American Journal of Mechanical Engineering, 2015, Vol. 3, No. 2, 63-71
Available online at http://pubs.sciepub.com/ajme/3/2/5

DOI:10.12691/ajme-3-2-5

BDR Modelling of Passenger Queues at Nnamdi Azikiwe International Airport, Abuja, Nigeria

Nuhu A. Ademoh*, Anosike Esther Nneka*

Department Of Mechanical Engineering, Federal University of Technology, Minna, Nigeria
*Corresponding author: Nuhuadam@Yahoo.Com, stanosike@yahoo.com

Received January 06, 2015; Revised February 09, 2015; Accepted May 04, 2015

Abstract A nation's air industry is vital to her development as it offers inter-linkages for all the economic sectors. International airport of a country's capital city acts as gateway and gives lots of first hand impression of her integrity. Nnamdi Azikiwe International Airport, the gateway to Nigeria's capital city, Abuja, faces problem of passengers queuing for boarding, departure and arrival at different rates due to ineffectiveness in management of travelers using the facility. This never gave travelers, particularly international passengers a good impression of the country. As part solution, this study developed a queuing model using Birth and Death Rate approach to simulate the problem and find enduring solution. Four air transport companies consisting two each of domestic and international operators that frequently use the facility was adopted as study samples. Their 2013 flight data were used to simulate model for validation. Result showed that in order to meet current daily passenger need each domestic airline required at least 5 aircrafts. Each international airline required one additional aircraft to effectively service the monthly average demands of 21,863 passengers. The system required 0.5 service factor and utilization factors of 0.4, 0.6 and 0.9 at 5% significance.

Keywords: *birth and death rate, modeling, airport, waiting line, service factor*

Cite This Article: Nuhu A. Ademoh, and Anosike Esther Nneka, "BDR Modelling of Passenger Queues at Nnamdi Azikiwe International Airport, Abuja, Nigeria." *American Journal of Mechanical Engineering*, vol. 3, no. 2 (2015): 63-71. doi: 10.12691/ajme-3-2-5.

1. Introduction

Nnamdi Azikiwe International Airport (NAIA) is located at Abuja, Nigeria's capital city. It operates both domestic and international terminals. As a gate way to Nigeria's capital, it experiences massive traffic of people arriving to and departing out of the facility for official, commercial, business and personal activities. Though the industry has witnessed tremendous growth in the past years, continuous population growth/urbanization with its attendant increase in official and other activities has drastically raised the demand for air transport services in Nigeria (Odufuwa, 2008 and Ogwude, 1986). This has put pressure on the industry for state of art logistic management system. Inadequacy in availability of such systems has forced the industry to face problems of travelers queuing for boarding, departures and arrivals at NAIA, Abuja. Queuing in the airport has become very complex to solve manually due to the patterns and irregularities in the arrivals, departures and service process. As the system has less ability to promptly service the arrivals and departures rowdiness/randomness occur resulting to some waiting lines. According to Mehri et al (2009), queuing manifests at arrival, service facilities and actual waiting lines. These can be modeled for solutions based on performance evaluation metrics that include flight delays, cancellations and passenger delays (Subramanian 2007).

In NAIA system waiting is consequent to irregularity in service for large user's demands for cargo handling, ticket clearance, departure and arrival. Queuing for service is made worse during airlifting of hajj pilgrims by which time passengers sleep in Nigerian airports awaiting flight. Aftermath of the cumbersome services is that most travelers through NAIA are stressed up and uncomfortable giving bad image to the Nigerian Civil Aviation Authority (NCAA). As a part solution to this problem, Ademoh and Anosike (2014) used Multi Server approach to develop queuing modeling to predict demands of travelers using NAIA and recommended that more aircrafts were needed to effectively serve both its international and domestic wings.

The main aim of this work is to develop an alternative queuing modeling using the birth and death rate (BDR) approach to predict and solve waiting line problem at Nnamdi Azikiwe International Airport, Abuja. The objectives are to adopt historical data used in previous work by Ademoh and Anosike (2014) to simulate the newly developed BDR queuing modeling for prediction of passengers' arrival and departure rates; determine service level of performance; harmonize passenger arrival/departure handling facilities and to cross compare the result with that of previous related work. The significance of the work as a follow-up to work of Ademoh and Anosike (2014) is that it would confirm the practical solution to the waiting line problem of NAIA and to justify the better method of the two modeling approaches to precisely solve the problem so as to encourage its use for solving similar problems at other airports.

2. Materials and Methods

2.1. Materials

Historical data on waiting line at NAIA, Abuja for ten months of the year of the study and used as main the material for the study. This data was categorized and treated as:

1. Case subsystem
2. Size of calling population; the passengers
3. System capacity.

2.1.1. Case Study Description

Similar case study; Nnamdi Azikiwe International Airport, Abuja, modeled with Multi Server method by Ademoh and Anosike (2014) was also chosen. The subsystem is BDR modeling of the same NAIA, Abuja and simulating it with historical data obtained from the under-listed companies for validation:

(a) Arik Airline Limited (AAL)
(b) British Airways (BA)
(c) Ethiopian Airline (EA)
(d) Aero Contractors (AC)

Arik Airline Ltd and Aero Contactors are local service providers while British Airways and Ethiopian Airline are international service companies used for simulating the new model for comparative performance analysis. They are major and most consistent airlines involved in passenger airlifting at NAIA.

2.1.2. Size of Calling Population

This was considered as infinite due to the arrival patterns taken from a large passenger population.

2.1.3. System Capacity

This was based on the total number of waiting room passengers and available servers (number of airplanes).

2.1.4. System Characteristics

They were:

(a) Arrival process: provided entry procedure
(b) Service process: provided the system operational procedure
(c) Number of channels: i.e. systematic way of solving the problem
(d) Queue discipline: The pattern for solving waiting line problem

2.1.5. Single Queue with Parallel Servers

Table 1. Queuing 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)

It is a type of model that deals with study of a single queue in equilibrium. There is more than one server and each server provides same type of service or provides identical parallel service. Passengers wait in one queue until one of the service channels is ready to take them in for servicing at the rate of a customer at a time per server. Each characteristic is shown in Table 1.

2.2. Methods

The Birth and Death Rate modeling was developed to predict the arrival and departure rates based on the performance of service level, stochastic/probabilistic processes, exponential and Chi-square distributions. As this work is a follow up to the work of Ademoh and Anosike (2014), similar distribution assumptions were used to enable close comparison. According to Mehri et al (2009), study assumptions are that;

(a) Arrivals come from an infinite or a very large population.
(b) Arrivals are Poisson distributed.
(c) Arrivals are treated on a first in first out basis and that passengers do not balk or renege; i.e. that an arriving passenger is patient and waits in the queue until he is served and that he does not switch between lines. People that balk are those who refuse to join queue. People that renege are those who enter the queue but later leave due to impatience. As the situation in queuing processes may be complicated by these and more issues, queuing theory//waiting lines analysis are modified as follows:

(a) Service time follows negative exponential
(b) Distributions are constant
(c) Average service rate is faster than average arrival rate.

2.2.1. Performance Characteristics of Queuing System

Blumenfeld (2001) adopted Little's law on performance of queue system as represented in equations 2.1 and 2.2:

$$L_q = \lambda W_q \qquad (2.1)$$

$$L = \lambda W \qquad (2.2)$$

$$L = L_q + \lambda / \mu \qquad (2.3)$$

$$L = W_q + 1/\mu \qquad (2.4)$$

$$L = \sum_{n=0}^{\infty} nP_n \qquad (2.5)$$

$$L_q = \sum_{n=0}^{\infty} (n-s)P_n \qquad (2.6)$$

$$\rho = \frac{\lambda}{s\mu} \quad (\rho < 1) \qquad (2.7)$$

Where:- n = number of passengers in 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 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 a queue plus the service time)

$N(t)$ = total number of passengers in 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 inter-arrival time
μ = service rate per unit server (number of passengers served per unit time)
$1/\mu$ = mean service time
ρ = traffic intensity.

2.2.2. Birth-and-death Rate Modeling Development

In accordance with the work of Hillier and Liebermann (2001), birth refers to arrival of a new customer into queuing system. Death refers to departure of served customer. An illustration of queuing system is in Figure 1.

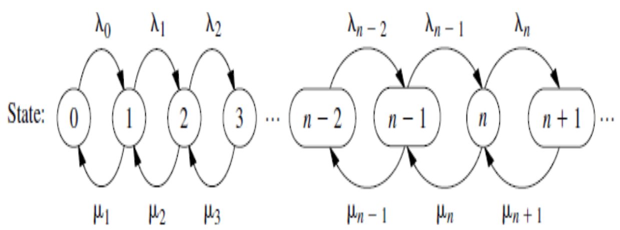

Figure 1. Illustration of passengers entering or leaving NAIA, Abuja

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

Mean entering rate of passengers = mean leaving rate of passengers

$$\mu_1 P_1 = \lambda_0 P_0 \tag{2.8}$$

$$\begin{aligned}\mu_{n-1}P_{n-1} + \mu_{n+1}P_{n+1} &= \lambda_n P_n + \mu_n P_n \\ \mu_{n-1}P_{n-1} + \mu_{n+1}P_{n+1} &= (\lambda_n + \mu_n) P_n\end{aligned} \tag{2.9}$$

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

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

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

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

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

$$P_{n+1} \cong \frac{\lambda_n P_n}{\mu_{n+1}} \tag{2.10}$$

From equation (2.3), if $n = 0$, we have: $\lambda_{n-2} \cdots \lambda_0$

$$P_1 = \frac{\lambda_0 P_0}{\mu_1} \tag{2.11}$$

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

If $n = 1$;

$$C_1 = \frac{\lambda_0}{\mu_1} \tag{2.12}$$

Therefore equation (2.11) becomes:

$$P_1 = C_1 P_0 \tag{2.13}$$

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

$$P_n = C_n P_0 \tag{2.14}$$

$$\sum_{i=0}^{n} P_n = 1 \tag{2.15a}$$

$$P_0 + \sum_{i=1}^{n} P_n = 1 \tag{2.15b}$$

$$\Rightarrow P_0 + \left(\sum_{n=0}^{\infty} C_n\right) P_0 = 1 \tag{2.16}$$

$$P_0 = \frac{1}{1 + \left(\sum_{n=0}^{\infty} C_n\right)} \tag{2.17}$$

$$\bar{\lambda} = \sum_{n=0}^{\infty} \lambda_n P_n \tag{2.18a}$$

$$L = \sum_{n=s}^{\infty} n P_n \tag{2.18b}$$

$$L_q = \sum_{n=s}^{\infty} (n-s) P_n \tag{2.18c}$$

Where: $\bar{\lambda}$ =Average arrival rate (Trani, 2011): C_n =Steady service rate

BDR solves queuing problems one at a time. Equations 2.10-2.18 were adopted and used to determine passenger arrival and departure rates and the system's service level of performance.

2.2.3. Assumptions

These are as follows:

(a) Given:-N(t)=λ_n; i.e. exponential probability distribution with parameter λ_n (n=0,1,2,3…) till the next birth (i.e. the next passenger arrival).

(b) Given:- N(t)=μ_n; i.e. exponential probability distribution with parameter μ_n (n=0,1,2,3…) until next death (i.e. when passenger service is completed and he departs).

(c) The random variable of assumption (i); and assumption (ii) are mutually independent. The next transition in system would be either:

$$n \to n+1 (\text{Single birth}) \text{ or}$$
$$n \to n-1 (\text{Single death}).$$

2.3. Statistical Testing of Modeling

Arrival and departure assumes Poisson's distribution as done by Asmussen (1987):

$$P(s) = \frac{e^{-\mu}\mu^n}{n!} \tag{2.19}$$

Where:- $P(s)$ = Probability of sample

μ Mean value; n Expected value.

Statistical testing is conducted on the modeling using Chi-square distributional assumption as given in equation (2.20):

$$T > \chi^2_{\alpha,k-p-1} = T > \chi^2_{\alpha,3} \tag{2.20}$$

i.e reject, otherwise accept an option.

$$E(s) = P(s)N \tag{2.21}$$

And expected sampling data is given as below:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{2.22}$$

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.

These are inputted into the modeling equations and tested to generate simulated results and then compared with the results obtained with Multi server approach (Ademoh and Anosike, 2014) for solving same NAIA queuing problem to enable careful conclusion on the differences and the better of these two approaches.

3. Results and Discussion

3.1. Presentation of Results

Flight data for year 2013 collected from four airlines companies including the British Airways, Ethiopian Airline, Arik Airline and Aero Contractors that use NAIA adopted for the modeling simulation are as shown in Table 2 -Table 5. Table 2 presents passenger data for British Airways for Abuja-London with the expected number of passengers averaged at 188 per day.

Table 2. British airways passengers in 2013

Month	Passengers	Passengers/day
January	5174	172
February	4484	149
March	4633	154
April	6125	204
May	5593	186
June	6266	209
July	6441	215
October	5719	191
November	5665	189
December	6320	211
Average	5620	188

Table 3. Ethiopian Airline Passengers in 2013

Month	Passengers	Passengers/day
January	2170	72
February	2165	72
March	2872	96
April	3644	121
May	3495	117
June	4085	136
July	3910	130
October	4016	134
November	3815	127
December	5966	199
Average	3614	120

Table 3 is Ethiopian Airline data for Abuja to Addis Ababa route with 120 passenger average daily expectation. Table 4 is that on passengers for year 2013 for Arik Airline for Abuja-Lagos with daily expected passenger average of 1573.

Table 4. Arik Airline Ltd Passengers in 2013

Month	Passengers	Passengers/day
January	25015	834
February	39292	1310
March	42498	1417
April	42739	1425
May	42876	1429
June	44307	1477
July	53332	1778
October	61334	2045
November	61467	2049
December	59027	1968
Average	47189	1573

Table 5 shows passenger data collected from Aero Contractor with expected passengers/day at an average of 1034. Table 6 presents average of passengers in system. Flight data were not made available by four airline operators used for simulating modeling for months of August and September. This was observed as general trend for most airlines that operate in Nigeria.

Table 5. Aero Contractor Passengers in 2013

Month	Passengers	Passengers/day
January	18821	627
February	25919	864
March	27753	925
April	28941	965
May	34994	1166
June	31779	1059
July	34093	1136
October	36074	1202
November	37017	1234
December	34894	1163
Average	31029	1034

Table 6. Average No. of Passenger in System

Parameters	Quantity
System utilisation factor	0.2, 0.25, 0.4, 0.6, 0.9
Time	30days
Estimated Passengers/month	21863
Estimated Passengers/day	729
Server (Aircraft)	2
Server capacity	160
Service factor	0.5, 0.9

3.1.1. Simulation of Queuing Modeling

Figure 2 shows Matlab graphical user interface program developed for modeling. The software was Installed was done in the following steps:

(a) Installation of MATLAB 2009 version or above into personal computer system.

(b) Loading file called queue fig onto screen

(c) Loading the basic parameter for analysis.

(d) Pressing of calculate button to display the result of the simulation.

(e) Press quit button once satisfied with result.

The GUI's calculate button in the software will automatically compute and display the result of the program based on the modeling equations 2.1-2.22 once the button is pressed after inputs.

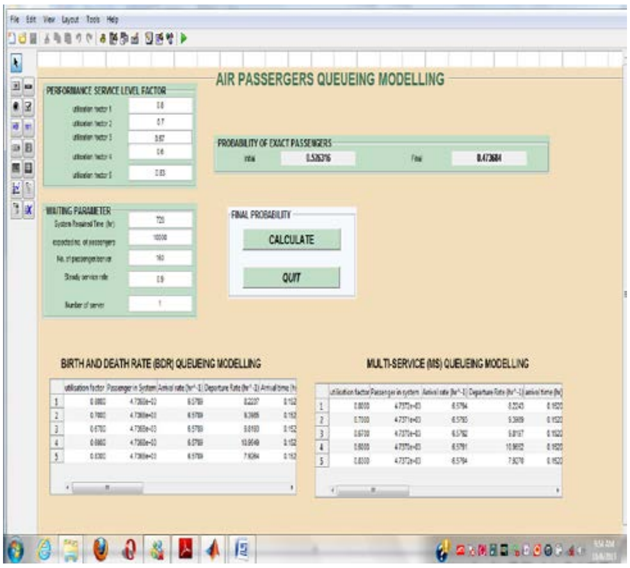

Figure 2. Graphical user interface for modelling the NAIA, Abuja system

3.1.2. Required Basic Parameter

Required basic parameters for the model to work referred to as boundary conditions are given in Table 7 as adopted by Ademoh and Anosike (2014).

Table 7. Boundary Conditions

Utilisat factor	Arrival rate/hr	Depart rate/hr	P(Arrival)	P(Departure)
0.2	10	25	0.125	0.0024
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
Averag	10	14		

3.1.3. BDR Modeling of the Arrival And Departure Rate with Service Factor 0.5

Arrival rate of passenger into the system was modelled with the BDR method at service factor 0.5 per month. The result is presented in Table 8.

Table 8. Modeling result of arrival/departure rate at 0.5 service factor

Utilisation Factors	0.2	0.25	0.4	0.6	0.9
Arriv 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 /passé (min)	2.37	2.96	4.74	7.12	10.67
Server capa.	486	486	486	486	486

3.1.4. Statistical Testing of Arrival and Departure Rate at 0.5 Service Factor

The result showed that arrival and departure rates of the modeling was same with Multi server approach (Ademoh and Anosike, 2014) except for server capacity that BDR gave 486 while Multi server gave 243 at all the utilisation factors. In Table 9 analysis of basic requirement for testing BDR method at service factor 0.5 showed it required more servers (aircrafts) at any given period. By it, modelling 160 passengers per server showed a requirement of 3 servers while MS (Ademoh and Anosike, 2014) required 2 aircrafts. BDR modeling gave an improvement of service level as 50% more passengers in MS modeling will be served by BDR at a specified period.

Table 9. Requirement of Service Factor 0.5

Parameters	Quantity
System utilisation factor	0.2, 0.25, 0.4, 0.6, 0.9
Time	30days
Estimated Passengers/month	21863
Estimated Passengers/day	729
Server (Aircraft)	2
Server capacity	160
Service factor	0.5, 0.9

The expected arrival and departure at a service factor of 0.5 is presented in Table 10. Null hypothesis criterion was used to analyse model result at service factor of 0.5. The result is as in Table 10. Table 11, the null hypothesis, shows that the arrival and departure rate should be within range 0-13 passengers per hour from tested criterion, otherwise it would be rejected.

Table 10. Expected arrival and departure at service factor 0.5

Utilisat factor	Arrival rate/hr	Depart rate/hr	E(Arrival)	E(Depart)
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		

Null hypothesis criterion was used to analyse result at service factor of 0.5 and Table 11 was generated as result of passenger arrival at a rate of 31 travelers/hr as follows:

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

The departure rate is given by;

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

Table 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%
Confidenc intervl(1- α)	0.950	0.975	0.99	0.995
χ^2 -Test (arrival)	13	13	13	13
χ^2 -Test (departur)	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 readily acceptable hypothesis showed that passengers arrived at a rate of 1-13 persons/hr; that is passengers arriving at 5% significance satisfied the condition at a service factor of 0.5. The passenger arrival and departure rates were rejected at service factor of 0.9 as it was above 13 persons. The hypothesis showed that arrival and departure rate must fall in a range of 0-13 passengers/hr from criterion, otherwise it will be rejected. To satisfy the condition each of the simulated airlines must fly2 more aircrafts/day.

3.1.5. Statistical Testing of Arrival and Departure Rate at 0.9 Service Factor

The result the BDR modeling simulation at service factor 0.9 is similar to that of MS modeling (Ademoh and Anosike 2014) except for server capacity in which BDR gave 690 but MS modeling gave 345 at all utilisation factors. Result of arrival rate of passengers to NAIA at service factor of 0.9 in a month is presented in Table 12 and Table 13. Table 12 shows expected arriva/departure at service factor 0.9. Table 13 shows requirement of service factor 0.9 which showed modeling 160passengers/server needed 4 planes for BDR while MS modeling required 2 aircrafts.

Table 12. Arrival/departure rate service factor 0.9

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/passn (min)	1.67	2.09	3.34	5.00	7.51
Server capacity	690	690	690	690	690

Table 13. Requirement of service factor 0.9

Utilisation factor	Arrival rate/hr	Depart rate/hr	P (Ar rival)	P (Dep arture)
0.2	14	36	0.095	0.0008
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	0.0007
Average	14	21		

BDR modeling had better of service level than MS modeling as double of the passengers of MS modeling will be served by BDR at any given period. Requirement for arrival/departure Expected arrival and departure at service factor 0.9 is as shown in Table 14.

Table 14. Expected arrival/departure at service of factor 0.9

Utilisation factor	Arrival rate/hr	Depart rate/hr	E (Arr ival)	E (Dep arture)
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		

Effect of service factor on arrival/departure rate for modeling was shown in Table 10 and Table 14 for service factors 0.5 and 0.9. Table 10 predicted average maximum arrival/departure rates of 10 passengers/hr and 25 passengers/hr respectively at 0.5 service factor with utilization factor 0.2. Arrival/departure rates were 14 passengers/hr and 36 passengers/hr at service factor 0.9 and same utilization factor 0.2. It showed average of 10 departing passengers/hr at service factor 0.5 and average of 21 departing passengers/hr at service factor 0.9. Utilization factor affected departure rates at both service factors 0.5 and 0.9 as rates decreased with increased utilization factor. Aarrival rate was given by:

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

And the departure rate was also given by:

$$\chi^2 = \frac{(29-2)^2}{2} + \frac{(18-8)^2}{8} + \frac{(12-1)^2}{1} = 498.$$

The analyses result presented in Table 15 shows that both arrival and departure rate should be in a range of 0-13 passengers/hour even at service factor 0.9 as modeling was tested using the chi-distribution assumption. Considering the result in Table 6 it was only the international airlines that were able to meet the required standard. Arriving passengers of the two local airlines didn't satisfy the condition because there were more travelers and over-utilisation that servers experienced. For a better service by the system, average arrival rate of 31passengers/hr were rejected as local airlines used only 2 aircrafts.

Table 15. Null hypothesis criterion at factor 0.9

Criteria (α)	0.05	0.025	0.01	0.005
Significance level (α)	5%	2.5%	1%	0.5%
Confidence intervl (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 hypoth sis (arrival)	Reject	Reject	Reject	Reject
Null hypoth sis (departr)	Reject	Reject	Reject	Reject

3.1.6. Expected Passengers in System

Table 16 shows result of expected passengers into the NAIA system based on arrival/departure rate at service factor 0.5 per month. It was estimated between the initial probability of 0.6667; final probability of 0.3333 and of expected 21863 passengers/month of initial evaluation. Initial probability was possibility of passengers; final probability was probability of passengers that actually entered from the expected passengers. Table 17 is expected passengers into NAIA.

Table 16. Expected passengers at 0.5 service factor

Utilisat Fact	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 Pass engers/month	7287	7287	7287	7287	7286
Expected pas senge/month	7288	7288	7288	7288	7288

Table 17. Expected passengers at 0.9 service factor

Utilisat Factor	0.2	0.25	0.4	0.6	0.9
Capacit/day	320	320	320	320	320
Expect cap/day	690	690	690	690	690
Reserve passeng	-370	-370	-370	-370	-370
waited pas/mon	10356	10356	10355	10355	10354
Expect pas/mon	10356	10356	10356	10356	10356

3.1.7. Performance of Service level of System

Passengers entering and leaving NAIA system was analyzed/tested for performance of service level time. The results are in Table 18 and Table 19.

Table 18. Service level's performance at 0.5 factor

Utilisa Factor	0.2	0.25	0.4	0.6	0.9
Service time/trip (hr)	12.65	15.81	15.81	15.81	15.8
Delay time/trip (hr)	11.35	8.19	-1.29	-13.94	-32.9
Total service time/trip (hr)	24	24	14.52	1.87	-17.1
Percent delay	47.29	34.13	0	0	0
Capacity/trip	320	320	320	320	320
Waited Pass enger/month	7287	7287	7287	7287	7286
Service comp letion (Days)	22.77	22.77	22.77	22.77	22.77

Table 19. Service level's performance at 0.9 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	-32.9
Total service time/trip (hr)	24	24	24	24	24
Percentage delay	47.29	34.13	0	0	0
Capacity/trip	320	320	320	320	320
Waited Pass enger/month	7287	7287	7287	7287	7286
Service comp letion (Days)	32.36	32.36	32.36	32.60	32.60

3.1.8. Required Servers Per Day

The raw data (Table 2-Table 5) showed that 2 servers carrying 160 passengers/server were required per day. When this BDR modeling was applied it gave a result of 156passengers/server per day. This exactly agreed with that of MS modeling (Ademoh and Anosike, 2014). Estimation was average arrival and departure rates of passengers in Table 10 and Table 14 for 0.5/0.9 service factors respectively. This server capacity was modeled to predict the required servers per airline; result of which is presented in Table 20 that clearly show that any airline carrying more than 1000 passengers/day required more than 5 aircrafts/daily operations.

Table 20. Average passengers and the daily number of required aircrafts in NAIA system

Airline Company	Passengers per day	Required servers/day
British Airways	188	2
Ethiopian Airline	120	1
Arik Airline	1573	10
Aero Contractor	1034	7
Average	729	5

3.2. Discussion

The effect of service factor on arrival/departure rates are shown in Figure 3 and Figure 4 to illustrate interrelationships between the two modeling approaches; BDR approach of this work and MS approach of Ademoh and Anosike (2014). Maximum server capacity was 312travelers per day for BDR modeling. Service factor 0.5 had maximum rate of 240 arriving passengers/day and factor 0.9 had 312 arriving passengers/day.

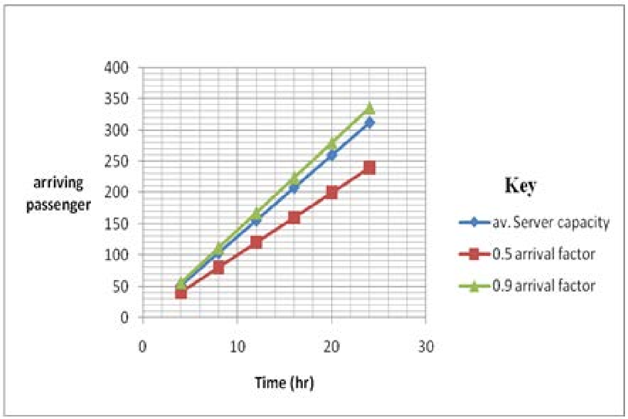

Figure 3. Effect of service factor on arrival rate

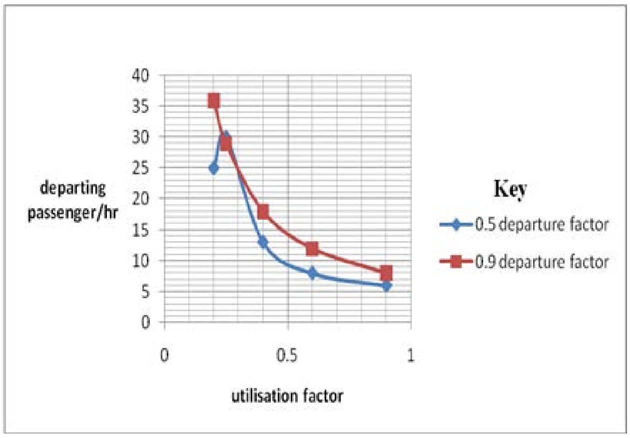

Figure 4. Effect of utilisation factor on departure rate

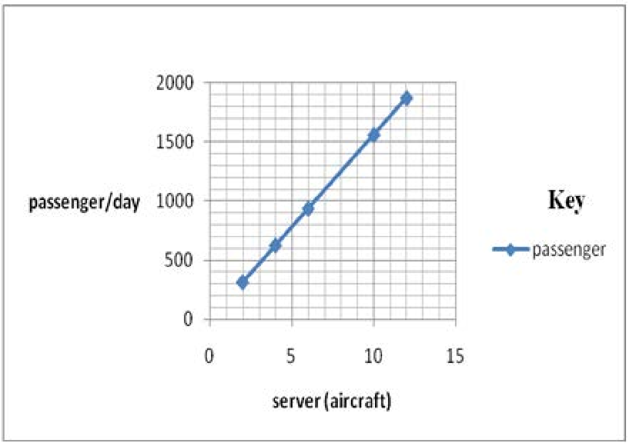

Figure 5. Expected passengers per server

In Figure 4 the departing passengers were estimated with different service factors with a utilization factor of 0.2. It gave the maximum passenger leaving the system as 25/hr. At the service factor of 0.9, passengers increased to

36/hr with utilisation factor of 0.2. Table 10 and Table 14 showed average departing passengers/hr was 10 and 21 at service factors of 0.5 and 0.9 respectively. Figure 5 illustrates the effects of server on passengers showing that airlines with over 1000 travelers per day required more than 5 aircrafts in her daily fleet.

Generally, the service factor requirement of 0.5 showed that by the BDR modeling, only 7,287 met the standard while 10355 passengers met the demand at service factor of 0.9. Service level was improved as there wasn't delay at the service factors 0.5 and 0.9 with the utilisation factors 0.4, 0.6 and 0.9 on model. As compared with the MS modeling (Ademoh and Anosike, 2014), the service level was delayed on service factors 0.5 and 0.9 at utilisation factors 0.4, 0.6 and 0.9. Operators will only meet the passenger demands, if each of the carriers on international routes add one more aircraft and each domestic airline add 6-7 more aircrafts/day in their fleets for effective services to forestall waiting lines. Then, NAIA system will become reliable and available with better service at 5% significance level based on service factor 0.9 and utilisation factors of 0.4, 0.6 and 0.9.

Service factor of 0.5 using BDR met the demand of 7,287passengers/month. The system was reliable without delay if under-utilised by which better quality service can be offered. But result showed that servers were over-utilised by more than 50% of their carrying capacities and therefore affected the system availability. International airlines offered better services as each operated with a daily carriage capacity of 312 passengers. This agreed with analysis with MS modeling by Ademoh and Anosike (2014).

The observed situation would have been worse if flight passenger data for August and September were available and included in the study as the two months are within peak flight periods of Muslim hajj airlifting operations, overseas holiday tours, schools end of session vacation journeys and other seasonal events. One of the main achievements of this work as compared with other previous studies is this discovery which is the general trend with all airline companies operating in the country. It is a possibility that operators deliberately kept passenger and revenue data away from public scrutiny for the purpose tax evasion purpose. The poor record keeping culture of operators in the system posed a big challenge to the information collection process of this work as it was quite difficult obtaining relevant data at initial stage of the study. To properly harness the full benefits of revenues generated by Nigerain Civil Aviation Authority (NCAA) and Federal Airports Authority of Nigeria (FAAN) it is very critical that adequate record keeping on the flight schedules and passenger patronages of operators within NAIA, Abuja and other Nigerian airports are monitored and possibly computerized.

4. Conclusions

The queuing modeling as developed and simulated using historical data from selected airlines would help in predicting the impact of the performance service level in air passenger management and quickly highlight out of order situations for management attention for prompt intervention. Overall benefit of this is expected improved service delivery through elimination of waiting lines in form of queues that not only stress up airport passengers but also frustrates them causing lack of trust in the industry.

The result of simulated model showed that the present demand by 21,863 passengers that need the services at the Nnamdi Azikiwe International Airport, Abuja per month can only be met if each airline operator sampled for study for local needs to increases its number of aircrafts plying routes studied from two planes per day to at least six planes per day and each on the international routes must increase her flights/day from one to two planes for effective coverage. NAIA will then become reliable and available with better service at 5% significance level based on the service factor of 0.9 with utilisation factors of 0.4, 0.6 and 0.9.

The service factor 0.5 using BDR model meets demand of 7,287 passengers per month. Using service factor of 0.9, demand of 10,355 passengers is met. It was estimated that 67% of the service is delayed to meet 21,863 status using service factor of 0.5 and 53% of the service was delayed using service factor 0.9. However, system was reliable without delay if it was under-utilised by which better quality of service will be achieved in the industry. The international airlines offered better services as they were operated within daily capacity of 312 passengers. In the modelling, existing aircrafts in NAIA Abuja were found to be over utilised at over 50% of current carrying capacity, thus affecting system's reliability and availability.

The main objective of this study was to use BDR modeling approach to solve queuing problem at the Nnamdi Azikiwe International airport, Abuja. The BDR modeling approach was more effective than Multi server modeling approach as it was able to predict total number of servers needed to effectively service demand of travellers through the system (Ademoh and Anosike, 2014). A major contribution that this work achieved is that this modeling approach can be applied to simulate similar airports that experience waiting problems and propound appropriate solution to the issue for improved service delivery and passenger convenience.

References

[1] Ademoh N. A and Anosike N. E (2014):-"Queuing modelling of air transport passengers of Nnamdi Azikiwe International Airport Abuja, Nigeria, using Multi Server approach". Middle-East Journal of Scientific Research Vol. 21 (12): Pp. 2326-2338.

[2] Asmussen, S. 1987. Applied probability and queues, John Wiley & Sons, First Edition, New York, pp. 25-67.

[3] Blumenfeld, D. E. 2001. Operation research calculations, First Edition, CRC Press, London, pp. 40-60.

[4] Hillier, F.S.; and Liebermann, G.J. 2001. Introduction to operations research, 7th Edition, McGraw-Hill, pp. 850-890.

[5] Mehri, H.; Djemel, T.; Kammoun, H. 2009. Solving of waiting lines models in Airport using queuing theory model and linear programming; Practice Case: A.I.M.H.B. Tunisia, pp 1-2.

[6] Odufuwa, B. O.; Ademiluyi, I. A.; and Adedeji, O.H. 2008. Transport poverty and deviant during Behaviour in Nigerian Intermediate Cities, CODATU III, pp.1-2.

[7] Ogwude, I. C. 1986. Industrial demand for freight transport in Nigeria, Ph.D. thesis, Department of Economics, University of Ibadan.

[8] Ukpere, W.I.; Stephens, M.S.; Ikeogu, C.C., Ibe, C.C. and Akpan, E.O.P. 2012. Determinants of airline choice-making: The Nigerian perspective, African J. Busin. Managemt. 6: 544-55.

[9] Salvendy, G. 2001. Handbook of industrial engineering. technology and operation management, First Ed., John Wiley and Sons, New York.

[10] Subramanian B. R. 2007. Aggregate statistical model for National Airspace System Performance". M. Sc. Systems engineering, University of Maryland, pp. 20-37.

[11] Trani, A. 2011. Introduction to transportation engineering and queuing theory, Virginia Polytechnic Institute and State University, US. pp. 2-46.