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AI Driven Model for Optimizing the Queuing System at Airport Security Checkpoints for Bagging Inspection

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Abstract

As air travel demand increases, passengers often face long wait times, especially during peak periods, leading to frustration and decreased satisfaction. Efficient queue management is crucial, as each passenger must be individually screened at security checkpoints. Optimizing operations can minimize delays and enhance service quality. This study aims to improve queue management, focusing on hand-baggage inspection at King Khalid International Airport(KKIA)'s security checkpoints. A simulation model was initially developed based on data from the airport to manage the hand baggage inspection queue. The results of this simulation will be used to implement a machine learning model to predict waiting times and allocate passengers to specific queue IDs, optimizing the inspection process and reducing waiting times. The proposed methodology promises to improve service quality, reduce delays, and maintain passenger engagement during the screening process. Expected outcomes include reduced passenger wait times through better resource allocation, improved operational efficiency via optimized real-time data integration, enhanced passenger experience with transparent, real-time queue updates, and the adoption of advanced technologies like the Internet of Things (IoT), Artificial intelligence (AI), and simulation-based tools at the airport. Additionally, this initiative will position KKIA among the best global practices. A scalable prototype of the system will also be developed, adaptable to other airports facing similar challenges, ensuring long-term operational benefits and applicability. Implementing this system at KKIA will likely boost operational efficiency, improve satisfaction, streamline baggage handling, and serve as a model for future airport optimization efforts.

Keywords
Operational Efficiency, Passenger Experience, Baggage Screening, Virtual Queuing, Artificial Intelligence

1. Introduction
Queues are common in-service systems, arising when demand exceeds available service capacity, and this issue is particularly problematic in high-demand environments like airports, where long waiting times significantly impact

customer satisfaction. Inefficient queue management leads to operational delays and increased frustration, making it crucial to address these challenges. Airports worldwide, including King Khalid International Airport (KKIA) in Saudi Arabia, struggle with managing security lines effectively, facing prolonged waiting times and poorly distributed queues that result in frustration, reduced satisfaction, and additional operational costs.
The increasing reliance on air travel and the growth in passenger numbers highlight the urgency of implementing advanced data-driven queue management systems. Inefficient queue systems not only frustrate passengers but also incur substantial operational costs for airports. Current queuing systems lack adaptability and real-time updates, leading to uneven queue distributions and prolonged delays, especially during peak travel periods.
This issue is prevalent across airports globally, including KKIA, which faces significant challenges in managing high traffic volumes, particularly in baggage inspection areas. The motivation for this research lies in the need to enhance operational efficiency and passenger satisfaction at airports. By introducing an innovative queue management approach leveraging real-time data, this study aims to enable passengers to make informed decisions, optimize the overall operation, and minimize delays.

1.1 Objectives

The main objective of this project is to develop an AI-driven smart queue management system that optimizes baggage inspection wait times by integrating real-time data, and predictive modeling to enhance operational efficiency and passenger experience at KKIA.

2. Literature Review

2.1 Defining Queuing in Operational System

Queuing theory is a mathematical study that examines the behavior of waiting lines or queues, focusing on the analysis of system performance, customer behavior, and service efficiency. In operational systems, queuing models are essential for optimizing resource allocation, minimizing wait times, and enhancing overall system performance. Recent research has advanced our understanding of queuing systems in various contexts. For instance, (Griesbach et al, 2023) explored the optimization of throughput and makespan in queuing systems through information design, providing insights into how information dissemination can influence system efficiency. Additionally, (Roy et al,2024) investigated the effects of resetting mechanisms in queues, demonstrating that service resetting can significantly reduce average queue lengths and waiting times, thereby improving system performance. Furthermore. (Coltraro et al. ,2024) introduced the logistic queue model, a continuous fluid flow queuing model with theoretical properties suitable for digital twins in communication networks, enhancing the accuracy and speed of performance evaluations in complex systems. These studies highlight the ongoing advancements in queuing theory and its applications in operational systems, emphasizing the importance of accurate modeling and optimization in complex service environments.

2.2 Introduction to Airport Baggage Inspection

Baggage inspection at airports is an essential part of aviation security to ensure the safety of passengers, crews, and airport infrastructure. It includes advanced scanning techniques and comprehensive inspections designed to detect prohibited or dangerous materials, in compliance with international standards (General Statistics Authority, 2023). Between 2020 and 2025, advancements in airport baggage inspection systems have focused on enhancing security and operational efficiency through innovative technologies. Modern systems now employ artificial intelligence (AI) and machine learning algorithms to detect prohibited and dangerous items with greater accuracy and speed. For instance, AI-based automatic threat recognition systems have been widely adopted to analyze scanned images, reducing human error and inspection time (IATA, 2021). The use of 3D computed tomography (CT) scanners, introduced in major airports, allows for detailed and automated screening of luggage without requiring manual unpacking, thereby streamlining the process during peak travel times (Smiths Detection, 2023).
Additionally, real-time monitoring and data-sharing platforms have been integrated to facilitate seamless communication between inspection points, improving operational flow and passenger satisfaction (ACI, 2022). Airports worldwide are also implementing biometric identification systems, such as facial recognition, which are integrated into baggage handling to link passengers to their luggage, ensuring both security and efficiency (SITA, 2023). These innovations align with global efforts to enhance passenger safety while minimizing delays, making baggage inspection systems more robust and passenger friendly.

2.3 Queue Management Systems: Overview and Application

Queue management systems (QMS) are frameworks designed to efficiently manage the flow of customers within service environments. The core purpose of QMS is to minimize wait times and optimize the use of available resources by effectively coordinating demand and supply. These systems rely heavily on queuing theory, which mathematically models service processes to ensure that resources are allocated in a way that minimizes inefficiencies. In recent years, technological advancements have significantly transformed QMS. Automation has been integrated into systems to allow real-time monitoring and adjustments, while AI has enabled predictive capabilities, allowing systems to anticipate demand and optimize resource allocation (Limlawan, 2020). Additionally, digital tools like virtual queues and mobile apps have improved user experiences by providing remote check-in options and live updates on waiting times, reducing physical queues and increasing customer convenience (Kiplagat et al., 2020). The applications of queuing management systems are in healthcare, airports, banking, and entertainment centers.

2.4 Traditional queue management system

QMS is designed to streamline the handling of customer queues in various service areas such as airports, hospitals, and government offices, enhancing both service experiences and operational efficiency. The primary objective of QMS is to reduce waiting times and improve service delivery by efficiently managing customer flow (Olayinka, 2024). This is particularly crucial in airports, which are notorious for crowded terminals, long queues, and extended waiting times. Passengers often arrive hours before departure, not only to clear security but also to account for potential delays in check-ins or boarding. With increasing passenger traffic, especially during peak seasons, airport management faces the challenge of maximizing space utilization and improving passenger flow (RSI Concepts, 2022).

2.5 Smart Queue Management System

Smart Queue Management Systems (SQMS) have been extensively researched for their ability to enhance service efficiency and improve customer satisfaction across industries. (Jain et al, 2020) analyzed and optimized queuing systems in airports using discrete event simulation to identify bottlenecks and propose solutions for smoother passenger and baggage flow. (Prasanna et al, 2021) introduced the C19-SmartQ system, which utilized predictive models to manage multi-organization queues while maintaining social distancing, showcasing the adaptability of SQMS during the COVID-19 pandemic. In the healthcare sector, SQMS solutions studied by (Zhang et al, 2023) optimized patient appointment scheduling and reduced wait times, leading to improved healthcare delivery. These systems also find significant applications in high-demand environments such as airports, banks, and retail, where dynamic resource allocation based on real-time data ensures smoother operations and shorter wait times. Collectively, these studies highlight SQMS as a transformative tool for operational efficiency and enhanced user experience.

2.6 Emerging Trends in Queue Management Technology

Queueing management technology has been developed significantly to enhance operational efficiency and customer satisfaction in different industries. Emerging trends focus on merging Internet of Things (IoT) devices, AI, and blockchain technology to address traditional inefficiency. Systems that are supported by IoT simplify operations by collecting and analyzing real-time data, enhancing the allocation of resources, and reducing waiting times (Eoh et al., 2024). These systems also include sensor networks to track customer traffic in real-time, which enables companies to enhance services actively. AI technologies, such as forecasting analytics, bring more improvements by predicting peak hours and automating employee scheduling, which ensures efficient service provision (Domingo et al., 2024). Blockchain technology is another emerging trend that provides security and transparency for data. It is important, particularly in the financial and healthcare sectors, where sensitive data is analyzed, which ensures compliance with privacy rules, and improves the efficiency of the service (Minto, 2024). Moreover, mobile apps enable users by providing self-service choices such as digital tickets and updating waiting times using real-time data, thereby reducing physical activities and improving users' independence. Digital twins are another remarkable innovation that creates virtual models of waiting systems to simulate and improve the process before execution (García-Buendía et al., 2024). These trends highlight a shift towards automation, personalization, and data-driven management, transforming traditional queue systems into more flexible and customer-focused solutions.

3. Methodology

The project develops a prototype of an intelligent queueing system to improve baggage screening at security checkpoints and enhance customer experience at KKIA. The methodology consists of data collection, simulation, and model building. Data is gathered from airport records, including passenger arrivals, service times, and queue lengths. Simulation techniques are used to adjust arrival patterns and queue behaviors, ensuring realistic operational representations. A predictive model based on feedforward neural networks is then developed, using independent variables such as queue count and service time to estimate waiting times. The model is trained and tested using airport-specific data, with Mean Squared Error (MSE) applied as the primary evaluation metric to assess accuracy. This methodology integrates advanced data mining and machine learning techniques, providing valuable insights for optimizing security checkpoint operations.

3.1 Data collection

The project leverages aggregate data provided by KKIA, which includes essential metrics such as passenger arrival times, service times at baggage inspection counters, queue lengths, and waiting times for individual queues during a specified timeframe. This data will undergo thorough analysis using advanced tools, including Excel for initial statistical evaluation and AI for deeper insights and predictive modeling. To address the absence of detailed raw data, AI will be employed to generate simulated datasets based on the provided averages. These simulated datasets will mimic real-world conditions by approximating distributions, such as Poisson for arrival rates or exponential for service times, ensuring the data reflects realistic operational dynamics. This approach ensures the project is equipped with a robust and representative dataset to inform subsequent methodologies and analyses.

3.2 Simulation

The dataset generation process incorporates elements of simulation but is not a full discrete-event simulation (DES). Instead, it follows a rule-based adjustment approach that mimics real-world passenger arrivals and queuing behavior while ensuring all necessary constraints are met. The airport provided average times for arrivals, service duration, and waiting times. Since we did not have access to full real-time data, we used these averages to set reasonable constraints for peak and non-peak periods. The constraints were applied through systematic adjustments, ensuring a realistic queue and arrival pattern.

3.2.1 Passenger Arrivals (Inter-Arrival Time)

Before applying the standard arrival rate formula, we dynamically adjusted the arrival times based on the given averages and enforced peak-hour adjustments. We also ensured arrivals were evenly distributed across all peak hours, preventing a sharp drop after the first hour of a peak period

$$Inter\ arrival\ time_n = Arrival\ time_n - Arrival\ time_{n-1} \tag{1}$$

3.2.2 Service Time

Since the airport provided only an average service duration, we imposed a maximum service time of 300 seconds.

3.2.3 Service End Time Calculation

Each new arrival had to check whether the previous passenger had finished their service before being processed using the following formula:

$$Service\ end\ time_n = Arrival\ time_n + waiting\ time_n + Service\ time_n \tag{2}$$

3.2.4 Waiting time

The airport provided only average waiting times, we imposed constraints on keeping values within a realistic range: Peak hours: Maximum 1200 seconds, minimum 10 seconds, non-peak hours: Maximum 300 seconds, minimum 5 seconds. This prevented cases where waiting time would be too long or zero too frequently. The waiting time for each passenger was calculated by comparing their arrival time with the previous passenger's service end time:

$$Waiting\ time_n = Max(0, Service\ end\ time_{n-1} - Arrival\ time_n) \tag{3}$$

3.2.5 Queue count

To track how many people were in the queue at the moment a passenger arrived ensuring an accurate queue representation at any given moment we used:

$$Queue\ count_n = \sum_{j=1}^{n} 1(Arrival\ time_n < Service\ end\ time_j) \tag{4}$$

3.2.6 Flight-to-Passenger Ratio in Peak Hours

The peak hours are 07:00-09:59 and 18:00-21:59. The airport operates between 9 and 15 flights per peak-hour period with 918 passengers in peak hours per hour, the ratio for different flights per peak hour is min ratio 1:61, max ratio 1:102 this means that in peak hours, each flight accommodates between 61 and 102 passengers, depending on the total number of flights. This approach did not use a full discrete-event simulation (DES) but incorporated simulation-like adjustments to ensure the dataset was realistic.

3.3 Model Building

To predict average wait times at airport security checkpoints, we worked on datasets with parameters such as number of queues, number of slots, peak hours, and service time as independent variables, with wait times as the dependent variable. Because of the complex relationship between inputs and outputs, we used feed-forward neural networks, which are efficient at modeling complex relationships between inputs and outputs. They consist of input layers corresponding to these features, multiple hidden layers, and output layers that produce continuous values representing wait times. Our model was compiled using the Adam optimizer, which efficiently adjusts learning rates, and the mean absolute error (MAE) as a loss function to measure prediction accuracy. The dataset was split into 80% training and 20% testing, ensuring that the model learns patterns before evaluating it on unseen data. The training was conducted over 13 epochs, with the network weights iteratively adjusted to improve accuracy. Finally, we evaluated the model's performance on the test set to assess its ability to accurately predict wait times, providing valuable insights for improving airport security operations.

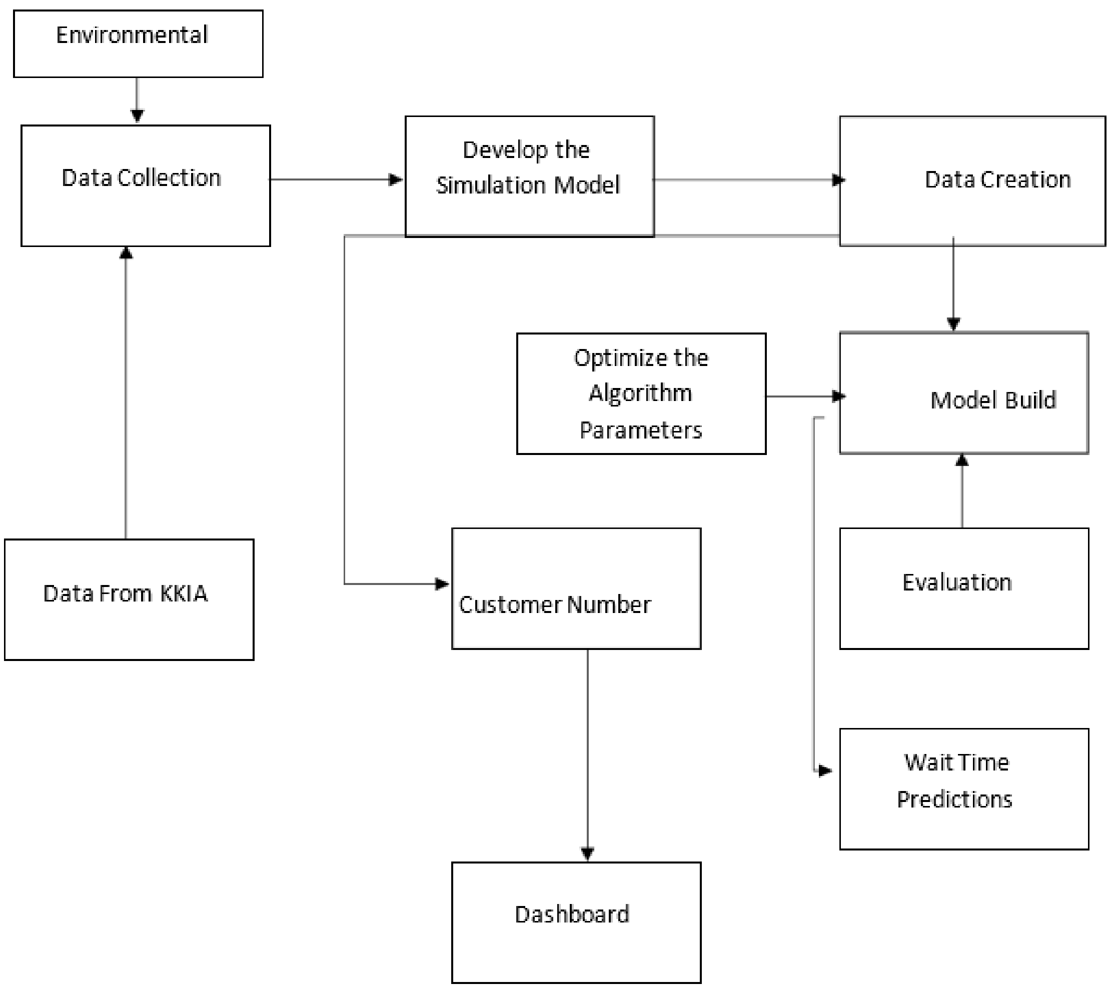

Figure 1. The Methodology Diagram

4. Results and Analysis

This paper introduces a novel approach to predicting waiting time at the baggage inspection area in KKIA. Data was collected from KKIA as averages. After that, simulation was used as a means of obtaining data that will be used for further analysis. Neural Network algorithms were then implemented to establish a model for the parameter prediction.

The goal was to predict the waiting time for a customer in the baggage inspection queue. Essentially, it is an important consideration to study which factors are affecting the waiting time for customers. The result and analysis cover two sections starting with analyzing the current queueing system to gain statistical insights that will be helpful later in evaluating the impact of different parameters on waiting time. Additionally, removing the outlier and manipulating the data to train and implement the model. Results show the parameters that influence the waiting time which are the queue count, interval number, peak/non-peak hour, and service time.
The model proposed obtained 88% accuracy this indicates that the model is relatively robust making it helpful for the airport operations management to understand the different parameters influencing waiting time therefore enabling them to make more informed decisions regarding which parameter to manipulate to reduce waiting time, enhance the customer overall experience, and better allocate resources. Additionally, presenting the predicted waiting times for different queues enables customers to make informed decisions about which queue to join therefore reducing congestion.

4.1 Parameters Evaluation

To train the model to predict the waiting time we need to evaluate the relationship that exists between the dependent variable which is the waiting time with several independent variables. In this research, we examine several parameters that might influence waiting times which are queue count, interval number, peak/non-peak hour, and service time.

4.1.1 Queue Count

Examining the relationship between queue count and waiting times reveals how queue length influences the pattern of service delays. Queue count represents the number of customers waiting for service at a given time. Waiting time indicates how long each customer spends before receiving service. Figure 2 illustrates the variation in queue counts over different periods within a 24-hour cycle. The results indicate that queue congestion peaks between 12:00-18:00, followed by 18:00-24:00, signifying high passenger inflow during these hours. Conversely, the lowest queue count is recorded between 06:00-12:00, reflecting reduced demand.

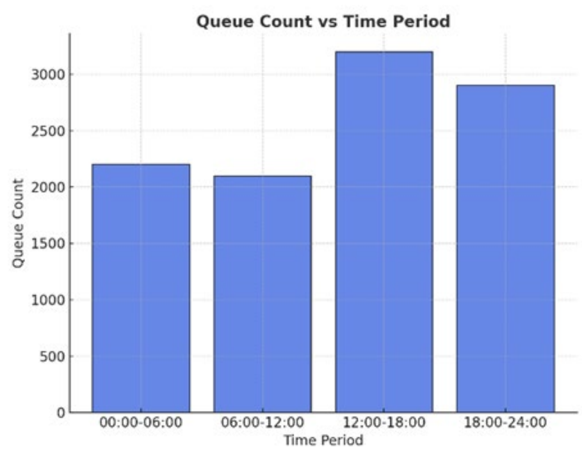

Figure 2. Queue Count Distribution Across Periods

Figure 3 visualizes the relationship between queue count and waiting time. The distribution pattern reveals a positive correlation, indicating that as queue size increases, waiting times proportionally rise. Notably, significant waiting times are recorded when queue counts exceed a specific threshold, reinforcing the necessity of real-time monitoring and efficient queue allocation mechanisms to minimize delays and enhance passenger experience.

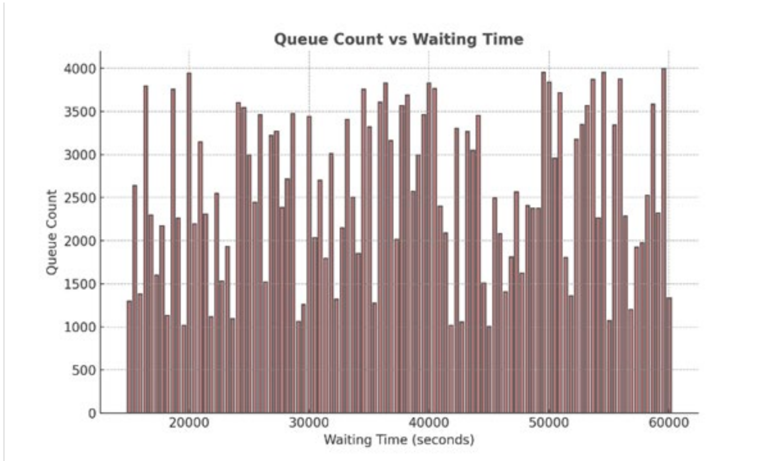

Figure 3. Correlation Between Queue Count and Waiting Time

4.1.2 Interval Number

A column was added to the dataset to divide the periods into 30-minute intervals. The reason for constructing a column with 30-minute intervals is to segment the data into manageable periods for more accurate analysis and prediction. Then, we added we added an interval column that assigns a numerical value to each 30 minutes. This allows the model to better interpret the data by treating each time slot as a distinct factor which can help improve the accuracy of predictions. Figure 4 demonstrates the fluctuation in arrival rates across different time segments. The highest arrival rates are observed during 00:00-06:00 and 12:00-18:00, whereas lower arrival rates are noted in the periods 06:00-12:00 and 18:00-24:00. These variations indicate dynamic passenger behavior throughout the day, emphasizing the need for adaptive queue management strategies that can efficiently handle peak periods while optimizing system performance.

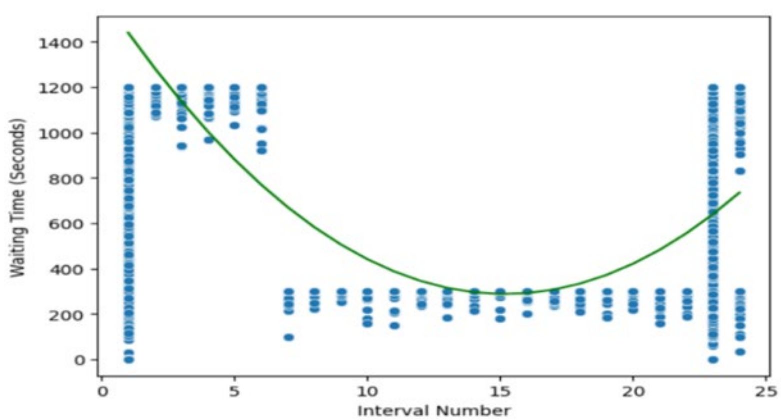

Figure 4. Arrival Rate Distribution Over Different Periods

Figure 5 shows the relationship between the interval number and the waiting time in seconds. The green curve in the graph represents the predicted pattern. The waiting time is high at early intervals, gradually decreasing and reaching its lowest point around the middle interval before increasing again towards the end. this suggests a non-linear relationship between interval number and waiting time, indicating peak and non-peak periods.

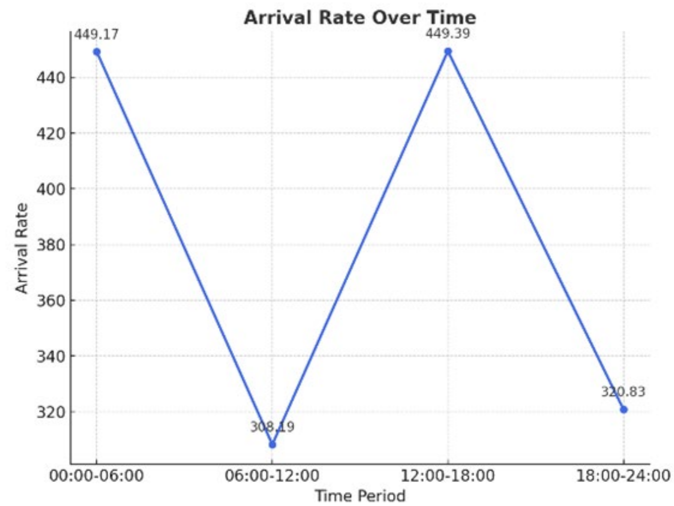

Figure 5. Relationship Between Interval Number and Waiting Time

4.1.3 Peak/non-peak periods

The peak and non-peak periods refer to the periods where the demand for service is either high(peak) or low (non-peak). To help the model interpret the categorical value of peak/non-peak periods, we converted these categories to numerical values using binary encoding assigning 1 to the peak period and 0 for the non-peak periods. By doing this, the model can interpret data more effectively by recognizing peak and non-peak periods as numbers contributing to predictions of the waiting time. Figure 6 demonstrates the relationship between peak and non-peak periods with waiting time. The waiting time is generally higher during peak periods indicated by the cluster of points around one on the X axis while it is lower during the non-peak periods around 0 on the X axis which reflects that demand for service and waiting time rise significantly during peak hours.

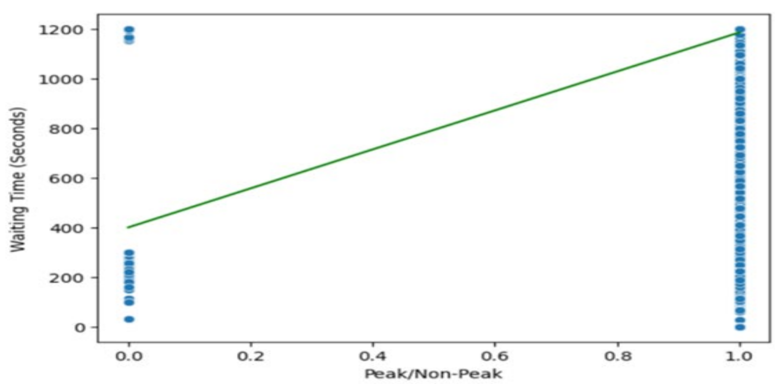

Figure 6. Relationship Between Peak/Non-Peak Periods and Waiting Time

4.1.4 Service Time

The service time refers to the time the service providers spend interacting or processing a customer. In the baggage inspection system, the service time would be the time it takes to inspect the passenger's luggage and ask security questions when needed.

4.2 Model Training and Evaluation

The model's performance is evaluated by calculating accuracy as the ratio of MAE to the mean value of the test set's dependent variable which is waiting time, and it was found to be indicating a reasonable model performance in predicting waiting times.

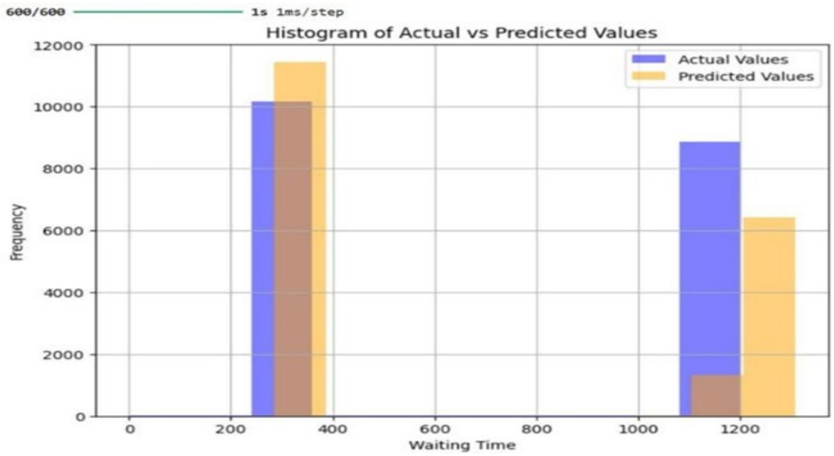

Figure 7. Histogram of Actual VS Predicated Waiting Time

Figure 7 is a histogram comparing the actual and predicted values. This illustrates that the model captures the general distribution of waiting times, particularly within the 200–400 second range, where the predictions align closely with the actual values. However, there exist some deviations when predicting higher waiting times, particularly around 1200 seconds. That suggests that the model accuracy tends to decrease when predicting longer waiting times. The model is considered effective in capturing the pattern seen in the data however there is still room for improvement. Enhancing the model's performance may require further refinement, such as handling data imbalances, or exploring more advanced prediction algorithms to reduce errors in extreme cases.

5. Conclusion

This research provides an innovative solution to the challenges of queue management in baggage inspection at KKIA. By integrating data analysis, queuing theory, simulation, and machine learning, the project addresses inefficiencies in traditional queue systems, such as prolonged waiting times and resource misallocation. The study utilized data from the airport, including passenger arrival patterns, service times, and queue lengths. Simulation techniques ensured the realism of the data, and a machine learning model was developed to predict waiting times based on key parameters like queue count and service times. The results demonstrate that peak congestion occurs between 12:00-18:00 and 18:00-24:00, with waiting times correlating directly with queue size. The machine learning model achieved an accuracy of 88%, effectively predicting waiting times in most cases, though some deviations were observed for higher durations. By implementing this smart queue management system, the airport could significantly reduce waiting times, optimize resource allocation, and improve passenger satisfaction. Real-time queue updates, priority-based scheduling, and adaptive allocation of resources are some of the key features that enhance operational efficiency. Furthermore, the proposed system is scalable and adaptable to other airports, providing a long-term, sustainable solution to queue management challenges. Future work aims to further enhance the model accuracy and scope of the proposed system, making it adaptable to different environments with further refinement to enhance efficiency and customer experience in high-demand environments.

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Biographies

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Sara Osama Sallam is a senior student majoring in Industrial Engineering at King Khalid University. With a strong interest in the field of queueing theory,which has developed expertise in problem solving, critical thinking and data analysis.

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