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Poisson Distribution for Dynamic Passenger Management: A Cost-Effective Strategy for Airports

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Abstract. *The rapid growth of global air traffic has made optimizing passenger flow in airports a critical challenge for the aviation industry. Efficient management of airport infrastructure is essential for minimizing wait times, enhancing passenger comfort, and improving operational efficiency. This paper explores mathematical-statistical modeling techniques and technological solutions, including the Internet of Things (IoT), artificial intelligence (AI), and big data analytics, for optimizing passenger mobility in the landside area of airports. A key aspect of this optimization is the development of an algorithm for dynamic passenger traffic management, designed to analyze real-time data and facilitate proactive decision-making. The proposed algorithm, implemented in MATLAB, employs a Poisson distribution model to centralize, sort, and filter passenger data. By analyzing distinct time intervals, the system identifies congestion hotspots and enables dynamic resource allocation, reducing processing delays and preventing overcrowding. Real-world applications of similar methodologies, such as those implemented at Schiphol Airport and Hong Kong International Airport, have demonstrated significant improvements in operational efficiency, including reduced wait times and optimized baggage handling processes. The paper further examines global trends in airport digitalization, multimodal transportation integration, and the increasing role of AI-driven predictive analytics. Additionally, statistical methods such as ARIMA, SARIMA, and machine learning-based neural networks are evaluated for their effectiveness in forecasting passenger flow and optimizing airport resources. The findings highlight the economic and operational benefits of intelligent passenger flow management, including reduced operational costs, improved airport revenue from commercial areas, and enhanced passenger satisfaction. By integrating real-time monitoring with predictive modeling, airports can maximize infrastructure utilization and provide a seamless travel experience. This research contributes to the development of future-ready airports by proposing scalable solutions for managing increasing passenger volumes through advanced analytics and automation.*

Keywords: Passenger flow optimization, airport landside management, IoT, predictive analytics, machine learning, Poisson distribution, smart mobility.

Introduction

In the context of the accelerated growth of global air traffic, optimizing passenger flow in airports has become a major challenge for the aviation industry.

Efficient management of airport infrastructure resources is essential for reducing waiting times, increasing passenger comfort, and enhancing operational safety. In this regard, statistical survey methods and mathematical-statistical modeling offer valuable tools for analyzing and optimizing these flows.

Landside areas in airports, which include all facilities accessible to the public before security control, have undergone significant transformations due to technological advances and

DOI: 10.2478/picbe-2025-0209

digitization. New solutions, such as the Internet of Things (IoT), artificial intelligence (AI), and big data analytics, contribute to improved management of passenger traffic and the creation of a more efficient and secure travel environment.

A crucial aspect of optimizing passenger mobility is the use of crowd control solutions, which enable the effective management of people flows in airports through advanced technologies and data analysis algorithms. Implementing a passenger traffic optimization algorithm in the landside area can generate significant economic and financial benefits, influencing several key factors of the airport.

By optimizing the allocation of human resources and infrastructure, airports can reduce operational expenses associated with security personnel, check-in services, and baggage management. Process automation and the use of predictive analytics allow for dynamic staffing adjustments based on passenger flow, eliminating excess operating hours and reducing salary costs.

Moreover, better management of passenger traffic in the landside area permits optimization of the time spent in the airport's commercial zones, potentially leading to increased revenues from retail, duty-free, and food services. Optimization algorithms can direct passengers toward more efficient routes, reducing time spent in queues and increasing consumption opportunities.

Intelligent management of passenger flow contributes to the balanced distribution of passengers among various control points and boarding gates, avoiding congestion and reducing the need for costly investments in terminal expansion. This enables better utilization of existing infrastructure, thereby increasing the financial yield of airport facilities. At the same time, employing advanced algorithms for traffic forecasting and real-time resource adjustment minimizes delays caused by congestion, providing passengers with seamless experience. Increased passenger satisfaction can, in the long term, attract a larger number of travelers and enhance the airport's reputation.

In addition to optimizing terminal passenger flow, the implementation of an intelligent mobility management system can improve the utilization of parking facilities and public transportation connected to the airport. Through the dynamic allocation of parking spaces and the integration of urban transport data, congestion in access areas can be reduced and the experience of passengers using multiple modes of transport can be enhanced.

The main idea of this work is the development and application of an algorithm for centralizing passenger flow in the airport's landside area, focused on critical transit points. The algorithm aims to collect and analyze real-time data to optimize passenger movement in essential locations such as parking entry, airport access, flight information areas, check-in, security control, and commercial service zones, including cafes, restaurants, currency exchange offices, and sanitary facilities.

Developed in MATLAB, the algorithm employs a Poisson distribution model for centralizing, sorting, and filtering passenger data. This approach analyzes distinct time intervals during key moments of the day to identify critical congestion points and enable dynamic resource adjustment. This methodology provides a clear perspective on traffic fluctuations and allows for the optimization of passenger flow based on real-time demand, thereby reducing delays and maximizing the airport's operational efficiency.

The objective of this article is to explore mathematical-statistical modeling methods applied to the management of passenger flows in airports. The paper examines global trends, the implementation of IoT solutions, the use of advanced statistical methods, and their impact on operational performance. Based on the studies presented in the article, strategies for optimizing passenger flows and the benefits of implementing innovative solutions for the airports of the future are evaluated.

Literature review

Global trends in landside airport traffic reflect the increasing need for efficiency, sustainability, and an enhanced passenger experience, while also highlighting growing challenges due to the rising number of passengers and the diversification of transportation methods (*Zhang, H., 2020)*.

Automation and digitalization are on an upward trend, with the implementation of self-check-in kiosks and automated baggage drop-off systems, thereby reducing waiting times. Mobile applications have become essential, offering functionalities such as parking reservations, real-time flight tracking, and contactless payments. Additionally, facial recognition and biometric technologies are increasingly used to facilitate access and enhance security.

Sustainability is a key priority, with airports collaborating with public transportation providers to promote the use of electric buses and trains. Parking facilities are equipped with charging stations for electric vehicles, while airport buildings integrate eco-friendly solutions such as solar panels and energy-efficient lighting.

The integration of multimodal transportation is gaining traction, with airports transforming into hubs that connect high-speed trains, buses, and other means of transport, thereby reducing transfer times between cities and terminals. Unified booking systems enable passengers to combine air travel with other transport options, making trip planning easier and simplifying transfers.

Airports are evolving from mere transport nodes into complex, multifunctional hubs (Baker et al., 2011), with an increasing focus on non-aeronautical revenue streams to enhance profitability (Franzet al., 2018). Passenger experience is being improved through modern facilities such as comfortable lounges, restaurants, duty-free shops, and relaxation areas. Airports now include entertainment zones, children's play areas, and dedicated spaces for passengers with reduced mobility, ensuring a travel experience tailored to diverse needs.

Data-driven analytical approaches are being developed to optimize ground traffic management (Tica et al., 2023). Passenger flow management is enhanced through data analytics and artificial intelligence, which monitor movement patterns to prevent overcrowding. Real-time guidance systems provide estimated times to gates, flight statuses, and congestion levels in various areas, improving the transit experience.

Safety remains a top priority, with intelligent video surveillance and advanced scanning technologies that shorten security check times. At the same time, airports offer modern parking services, such as online reservations and premium options like valet parking.

From a social perspective, airports collaborate with local communities to create jobs and support the economy. Additionally, noise reduction technologies are being implemented to minimize the impact on nearby residential areas. These trends are transforming airports into more efficient, sustainable, and passenger-centric spaces, addressing global challenges such as increasing air traffic and environmental impact.

IoT implementation in airports

Internet of Things (IoT) technologies, as shown in figure 1, are increasingly being deployed in airports to optimize operations and enhance the passenger experience, including in the landside area.

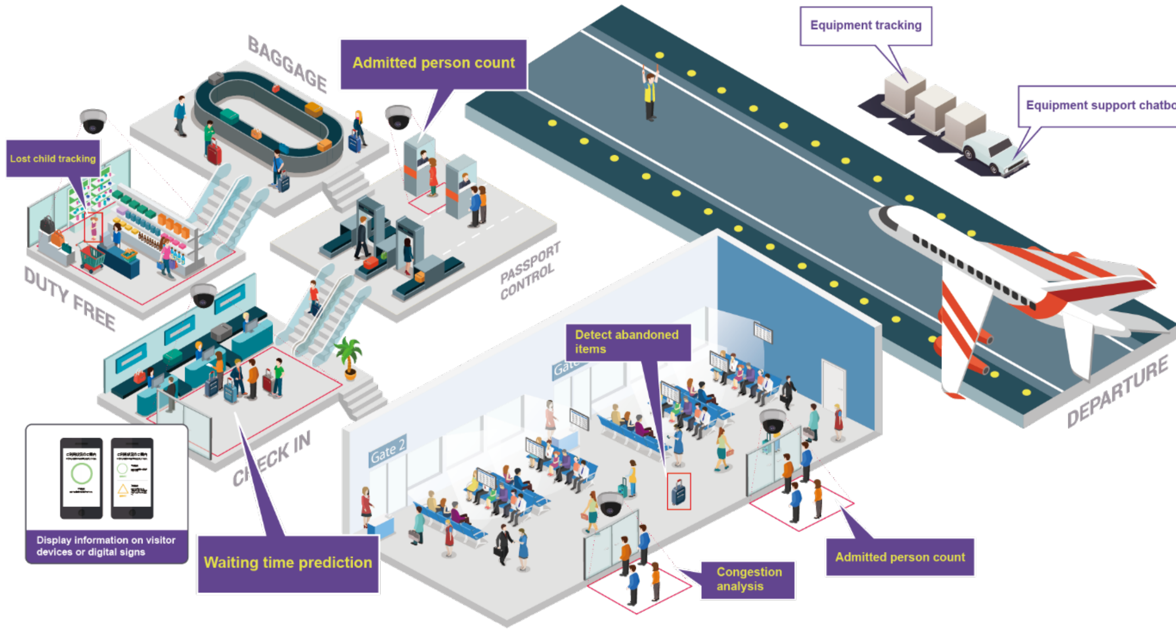

Figure 1. Implementation of IoT Technologies in Airports
Source:https://en.optim.cloud/industries/airport/

At Dallas/Fort Worth International Airport (DFW), time series analysis is used to monitor passenger traffic at security checkpoints in real time. Sensors collect data on passenger flows, while statistical algorithms identify congestion patterns and estimate waiting times.

The airport has implemented sensors that track the number of people at security checkpoints in real time, providing accurate wait time estimates. This information is displayed on monitors, allowing passengers to plan their route to the boarding gates more efficiently (Hudson, 2023).

At Miami International Airport (MIA), beacon technology is used to precisely locate passengers within the terminal. Through a mobile application, passengers receive step-by-step navigation to their boarding gates or other facilities, such as restaurants, bookstores, or restrooms, contributing to a smoother travel experience.

Cluster analysis is employed to personalize notifications sent to passengers via the mobile app, directing them to the nearest facilities based on their location. Additionally, cluster analysis helps segment passengers based on their behavior (e.g., tourists vs. business travelers) to optimize both user experience and resource allocation (Hudson, 2023).

Hong Kong International Airport (HKIA) was the first airport in the world to implement RFID technology in its baggage handling system. This system enables real-time tracking of luggage throughout the journey, reducing the risk of loss and increasing passenger satisfaction.

At HKIA, predictive analytics based on RFID data allows for forecasting delays in baggage handling and proactive resource allocation. Machine learning methods, relying on predictive statistics, help anticipate infrastructure demands and prevent issues such as overcrowding (Shrivastav, 2022).

At London Heathrow Airport, autonomous electric vehicles are used to transport passengers between terminals and parking areas. These vehicles, equipped with sensors and cameras, showcase the application of IoT in improving landside mobility.

Linear regression is used to determine correlations between variables such as the number of flights, passenger traffic, and waiting times. Logistic regression can be applied to assess the probability of events such as terminal overcapacity. These methods are utilized to model and optimize the deployment of autonomous vehicles, considering factors such as passenger demand and vehicle availability (Shrivastav, 2022).

Changi Airport is an excellent example of how advanced statistical techniques, such as Monte Carlo simulations, are used to maintain its global leadership in innovation and operational efficiency.

Monte Carlo simulations are a statistical technique used to manage and optimize various aspects of landside operations. This method involves generating a large number of possible scenarios by using probabilistic distributions to model uncertainties and variations in airport traffic. The primary goal is to evaluate the impact of these scenarios on airport resources and passenger experience (Haojie, 2020).

These implementations demonstrate how IoT is transforming airports, enhancing both operations and the passenger experience, particularly in the landside area.

Statistical methods used

Time series analysis is a branch of statistics used to identify patterns in sequential data over time. In the case of an airport, forecasting passenger flow is essential for optimizing resources, reducing wait times, and ensuring a seamless travel experience. This section presents time series analysis methods for estimating passenger flow in an airport, using techniques such as ARIMA (Autoregressive Integrated Moving Average) models, seasonal models, and machine learning algorithms.

A crucial step in sorting, filtering, and processing information in a real-time prediction system is data collection. Given the high variability of passenger movement parameters in an airport, data sources play an essential role. Historical data includes the daily, monthly, or annual number of passengers. External factors such as holidays, special events, weather conditions, and regulatory changes are also considered. Additionally, seasonal data is relevant for identifying travel patterns during peak vacation periods.

For accurate data interpretation and processing, data preprocessing is necessary. This step involves removing outliers and handling missing values. Normalization helps transform data to reduce variability. Identifying seasonality and trends requires decomposing time series into their main components. After sorting the data, they are analyzed using time series analysis methods.

The ARIMA (Autoregressive Integrated Moving Average) method is used for analyzing and modeling univariate time series with a well-defined temporal structure. ARIMA combines three components: autoregression (AR), which analyzes linear relationships between current and past values; integration (I), which makes the series stationary by removing trends or seasonality; and moving average (MA), which models the relationship between current observations and past errors. The ARIMA method offers flexibility and the ability to handle non-stationary data, but it is sensitive to parameter selection and has limitations in the case of highly complex or strongly seasonal data. It is particularly suitable for short-term predictions (C. Narendra Babu, 2014).

Seasonal time series analysis models are used to identify and model recurring patterns that appear at regular intervals, influenced by factors such as seasons or days of the week. The SARIMA (Seasonal Autoregressive Integrated Moving Average) model extends ARIMA by incorporating seasonal components, with specific parameters for autoregression, moving average, and seasonal differentiation, along with a defined seasonality period. Advanced models such as VARIMA

(Vector Autoregressive Integrated Moving Average) and SARIMAX (Seasonal ARIMA with Exogenous Variables) extend seasonal approaches to multiple time series or incorporate external variables, allowing for more complex modeling. These models are applied in various domains, including seasonal demand forecasting, energy consumption prediction, and tourism flow estimation (C. Narendra Babu, 2014).

Machine learning algorithms are widely used for time series analysis, providing advanced tools for identifying complex patterns and making accurate predictions. Neural networks, such as RNN (Recurrent Neural Networks), LSTM (Long Short-Term Memory), and GRU (Gated Recurrent Unit), are designed to work with sequential data and can learn dependencies between past and future values. These models are particularly effective in capturing long-term relationships within data. Regression algorithms, including linear, elastic, and polynomial regression, are used to describe relationships between variables and predict future values based on past behavior (Hewamalage et al., 2021). Choosing an appropriate algorithm depends on the nature of the problem, the complexity of the data, and the specific requirements of the project. These algorithms play a crucial role in process optimization, strategic decision-making, and improving system performance.

Combining classical methods with machine learning enables the exploitation of the strengths of both approaches. Time series analysis is a powerful technique for forecasting passenger flow in an airport. The choice of methods depends on data characteristics and the specific objectives of the forecast. Hybrid models, which integrate classical statistical approaches with machine learning techniques, often yield the most accurate results. Implementing a robust solution requires high-quality data, rigorous validation, and continuous adaptation to changes in the airport's operational environment.

Recent research on optimizing crowd control in airports has focused on various aspects of passenger flow management. Studies have explored the optimization of check-in processes, security control, and passenger migration (Adacher et al., 2020), as well as improving flight scheduling and gate assignments (Shambour et al., 2023). Unified approaches have been proposed for optimizing airport operations, addressing runway configuration, flight sequencing, and routing (Bertsimas et al., 2015).

Researchers have also developed models to analyze and simulate crowd behavior across multiple transportation modes (Yi et al., 2020) and have applied queuing theory to characterize passenger flow at security checkpoints (Wang et al., 2017). Advanced decision-making tools using AI simulations have been suggested for proactive risk mitigation and strategy evaluation (Anagnostopoulou et al., 2024). A systematic review of evacuation optimization methods has identified architectural, mathematical, and behavioral approaches, with behavioral modification emerging as a promising area for future research (Shadman et al., 2024).

Methodology

The physical implementation of integration and passenger flow optimization solutions in airports involves the use of advanced technologies such as IoT, artificial intelligence, big data, and mathematical modeling to ensure efficient operations and an enhanced passenger experience.

Among the implemented technologies are automated security gates that use biometric identification, as shown in figure 2. These systems can be supported by Poisson distribution models, which can be used to evaluate the impact of passenger flow variations on the performance of automated gates.

Such simulations involve generating a large set of possible scenarios, each representing different combinations of factors such as passenger volume, processing times, and gate capacity. For example, a simulation may analyze how a sudden increase in passengers (due to delayed flights) would affect the average processing time at the gates. The results of these simulations are then used in optimization models to determine the most efficient resource allocation and to establish the optimal number of active gates based on current conditions. This process enables rapid and proactive adjustments, thereby reducing average processing time and preventing congestion.

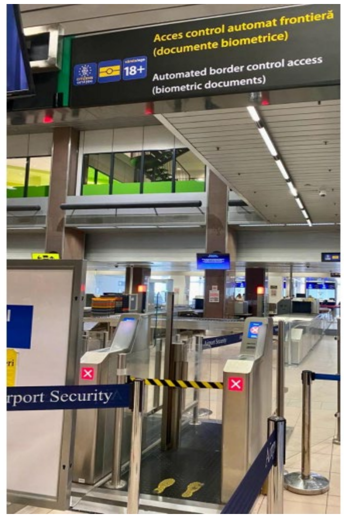

Figure 2. Biometric Gates Installed at Henri Coandă International Airport Bucharest

Source: https://www.bucharestairports.ro/cnab/ro/presa/comunicate-de-presa/flux-rapid-pentru-posesorii-de-pasapoarte-biometrice-la-aeroportul-henri-coanda1685357546

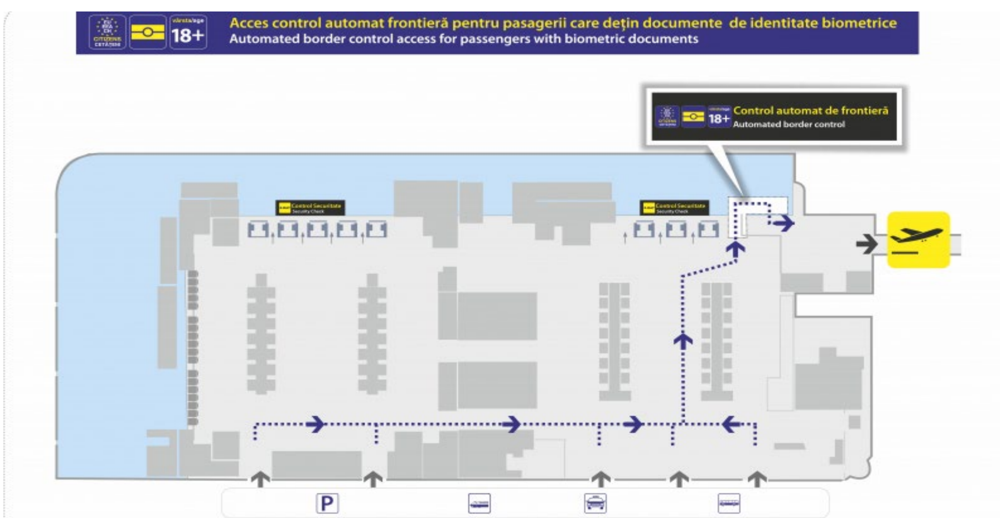

Figure 3. Passenger Flow with Biometric Passport

Source: https://www.bucharestairports.ro/cnab/ro/presa/comunicate-de-presa/flux-rapid-pentru-posesorii-de-pasapoarte-biometrice-la-aeroportul-henri-coanda1685357546

IoT sensors installed in terminals provide data on passenger density, which is analyzed using statistical models such as time series analysis. These models enable the identification of patterns and the forecasting of peak hours, helping to dynamically adjust resources and prevent

DOI: 10.2478/picbe-2025-0209, pp. 2712-2723, ISSN 2558-9652 |
Proceedings of the 19th International Conference on Business Excellence 2025

overcrowding. For example, at Schiphol Airport in Amsterdam, such analyses have contributed to a 30% reduction in security checkpoint wait times [35].

Big data plays a crucial role in these processes, allowing for the analysis of data from multiple sources. Machine learning algorithms, such as neural networks, are used to detect anomalies and predict critical situations, such as sudden increases in passenger numbers in a specific area. These models have been successfully implemented at Hong Kong International Airport to optimize baggage management, reducing the lost baggage rate by 40% (Shrivastav, 2022).

The main objective of this integration is to ensure the real-time display of the occupancy level in the landside area, regardless of various scenarios such as weather conditions, seasonal events, or ongoing works. The system is designed to quickly identify, transmit, and manage information from the landside area using a series of specific sensors (video monitoring systems, ultrasonic sensors), ensuring a prompt response and efficient decision-making to optimize economic and financial factors.

To achieve this, the algorithm is developed using the MATLAB platform. To ensure efficient passenger flow management in the landside area, a real-time algorithm was developed for identifying, monitoring, and sorting passengers based on their arrival patterns. The algorithm utilizes the Poisson distribution, which is widely used in stochastic modeling of arrival processes, particularly in transportation and service industries.

Results and discussions

Passenger identification is performed using a combination of video monitoring systems and ultrasonic sensors, strategically placed at key entry and exit points. These sensors provide continuous data on passenger counts at different time intervals, enabling accurate tracking of traffic fluctuations. The data is then preprocessed to filter out anomalies, such as sensor misreads or unusual congestion patterns.

To model passenger arrivals, the algorithm assumes that arrivals follow a Poisson process, where events (passenger entries) occur randomly but with a known average rate. The arrival rate λ varies depending on the time of day and the day of the week.

The Poisson probability mass function (PMF) is given by:

$$P(X = k) = \frac{e^{-\lambda}\lambda^k}{k!}$$

where:

- X represents the number of passengers arriving in a given time interval;
- λ is the average arrival rate;
- k is the actual number of arrivals;
- e is Euler's number (≈2.718).

To optimize operations, the system continuously tracks and analyzes passenger arrivals across multiple time frames, allowing for dynamic adjustments based on real-time demand fluctuations. The monitoring approach is structured into two key temporal perspectives: hourly tracking over a 24-hour period and peak-hour analysis over a weekly period.

Passenger arrivals are categorized into hourly segments. The analysis identifies congestion points and enables real-time adjustments. Morning rush hours, typically from 6 AM to 10 AM, see the highest passenger influx due to business travelers and early flights. A secondary peak occurs in the evening, between 4 PM and 8 PM, as international and leisure travelers contribute to congestion. The period from 10 AM to 4 PM shows moderate but steady passenger arrivals, while late-night hours from 8 PM to 6 AM experience a significant decline.

The hourly slot analysis, as shown in Figure 4, captures passenger flow at one-hour intervals over a full day. Morning rush hours exhibit the highest demand, necessitating increased staffing levels at check-in counters and security control points. Midday traffic is stable but steady, allowing for balanced resource allocation. Evening hours see another peak, requiring additional operational adjustments, while late-night hours allow for reduced staffing and resource optimization. This allows the system to identify intraday fluctuations, detect congestion patterns, and anticipate service demands.

Hourly monitoring is particularly useful for real-time decision-making, enabling proactive adjustments in staff deployment, security checks, and automated gate operations. By continuously updating the Poisson arrival rate λ using real-time sensor input, the system ensures that short-term fluctuations are effectively managed.

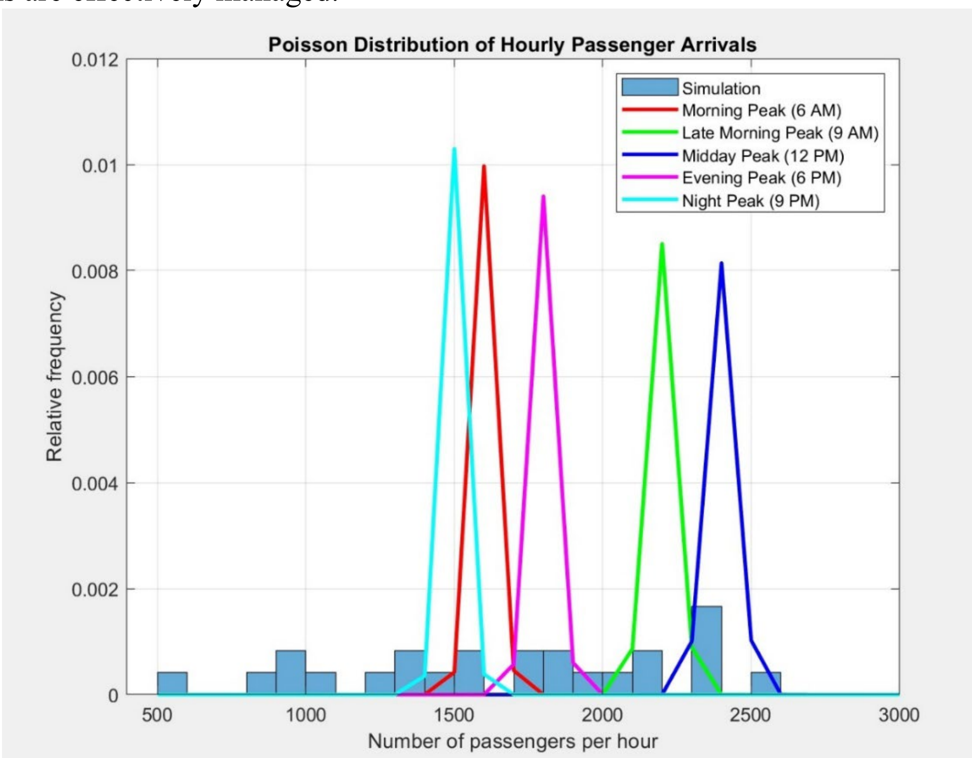

Figure 4. Poisson distribution hourly slot analysis

Source: Authors' own research results/contribution.

The comparison of peak traffic periods during weekdays and weekends, as shown in Figure 5., provides insights into long-term passenger flow trends. Weekday traffic follows a predictable pattern, allowing for structured staff scheduling and resource allocation. Weekend traffic is more volatile, requiring dynamic adjustments to staffing and service operations. The data indicates that weekday peak hours demand higher operational efficiency at security checkpoints and check-in counters, while weekend patterns call for flexible infrastructure management to accommodate unpredictable demand shifts.

By aggregating data across multiple days, the system identifies differences between workweek commuter traffic and leisure-oriented weekend travel. Weekday peak hours, typically concentrated in morning and evening rush periods, are characterized by a more predictable and structured demand pattern. In contrast, weekend traffic tends to be more variable, influenced by factors such as seasonal events, tourism activity, and social gatherings. Understanding these variations allows for optimized scheduling of operational resources, queue management strategies, and infrastructure planning.

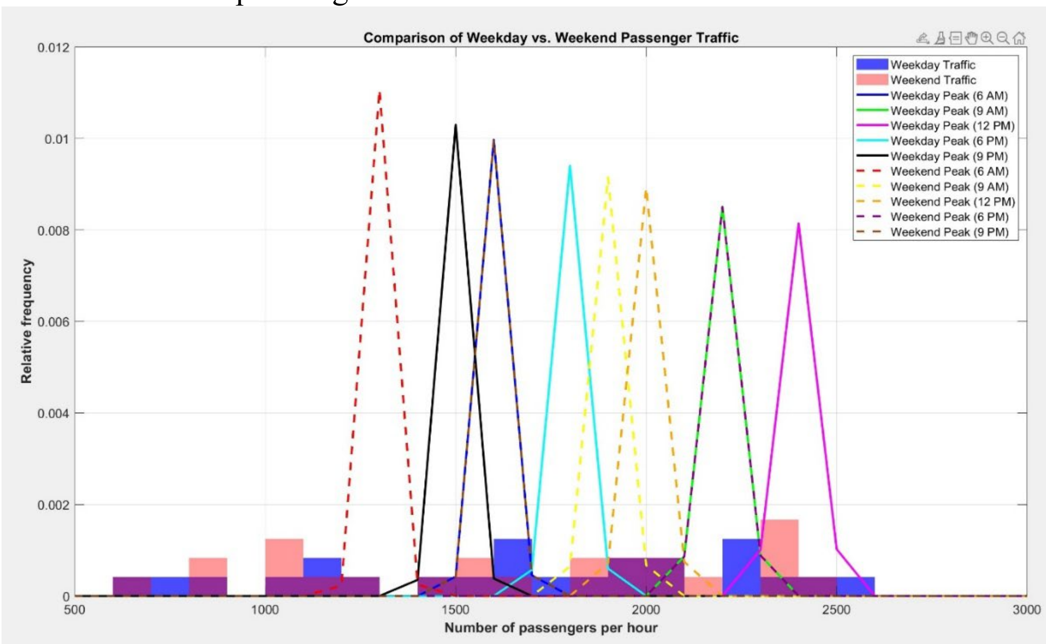

Figure 5. Poisson Distribution weekly peak-hour analysis comparison

Source: Authors' own research results/contribution.

To enhance accuracy, the monitoring system employs adaptive smoothing techniques, where the Poisson rate λ is dynamically adjusted using weighted moving averages of past arrival rates. This ensures that both short-term variations and long-term trends are incorporated into the predictive model.

Decision-Making and System Optimization

The algorithm plays a crucial role in real-time decision-making, enabling proactive congestion management and optimal resource allocation. By continuously analyzing passenger flow patterns, the system assists in several key operational areas, including workforce management, infrastructure utilization, and passenger service optimization.

One of the primary applications is dynamic resource allocation, where real-time passenger data is used to adjust staffing levels, gate operations, and security screening personnel based on expected demand. For instance, during peak hours identified through Poisson-based modeling, additional check-in counters and security lanes can be activated to prevent bottlenecks. Conversely, during off-peak periods, resource allocation can be optimized to minimize unnecessary operational costs.

Another critical function is queue management and congestion prediction. By leveraging real-time sensor input, the system can anticipate overcrowding in specific zones and implement mitigation strategies, such as redirecting passengers to alternative entry points, opening additional service counters, or adjusting digital signage to guide passenger flow. The integration of machine learning techniques with Poisson-based forecasting further enhances the algorithm's ability to predict future congestion levels with high accuracy.

The system also contributes to economic and financial optimization by reducing operational inefficiencies. By minimizing passenger wait times and optimizing service capacity, the algorithm helps airports, railway stations, and transit hubs reduce unnecessary labor costs, improve customer satisfaction, and increase overall throughput. Additionally, predictive insights generated from the system can be used for revenue optimization, such as adjusting pricing strategies for premium services during high-demand periods.

Beyond operational efficiency, the system enhances the passenger experience by ensuring smoother transitions through the landside area. Real-time updates on expected wait times, automated notifications for congestion-prone areas, and personalized route recommendations contribute to a seamless and stress-free travel experience.

Conclusion

The rapid growth of global air traffic necessitates the continuous optimization of airport passenger flow to enhance operational efficiency and passenger experience. This paper highlights the critical role of advanced technologies such as IoT, artificial intelligence, big data analytics, and mathematical-statistical modeling in streamlining passenger mobility within the landside area of airports. By integrating real-time monitoring with predictive modeling, airports can proactively manage congestion, optimize resource allocation, and reduce operational costs.

The proposed passenger traffic optimization algorithm, developed in MATLAB using a Poisson distribution model, provides a data-driven approach to analyzing and forecasting congestion points. By leveraging real-time sensor data, the system enables dynamic adjustments in staffing, security control, and infrastructure utilization, thereby preventing overcrowding and improving airport throughput. Case studies from leading international airports, such as Schiphol and Hong Kong International Airport, demonstrate the effectiveness of similar methodologies in reducing wait times and enhancing service efficiency.

Beyond operational improvements, intelligent passenger flow management contributes to increased economic and financial benefits for airports. The optimization of human resources and commercial areas enhances revenue generation, while predictive analytics allow for strategic planning to accommodate fluctuating passenger demand. Additionally, the integration of multimodal transport solutions and real-time mobility data ensures a seamless travel experience for passengers.

This research underscores the significance of integrating statistical and machine learning-based forecasting techniques to develop future-ready airports. By continuously refining predictive models and adopting adaptive resource management strategies, airports can effectively handle increasing passenger volumes while maintaining high service quality. Future studies should explore hybrid modeling approaches and real-time AI-driven decision-making systems to further enhance airport mobility and operational resilience.

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