Estimating Arrival and Departure Headways at Akure Airports: A Data-Driven Approach

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ABSTRACT

Efficient management of arrival and departure headways is essential for optimizing runway utilization and minimizing delays at airports, particularly under high traffic conditions. This study presents a data-driven approach to estimate arrival and departure headways using predictive models and queue modelling techniques. By analyzing historical and real-time data from multiple sources, including flight operations, air traffic control, and weather conditions, we developed a model. These models dynamically estimate headway intervals based on factors like aircraft type, weather, and congestion levels. The study also incorporates queue models to simulate different operational scenarios, enabling more effective planning and runway capacity management. Key findings indicate that machine learning models can reliably predict headway intervals, allowing for real-time adjustments that balance safety and efficiency. Queue modelling further aids in understanding congestion patterns and optimizing runway allocation, reducing delays during peak periods. It also revealed that the time for length of arrival, and departure headways at Akure Airport. This research provides valuable insights into the potential of predictive and simulation-based methods for enhancing airport operational efficiency. It recommends the integration of these models into collaborative decision-making platforms, along with continuous model validation and compliance with regulatory safety standards. The approach demonstrates significant potential for airports seeking to manage capacity more dynamically and improve overall service quality.

Keywords- Estimating, Arrival and Departure, Headway, Modelling, Data-Driven Approach

INTRODUCTION

As global air traffic volumes continue to grow, airports are facing increasing pressure to enhance operational efficiency while maintaining safety and minimizing delays. The concept of headway the time interval between consecutive arrivals or departures on a given runway plays a central role in determining airport capacity and performance. Inadequate management of headways can lead to congestion, flight delays, and safety risks. On the other hand, optimal headway estimation enables airports to maximize runway throughput, reduce fuel consumption during taxiing or holding patterns, and improve the passenger experience (Yuan et al., 2014). Runway operations are constrained by both physical and regulatory factors.

International guidelines such as those provided by the International Civil Aviation Organization (ICAO) specify minimum separation standards between aircraft based on their wake turbulence categories. Large aircraft generate stronger wake vortices, requiring greater separation between them and following flights to ensure safe operations (ICAO, 2018). Additionally, factors such as weather, runway occupancy time, aircraft types, and air traffic control procedures influence the intervals between takeoffs and landings, complicating the estimation process (Balakrishnan & Khadilkar, 2013).

Traditional methods of scheduling runway operations have relied on static rules and pre-defined time intervals between flights. While these methods are useful for baseline planning, they lack the flexibility to adapt to real-time variations such as sudden changes in weather conditions, flight delays, or runway incidents (Budd & Ison, 2017). As a result, many airports are shifting towards data-driven approaches to better estimate and manage headway. Data analytics allows airports to develop adaptive models that incorporate real-time information and historical patterns to forecast optimal arrival and departure intervals under varying conditions.

Machine learning and predictive analytics have emerged as key tools in this domain. For example, time-series forecasting models and neural networks can predict fluctuations in runway occupancy times and dynamically adjust headway to prevent bottlenecks (Gopalakrishnan & Balakrishnan, 2020). These models leverage large datasets, including flight schedules, aircraft positions, weather reports, and operational constraints, to provide more accurate and efficient solutions. Notably, several major airports, such as those in New York, London, and Singapore, have successfully implemented data-driven decision support systems, achieving measurable improvements in runway capacity and operational reliability (Soni et al., 2020).

Given the growing complexity of air traffic management, this paper seeks to explore the methodologies, and benefits associated with data-driven approaches to headway estimation. Specifically, it aims to highlight how predictive models, are been used in transforming airport operations. By examining both the theoretical foundations and practical implementations of data-driven systems, this work aims to contribute to the development of more resilient, efficient, and adaptive airport operations. The objectives of the study are as follows.

a. estimate the arrival and departure headways in the study area

b. develop a queue model for aircraft movements in the study area

RELATED LITERATURE

The estimation and management of aircraft headways have become critical areas of research in aviation operations, driven by growing air traffic and the need to optimize airport capacity. This section reviews key literature on headway estimation, focusing on traditional models, the limitations of current practices, and the emergence of data-driven methods using machine learning, predictive analytics, and big data. It also highlights the factors influencing headways, such as aircraft categories, weather, and air traffic control strategies.

Earlier models for runway operations relied heavily on static, rule-based frameworks. These approaches focus on regulatory separation standards, such as wake turbulence separation minima, which determine the time intervals between aircraft to prevent safety hazards. ICAO (2018) provides specific guidelines on separation standards based on aircraft size, wake turbulence categories, and runway occupancy times. While these standards ensure safety, they are often conservative, resulting in underutilization of runway capacity during favorable conditions (Budd & Ison, 2017).

Research by Khadilkar and Balakrishnan (2012) explored the use of queueing theory to model airport taxi-out processes and estimate runway delays. Similarly, Hansen and Zhang (2014) investigated the impact of airport congestion on operational efficiency, concluding that static models are inadequate to manage variable flight schedules and disruptions effectively. These studies highlight the rigidity of traditional approaches, which struggle to adapt to real-time operational changes. Several dynamic factors affect the spacing between aircraft on runways, including aircraft types, weather conditions, and traffic patterns. Balakrishnan and Khadilkar (2013) examined the influence of aircraft size on runway occupancy times, noting that larger aircraft require greater separation due to their wake turbulence. Weather conditions such as strong winds, rain, or low visibility can further complicate headway estimation, forcing air traffic controllers to apply longer separation intervals to ensure safe operations (Yuan et al., 2014).

Additionally, the variability in traffic demand—such as peak-hour surges and unpredictable delays makes it difficult to maintain optimal runway performance. Air traffic controllers also face challenges in balancing arrival and departure flows, often prioritizing one over the other based on operational needs (Fleurquin et al., 2013). These factors underscore the need for adaptive, real-time solutions to headway management.

In response to the limitations of traditional methods, airports are increasingly adopting data-driven models that leverage historical data, real-time information, and advanced analytics to optimize runway operations. Predictive analytics and machine learning have emerged as key tools for estimating headway under varying conditions. Gopalakrishnan and Balakrishnan (2020) developed machine learning models that use flight schedules, radar data, and weather forecasts to predict runway occupancy times and adjust headway dynamically.

Soni et al. (2020) demonstrated the effectiveness of neural networks in forecasting aircraft arrival and departure times at busy airports. Their study showed that predictive models significantly improved the accuracy of headway estimation, reduced delays, and enhanced runway throughput. Similarly, Yuan et al. (2014) emphasized the role of time-series forecasting in predicting peak demand periods, enabling proactive management of runway capacity. These studies highlight how data-driven approaches can address the operational complexities that traditional models cannot.

Several studies have explored the potential of big data and artificial intelligence in optimizing airport operations. Data from various sources such as Automatic Dependent Surveillance-Broadcast (ADS-B) systems, weather sensors, and flight management systems can be integrated to develop more robust headway models (Budd & Ison, 2017). Advanced algorithms such as reinforcement learning and ensemble models have been employed to recommend optimal runway configurations and aircraft sequencing strategies (Gopalakrishnan & Balakrishnan, 2020). The concept of Collaborative Decision-Making (CDM), which promotes information sharing between airlines, airports, and air traffic control, has also been enhanced by data analytics. CDM platforms enable stakeholders to make joint decisions on runway operations based on real-time data, improving efficiency and reducing delays (ICAO, 2018). Such systems exemplify how data-driven technologies are transforming the way airports manage headways and other operational parameters.

Despite their advantages, the implementation of data-driven headway models is not without challenges. One significant issue is data quality and availability. Inconsistent or incomplete data can undermine the performance of predictive models (Fleurquin et al., 2013). Additionally, integrating multiple data sources into a unified platform requires significant technical infrastructure and coordination between various stakeholders.

Another challenge lies in the interpretability of machine learning models. While these models can offer accurate predictions, they often function as black boxes, making it difficult for operators to understand how specific predictions are made (Soni et al., 2020). Ensuring that predictive models align with regulatory frameworks and safety standards is also essential for widespread adoption. The future of headway estimation lies in further integration of emerging technologies such as the Internet of Things (IoT) and cloud-based platforms. Airports are exploring the use of digital twins virtual representations of physical systems to simulate and optimize runway operations under various scenarios (Gopalakrishnan & Balakrishnan, 2020). Additionally, the use of blockchain technology for secure data sharing between stakeholders is being investigated to enhance CDM processes (Budd & Ison, 2017).

The continued development of performance based navigation (PBN) and satellite-based technologies will further enhance the precision of headway management, allowing for reduced separation minima without compromising safety (ICAO, 2018). These trends suggest that data-driven approaches will play an increasingly central role in ensuring sustainable airport operations in the face of rising traffic volumes.

METHODOLOGY

The Study Area

Akure city is located in Akure South Local government area located in the Central Senatorial District of Ondo state, with over 353,211 populations (National Population Commission, 2006). It has a land area of 331km square. The town is located within $7^0 15'$North of the Equator and Longitude $5^0 05'$ East of the Greenwich Meridian (Figure 1). Presently, as the state capital of Ondo State, it has the largest volume of vehicular traffic with the highest number of vehicles and road network which makes its environment subjected to the impact of road operation in the state. In the current study, Sampling was planned only for weekdays and weekend.

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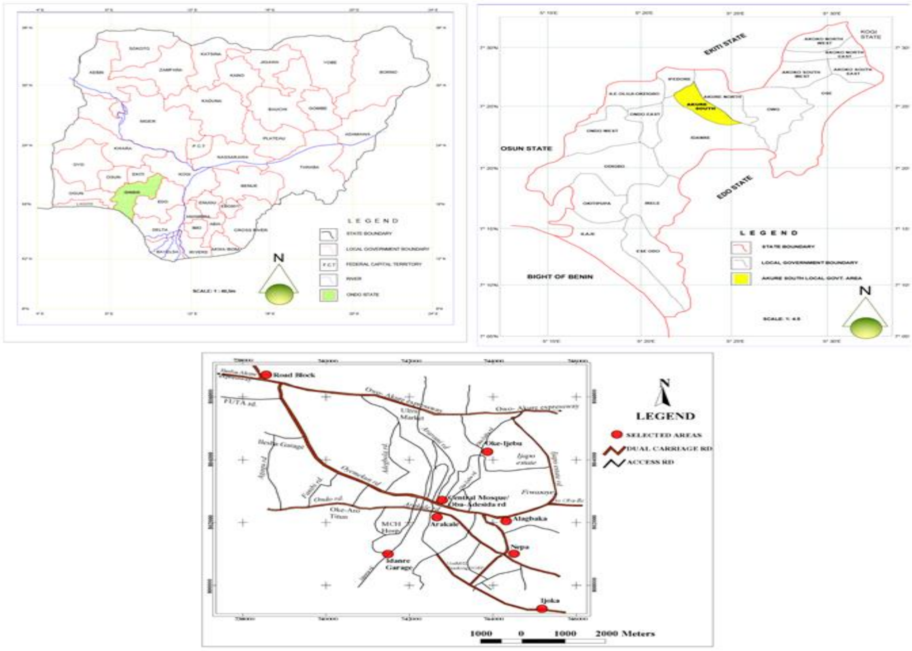
Figure 1: Map showing the study area



Source: Ministry of Works, Akure Ondo State

The research methodology covers data for estimating the arrival and departure headway, developing a queue model for the Akure Airport, using data of aircraft movements and numbers of passengers enplaned and deplaned over a three-month period from January 01, 2023 to March 31, 2023 using extracted data from NCAA and FAAN records (secondary data).

The following were noted for each aircraft movements: operator (airline); aircraft type; estimated time of arrivals; actual time of arrivals; arrivals delays; time between arrivals; number of passengers deplaned (brought in by the aircrafts); estimated time of departure; actual departure time; departure delays; time between departures; number of passengers enplaned (taken away from the study area); difference between deplaned and enplaned passenger for each aircraft; reported and observed causes of delay in arrivals and departures respectively such as bad weather, air traffic congestion at departing airport, and repositioning of aircraft for the journey.

Research Design

The research design for this study is descriptive and experimental in nature as it attempts to study recorded delays in the boarding process and airport in general and using QUEING model to forecast future delays trends for the Olumuyiwa Bernard Aliu Airport, Akure. Being a descriptive dataset, the research used mathematical model to depict what is happening in the airports with regards to delays. Meanwhile, it is experimental in nature as it will keep adjusting the models until a perfect model is achieved.

Sample Size and Sampling Technique

The study's sample size is the same as the research population since the study is using the records of all aircrafts that called at the airport during the study period.

This simply mean that there is no sampling technique adopted because the entire data retrieved from the records of the Federal Airport Authority of Nigeria for the period were used as recorded.

Assumptions in Model Building

When fitting dynamic models, their theoretical analysis can occasionally inform us of the best model form and the accurate numerical values of the model's parameter. They are:

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a) the model theory's findings, which are based on the notion that variables are stationary;

b) where data is non-stationary, conventional approaches are generally ineffective;

c) the data utilised in the model do not contain any white noise;

d) the non-stationary nature of the time series may lead to autocorrelation and

e) the spurious regression may also be caused by non-stationary time series regress

For Objective two

Simple descriptive analysis was used and the data collected reveal the average arrival and departure delays in the study area.

RESULT AND DISCUSSION

The analysis covers the secondary data gathered from the Federal Airport Authority of Nigeria and Nigeria Civil Aviation Authority. The data analysis reveals the estimate of the arrival and departure headways in the study area; using descriptive method.

a. to estimate the arrival and departure headways in Akure Airport

Table 4.1: Time between Arrivals

Variables	Value in Time (h/m/s)
Summation of time between arrivals	2148:44:00
Average time between arrivals	4:47:08

Source: Author, 2024

The time between arrival is the successful time between arrival of aircraft into the airport. The table 4.1 above shows that the average time between arrival is 4hour, 47 minutes, 8seconds.

Table 4.2: Time between Departures

Variables	Value in Time (h/m/s)
Summation of time between departures	1080399:48:00
Average time between departures	4:46:30

Source: Author, 2024

The time between departure is the successful time between departure of aircraft from airport. The table 4.2 above shows that the average time between arrival is 4hour, 46 minutes, 30seconds. The similarity in the arrival and departure headway shows that delay has already happen before the aircraft arrival to Akure airport.

For objective two

For queues of arriving and departing aircrafts in the study area, their respective queues scenarios can be depicted using the general form for any queue which is denoted by the following variables:

A denotes the distribution of inter-arrival times;

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B denotes the distribution of service times;

m denotes the number of servers in parallel;

L_Q = average queue length (average number of aircraft in queue);

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

W_Q = average waiting time in queue (average time an aircraft spends in queue);

W = average time in system (average time an aircraft spends in queue plus service)

N = number of aircraft in system ($E[N] = L$) =450

T = time aircraft spends in system ($E[T] = W$); = 54 mins

m = number of servers = 1

λ = arrival rate (number of aircraft arriving per unit time); = 1/4hr47min = 1/ ((4*60) +47) = 1/287 = 0.0035

$\frac{1}{\lambda}$ = mean inter-arrival time = 287

μ= service rate at one server (number of aircraft served per unit time) = 1/54 mins = 0.019

1/μ = mean service time = 54

$\rho = \lambda/_{m\mu}$= traffic intensity ($\rho < 1$) = 0.0034843/ (0.01851) = 0.188153

σ_a^2 = variance of inter-arrival times = 0.075800034

σ_s^2 = variance of service time = 0.002652152

Little's Law and general queuing System Relationships (Raton, 2009)

$$\left.\begin{matrix} L_{q} = \lambda W_q \\ L = \lambda W \end{matrix}\right\} \text{Little's Law} \ldots\ldots\ldots 5$$

$$L = L_q + \frac{\lambda}{\mu} \ldots\ldots\ldots 6$$

$$L = 1 + \frac{0.0035}{0.019} = 1 + 0.1842 = 1.1842$$

$$W = W_q + \frac{1}{\mu} \ldots\ldots\ldots 7$$

$$W = 9.02 + \frac{1}{0.019} = 9.02 + 52.632 = 61.652 \text{ min.}$$

Extension of Little's Law

For the M/G/1 queue, Little's Law L= λW given earlier can be extended to higher moments. For the Kth moment.

$$E[N(N-1)(N-2) \ldots \ldots (N-K+1)] = \lambda^k E[T^k] \ldots . 8$$

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where

N= number of aircraft in system

T= time aircraft spends in system

Special cases:

$$K = 1: E[N] = \lambda E[T] (i.e., L = \lambda W) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ 9$$

$$K = 2: \ E[\,N(N-1)] = \lambda^2 E[T^2] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 10$$

Hence

$$Var[N] = \lambda E\ [T] + \lambda^2 Var\ [T] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 11$$

Formulae for Average Queue Length, $\boldsymbol{L_q}$

$$L_q = \frac{p(pc)^c}{c!\,(1-p)^2 c\mu} P_o + pc$$

Formulae for Average Time in Queue, $\boldsymbol{W_q}$

$$W_q = \frac{(pc)^2}{c!\,(1-p)^2 c\mu} P_o + \frac{1}{\mu}$$

Formulae for Average Time in the Queue plus the service, $\boldsymbol{W_t}$

$$W_t = \frac{(pc)^2}{c!\,(1-p)^2 c\mu} P_o$$

Formula for probability of queuing on arrival, $Q_{\boldsymbol{a}}$

$$Q_a = \frac{(pc)^c}{c!\,(1-p)} P_o$$

Formula for probability of queuing on arrival, $Q_{\boldsymbol{a}}$

$$Q_a = \frac{1-(pc)^c}{c!\,(1-p)} P_o$$

CONCLUSION AND RECOMMENDATIONS

This study aimed to develop a data-driven approach to accurately estimate arrival and departure headways and queue models for airport operations. By leveraging historical and real-time data, the proposed methodology demonstrated the potential of machine learning models to provide dynamic headway predictions. Key findings highlight that factors like weather conditions, runway occupancy time, and congestion levels significantly impact headway intervals. The chosen predictive models, proved effective in capturing these complex relationships, offering a reliable solution for proactive airport management. The queue modeling component allowed us to simulate and understand the impact of various operational strategies on congestion and efficiency. By modeling queues, we identified optimal headways that balance efficiency and safety, reducing delays during peak times and improving overall runway utilization. Integrating these models into decision support systems and collaborative platforms showed promise for facilitating real-time data sharing among stakeholders, thereby enhancing coordinated decision-making and operational efficiency.

Recommendations

1. Implement Real-Time Predictive Models in Airport Operations: It is recommended that airports integrate real-time predictive models into existing decision support systems. Models for estimating headways, paired with queue simulations, can help air traffic controllers anticipate congestion, adjust intervals dynamically, and manage runway allocations more effectively. Deploying these models within Collaborative Decision-Making (CDM) platforms will ensure that all stakeholders, including airlines and ground services, can adjust operations in response to real-time data.

2. Prioritize Data Quality and Access: Reliable and comprehensive data is essential for the accuracy of predictive models. Airports and aviation authorities should prioritize investments in infrastructure to improve data collection from Automatic Dependent Surveillance-Broadcast (ADS-B) systems, weather sensors, and air traffic control systems. Ensuring data standardization and accessibility across airport systems will further enhance model performance and enable continuous improvement.

3. Use Queue Models for Scenario Testing and Planning: Queue modelling should be adopted as a tool for simulating various traffic scenarios and optimizing headway settings under different conditions. By evaluating the impact of factors like peak-hour congestion and adverse weather on queues, airports can develop contingency plans to adjust operational practices accordingly, ensuring smoother flows even during disruptions.

4. Regular Model Validation and Update: Machine learning models must be regularly validated and retrained to account for evolving patterns in air traffic and seasonal changes. This includes performing sensitivity analyses and scenario testing to keep models accurate and relevant. Regular updates will ensure that models adapt to changes in flight patterns, airport infrastructure, and weather trends.

5. Ensure Compliance with Safety and Regulatory Standards: While optimizing efficiency, it is essential to ensure that headway adjustments adhere to safety standards outlined by regulatory authorities like ICAO. This study emphasizes the importance of balancing operational efficiency with safety, especially when reducing headways in high-traffic periods.

In summary, the implementation of predictive headway estimation models and queue modelling holds significant promise for improving airport efficiency and reducing delays. When incorporated within a coordinated operational framework, these models can serve as a foundation for smarter, more adaptive air traffic management, meeting both the immediate needs of airport operations and the strategic goals of capacity expansion.

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