from today's control imprecision and lack of predictability, and enable reduced separation between aircraft, resulting in increased capacity. Operational management of 4DTs may allow more efficient control and spacing of individual flights, especially in congested arrival/departure rate of airspace and busy runways.

Overall, flight operations are expected to be more consistent, allowing operators to maintain schedule integrity without the schedule buffers that are built into today's published flight times. However, even with the deployment of the very best 4DT trajectory precision and navigation tools, there will still be stochastic effects causing some deviation from an ideal metering schedule. Thus, the level of uncertainty in trajectory prediction can be viewed as a continuum, ranging from high levels, roughly corresponding to most current day-to-day operations, to greatly reduced ones, where (near) perfect information on trajectories is available to managers and controllers, enabling, among other things, optimal metering of flights and traffic initiatives. Between these two endpoints lies a broad spectrum, resulting from different choices of technology deployment and operational concepts.

2.10 Queuing modelling of manufacturing and services systems

According to Salvendy (2001), design and improvement of the performance of manufacturing and service systems requires efficient ways for:

a) Predicting the performance of the systems and

b) Identifying the effects of key design parameters on the system performance

c) Manufacturing and service systems have to cope with a wide range of variability, uncertainty and disturbances.

Different customers require different tasks to be performed, people and machines can vary in their time to perform standardized tasks, machines can break down unexpectedly, and repair can prove more complicated than anticipated. There are needs for predicting the performance that takes into account this uncertainty and variability also helps us to reduce their adverse impacts on systems (Altiok, 1997).

Queueing models are particularly useful in describing variability and predicting its impact on performance. Queueing models can be used at the system-design stage to rapidly explore alternatives and see the sensitivity to parameter values. The models can also be of great value in assessing the performance of systems once they are installed because they enable the sources of loss of productivity to be identified. Most service systems have to deal with the requirements of individual customers (Buzacott and Shanthikumar 1994)

In service applications, we will call each order or person a customer. While each job or customer is distinct, different jobs or customers can be in all respects identical and in particular have the same processing requirements. For a system to provide for only one type of job or customer, then some aspects of its design and operation will be simplified because all jobs or customers can then be handled the same way (Buzacott, 1996 and Buzacott, 2000).

However, if the system processes many different types of jobs or customers, instructions for each type will be required and control will tend to be more complex. In service systems particularly, it is often not known what the processing requirements of a customer will be until after the customer arrives and some diagnosis can be carried out.

Models are needed to represent this evolution of knowledge about processing requirements and how the information is used to modify instructions on what to be done (Buzacott *et al.,* 1995 and Buzacott *et al.,* 1992).

2.11 Modelling of service systems

Air Transport System (ATS) could be described as a service system. There is yet to be an established approach for categorizing the different configurations of service systems; although there are a variety of approaches. From the perspective of developing queueing models, perhaps the most useful approach is to focus on the range and features of the tasks assigned to people providing service (Buzacott 2000). Based on this, services can be categorized as follows:

a) Narrow-Range Tasks: If the system is configured such that each individual server performs a narrow range of tasks, then this usually means that a number of different servers are required in order to perform all the required tasks for a customer. This means that the system will often be similar to a manufacturing flow line and so can be represented by queues in series. Of course, if there is some flexibility in the sequence in which tasks are done, then the system becomes more like a manufacturing job shop and can be represented by a network of queues.

b) Broad-Range Tasks: Alternatively, individual servers can be assigned a broad range of tasks. This means that they are often able to do all the tasks required by a specific customer. However, in order to cope with increasing volume of customers, many servers are required. The system can then be represented by a number of servers in parallel. There are a variety of ways in which customers can be allocated to servers. As an example, some servers may specialize on particular types of customers. Alternatively, customers can be allocated to servers according to some allocation rule, such as allocate to free servers in order of customer arrivals or allocate according to a round-robin or cyclical rule as follow:

    i. First arrival, to server 1,
    ii. Next arrival to server 2,
    iii. Next arrival to server 1,
    iv. Next arrival to server 2, and so on.

c) Specialized Diagnosis: In many service situations the tasks to be done for a customer are not known until the customer arrives and some diagnosis is carried out. It is good to have a first stage of service that determines the require task. The appropriate queuing model now consists of a network of queues in which customers flow out of diagnosis to a specific specialized facility is random, with probability equal to the frequency of the facility being required by the diagnosis. In some situations, multiple diagnostic steps are required, depending on whether a step is able to determine the service requirements or need further diagnoses.

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1 Materials

Queueing data (materials) are required for modelling air transport system for the passengers' of Nnamdi Azikiwe International Airport, (NAIA) Abuja. The data of waiting line for the past ten months of the system were collected because it was available at the time of study and they were categorised based on the following:

a) Case subsystem

b) Size of calling population; the passengers

c) System capacity

3.1.1 Case subsystem

The case study is Nnamdi Azikiwe International Airport (NAIA), Abuja. The subsystem involved for modelling NAIA system are the following four airline transport companies:

a) Arik Airline Limited (AA)

b) British Airways (BA)

c) Ethiopian Airline (EA)

d) Aero Contractors (AC)

Both Arik Airline Ltd and Aero Contactors are local air service companies while British Airways and Ethiopian Airline are international air service companies. The local and international companies were selected for comparative analysis and performance purpose. They are also the major airlines in terms of passenger airlifting in NAIA, Abuja.

3.1.2 Size of calling population

The size of calling population is infinite because of arrival pattern from large passenger population.

3.1.3 System capacity

The system capacity was based on the total number of waiting room or passengers and server (number of airplanes).

3.1.3.1 System characteristics

The system characteristics to be considered are the following:

a) Arrival process: The entry procedure

b) Service process: The system operational procedure

c) Number of channels: The systematic way of solving the problem

d) Queue discipline: The pattern for solving waiting line problem

Each of these characteristics is described in Table 3.1.

Table 3.1 Queueing system characteristics

Characteristics	Description
Arrival process	Exponential distribution
Service process	Parallel service for single queue
Number of channels	Multi-channel
System capacity	Infinite
Queue discipline	First come first served (FCFS)

Single Queue with Parallel Servers (SQPS): This is the type of model which deals with the study of a single queue in equilibrium. There is more than one server and each server provides the same type of service or it is to provide identical parallel service. The customers (passengers) wait in a single queue until one of the service channels is ready to take them in for servicing at the rate of one customer at a time per server

3.2 Methods

In the study, the following methods are employed:

a) Queue modelling based on stochastic/probabilistic process (general and exponential distribution)
b) Birth and Death Rate (BDR) model
c) Multi-Server (MS) model
d) Chi-square distribution assumption

3.2.1 Study assumption

The Queues represent the state of a system such as the number of people inside an airport terminal (Trani, 2011). Considering multiple servers with infinite calling population, they based on references to previous related work. The mathematical models for analysing waiting lines have the following assumptions as adopted from Mehri, et al. (2009).

a) arrivals come from an infinite or very large population
b) arrivals are Poisson distributed
c) Arrivals are treated on a first in first out (FIFO) basis and do not balk or renege.

The arrival of most queuing models assumes that an arriving passenger is a patient traveller. Patient customer is people or machines that wait in the queue until they are served and do not switch between lines. Unfortunately, life and quantitative analysis are complicated by the fact that people have been known to balk or renege.

Balking refers to passengers who refuse to join the waiting lines because it is not suitable to their needs or interests. Reneging passengers are those who enter the queue but then become impatient and leave; hence the need for queueing theory and waiting lines analysis

d) Service times follow the negative exponential distribution or are constant

e) The average service rate is faster than the average arrival rate

3.2.2 Performance characteristics of queueing systems

Using Little's law, the performance of queue system are adopted by Blumenfeld, (2001) can be assessed as follows:

$$L_q = \lambda W_q \tag{3.1}$$

$$L = \lambda W \tag{3.2}$$

$$L = L_q + \lambda/\mu \tag{3.3}$$

$$L = W_q + 1/\mu \tag{3.4}$$

$$L = \sum_{n=0}^{\infty} nP_n \tag{3.5}$$

$$L_q = \sum_{n=0}^{\infty} (n - s)P_n \tag{3.6}$$

$$\rho = \frac{\lambda}{s\mu} \qquad (\rho < 1) \tag{3.7}$$

Equations (3.1) and (3.2) are the mathematical representation of Little's law.

Where:

n = number of passengers in the system

$P_n\ (t)$ = probability of exactly (n) passenger in queueing system at time (t)

L_q = average queue length (average number of passengers in queue)

L = average system length (average number of passengers in system, including those being served)

W_q = average waiting time in queue (average time a passenger spends in a queue)

W = average time in system (average time a passenger spends in queue plus service)

$N(t)$ = total number of passengers in the system at a particular time

T = time that a passenger spends in the system

s = number of servers

λ = arrival rate (number of passengers arriving per unit time)

$1/\lambda$ = mean interarrival time

μ = service rate per unit server (number of passenger served per unit time)

$1/\mu$ = mean service time

ρ = traffic intensity

3.2.3 Modelling based on the birth-and-death process

According to Hillier and Liebermann (2001), the term birth refers to the arrival of a new customer into the queueing system, and death refers to the departure of a served customer. The queue system is simply illustrated as shown in Figure 3.1.

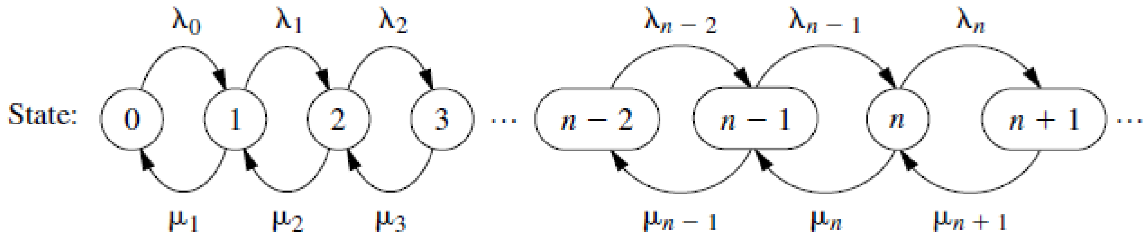

Figure 3.1 Birth rate and Death rate of the passenger in NAIA, Abuja

The pattern of the system with n passenger is given by steady state balancing equation.

Mean entering rate of passenger = mean leaving rate of passenger

$$\mu_1 P_1 = \lambda_0 P_0 \tag{3.8}$$

$$\mu_{n-1}P_{n-1} + \mu_{n+1}P_{n+1} = \lambda_n P_n + \mu_n P_n$$

$$\mu_{n-1}P_{n-1} + \mu_{n+1}P_{n+1} = (\lambda_n + \mu_n)P_n \tag{3.9}$$

$$\mu_{n+1}P_{n+1} = (\lambda_n + \mu_n)P_n - \lambda_{n-1}P_{n-1}$$

$$P_{n+1} = \frac{(\lambda_n + \mu_n)P_n}{\mu_{n+1}} - \frac{\lambda_{n-1}P_{n-1}}{\mu_{n+1}}$$

$$P_{n+1} = \frac{\lambda_n P_n}{\mu_{n+1}} + \frac{\mu_n P_n}{\mu_{n+1}} - \frac{\lambda_{n-1}P_{n-1}}{\mu_{n+1}}$$

$$P_{n+1} = \frac{\lambda_n P_n}{\mu_{n+1}} + \frac{1}{\mu_{n+1}}(\mu_n P_n - \lambda_{n-1}P_{n-1})$$

If $\frac{1}{\mu_{n+1}}(\mu_n P_n - \lambda_{n-1}P_{n-1}) \to 0$

$$P_{n+1} \cong \frac{\lambda_n P_n}{\mu_{n+1}} \qquad (3.10)$$

From equation (3.3), if $n = 0$, we have: $\lambda_{n-2} \ldots \quad \lambda_0$

$$P_1 = \frac{\lambda_0 P_0}{\mu_1} \qquad (3.11)$$

Let $C_n = \frac{\lambda_{n-1}\lambda_{n-2} \cdots \quad \lambda_0}{\mu_n \mu_{n-1} \cdots \quad \mu_1}$ for $n = 1,2, \ldots$

If $n = 1$;

$$C_1 = \frac{\lambda_0}{\mu_1} \qquad (3.12)$$

Therefore equation (3.11) becomes:

$$P_1 = C_1 P_0 \qquad (3.13)$$

Thus, the steady-state probability would be given by (Hillier and Liebermann, 2001):

$$P_n = C_n P_0 \qquad (3.14)$$

$$\sum_{i=0}^{n} P_n = 1 \qquad (3.15a)$$

$$P_0 + \sum_{i=1}^{n} P_n = 1 \qquad (3.15b)$$

$$\Longrightarrow P_0 + \left(\sum_{n=0}^{\infty} C_n\right) P_0 = 1 \qquad (3.16)$$

$$P_0 = \frac{1}{1 + \left(\sum_{n=0}^{\infty} C_n\right)} \qquad (3.17)$$

$$\bar{\lambda} = \sum_{n=0}^{\infty} \lambda_n P_n \qquad (3.18a)$$

Therefore, $L \; and \; L_q$ are given by the equation below (Trani, 2011):

$$L = \sum_{n=s}^{\infty} n P_n \qquad (3.18b)$$

$$L_q = \sum_{n=s}^{\infty}(n-s)P_n \tag{3.18c}$$

Where

$\bar{\lambda}$ = Average arrival rate over the long run

C_n = Steady service rate

The BDR approach solves waiting line problems as one after the other. The equation 3.10-3.18 were adopted equation for the modelling of BDR approach in which arrival and departure rate of passengers with system service's level of performance are determined.

3.2.3.1 Assumptions for birth and death rate modelling

The following assumptions were adopted in using birth and death rate modelling

a) Given: $N(t) = n$, present probability distribution is exponential with parameter λ_n $(n = 0,1,2,..)$ until next birth (passenger arrival)

b) Given: $N(t) = n$, present probability distribution is exponential with parameter μ_n $(n = 0,1,2,...)$ until next death (passenger service completion)

c) The random variable of assumption (a) and the random variable of assumption (b) are mutually independent.

The next transition in the system would be either:

$n \rightarrow n + 1$ (Single birth) or

$n \rightarrow n - 1$ (Single death)

3.2.4 Modelling based on the multi-server with infinite source

The use of the following notation is adopted:

M/M/s/Y/Z and this is a Kendall's Notation and in generalised form is given by:

A/B/c/K

A describes the interarrival time distribution

B is the service time distribution

c is the number of server

K is the size of the system capacity (including the node or server)

Symbols traditionally used for A and B is as follows:

M for exponential distribution (M stands for Markov)

D for deterministic distribution

G for general distribution

In the study the Kendal notation was adopted as follows.

A/B/s/Y/Z

Where:

A stands for arrival distribution

B stands for service pattern distribution

s stands for number of servers

Y stands for system capacity

Z stands for queueing discipline

In this case considered, $s > 1$.

Thus:

$\lambda_n = \lambda$ For $n = 0,1,2,..$

$$\mu_n = \begin{cases} n\mu & \text{for } n = 0,1,2,..s \\ s\mu & \text{for } n = s, s+1, \ldots.. \end{cases}$$

Figure 3.2 shows the modelling pattern of multi-service and this is adopted in the study.

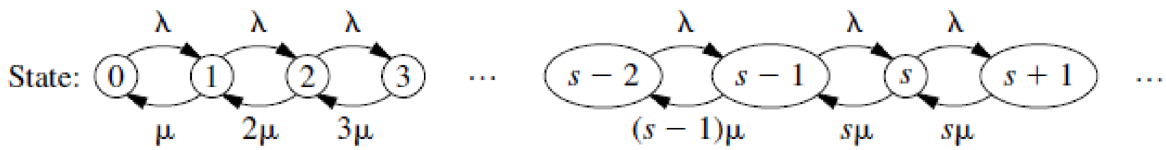

Figure 3.2 Multiservice of a single stage NAIA system.

The steady service rate in multi-service is given by the following equations:

$$C_n = \begin{cases} \dfrac{\left(\frac{\lambda}{\mu}\right)^n}{n!} & \text{for } n = 0,1,2,..s \\ \dfrac{(\lambda/\mu)^s}{s!}\dfrac{(\lambda)^{n-s}}{s\mu} = \dfrac{(\lambda)^n}{s!s^{n-s}} & \text{for } n = s, s+1, \ldots.. \end{cases} \qquad (3.19)$$

Consequently, if $\lambda < s\mu;\ \therefore \rho = \frac{\lambda}{s\mu}$ $\quad (utilisation\ factor) \quad (\rho < 1)$

$$P_0 = \frac{1}{1 + \sum_{n=1}^{s-1} \frac{\left(\frac{\lambda}{\mu}\right)^n}{n!} + \frac{\left(\frac{\lambda}{\mu}\right)^s}{s!} \sum_{n=1}^{s-1} \frac{\left(\frac{\lambda}{\mu}\right)^{n-s}}{s\mu!}}$$

If n=0 term in the last simulation yields the correct value of 1, n! = 1

$$P_0 = \frac{1}{\sum_{n=0}^{s-1} \frac{\left(\frac{\lambda}{\mu}\right)^n}{n!} + \frac{\left(\frac{\lambda}{\mu}\right)^s}{s!} \cdot \left(\frac{1}{1-\lambda/s\mu}\right)} \tag{3.20}$$

Thus, substituting equation (3.19) into equation (3.14) gives idle probability of the system:

$$P_n = \begin{cases} \frac{\left(\frac{\lambda}{\mu}\right)^n}{n!} P_0 & \text{if } 0 \leq n \leq s \\ \frac{(\lambda)^n}{s! s^{n-s}} P_0 & \text{if } n \geq s \end{cases} \tag{3.21}$$

P_n is the probability of n entity in the system. The following equations were adopted from (Trani, 2011).

$$L = \rho P_0 \frac{(\lambda/\mu)^s}{s!(1-\rho)^2} + \lambda/\mu \tag{3.22}$$

$$L_q = \rho P_0 \frac{(\lambda/\mu)^s}{s!(1-\rho)^2} \tag{3.23}$$

$$W_q = \frac{L_q}{\bar{\lambda}} \tag{3.24}$$

$$W = \frac{L}{\bar{\lambda}} = W_q + 1/\lambda \tag{3.25}$$

According to Blumenfeld (2001) equation (3.23 and 3.24) could be stated in approximate form as follows:

$$L_q = \frac{\rho^{\sqrt{2(s+1)}}}{1-\rho} \tag{3.26}$$

$$W_q = \frac{\rho^{\sqrt{2(m+1)-1}}}{\mu(1-\rho)} \tag{3.27}$$

However, the probability distribution of waiting time is given by Hillier and Liebermann, (2001) as follows:

$$P(W > t) = e^{-\mu t}\left[1 + \frac{P_0\left(\frac{\lambda}{\mu}\right)^s}{s!(1-\rho)}\left(\frac{1-e^{-\mu t(s-1-\frac{\lambda}{\mu})}}{s-1-\frac{\lambda}{\mu}}\right)\right] \quad (3.28a)$$

If $s - 1 - \frac{\lambda}{\mu} = 0$, then we have:

$$\frac{1-e^{-\mu t(s-1-\frac{\lambda}{\mu})}}{s-1-\frac{\lambda}{\mu}} = \mu t$$

$$P(W > t) = e^{-\mu t}\left[1 + \frac{P_0\left(\frac{\lambda}{\mu}\right)^s}{s!(1-\rho)}\ (\mu t)\right] \quad (3.28b)$$

The equation 3.19-3.28 were adopted equation for the modelling of MS approach in which arrival and departure rate of passengers with system service's level of performance are determined. The MS approach uses multi-channel or task in solving the problem at hand.

3.3 Statistical testing of the modelling

The arrival and departure assumes Poisson distribution as follows (Asmussen, 1987):

$$P(s) = \frac{e^{-\mu}\mu^n}{n!} \quad (3.29)$$

Where:

$P(s) =$ Probability of sample

$\mu =$ Mean value

$n =$ Expected value

The statistical testing is conducted on the modelling using Chi-square distributional assumption as given in equation (3.30):

$T > \chi^2{}_{\alpha,k-p-1} = T > \chi^2{}_{\alpha,3}$ Reject, otherwise accept it. (3.30)

$E(s) = P(s)N$ And this is expected sampling data (3.31)

$$\chi^2 = \Sigma \frac{(O_i - E_i)^2}{E_i} \tag{3.32}$$

Where:

$T =$ Statistical testing

k = number of rows

$p =$ Number of columns

$N =$ Total number of data

χ^2 = chi-square distribution

$O_i =$ Observed frequency

$E_i =$ Expected frequency

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Results

This section present the study results of queueing modelling in which minimising of waiting line of air transport services system in Nnamdi Azikiwe International Airport (NAIA) Abuja is predicted based on the performance of service level. Four major air transport companies in NAIA, Abuja were selected for the model. They include British Airways, Ethiopian Airline, Arik Airline Ltd and Aero Contractor.

Table 4.1 presents collected data of passengers for the year 2012 from British Airways for Abuja to London route.

Table 4.1 British airways passengers in 2012

Month	Passengers	Daily Average
January	5174	172
February	4484	149
March	4633	154
April	6125	204
May	5593	186
June	6266	209
July	6441	215
August*	6700	216
September *	-	-
October	5719	191
November	5665	189
December	6320	211

Total Monthly	56420	1880
Average	5642	188

(Source: Nigerian Civil Aviation Authority, NAIA, Abuja**)**

The table depicts an annual total passenger for the year 2012 of British Airways from Abuja to London. This gives a monthly average of 5642 which further gives a daily passenger average of 188

Table 4.2 is collected data of passengers for the year 2012 from Ethiopian Airline for Abuja to Addis Ababa with number of passengers/day at an average of 120.

Table 4.2 Ethiopian Airline Passengers in 2012

Month	**Passengers**	**Daily Average**
January	2170	72
February	2165	72
March	2872	96
April	3644	121
May	3495	117
June	4085	136
July	3910	130
August*	-	-
September*	-	-
October	4016	134
November	3815	127
December	5966	199
Total Monthly	36138	1204
Average	3614	120

(Source: Nigerian Civil Aviation Authority, NAIA, Abuja**)**

The table shows the compilation of passenger data for 2012 from Ethiopian Airline from Abuja to Addis Ababa only. Ethiopian Airline passenger average is 0.68% less than British Airways

Table 4.3 presents data collected of passengers for the year 2012 from Arik Airline Limited with daily passenger's average of 1573.

Table 4.3 Arik Airline Ltd Passengers in 2012

Month	Passengers	Daily Average
January	25015	834
February	39292	1310
March	42498	1417
April	42739	1425
May	42876	1429
June	44307	1477
July	53332	1778
August *	-	-
September *	-	-
October	61334	2045
November	61467	2049
December	59027	1968
Total Monthly	471887	15732
Average	47189	1573

(Source: Nigerian Civil Aviation Authority, NAIA, Abuja**)**

Table 4.3 represents the annual total of passengers for 2012 on Arik Airline for their different domestic routes originating from Abuja. Arik Airline has an approximate monthly average of 47189 passengers.

Table 4.4 shows the collected data of passengers for the year 2012 from Aero Contractor with expected number of passengers/day at an average of 1034.

Table 4.4 Aero Contractor Passengers in 2012

Month	Passengers	Daily Average
January	18821	627
February	25919	864
March	27753	925
April	28941	965
May	34994	1166
June	31779	1059
July	34093	1136
August*	35903	1158
September*	-	-
October	36074	1202
November	37017	1234
December	34894	1163
Total Monthly	310285	10341
Average	31029	1034

(Source: Nigerian Civil Aviation Authority, NAIA, Abuja**)**

The table represents an annual total for passengers on different domestic routes of Aero Contractors from Abuja for the year 2012. It has a monthly average of 31029 and daily average of 1034. This figure is about 5.4% less than Arik Airline’s passengers figure.

Table 4.5 presents the average of the passengers in the system for the year 2012.

Table 4.5 Average Number of Passenger in the System in 2012

Airline Company	Passengers	Daily Average	Arrival/hr
British Airways	5642	188	8
Ethiopian Airline	3614	120	5
Arik Airline	47189	1573	66
Aero Contractor	31029	1034	43
Total	87474	2915	122
Average	21869	729	31

(Source: Nigerian Civil Aviation Authority, NAIA, Abuja)

The table above shows the average numbers of passengers from the four different airlines under consideration. For the purpose of uniformity we considered ten months each from the data obtained. That means we did not consider the months on August and September in all the four airlines.

4.2 Simulation of queueing modelling

Figure 4.1 is the Matlab Graphical User Interface (GUI) program which is developed for the study and the installation of the software has the following procedure:

i. Installation of MATLAB 2009 version or above into personal computer system
ii. Loading the file called queue.fig onto screen
iii. Loading the basic parameter for analysis
iv. Pressing of calculate button to observe the simulated result
v. Pressing of quit button after being satisfied with the result

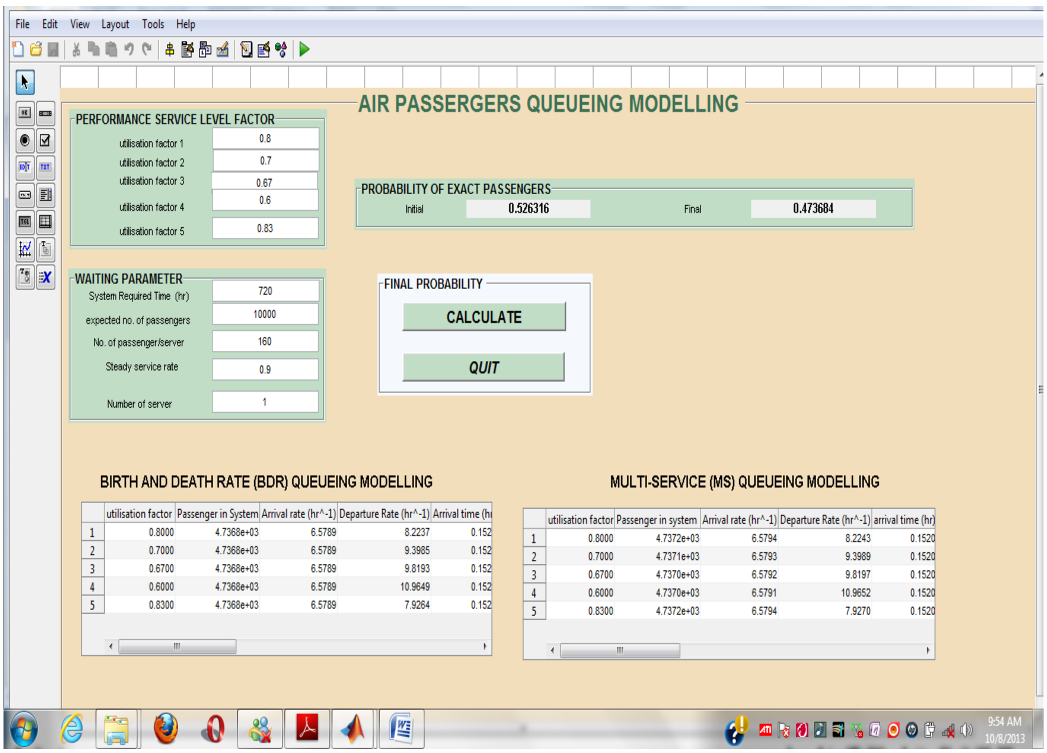

Figure 4.1 Graphical user interface for modelling NAIA system

GUI's calculate button displays the program result of Chapter Three (3) queueing modelling equation of both BDR and MS on pressing the button.

4.2.1 Basic parameters

The basic parameters that are required for this study are as given in Table 4.6 which gives values of the boundary conditions needed to make the model work.

Table 4.6 Boundary Condition

Parameters	Quantity
System utilisation factor	0.2, 0.25, 0.4, 0.6, 0.9
Time	30days
Estimated Monthly passengers	21869
Estimated Daily passengers	729
Server (Aircraft)	2
Server capacity	160
Service factor	0.5, 0.9

Table 4.6 shows the required basic parameters input to carry out the modelling

4.3 Arrival and departure rate of passengers with service factor of 0.5

The arrival rate and departure rate of passengers were modelled using the two method of queueing modelling discussed in chapter three.

4.3.1 The Birth and Death Rate Model for service factor of 0.5

The arrival rate of passengers into the NAIA, Abuja is modelled using Birth and Death Rate (BDR) Model at service factor of 0.5 per month is as given in Table 4.7.

Table 4.7 Arrival and Departure Rate Using BDR Model at 0.5 Service Factor

Utilisation Factor	0.2	0.25	0.4	0.6	0.9
Arrival rate/hr	10	10	10	10	10
Departure rate/hr	25	20	13	8	6

Arrival time (min)	5.93	5.93	5.93	5.93	5.93
Service time/passenger (min)	2.37	2.96	4.74	7.12	10.67
Server capacity	486	486	486	486	486

The table above shows the arrival and departure rate using BDR model at service factor 0.5, this gives a constant value of 10 and 486 for arrival time and server capacity respectively. The departure rate decreases as the utilisation factor increases.

4.3.2 The Multi Server Model for service factor of 0.5

The arrival rate of passengers into the NAIA, Abuja is modelled using Multi-Server (MS) Model at service factor of 0.5 per month as in Table 4.8 in which are expected values of the are obtained using the model.

Table 4.8 Arrival and Departure Rate Using MS Model at 0.5 Service Factor

Utilisation Factor	0.2	0.25	0.4	0.6	0.9
Arrival rate/hr	10	10	10	10	10
Departure rate/hr	25	20	13	8	6
Arrival time (min)	5.93	5.93	5.93	5.93	5.93
Service time/passenger (min)	2.37	2.96	4.74	7.12	10.67
Server capacity	243	243	243	243	243

The table above shows results obtained with the use of MS model at a service factor of 0.5. There is a decrease in server capacity of 243 when compared with BDR model of same service factor.

4.3.3 Statistical testing of arrival and departure rate at 0.5 service factor

It is observed that arrival/departure rate of the two models are the same except for server capacity in which BDR model is 486 and MS model is 243 at all utilisation factors as shown in Tables 4.7 and 4.8 respectively. Table 4.9 is the basic requirement for testing the model at service factor 0.5. It is observed that using BDR model requires more servers (aircraft) in comparison to MS model at the specified period of time. For instance, in modelling of 160 passengers per server, it is observed that BDR requires 3 servers while MS requires 2 servers. BDR model gives classical improvement of service level because double of the passenger of MS model would be served at specified period of time. The requirement of the model at a service factor of 0.5 was analysed as presented in Table 4.9. The expected arrival/departure at service factor of 0.5 is presented in Table 4.10.

Table 4.9 Requirement of Service Factor 0.5

Utilisation factor	**Arrival rate/hr**	**Departure rate/hr**	**P(Arrival)**	**P(Departure)**
0.2	10	25	0.125	0.00241
0.25	10	20	0.125	0.0286
0.4	10	13	0.125	0.106
0.6	10	8	0.125	0.0304
0.9	10	6	0.125	0.0087
Average	10	14		

Table 4.9 is the basic requirement for testing the model at service factor 0.5.

Table 4.10 Expected arrival and departure at Service Factor 0.5

Utilisation factor	Arrival rate/hr	Departure rate/hr	E(Arrival)	E(Departure)
0.2	10	25	6	0
0.25	10	20	6	2
0.4	10	13	6	8
0.6	10	8	6	2
0.9	10	6	6	0
Average	10	14		

The arrival rate, $\chi^2 = \frac{(10-6)^2}{6} + \frac{(10-6)^2}{6} + \frac{(10-6)^2}{6} + \frac{(10-6)^2}{6} + \frac{(10-6)^2}{6} = 13$

The departure rate, $\chi^2 = \frac{(20-2)^2}{2} + \frac{(13-8)^2}{8} + \frac{(8-2)^2}{2} = 183$

The null hypothesis criterion was used to analyse the model result at service factor of 0.5 and the result is presented in Table 4.11

Table 4.11 Criterion of Null Hypothesis at Service Factor 0.5

Criteria (α)	**0.05**	**0.025**	**0.01**	**0.005**
Significance level (α)	5%	2.5%	1%	0.5%
Confidence interval (1- α)	0.950	0.975	0.990	0.995
χ^2-Test (arrival)	13	13	13	13
χ^2-Test (departure)	183	183	183	183
$\chi^2{}_{\alpha,3}$ (chi- from Table)	7.81	9.35	11.34	12.84
Null Hypothesis (arrival)	Reject	Reject	Reject	Accept

Null Hypothesis (departure)	Reject	Reject	Reject	Reject

The result in Table 4.11 shows that both the arrival and departure rate should be within the range of 0-13 passengers per hour from the tested criterion, otherwise it will be rejected.

4.4 Arrival and departure rate of passengers with service factor of 0.9

The modelling result of arrival rate of passengers in the NAIA, Abuja system by Birth and Death Rate (BDR) Model at service factor of 0.9 per month was also done.

4.4.1 The Birth and Death Rate model for service factor of 0.9

The arrival rate of passengers into the NAIA, Abuja is modelled using Birth and Death Rate (BDR) Model at service factor of 0.9 per month is as given in Table 4.12.

Table 4.12 Arrival and Departure Rate Using BDR Model at 0.9 Service Factor

Utilisation Factor	**0.2**	**0.25**	**0.4**	**0.6**	**0.9**
Arrival rate/hr	14	14	14	14	14
Departure rate/hr	36	29	18	12	8
Arrival time (min)	4.17	4.17	4.17	4.17	4.17
Service time/passenger (min)	1.67	2.09	3.34	5.00	7.51
Server capacity	690	690	690	690	690

4.4.2 The Multi Server model for service factor of 0.9

The modelling result of arrival rate of passengers in the NAIA, Abuja system by Multi-Server (MS) Model at service factor of 0.9 per month is shown in Table 4.13.

Table 4.13 Arrival and Departure Rate Using MS Model at 0.9 Service Factor

Utilisation Factor	**0.2**	**0.25**	**0.4**	**0.6**	**0.9**

Arrival rate/hr	14	14	14	14	14
Departure rate/hr	36	29	18	12	8
Arrival time (min)	4.17	4.17	4.17	4.17	4.17
Service time/passenger (min)	1.67	2.09	3.34	5.00	7.51
Server capacity	345	345	345	345	345

4.4.3 Statistical testing of arrival and departure rate at 0.9 service factor

The model result at service factor of 0.9 are the same except for server capacity in which BDR model is 690 and MS model is 345 at all utilisation factors as shown in Tables 4.12 and 4.13 respectively. Table 4.14 is the basic requirement for testing the model at service factor 0.9. Modelling of 160 passengers per server gives BDR model to require 4 servers while MS model to require 2 servers. BDR model gives classical improvement of service level because double of the passenger of MS model would be served at specified period of time. The expected arrival/departure at service factor of 0.9 is presented in Table 4.15.

Table 4.14 Requirement of Service Factor 0.9

Utilisation factor	Arrival rate/hr	Departure rate/hr	P(Arrival)	P(Departure)
0.2	14	36	0.095	0.00081

0.25	14	29	0.095	0.02
0.4	14	18	0.095	0.075
0.6	14	12	0.095	0.012
0.9	14	8	0.095	0.00071
Average	14	21		

Table 4.15 Expected arrival and departure at Service Factor 0.9

Utilisation factor	Arrival rate/hr	Departure rate/hr	E(Arrival)	E(Departure)
0.2	14	36	7	0
0.25	14	29	7	2
0.4	14	18	7	8
0.6	14	12	7	1
0.9	14	8	7	0
Average	14	21		

The arrival rate, $\chi^2 = \frac{(14-7)^2}{7} + \frac{(14-7)^2}{7} + \frac{(14-7)^2}{7} + \frac{(14-7)^2}{7} + \frac{(14-7)^2}{7} = 35$

The departure rate, $\chi^2 = \frac{(29-2)^2}{2} + \frac{(18-8)^2}{8} + \frac{(12-1)^2}{1} = 498$

The result in Table 4.16 shows that both arrival and departure rate should be within the range of 0-13 passengers per hour even at service factor of 0.9 after testing the modelling using chi-distributional assumption. Considering the result stated in Table 4.5, only the two international airlines were able to meet this standard. The arriving passengers of the two local airlines do not satisfy this condition because there more travellers within nation and over-utilisation of server would experience. For better service of the system average arrival rate of 31 passengers per hour would be rejected if the local company are to be using only 2 servers (aircraft) for her services.

The null hypothesis criterion was also used to analyse the model result at service factor of 0.9 and the result is presented in Table 4.16

Table 4.16 Criterion of Null Hypothesis at Service Factor 0.9

Criteria (α)	**0.05**	**0.025**	**0.01**	**0.005**
Significance level (α)	5%	2.5%	1%	0.5%
Confidence interval (1- α)	0.950	0.975	0.990	0.995
χ^2-Test (arrival)	35	35	35	35
χ^2-Test (departure)	498	498	498	498
${\chi^2}_{\alpha,3}$ (chi- from Table)	7.81	9.35	11.34	12.84
Null Hypothesis (arrival)	Reject	Reject	Reject	Reject
Null Hypothesis (departure)	Reject	Reject	Reject	Reject

The result in Table 4.16 shows that both arrival and departure rate should be within the range of 0-13 passengers per hour even at service factor of 0.9 after testing the modelling using chi-distributional assumption

4.5 Graphs of arrival and departure rate

The effects of the choice of service factor for the models were plotted in graphical forms to show their significance. Figures 4.2 and 4.3 show the effect of service factor on both arrival and departure rate respectively based on expected passengers in the NAIA system.

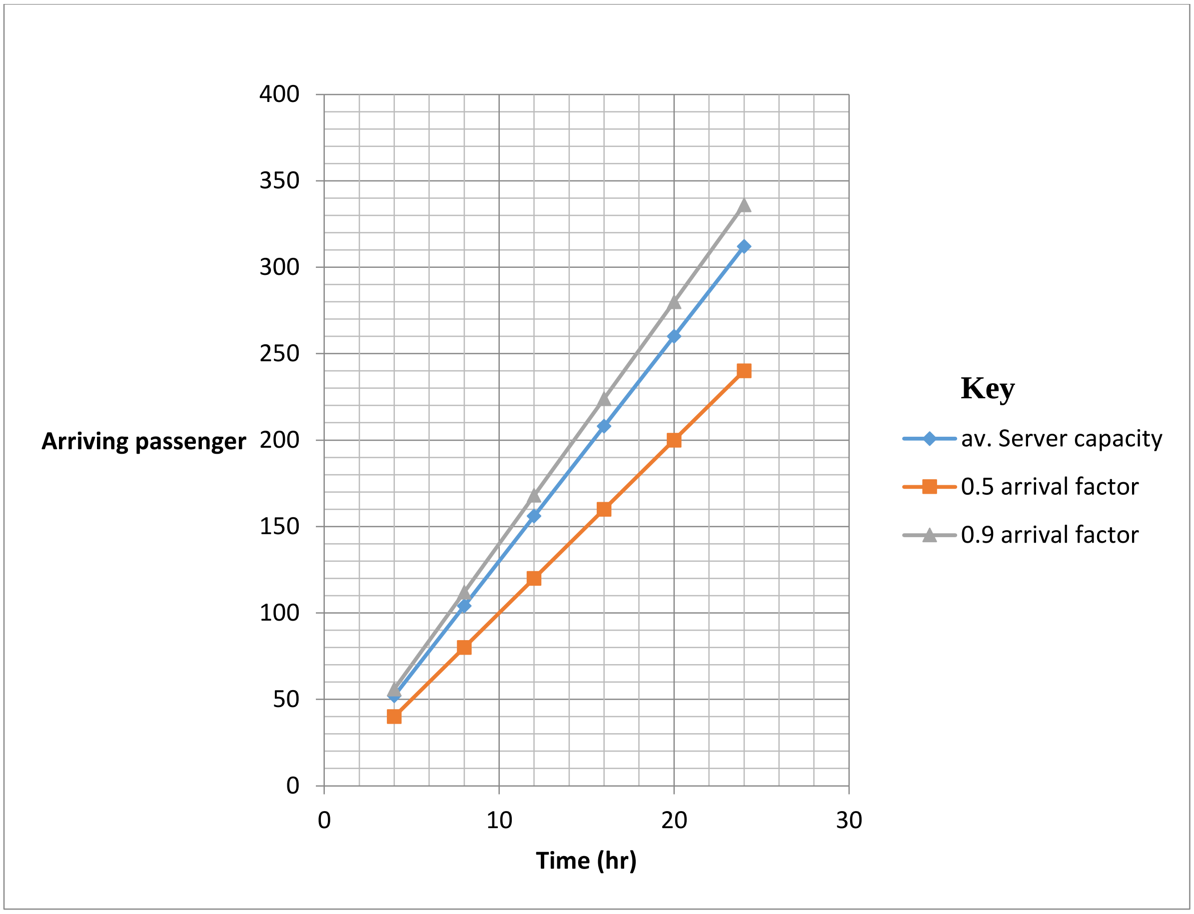

Figure 4.2 Effect of service factor on arrival rate

In Figure 4.2, the maximum server capacity per day was 312 passengers for both BDR and MS Model. The service factor 0.5 (BDR and MS Model) had maximum arrival rate of passenger of 240 per day while service factor 0.9 (BDR and MS Model) has 312 passengers on arrival per day.

In Figure 4.3, the departing passenger was estimated with different service factors in which using service factor of 0.5 (BDR and MS Model) with utilisation factor of 0.2 had maximum passenger leaving the system with 25 per hour. Using service factor of 0.9 (BDR and MS Model), number of passengers increases to 36 per hour with utilisation factor 0.2. In Tables 4.10 and 4.14 it was observed that the average departing per hour was 10 passengers on using service factor 0.5 and 21 passengers with service factor 0.9.

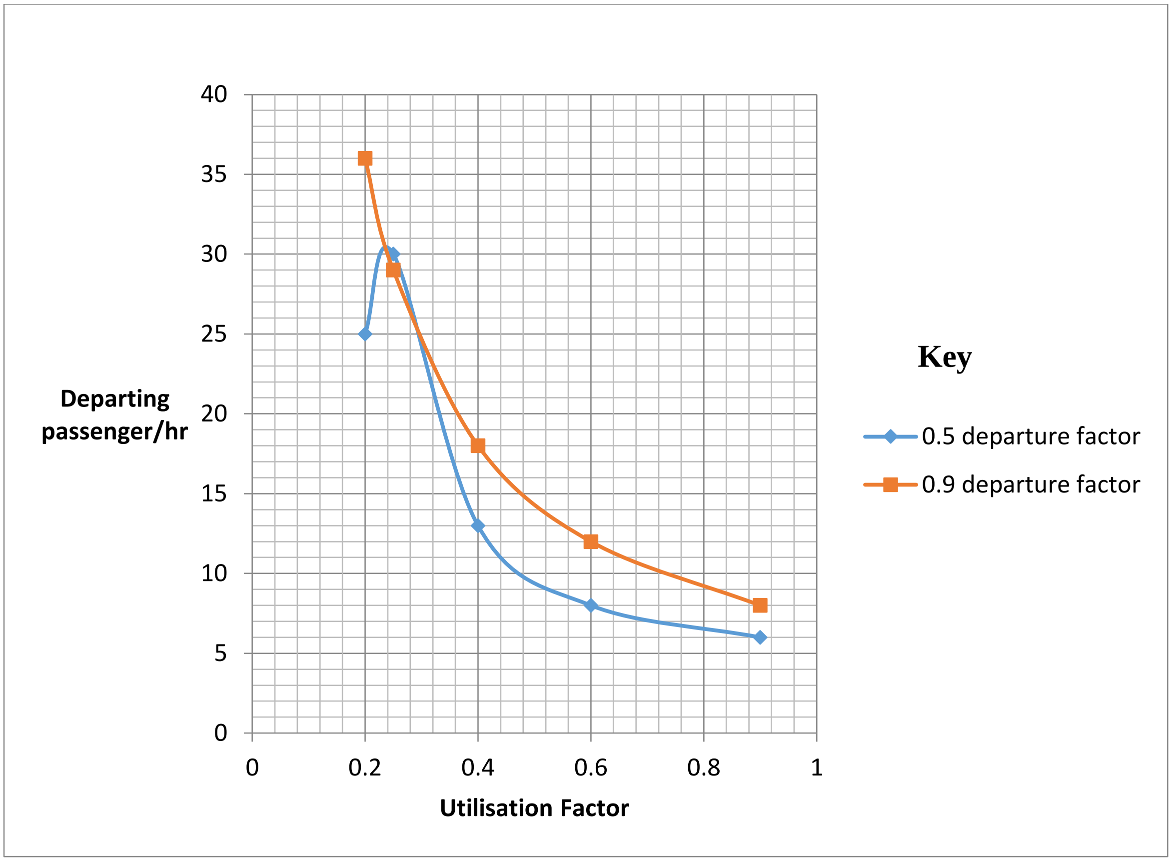

Figure 4.3 Effect of Utilisation Factor on Departure Rate

4.6 Expected number of passengers in system

Tables 4.17 and 4.18 showed the result of expected number of passengers into aviation system. The result is based on arrival and departure rate in section 4.3 using the Birth and Death Rate (BDR) and Multi-Server (MS) Models respectively at a service factor of 0.5 per month.

Table 4.17: Expected Passengers Using BDR Model at 0.5 Service Factor

Utilisation Factor	0.2	0.25	0.4	0.6	0.9
Capacity/day	320	320	320	320	320
Expected capacity/day	486	486	486	486	486
Reserved passengers	-166	-166	-166	-166	-166
Waited Passenger/month	7287	7287	7287	7287	7286
Expected passenger/month	7288	7288	7288	7288	7288

The results are estimated between initial probability of 0.6667 and final probability of 0.3333 of expected monthly passengers of 21869 from initial evaluation. The initial probability is the probability of possible expected passenger while final probability is the probability of total number of passenger that succeeded in entering the aviation system from expected passenger.

Table 4.18: Expected Passengers Using MS Model at 0.5 Service Factor

Utilisation Factor	0.2	0.25	0.4	0.6	0.9
Capacity/day	320	320	320	320	320
Expected capacity/day	243	243	243	243	243
Reserved passengers	77	77	77	77	77
Waited Passenger/month	7287	7287	7287	7287	7287
Expected passenger/month	7288	7288	7288	7288	7289

The result showed the expected delay rate to be 50% less than the BDR at 0.5

Tables 4.19 and 4.20 are expected passengers into aviation system of NAIA, Abuja which is based on arrival and departure rate in section 4.4 using Birth and Death Rate (BDR) and Multi-Server (MS) Models respectively at service factor of 0.9 per month.

Table 4.19 Expected Passengers Using BDR Model at 0.9 Service Factor

Utilisation Factor	**0.2**	**0.25**	**0.4**	**0.6**	**0.9**
Capacity/day	320	320	320	320	320
Expected capacity/day	690	690	690	690	690
Reserved passengers	-370	-370	-370	-370	-370
Waited Passenger/month	10356	10356	10355	10355	10354
Expected passenger/month	10356	10356	10356	10356	10356

The results are estimated between initial probability of 0.5263 and final probability of 0.4737 of expected monthly passengers of 21869 from initial evaluation.

Table 4.20 Expected Passengers Using MS Model at 0.9 Service Factor

Utilisation Factor	**0.2**	**0.25**	**0.4**	**0.6**	**0.9**
Capacity/day	320	320	320	320	320
Expected capacity/day	345	345	345	345	345
Reserved passengers	-25	-25	-25	-25	-25
Waited Passenger/month	10355	10355	10355	10355	10355
Expected passenger/month	10356	10356	10356	10356	10357

The expected passengers using the MS Model at 0.9 service factor showed an appreciable decrease in the number of waiting passengers.

4.7 Performance of service level of the system

The passengers entering and leaving the system was analysed based on aforementioned model and the system was tested for based on performance of the service time as presented in Table 4.21 through Table 4.24.

Table 4.21: Service Level's Performance using BDR Model at 0.5 Factor

Utilisation Factor	0.2	0.25	0.4	0.6	0.9
Service time/trip (hr)	12.65	15.81	15.81	15.81	15.81
Delay time/trip (hr)	11.35	8.19	-1.29	-13.94	-32.91
Total service time/trip (hr)	24	24	14.52	1.87	-17.10
Percent delay (%)	47.29	34.13	0	0	0
Capacity/trip	320	320	320	320	320
Waited Passenger/month	7287	7287	7287	7287	7286
Completion of Service in days	22.77	22.77	22.77	22.77	22.77

Table 4.22: Service Level's Performance using MS Model at 0.5 Factor
Table 4.23 Service Level's Performance using BDR Model at 0.9 Factor

Utilisation Factor	0.2	0.25	0.4	0.6	0.9
Service time/trip (hr)	12.65	15.81	25.29	37.94	56.90
Delay time/trip (hr)	11.35	8.19	-1.29	-13.94	-32.91
Total service time/trip (hr)	24	24	24	24	24
Percent delay (%)	47.29	34.13	0	0	0
Capacity/trip	320	320	320	320	320
Waited Passenger/month	7287	7287	7287	7287	7287
Completion of Service in days	32.36	32.36	32.60	32.60	32.60

Table 4.24

Service Level's Performance using MS Model at 0.9 Factor

Utilisation Factor	0.2	0.25	0.4	0.6	0.9
Service time/trip (hr)	8.90	11.12	11.12	11.12	11.12
Delay time/trip (hr)	15.10	12.88	6.20	-2.70	-16.05
Total service time/trip (hr)	24	24	17.32	8.42	-4.93
Percent delay (%)	62.92	53.67	35.80	0	0
Capacity/trip	320	320	320	320	320
Waited Passenger/month	10356	10356	10355	10355	10354
Completion of Service in days	32.36	32.36	32.60	32.60	32.60

Utilisation Factor	0.2	0.25	0.4	0.6	0.9
Service time/trip (hr)	8.90	11.12	17.80	26.69	40.04
Delay time/trip (hr)	15.10	12.87	6.20	-2.70	-16.04
Total service time/trip (hr)	24	24	24	24	24
Percent delay (%)	62.92	53.62	25.8	0	0
Capacity/trip	320	320	320	320	320
Waited Passenger/month	10355	10355	10355	10355	10355

Completion of Service in days	22.77	22.77	22.77	22.77	22.77

4.7.1 Server per day

The model was based on 2 servers per day. The result is estimated based on arrival/departure rate of 13 passengers as in Tables 4.11 (0.5 service factor) and 4.16 (0.9 service factor) and with this possibility a server has capacity of 156 passengers. The modelling result of 156 passengers was adopted for presenting the require server in Table 4.25 presents required server for each airline operator. From the data collected, the average number of passengers required per server (aircraft) was 160 but on applying the BDR and MS models, require number of passengers per server are 156.

Table 4.25 Average Number of Passenger in the System

Airline Industry	**Daily Passenger**	**Required server**
British Airways	188	2
Ethiopian Airline	120	1
Arik Airline	1573	10
Aero Contractors	1034	7
Average	729	5

The table shows the number of servers required by each airline based on passenger capacity for efficient services

Figure 4.4 depicts effect of servers on passenger on board. In the graph, Airline with above 1000 daily passenger requires more than 5 aircraft for its operations.

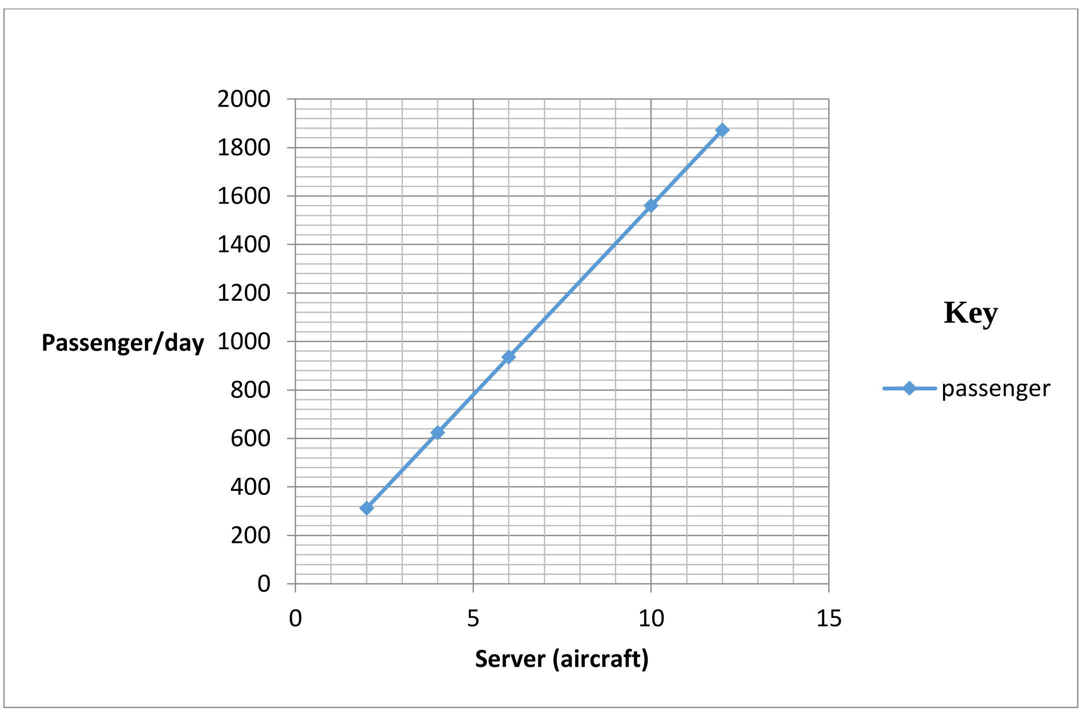

Figure 4.4 Expected passengers per Server

4.8 Discussion of results

Tables 4.1-4.4 are the collected data of passengers in four different airline operators which are international and local Airlines. The international operators included British Airways and Ethiopian Airline. The local operators include Arik Airline and Aero Contractors.

In Table 4.5, the British Airways had an average passenger of 188 per day. Ethiopian Airline had average passenger of 120 per day. Arik Airline has average passenger of 1573 daily while Aero Contractors has average daily passenger of 1034. The expected passengers per day into the system were 729 with arrival rate of 31 passengers per hour.

Table 4.6 specified the boundary condition for modelling the waiting line of NAIA, Abuja with monthly passenger's rate of 21869 which would be ready for service every month. The result show that most airline operators has two aircrafts or servers per day based on service factors of 0.5 and 0.9 and different utilisation factors of 0.2, 0.25, 0.4, 0.6 and 0.9 respectively.

In Table 4.11, the hypothesis of 31 passengers arriving per hour was tested. The acceptable hypothesis is passengers arriving within ranges of 1 to 13 per hour. The arriving passengers at 5% significance satisfied the condition at service factor of 0.5. Also, both arrival and departure rate of passengers were rejected at service factor of 0.9 because all passengers were above 13. Meeting this condition required each airline to be operating with more than 2 aircrafts per day.

In Figure 4.2, both models, BDR and MS, showed that arriving passengers required service factor of 0.9 per hour. This factor would meet the demands ready for service per day. This was because the 310 passengers on the waiting line required service factor of 0.9 that met the demand of 340 passengers per day. On the other hand, service factor of 0.5 met demand of just 240 passengers per day and therefore 70 passengers would be delayed per day for necessary service.

The service factor of 0.9 in Figure 4.3 with utilisation factor of 0.25, 0.4 and 0.6 were very effective on average for completing service of 21 passengers per hour.

In section 4.7, 21869 passengers needed the service based on collected data but on the services requirement of 0.5 using both BDR and MS models only 7287 would meet the demand. Using service factor of 0.9, 10355 passengers would meet the demand based on the two models.

The service level would be improved because there was no delay using the service factor of 0.5 and 0.9 with utilisation factor of 0.4, 0.6 and 0.9 based on BDR model. The service level would be somewhat delayed with the service factor of 0.5 and 0.9 with utilisation factor of 0.4, 0.6 and 0.9 based on MS model. If the airline operators in the system are to meet current demand the international operators requires single aircraft per day while the local requires up to 5 aircrafts per day as are given in Table 4.25.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The foregoing presented helps in predicting impact of performance of service level. The modelling would help to explore alternatives such as BDR model or MS model that sensitize parameter and values. The model has helped in assessing the performance of the systems by minimising the waiting line of air transport services system of the airport. Meeting the current demand of passenger in NAIA Abuja requires each airline to be operating with minimum of 6 aircrafts for daily service especially local airline industry. The delay would be minimised using 5 aircrafts per day than the current average usage of 2 aircrafts per day if the demands of 21869 passengers are to be met per month. The NAIA will be reliable and available with better services at 5% significance level based on service factor of 0.9 with utilisation factor of 0.4, 0.6 and 0.9.

The service factor of 0.5 using both BDR and MS models meets demand of 7287 passengers per month. Using service factor of 0.9, demand of 10355 passengers are met based on the two models. It is estimated that 67% of the service is delayed to meet 21869 status using service factor of 0.5 and 53% of the service is delayed using service factor 0.9.

However, international airlines have better service because they are operated within daily capacity of 312 passengers per day. In the modelling, the existing aircraft in NAIA Abuja is over utilised with more than 50% of current capacity which affect the reliability and availability of the system.

5.2 Recommendations

This study has made some observations on the subject matter. Based on these observations, the following recommendations are hereby proffered that could help to remedy or ameliorate the situation.

1. Further work needs to be done to investigate the effect of utilisation factor on aircraft maintenance to determine the safety levels.

2. A research work on predictive maintenance and reliability analysis of aircraft facility and components will be necessary.

3. Optimisation modelling of waiting line in airline industry

4. Modelling of effect of service factor on airline waiting line

5. Application of BDR and MS models to minimise delay in other local and international airports in Nigeria

6. It is hereby recommended that the relevant organisations such as Federal Inland Revenue Services, Federal Airport Authority of Nigeria, and State Security Services should investigate the issues of under-recording and under declaration of the correct statistics of passenger patronage of Airlines using Nigerian Airports for tax evasion. This will not only avail researchers in the sector with accurate data but would most significantly enable proper estimation and collection of taxes from industry operators for higher revenues that would aid periodic upgrading of airport facilities to meet the standards in the developed countries.

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APPENDIX

CHI SQUARE DISTRIBUTION TABLE

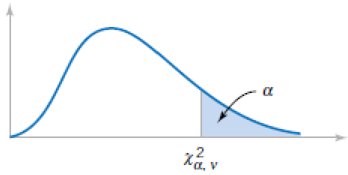

Table III Percentage Points $\chi^2_{\alpha,\nu}$ of the Chi-Squared Distribution

ν \ α	.995	.990	.975	.950	.900	.500	.100	.050	.025	.010	.005
1	.00+	.00+	.00+	.00+	.02	.45	2.71	3.84	5.02	6.63	7.88
2	.01	.02	.05	.10	.21	1.39	4.61	5.99	7.38	9.21	10.60
3	.07	.11	.22	.35	.58	2.37	6.25	7.81	9.35	11.34	12.84
4	.21	.30	.48	.71	1.06	3.36	7.78	9.49	11.14	13.28	14.86
5	.41	.55	.83	1.15	1.61	4.35	9.24	11.07	12.83	15.09	16.75
6	.68	.87	1.24	1.64	2.20	5.35	10.65	12.59	14.45	16.81	18.55
7	.99	1.24	1.69	2.17	2.83	6.35	12.02	14.07	16.01	18.48	20.28
8	1.34	1.65	2.18	2.73	3.49	7.34	13.36	15.51	17.53	20.09	21.96
9	1.73	2.09	2.70	3.33	4.17	8.34	14.68	16.92	19.02	21.67	23.59
10	2.16	2.56	3.25	3.94	4.87	9.34	15.99	18.31	20.48	23.21	25.19
11	2.60	3.05	3.82	4.57	5.58	10.34	17.28	19.68	21.92	24.72	26.76
12	3.07	3.57	4.40	5.23	6.30	11.34	18.55	21.03	23.34	26.22	28.30
13	3.57	4.11	5.01	5.89	7.04	12.34	19.81	22.36	24.74	27.69	29.82
14	4.07	4.66	5.63	6.57	7.79	13.34	21.06	23.68	26.12	29.14	31.32
15	4.60	5.23	6.27	7.26	8.55	14.34	22.31	25.00	27.49	30.58	32.80
16	5.14	5.81	6.91	7.96	9.31	15.34	23.54	26.30	28.85	32.00	34.27
17	5.70	6.41	7.56	8.67	10.09	16.34	24.77	27.59	30.19	33.41	35.72
18	6.26	7.01	8.23	9.39	10.87	17.34	25.99	28.87	31.53	34.81	37.16
19	6.84	7.63	8.91	10.12	11.65	18.34	27.20	30.14	32.85	36.19	38.58
20	7.43	8.26	9.59	10.85	12.44	19.34	28.41	31.41	34.17	37.57	40.00
21	8.03	8.90	10.28	11.59	13.24	20.34	29.62	32.67	35.48	38.93	41.40
22	8.64	9.54	10.98	12.34	14.04	21.34	30.81	33.92	36.78	40.29	42.80
23	9.26	10.20	11.69	13.09	14.85	22.34	32.01	35.17	38.08	41.64	44.18
24	9.89	10.86	12.40	13.85	15.66	23.34	33.20	36.42	39.36	42.98	45.56
25	10.52	11.52	13.12	14.61	16.47	24.34	34.28	37.65	40.65	44.31	46.93
26	11.16	12.20	13.84	15.38	17.29	25.34	35.56	38.89	41.92	45.64	48.29
27	11.81	12.88	14.57	16.15	18.11	26.34	36.74	40.11	43.19	46.96	49.65
28	12.46	13.57	15.31	16.93	18.94	27.34	37.92	41.34	44.46	48.28	50.99
29	13.12	14.26	16.05	17.71	19.77	28.34	39.09	42.56	45.72	49.59	52.34
30	13.79	14.95	16.79	18.49	20.60	29.34	40.26	43.77	46.98	50.89	53.67
40	20.71	22.16	24.43	26.51	29.05	39.34	51.81	55.76	59.34	63.69	66.77
50	27.99	29.71	32.36	34.76	37.69	49.33	63.17	67.50	71.42	76.15	79.49
60	35.53	37.48	40.48	43.19	46.46	59.33	74.40	79.08	83.30	88.38	91.95
70	43.28	45.44	48.76	51.74	55.33	69.33	85.53	90.53	95.02	100.42	104.22
80	51.17	53.54	57.15	60.39	64.28	79.33	96.58	101.88	106.63	112.33	116.32
90	59.20	61.75	65.65	69.13	73.29	89.33	107.57	113.14	118.14	124.12	128.30
100	67.33	70.06	74.22	77.93	82.36	99.33	118.50	124.34	129.56	135.81	140.17

ν = degrees of freedom.