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Analysis of Flight Based Airport Passenger Arrival Patterns

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ABSTRACT

Maintaining effective and successful work in uncertainty is challenging in a niche sector such as aviation and all industries and situations. The situation is a little more complicated, especially in a sector such as the aviation sector, where the rules are not stretched and where one should always be on the alert. For these reasons, it is precious for businesses that carry out airline operations to analyze arriving passengers and understand whether there is a pattern among passengers. Although there are many factors affecting the arrival patterns of passengers, some of them are particularly noteworthy. For example, factors such as whether the flight is domestic or international, the season in which the flight takes place, and the flight hours take place to provide a broad perspective on the arrival patterns of the passengers at the airport. For example, it can be stated that while passengers on international flights see earlier arrival patterns at the airport, last-minute arrivals are more frequent on domestic flights. Similarly, in domestic flights, different passenger arrival patterns have been determined for the arrival airport, depending on the seasonality of the countries. On the other hand, according to the seasonality of the nations (for example, the opening of schools and national holidays), different passenger arrival patterns have been determined for the destination airport. Analyzes were carried out in Python and Excel and included case study outputs.

Keywords: Aviation, Pattern Analysis, Passenger, flights.

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Introduction

Although it is not very long ago that people make sense of data in the business world, the development of the concept of data analysis has accelerated with the digitalization of our world [1]. The key to successful business progress is correctly analyzing the factors affecting the business. Data analysis has gained meaning, especially recently, and it has given importance to the work done by providing various predictions to business owners. If the data analysis is done correctly, it is helpful to see the business's different aspects and negative or positive factors. It even enables accurate and successful predictions by taking it one step further. Considering the value that a business model built on successful forecasts will bring, the importance of data analysis is emphasized.

Since the aviation industry, whose rules are strictly defined, is a niche industry, the results are striking when data analysis is performed. Factors such as flight time, departure and arrival point, flight season, and whether the flight is on weekdays or weekends are essential factors in the classification of flights as well as passengers. A meaningful data analysis can only be made from existing data, new features can be created using existing data, and extended results can be obtained by including them in the analysis.

Researchers in transportation and operations management have extensively studied airport passenger arrival patterns. These studies aim to understand the behavior of passengers arriving at airports and to develop strategies to manage the associated risks and challenges. Airport passenger arrival patterns refer to the distribution of passenger traffic at an airport throughout the day, week, month, and year. This concept is vital in airport planning, design, and management. Understanding passenger arrival patterns help airport operators optimize resource allocation, plan for adequate staffing levels, and ensure the passenger experience is as smooth and efficient as possible. Studies have shown that various factors, including flight schedules, holiday periods, economic conditions, and local weather conditions, influence passenger arrival patterns. For example, a study by Chen and Li [2] found that passenger arrival patterns at Beijing Capital International Airport were strongly influenced by flight schedules, with the majority of passengers arriving in the early morning and late evening. Similarly, a study by Wang and Zhang [3] found that passenger arrival patterns at Shanghai Pudong International Airport were influenced by holiday periods, with increased passenger traffic during national holidays and peak travel periods. Advanced technologies, such as artificial intelligence and predictive analytics, have also been useful in modeling and understanding airport passenger arrival patterns. For example, a study by Wang et al. [4] used machine learning algorithms to predict passenger arrival patterns at Guangzhou Baiyun International Airport and found that the models could accurately predict passenger traffic levels with a high degree of accuracy.

One of the latest studies on airport passenger arrival patterns was conducted by Yang et al. [5] using data from two major airports in China. The authors analyzed the passenger arrival patterns based on flight schedules and passenger travel characteristics and found that passengers tend to arrive at the airport in clusters before their flight departure time, leading to congestion and delays. Another recent study by Kim et al. [6] used data from an airport in South Korea to examine the impact of passenger arrival patterns on airport resource utilization, such as parking spaces, check-in counters, and security checkpoints. The authors found that passenger arrival patterns have a significant impact on the utilization of airport resources and recommended the use of dynamic resource allocation strategies to improve airport operations and reduce passenger waiting times. In a study by Chen et al. [7] the authors used simulation and optimization models to analyze the impact of passenger arrival patterns on airport security checkpoint operations. The study found that passenger arrival patterns significantly impacted the efficiency and effectiveness of airport security operations and recommended using dynamic queuing strategies to improve the performance of security checkpoints.

Overall, the latest research indicates that passenger arrival patterns play a crucial role in the performance and efficiency of airport operations. Developing strategies to manage passenger arrival patterns is essential for improving airport performance and reducing passenger waiting times. In conclusion, these studies provide valuable insights into the behavior of airport passengers in arriving at airports and the impact of their arrival patterns on airport operations. They highlight the importance of understanding passenger arrival patterns and developing strategies to manage the associated risks and challenges, which can help to improve airport performance and reduce passenger waiting times. Moreover, the literature suggests that various factors, including flight schedules, holiday periods, economic conditions, and local weather conditions, influence airport passenger arrival patterns. The use of advanced technologies [8] such as machine learning algorithms, can also be useful in understanding and predicting passenger arrival patterns. These models can be used to support decision-making in the context of airport planning, design, and management.

Before the data world was so digitalized, descriptive statistical analyses were carried out. Then exploratory data analysis (EDA) [9][10] and later machine learning analyses developed with the development of technology [11]. Simultaneously, data visualization processes have also improved. Advanced data analyses and visualizations are now performed on Excel and in programming languages such as Python and R libraries. In this way, data analysis and visualization have reached vital importance not only in the academic field but also in the industry. Descriptive Statistical Analysis only describes the data, but exploratory data analysis (EDA) questions whether there are any anomalies or salient points in the data [12]. In this case, descriptive analysis is performed by accepting the hypothesis at first, then exploratory data analysis (EDA) is applied to the dataset, and the data is visualized so that it can be read meaningfully. Data that makes sense with visuals are frequently encountered in business reports. Instantly changing pages in many sectors, such as the aviation industry, are based on these analyses. For example, interactive graphics can be included on the home pages of the applications to track the instantaneous change in passenger numbers according to various factors. Thus, both passengers and airline operators can follow instant changes and take action for their own benefit.

Indeed, recent studies have continued to analyze and understand airport passenger arrival patterns to understand the factors that influence passenger traffic and develop models that can be used to predict passenger arrival patterns. with a focus on utilizing advanced technologies and data analysis techniques. For example, a study by Gursoy et al. [13] used statistical models to analyze passenger arrival patterns at Denver International Airport. The study found that flight schedules influenced passenger arrival patterns, and the authors developed a model that could be used to [14] predict passenger arrival patterns based on flight schedules. Another study by Hu et al. [15] used a queuing theory model to analyze passenger arrival patterns at Hong Kong International Airport. The study found that passenger arrival patterns were influenced by a combination of flight schedules, local weather conditions, and other factors, and the authors developed a model that could be used to predict passenger arrival patterns based on these factors. In addition, several studies have analyzed the impact of airline alliances and codeshare arrangements on passenger arrival patterns. For example, a study by Song et al. [16] found that codeshare arrangements between airlines significantly impacted passenger arrival patterns at Incheon International Airport in South Korea. In addition, the authors found that passenger arrival patterns were more spread out when airlines had codeshare arrangements as compared to when they did not.

One recent Li et al. [17] study used big data analytics to analyze passenger arrival patterns at Beijing Capital International Airport. The authors found that a variety of factors, including flight schedules, holiday periods, and local weather conditions influenced passenger arrival patterns. Additionally, the authors used machine learning algorithms to develop a model that could be used to predict [18] passenger arrival patterns, with the aim of improving airport planning and management. Another recent study by Chen et al. [19] analyzed passenger arrival patterns at San Francisco International Airport using a combination of spatial analysis and machine learning techniques. The authors found that a range of factors, including flight schedules, airport accessibility, and local demographic characteristics, influenced passenger arrival patterns. As a result, the authors developed a model that could be used to predict passenger arrival patterns based on these factors, and they suggest that this information could be used to improve airport planning and management.

In conclusion, recent studies have continued to analyze and understand airport passenger arrival patterns, utilizing advanced technologies and data analysis techniques. Results from these studies suggest that a range of factors, including flight schedules, holiday periods, local weather conditions, airport accessibility, and local demographic characteristics, influences passenger arrival patterns. A variety of models have been developed to [20] analyze and predict passenger arrival patterns and improving airport planning and management, including statistical models, queuing theory models, big data analytics and machine learning algorithms.

Ease of Use

The study was analyzed on real data from a niche sector such as the airport. It is comparable to analyzes for airports and includes actionable results for a better passenger experience. As different data sets can be created at various airports, passenger behaviors vary according to many factors. Therefore, much more data is needed to generalize the outputs. For example, analysis results may differ when data containing more airports and flights are included.

Analysis

This paper uses our private airport data, which has 32907 rows and 27 columns, however some of the columns are not relevant and unnecessary for this analysis therefore it was used only 18 of them. Columns are listed in the table-1 with descriptions, non-null counts, types, and examples. Also, new features were generated based on the Scheduled Time Departure (STD) column listed in Table 2 with the same explanations as Table 1. Therefore, there are 18 columns came from raw data and 7 columns from generated data so that total 25 column was used to make an analysis.

The Python libraries used in the analysis are mainly as follows; *pandas, numpy*, *matplotlib*, *seaborn* and *datetime*. *Matplotlib* and *seaborn* libraries are used for visualization. Year, month, and week are generated with the Python *datetime* library based on the STD column. Monday, Tuesday, Wednesday, Thursday, and Friday are weekdays, and Saturday and Sunday are weekends. Seasons are generated with the following rule: December, January, and February are defined as winter; March, April, and May are defined as spring; June, July, and August are defined as summer; and September, October, and November are defined as fall seasons.

Table 1. Raw Data set (Some Features)

Column Name	Column Description	Non-Null Count	Data Type	Example
INT/DOM	Whether the flight is international or domestic	320907	Object	I
STD	Scheduled Time Departure	320907	Datetime64[ns]	2021-11-07 11:50:00
tota_pax_count_all_points	Total passenger number for all points at the airport	320907	Int64	185
total_pax_count_checkin	Check in Passenger number	320907	Int64	145
checkin_rate	Rate of check ins	320907	Float64	0.7837
360-330	Time slot before 360-330 minutes of the flight (There are 12 time slot columns at half hour intervals)	320907	Int64	0
delay	Delay of flight in minutes	320907	Float64	27.000

Table 2. Generated Features

Column Name	Column Description	Non-Null Count	Data Type	Example
day_of_week	Day of the week for flight	32854	Int64	0
week	Weekday or weekend information	32854	Object	weekday
day_of_year	Day of the year for flight	32854	Int64	101
month	Month of the flight	32854	Int64	3
seasons	Seasons of the year	32854	Object	Summer
my_timezones	According to hours, name the timezone	32854	Object	Morning
flight_count	Whether the flight is less than 400 or not	32854	Object	Few_flight

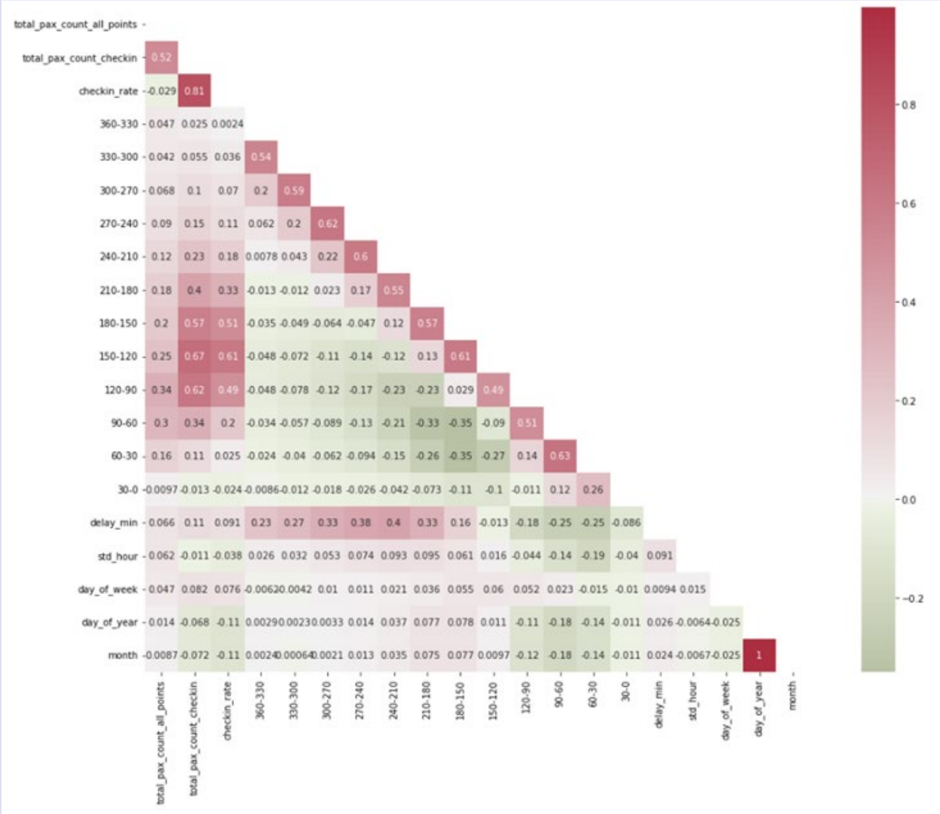

Figure 1. Correlation Heatmap of Data Set

According to the flight industry, between 2 AM and 5 AM are defined as night, between 5 AM and 11 AM as the morning, between 11 AM and 8 PM as noon, and between 8 PM and 2 AM are defined as evening. The dataset needs to be well-distributed for the number of flights, so flights with less than 400 views are labeled as few, and flights with more than 400 views are labeled as many.

After generating new features, there might be irrelevant rows in the data frame; for instance, if there are no passengers in all time slots, this analysis will be unnecessary; therefore, these rows are deleted. In our private data, all departure airports are ADB, so it is nonsense to use the *from_airport* feature so that the column is deleted. Moreover, there are some unknown aircraft types written as 'XXX,' which is also irrelevant to the analysis; therefore, rows with aircraft types are XXX also deleted. Finally, data is not well distributed, so there are various airlines and flights. For the analysis's sake, airlines that occurred less than six times are deleted from the data set.

Correlation values were calculated based on pairwise correlation of columns, excluding NA/null values with python *corr()* function [21] and shown on a heatmap in order to see the features that may be related to each other in the data set. Correlation is calculated between the numeric values in the data frame, and other than the numeric values are ignored in the calculation. Although there are three main calculation methods for correlation, such as Pearson, Kendall, and Spearman, python takes Pearson standard correlation coefficient as default, so in this analysis, Pearson calculation is used. Calculation results rely on -1 and 1. 1 means a perfect positive relationship, -1 means a perfect negative relationship, also 0 means there is no relationship between variables [22]. Pearson standard correlation coefficient is calculated as given in the equation 1, where $\bar{X}$ is mean of X variable and $\bar{Y}$ is the mean of Y variable. It has 4 assumptions:

- Each observation should have a pair of values.
- Each variable should be continuous.
- It should be the absence of outliers.
- It assumes linearity and homoscedasticity.
-

$$r = \frac{\sum(X-\bar{X})(Y-\bar{Y})}{\sqrt{\sum(X-\bar{X})^2 . \sum(Y-\bar{Y})^2}} \quad (1)$$

According to the heatmap in Fig. 1, a high positive correlation was observed between the periods in the 180-90 range and the check-in rate. In other words, it can be said that the passengers arriving at the airport during this period are those who have checked in. As seen in the following chapters of the study, most passengers arriving at the airport by checking in between 180-90 times are passengers on international flights. In addition, a relatively high correlation was calculated between the delay time and the 240-210-time interval. Negative correlation computed values do not make sense since they are very close to 0. Therefore, in general, it can be said that there is no negative correlation.

The analysis is based on the flights, passengers, check-in rates, and flight delays.

Flights

In Fig. 2, the x-axis gives the number of flights, and the y-axis shows the information on domestic/international, weekend/weekday, and time zone of flights. Colors are distributed for the seasons.

According to the Fig. 2, flights are grouped with international/domestic, weekday/weekend, time zone, and seasons. It can be said that a maximum number of flights occurs in Domestic, weekday, and morning during the fall season, and the minimum number of flights occurs a domestic, weekend, and night for all seasons. Also, domestic, weekday and noon flights are much more than the rest of the data set. For international flights, it can be said that the maximum number of flights are in the summer season with the information of weekdays, noon. It can be stated that for the international weekday night flights, in the winter season, there are few flights. Overall, it can be noted that the fewest flights took place at night. While the mornings are suitable for domestic flights, noon is preferred for international flights.

Passengers

Passenger analyses are made into three groups. The first group is named all passengers, and the second is check-in passengers. The third group is analyzed under the 12-time slots based on their arrivals at the airport. Moreover, data is grouped with domestic/international flights, weekend/weekday flights, time zones, and the seasons of flights.

In Fig. 3, the x-axis gives the number of passengers, and the y-axis gives the information on domestic/international, weekend/weekday, and time zone of flights. Colors are distributed for the seasons. According to the Fig. 3, like the distribution of the flights, there is a difference between international and domestic flights. For domestic flights, weekday morning and weekday noon are the most preferred time zones in all seasons. On the contrary, weekday and weekend nights are the least preferred time zones for domestic flight passengers.

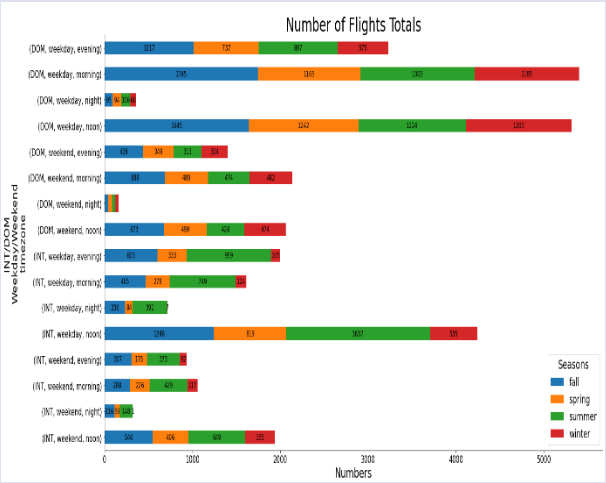

Figure 2. Distribution of Flights

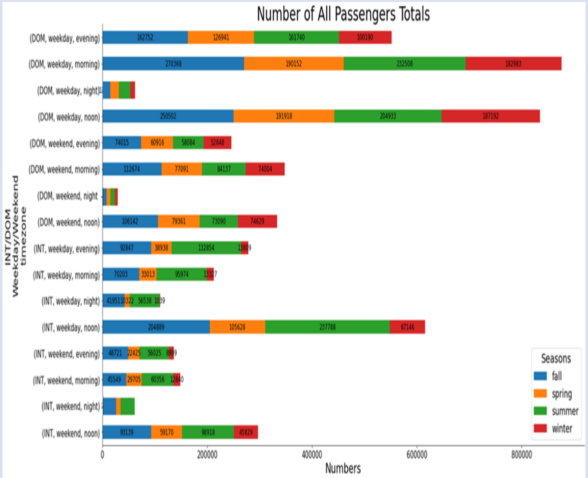

Figure 3. Distribution of All Passengers

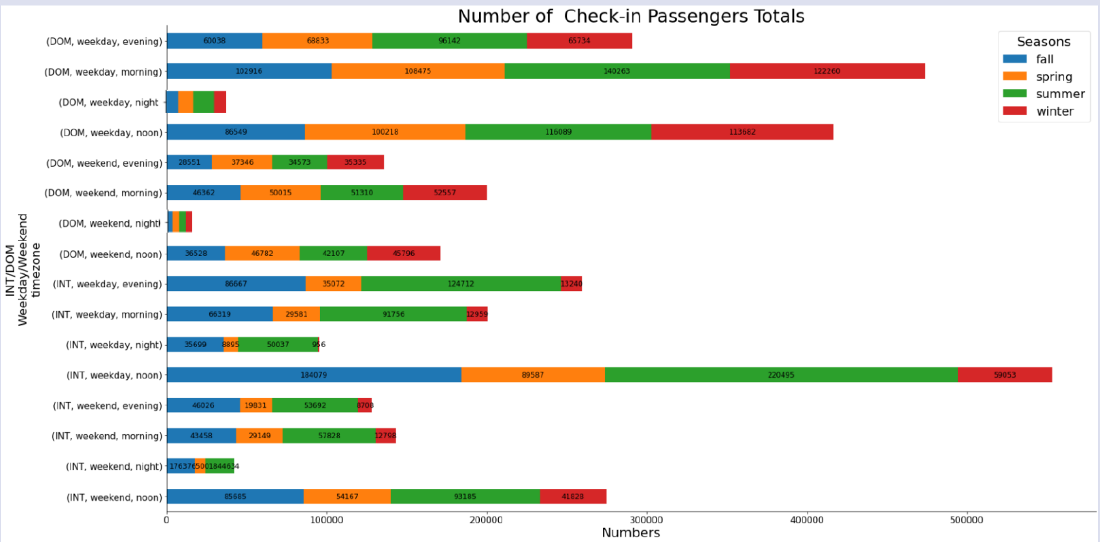

Figure 4. Distribution of Check in Passengers

For international flights, passengers preferred weekday noon flights with respect to other time zones in all seasons. It can be said that international flights are increased in the fall and summer seasons. However, the winter season is the least preferred season for international flights. The preferences are based primarily on the national holidays and the exact seasons, such as school opening closings.

In Fig. 4, the x-axis gives the number of passengers who made check-in procedures at the airport, and the y-axis shows the information on domestic/international, weekend/weekday, and time zone of flights. Colors are distributed for the seasons. Contrary to the all-passenger plots in Fig. 3, international passengers are made check-in procedures more than domestic passengers especially on weekday, noon group. Even though, domestic passengers also made check-in procedures at the airport specifically on weekdays morning and noon, total number of check-in passengers of domestic flights are quite a few than total number of check-in passengers of international flights. Therefore, in Fig. 4, the maximum number of passengers is located on the international, weekday, and noon flights, especially for the summer and fall seasons. It can be said that international passengers tend to make check-ins for the summer flights but not for the winter flights. It can be seen from the Fig. 4; check-in procedures are made less for domestic flights. On the contrary to international flights, domestic flights mostly happen in the summer and winter seasons. Most domestic passengers preferred weekday mornings for their flights.

Passengers over Time Slots

Passengers are grouped by the 30 minutes periods. It starts with a 360-300 slot that is 360 minutes before the flight and continues like that. The difference is noticeable, especially for domestic and international flights. Most of the passengers arrive at the airport between 120-90 minutes; from Fig. 13, it can be easily seen the number of passengers from the x-axis. For domestic flights, the last period arrivals are more usual than for international flights, specifically between 90-0 minutes. However, when international flight passenger arrives at the airport between 180-120 minutes, domestic flight passenger has yet to be seen at the airport.

Since both international and domestic flight passengers usually choose to come to the airport between 120-90 time slots, it can be stated from Fig. 5-16 that arrival patterns are distributed mainly on the type of flight domestic or international.

Check in Rates

When the check-in rates of incoming passengers are examined according to whether the flight is domestic or international, season, time, and weekdays, it can be seen from Fig. 7 that the most significant difference is between domestic and international flights. The check-in rates of domestic flights are much lower than the check-in rates of international flights. Especially in the autumn period, there is a severe proportional difference between them. Therefore, check-in rate differences may be due to the fact that domestic flights are fewer in autumn.

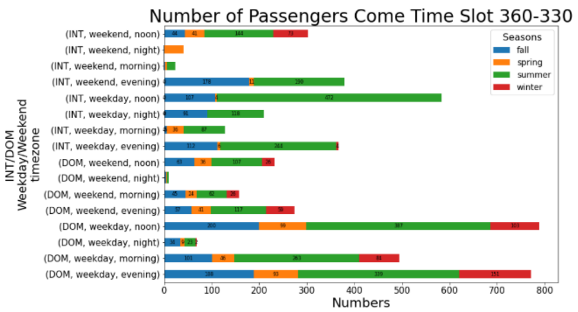

Figure 5. Distribution of Check-in Passengers come in Time Slot 360-330

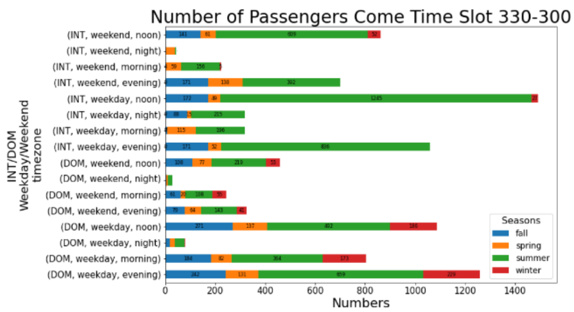

Figure 6. Distribution of Check-in Passengers come in Time Slot 330-300

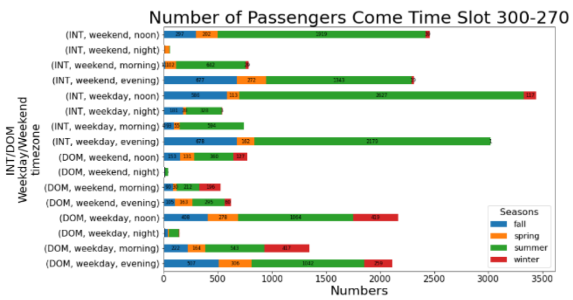

Figure 7. Distribution of Check-in Passengers come in Time Slot 300-270

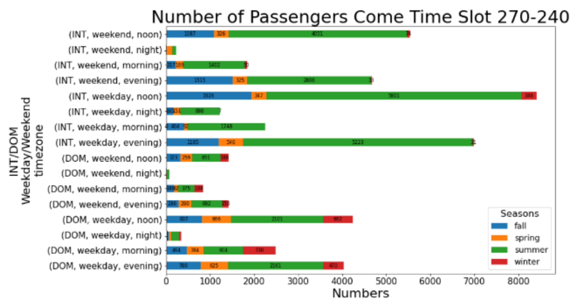

Figure 8. Distribution of Check-in Passengers come in Time Slot 270-240

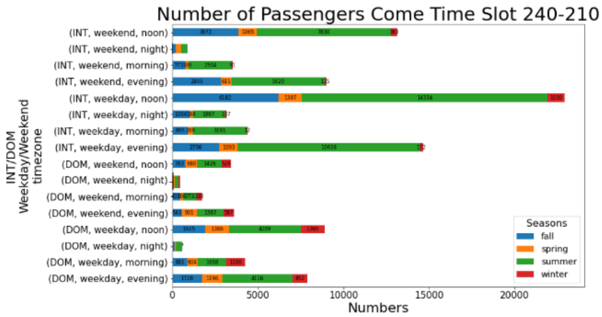

Figure 9. Distribution of Check-in Passengers come in Time Slot 240-210

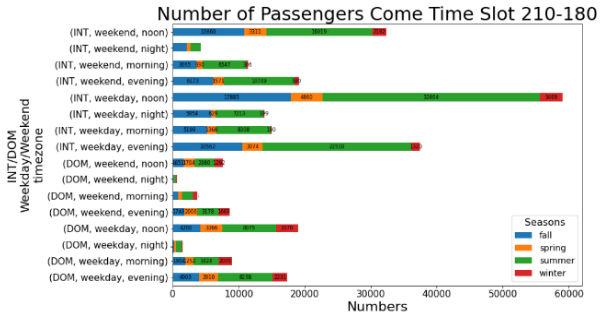

Figure 10. Distribution of Check-in Passengers come in Time Slot 210-180

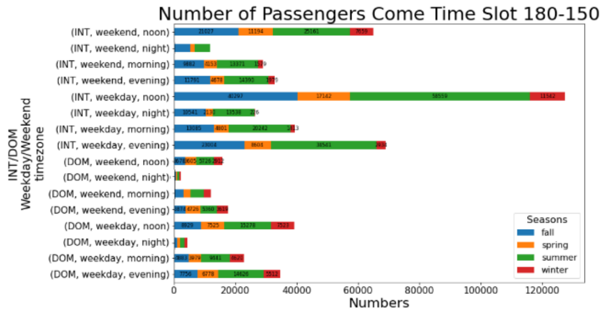

Figure 11. Distribution of Check-in Passengers come in Time Slot 180-150

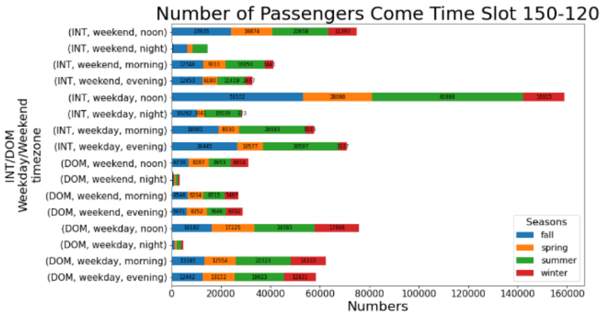

Figure 12. Distribution of Check-in Passengers come in Time Slot 150-12

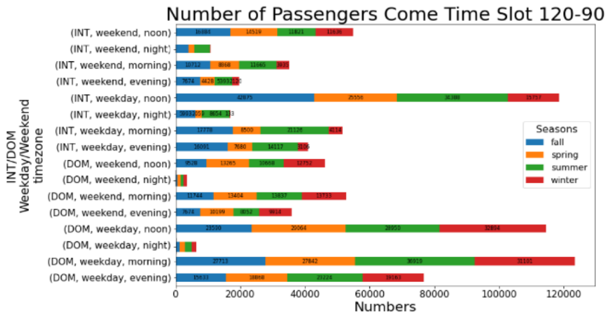

Figure 13. Distribution of Check-in Passengers come in Time Slot 120-90

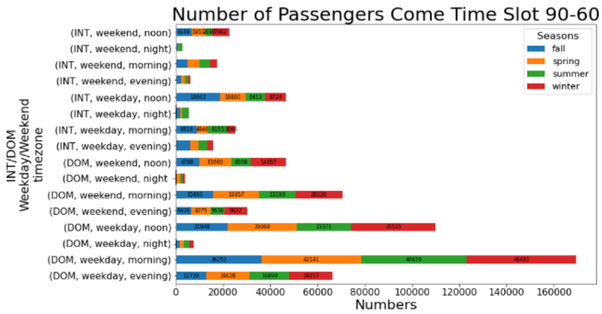

Figure 14. Distribution of heck-in Passengers come in Time Slot 90-60

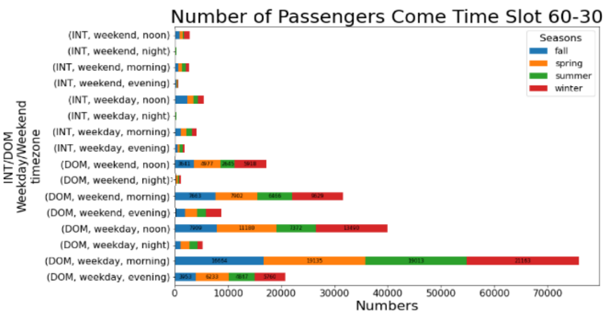

Figure 15. Distribution of Check-in Passengers come in Time Slot 60-30

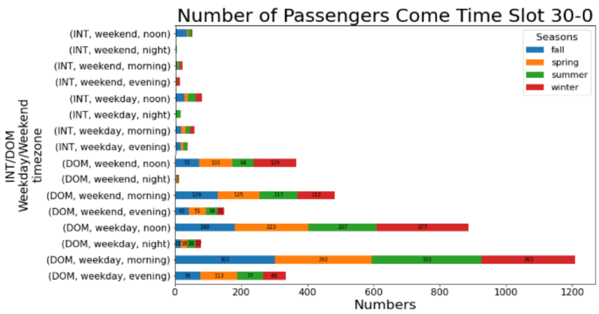

Figure 16. Distribution of Check-in Passengers come in Time Slot 30-0

Figure 17. Distribution of Check in Rates

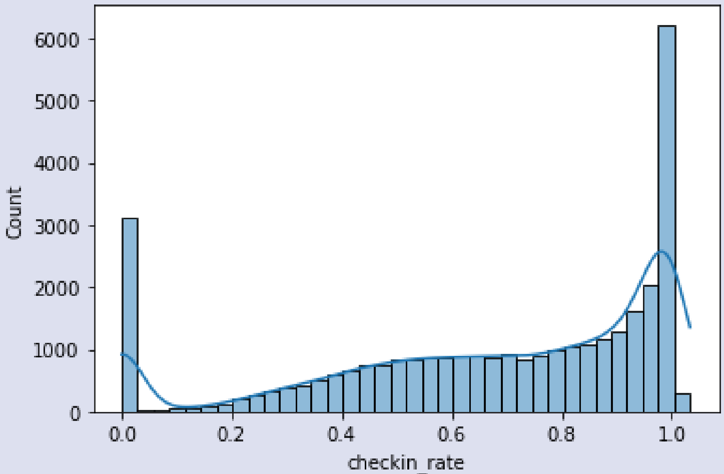

Figure 18. Distribution of Check in Rates-Ungrouped

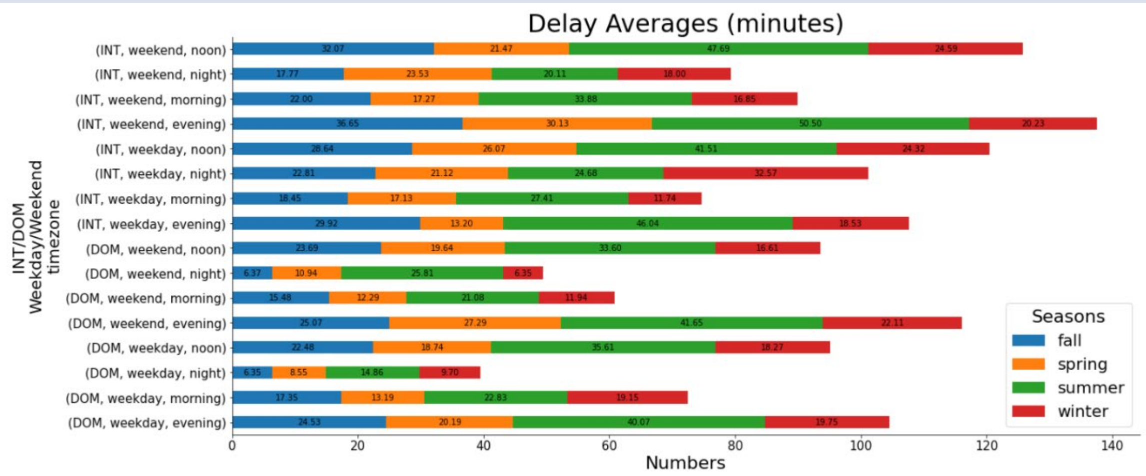

Figure 19. Distribution of Delays in Averages

The check-in rate distribution of all flights without any grouping can be found in Fig. 8. The reason for the check-in rate appearing above 1 is that there are people who appear twice in our dataset, but we decided to keep it as this did not disrupt the course of the analysis. When we look at the check-in rate distribution graph, it is possible to say from Fig. 8 that 0s and 1s are in weight, but the average is 0.5.

Delay Averages

Fig. 9 shows the average delays of the flights. Accordingly, it can be said that most delays occur in the summer months. In this chart, the distribution according to the season distinction and the period of the day of the flight rather than the domestic/international distinction draws attention. The average delays are directly proportional to the excess flights in those periods. The highest average in international, weekend, and evening summer flights was recorded as 50.50 minutes. The lowest average was recorded as 6.35 minutes for domestic flights in the winter and autumn, from the periods with the least flights.

Discussion and Further Works

Analyzing flight-based airport passenger arrival patterns is an essential aspect of airport management. It provides valuable insights into passenger behavior and helps airport authorities optimize their resources to improve the overall efficiency of airport operations. By analyzing passenger arrival patterns, airport authorities can identify the busiest times of the day, week, or year and allocate resources accordingly, such as deploying more staff at peak times, opening additional security checkpoints, or providing more parking spaces. The relevant analysis leads to a more seamless and efficient passenger experience, reducing wait times and congestion and enhancing the airport's overall reputation.

Moreover, analyzing passenger arrival patterns also has implications for airport security. By monitoring passenger arrival times, airport authorities can identify potential security risks, such as suspicious behavior or irregular travel patterns, which enables airport security personnel to respond quickly and appropriately, enhancing the safety and security of the airport and its passengers.

Firstly, data analytics techniques such as statistical analysis, data mining, and machine learning can be used to analyze passenger arrival patterns and identify trends and patterns. Then, data visualization tools such as heat maps, scatter plots, and histograms can be used to display and interpret the data. For example, a study by Chen et al. (2019) [23] used data mining and visualization techniques to analyze Hong Kong International Airport passenger arrival patterns. The study found that most passengers arrived between 6 am and 8 am and 2 pm and 6 pm and recommended that airport authorities allocate more resources during these peak periods.

Secondly, predictive modeling techniques such as regression analysis, time series analysis, and neural networks can be used to predict passenger arrival patterns and forecast demand. For example, a study by Gao et al. (2019) [24] used a predictive modeling approach to estimate passenger arrival times at Beijing Capital International Airport. The study found that the model achieved an accuracy of over 80% in predicting passenger arrival times and recommended that airport authorities use it to optimize their resources and improve airport efficiency.

In this study, a special data set was created, and some analyzes were carried out by questioning the similarities and differences of the flights in different categories, the analysis of the behavior of the passengers at the airports, and whether there was a specific pattern. The most apparent difference from the outputs is the differences between domestic and international flights. The following output is that the flight frequency increased and decreased according to the time of day the flight took place. In addition, seasonal flight differences also differed in domestic and international flights. Flights and passengers were examined in terms of season, flight type, and temporal, as well as flight delays and check-in rates. In addition, the features that can be positively or negatively related to each other according to the correlation between the components in the data set were examined.

Overall, the analysis of flight-based airport passenger arrival patterns is crucial for optimizing airport operations, improving the passenger experience, and enhancing airport security. As airports continue to grow in size and complexity, the importance of this analysis will only increase, making it a vital area of research for airport management professionals.

Future studies it is aimed to develop the analysis with a more extensive and diverse data set. The scope and results of the analysis will be developed with data from different airports and parameters that can be generated. Thus, the passenger arrival pattern will be drawn, the flights will be classified, and studies will be carried out to provide a more effective airport experience.

Despite the importance of analyzing flight-based airport passenger arrival patterns, several challenges and limitations exist. For instance, data collection and processing can be time-consuming and costly, requiring significant investment in technology and resources. Additionally, the accuracy and reliability of the data can be impacted by several factors, such as incomplete or inconsistent data, errors in data entry or processing, or changes in passenger behavior.

To address these challenges, researchers and practitioners must continue to explore and develop new techniques and tools for analyzing flight-based airport passenger arrival patterns. For instance, machine learning algorithms and predictive modeling techniques can help accurately identify and predict passenger arrival patterns, enabling airport authorities to plan and allocate resources more effectively. Similarly, new data collection methods like mobile applications and sensors can help capture real-time data on passenger arrival patterns, providing a more comprehensive and accurate view of airport operations.

Moreover, as airports continue to face increasing pressure to reduce their environmental impact, analyzing passenger arrival patterns can also promote sustainable airport operations. Airport authorities can optimize ground transportation and reduce congestion and emissions by identifying peak times and routes and upgrading more sustainable and efficient transport systems.

In conclusion, the analysis of flight-based airport passenger arrival patterns is an important area of research for airport management professionals. By leveraging new technologies and data collection methods, researchers and practitioners can develop more accurate and effective strategies for optimizing airport operations, improving the passenger experience, and enhancing airport security and sustainability.

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