Data-Driven Insights for Moroccan Airports: PCA and Clustering to Enhance Operational Performance

H. Fatih[1] A. Bentaleb[2], M. Lazaar[3], B. Bentalha[4]
ENSIAS, Mohammed V University in Rabat, Morocco[1,3]
ENCG, Sidi Mohamed Ben Abdellah University, Fez, Morocco[2,4]

***Abstract*—Following the trend of increasing complexity among systems, in an attempt to meet air passengers' demands for higher quality service, this paper contributes to this stream of research by studying the operational efficiency of Moroccan airports through a novel multivariate approach. This research examines the following five performance metrics: baggage handling time, police screening time, customs processing time, passenger traffic, and flight delays. In this context and making use of Principal Component Analysis (PCA) with K-Means clustering, this paper aims at identifying the causes of operational variability, their significance in terms of performance management, and differentiating flights with similar operational profiles. Turning so particular techniques to the data of the moroccan airports this study reveals hidden patterns within airport interrelated activities, that in most cases were neglected by the traditional system of measurement. The findings make methodologies advancement in multivariate analysis of transport systems as well as practical improvement in the management of airport operations, and eventually impact on coordinated strategies of resource allocation for the systemic profit and the passenger utility. Through the use of PCA and K-means on the unreleased data of airports in Morocco, this paper is the first to offer a full multivariate study of the airport in the whole North African region. In contrast with standard monitoring systems which treat metrics as isolated entities, the study concurrently analyzes the dependencies among five key measures, discloses latent operational patterns, and promotes the formulation of context-based management policies suitable for an immature aviation market.**

Keywords*—*Principal Component Analysis (PCA); airport performance; transportation systems; K-means clustering; operational optimization; airport efficiency; airport operations management; air traffic; passenger experience

I. Introduction

Airline operations management takes into account the customer satisfaction, efficiency, and safety. Moroccan airports connect Europe, Africa and the Middle East, and struggle to keep pace with rising traffic and ensure safety and service. With international air traffic on the rise, notably in developing regions such as North Africa, airport efficiency has turned into a significant concern both for competitiveness and the passenger experience [20]. Moroccan airports, which link the country to Europe, Africa and the Middle East, are under growing pressure to enhance operations throughput along with high standards of security and service.

Among the many problems in airport management, three processes are especially critical: baggage handling, security screening (police checks), and customs .Three Particularly Critical Processes: baggage handling, security screening, and customs Among the numerous problems in managing airports, three procedures in particular are critical: handling of baggage, security screening (police reviews) and clearing of customs. These procedures, with the weight of passengers and potential flight delays, determine the general performance of the airport's operation. Yet these processes are linked and influenced by core and sometimes surprising elements. Traditional performance measurement tends to consider processes one at a time. Passenger throughput and on-time aircraft performance affect airport efficiency. Many airports monitor these activities independently and miss the significant pattern owing to the blind spot. The evaluation of complex airport systems requires advanced analytical tools to produce meaningful results [4]. Our method combines multiple ML and statistical approaches. In particular, cluster-based techniques such as K-means are used to cluster the operative data and find groups of flights that share similar patterns of flight activities, that is to say to discover hidden structures in the operational schedule. At the same time, Principal Component Analysis (PCA) is applied to analyze high-dimensional multivariate data sets to find key factors and causes of variability in operations [21]. The integration of these methods results in a decision-support system providing enroute and ground controllers with a clear, high-fidelity depiction of the real-time operational picture, enabling the identification of subtle and/or developing performance anomalies, and facilitating the smart, data-informed management of critical resources. This paper has been particularly focusing on the operational data that were obtained from major airports in Morocco. The analysis is based on five critical Key Performance Indicators (KPIs) that were demonstrated to be important for both the service and the optimisation of the airport function as well as in the passenger journey quality of experience [13]. These performance measures are not some random statistical averages but rather critical quantitative indicators of how well the system is working. The KPIs that undergo stringent evaluation are as follows: the flight schedule adherence (expressed as flight delays), baggage processing time, security screening queueing time, customs and immigration clearance time, and passenger flow (passenger traffic volume). The second concentration of this scientificpapaer is the theicha are the principal component analysis (PCA) Morocco airport operation data.

The purpose of this study is established through three interrelated goals that naturally flow into and support each other in a grounded, practical model of airport operations. Our second objective is to demonstrate to the airport manager how these critical influencers can be exploited. Moving from raw statistical results to decisions about staff to leverage resources or to modify the process that captures them completes the loop in the production and analysis of information. In the end, "similar" is defined by a set of trip features and the origin and destination airports. They could be high-volume, lots of turnarounds, not tricky roads. With profile information, airport managers can anticipate areas of financial risk, adjust practices, redeploy personnel, and highlight potential bottlenecks of activity. It enables the airport operator to raise its own performance and that of its customers, and demonstrates how sophisticated analytical methods can be profitably applied to transport systems. Accordingly, the rest of the paper is organized as follows. First, we develop a conceptual model of airport flight operations. Then, we present the approach, PCA and clustering analyses, applied to the Moroccan airport data. Thirdly, our multivariate findings suggest to different profiles of dynamics and performances. The significance of these findings for managerial actions and for airpot efficiency policy are finally discussed.

A. Conceptual Framework: Airport Flight Operations

Every day the airport has to balance aircraft, passengers, and cargo safety with service quality — the truth is that they are expected to be consistent and secure and efficient levels of service every day. The level of coordination among the different parts of an airport is how effective it is as an airport. Today airport safety is all about technology. They have-advanced sensors; networks giving wall information; and automated alerts that can warn of potential issues even before humans are watching. Response teams in crisis situations often train with local law enforcement, airline operation centers, and air traffic controllers to build coordination. Contemporary airport management must strictly comply with rigid safety and regulatory standards, which today requires copious real time monitoring, recording, and reporting to aviation authorities. In the current airport environment, however, central command is exercised through the sophisticated Airport Management System (AMS) [16]. Airport security operations combine sophisticated surveillance technology, live monitoring capabilities and automated alert systems to identify threats early in their development. Response teams are regularly exercised at various levels to maintain readiness levels, and they are coordinated with local emergency services, air traffic control agencies, and airline operators to provide a quick and cohesive response at the incident scene. Compliance with regulations requires ongoing auditing, documentation and reporting to the aviation authorities in order to keep the operating approval and safety status [18].

It is well known that airports all over the world are struggling with enormous impact of weather on their operations,and therefore need to be equipped with a well-developed resilience strategy to resist that impact and, if possible, to recover from it as quickly as possible. Weather-related delays and cancellations are among the largest sources of perturbation and demand for mitigation and adaptive management. Literature review has shown that airports are capable of exerting disruptive potential at different levels when exposed to various meteorological hazards, ranging from minor hold or delay actions to complete shutdown [12]. Thunderstorms are dangerous and destructive, but tend to have more predictable patterns of disruption than widespread weather phenomena such as sandstorms that can reduce visibility and contaminate the air for days or weeks over large swathes of lands. The time-space attributes of meteorological events have a non-negligible effect on the recovery rate and restoration of operations [10].

Airports are starting to use smart technology like artificial intelligence and machine learning to make their systems better. They look at past patterns, current conditions, and future predictions to come up with the best plans for how to operate. The integration of artificial intelligence and machine learning algorithms enhances decision-making processes by analyzing historical patterns, current conditions, and future projections to recommend optimal operational strategies [19]. While a thunderstorm is typically easier to anticipate, it can still cause delays and scheduling uncertainty. Rather than just responding to the weather, intelligent airports aspire to predict the weather long before it arrives. They invest in models and sophisticated weather monitoring systems that enable them to anticipate the impact of the weather on their operations and make operational adjustments. When the weather turns bad, the teams on the ground alter their priorities with a new emphasis on rerouting, safety protocols intensified and equipment used differently. “And then the physical lay of the land of the airport, as well, like wind instruments, drainage systems for heavy rain and snow removal machinery that allows the facility to keep functioning during inclement weather.”

Streaming information about the weather and the status of the equipment, thanks to IoT sensors. “Airports control it through a cloud-based system, which also allows them to operate remotely when necessary,” he adds. And they are using more and more artificial intelligence to schedule operations, to determine when equipment requires maintenance and in real-time resource management. Any modifications must meet the high standards that we set. Airports need to stay abreast of changing regulations and constantly maintain operational approval via reviews. The influence of environmentalism on the aviation sector is reverberating. Airports are beginning to improve their emissions, energy efficiencies and sustainable building practices. The sector has been able to demonstrate change for the better – electrifying support vehicles, and investing in sustainable aviations fuels. Air travel is in higher demand, but airports must consider their environmental impact and be good stewards of the land. Successful resources management is important and include flexible use of resources, facilities, and prediction of demands. Our aim is to expand responsibly, delivering high-quality service to travelers.

We investigated the related work to discuss the connections between our work prior work. Our review comprised 20 recent academic studies, published between 2020 and 2024, related to different facets of airport operations. We have considered peer-reviewed articles, conference papers, book chapters and patents to extract knowledge about the management of airport operations. From the literature, six salient themes were therefore identified. These themes are useful in giving structure to the multifaceted domain of airport operations, and provide a direction, the way problems can be approached and the manner of significant technological alterations in every day airport processes.

1) Combining data analytics and artificial intelligence: Artificial intelligence and big data are transforming airport operations. The [1] shows AI is improving flight operations, reducing delays and increasing flight capacity. The industry is adopting a tech-driven approach, with airports using business intelligence tools to turn raw data into insights for better sustainability and performance management [2]. The study [3] focused on ground operations, coordinating plane movements, which resulted in more on-time departures, shorter taxi times, and improved safety. The study [4] combined computer simulations with traffic flow models to forecast airport traffic and management strategies. These AI applications are enhancing airport operations daily in measurable ways.

2) Methods of mathematical modeling and optimization: Scientists are applying sophisticated mathematical techniques to airport operations problems. The study [5] formulated a Mixed-Integer Linear Programming model for the runway sequencing and timing problem, minimizing the number of unnecessary aircraft movements and maximizing the number of aircraft served while maintaining safety. The 2022 study of Tokyo International Airport by study [11] achieved almost 30% cuts in taxi times and nearly 19% reductions in taxi distances. The success was attributable to the integration of live flight data and the creation of dynamic models to reflect changing scenarios. The study [14] addressed the slot allocation problem under capacity uncertainty and airline flexibility. Their simulation analysis demonstrates that such an optimization positively affects the technical results and the passenger satisfaction in a high-traffic airport.

3) Safety management and risk assessment: Safety studies concentrate on recognition and reversal of hazards. The study [9] Risk model for flight operations developed a risk model for flight operations based on fuzzy analytic hierarchy processes and entropy for enhanced safety hazard assessments. Progress in aeronautical technologies also affect safety research. [15] investigated drone integration in airport air space by employing mathematical modelings as well geofencing techniques to avoid collision risks with commercial aircraft, which is essential due to the emergence of aviation technologies and aircraft types.

4) Operational continuity and weather resilience: Airports are threatened by severe weather, so research is underway to prepare for stormy conditions. The study [10] investigated the management of airports in extreme weather via departure rate analysis and built update parameters considering vulnerability, impact mitigation, emergency response, and recovery time, validating their model at Beijing Capital Airport.

5) Efficiency improvement and process optimization: Study seeks to raise efficiency of airport operations. The study [6] proposed an Aircraft Turnaround Manager system to mitigate delay by analyzing on-the-fly parameters including passenger boarding and baggage reclaiming. On the other hand, [8] applied process mining technology on about 101 aircrafts in international airports to recommend the intervention of fleet capacity and operational performance, demonstrating the optimal space with data-driven.

6) Routing and traffic control optimization for 2D airspace: There are also ongoing researches about aircraft scheduling and routing in air traffic management. The study [7] showed that adjusting STARS (Standard Terminal Arrival Routes) and CDOs (continuous descent operations) could greatly enhance safety and efficiency. The study [17] proposed a flight scheduling algorithm which improved the airport throughput and delay over 31% and maximum throughput up to 12% using multi-objective optimization mechanisms.

Several, but well defined trends are reshaping the activities operated in airports. Cloud-based architectures, real-time analytics and IoT sensors being rolled out in more airports are driving a digital refresh. But interaction with drones and autonomous ground vehicles presents an industry-specific array of challenges. The procedure is applicable not only to the process of deciding how efficient and how tightly the aircraft need to be packed on the ground, but also to determining related quantification including fuel burn, emission reduction, green practice and environmental impact of work practice.

II. Methodology

A. Data Description

To conduct the analysis, it was first necessary to identify a set of operational variables that adequately reflect the dynamics of airport performance. The selection process was guided by both theoretical insights from the literature and the practical realities of Moroccan airports, ensuring that the variables chosen would capture the most critical stages of passenger processing and flight operations.

The five variables retained, passenger volume, baggage processing time, security screening time, customs processing time, and flight delay, were selected because they capture the main operational stages that shape both passenger experience and airport efficiency. They reflect key managerial bottlenecks (workload, flow management, punctuality), provide quantitative and complementary measures suitable for multivariate analysis (PCA and clustering), and are consistent with empirical findings in the literature as well as the specific challenges of Moroccan airports.

The dataset comprises 500 flight observations from ten Moroccan airports, with sampling weighted toward major hubs, Casablanca, Rabat, Tangier, Marrakech, and Fes that collectively account for the majority of national passenger traffic. Smaller regional airports were also included to capture operational diversity and a range of airport sizes. This stratified approach ensures that the dataset is statistically representative of Morocco's aviation network, enhancing the reliability and generalizability of the analysis, each described by five operational variables (Fig. 1):

- nb_passagers (Number of Passengers): Total number of passengers on board a given flight. It represents the intensity of the human flow associated with the flight and is a key workload indicator across the entire passenger journey (baggage handling, security checks, boarding, etc.).
- emps_bagages (Baggage Processing Time): Average total time required to process baggage for a given flight (check-in, sorting, transfer). This variable may be influenced by the number of passengers, the type of flight (domestic vs. international), and the performance of agents or equipment.
- temps_police (Police Screening Time): Average time passengers of a given flight spend at police and security control (identity and safety checks). It reflects queue length, checkpoint capacity, and applied procedures (standard, fast-track, or random checks).

- temps_douane (Customs Processing Time): Average time spent at customs after police screening, mainly for international flights. It may vary depending on the type of flight, the customs procedures applied, and perceived risk levels.
- retard_vol (Flight Delay): Effective departure (or arrival) delay of the flight, depending on the chosen reference point. It may result from cumulative delays in previous stages (baggage, customs, security), as well as from weather conditions or airport constraints.

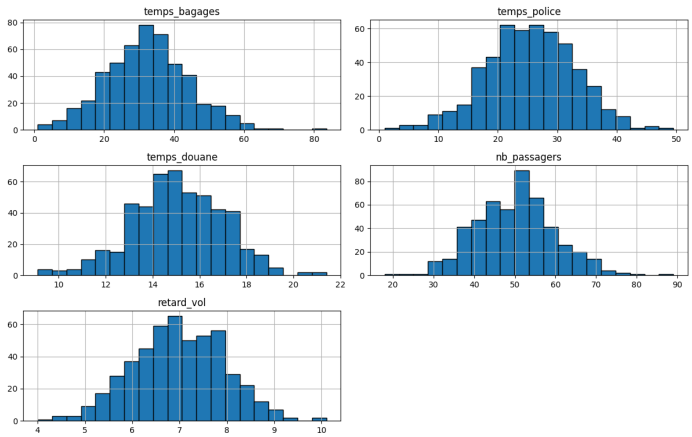

Fig. 1. Distribution of variables. Source: statistical results.

These variables were selected as they capture the main operational stages affecting both passenger flow and airport efficiency. Their descriptive statistics show heterogeneous scales and variabilities: passenger counts (≈17–88) and baggage times (≈5–85 minutes) exhibit wide ranges, while customs and delays are much more stable. Without normalization, variables with larger numeric ranges would dominate variance-based methods. The five variables, once standardized, provide a consistent and comparable basis for multivariate analysis, allowing Principal Component Analysis (PCA) and clustering methods to reveal the underlying patterns and operational profiles of Moroccan airport flights.

B. Data Preprocessing

To ensure comparability across variables, all features were centered and scaled (mean = 0, standard deviation = 1). This standardization step is essential for PCA, as it prevents large-scale features such as passenger numbers or baggage time from overshadowing smaller-range variables (e.g., customs or delays).

Boxplot analysis confirmed that before scaling, baggage time and passenger load exhibited strong right-skewness and outliers, while customs and delays were more symmetric (Fig. 2). After scaling, all variables contributed equally to variance, enabling a balanced multivariate analysis.

C. Principal Component Analysis (PCA)

PCA was performed on the standardized data using the correlation matrix. Eigenvalues and eigenvectors were computed to extract the main principal components. The first three components captured 96.7% of the total variance:

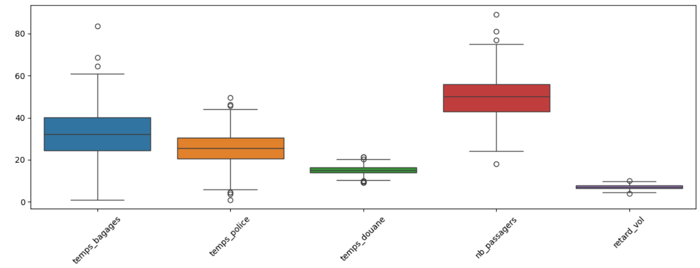

Fig. 2. Box plot showing variable values before standardization. Source: statistical results.

• PC1 (56.8%) – contrasted passenger load and baggage time with police screening;

• PC2 (21.7%) – represented the trade-off between flight delays and customs clearance;

• PC3 (18.2%) – highlighted coupled customs and delay bottlenecks.

These three axes together provided a reduced but highly representative multidimensional view of airport operations.

D. Clustering Analysis

To complement PCA, K-means clustering was applied to the PCA scores. The optimal number of clusters was determined using the elbow method, which suggested k = 3 as a meaningful balance between model simplicity and explanatory power. However, for operational interpretation, a two-cluster segmentation was particularly insightful:

• Cluster 0 – "Light-load, Heavy Screening": flights with fewer passengers, shorter baggage times, but longer police screening.

• Cluster 1 – "High-volume, Streamlined Screening": flights with heavier passenger loads, longer baggage times, but more efficient police checks.

This dual segmentation highlights two distinct operational profiles with clear implications for staffing and resource allocation.

III. Results

A. Standardization of Variables

Prior to multivariate analysis, all five variables were centered and reduced. Boxplots before standardization showed very different ranges: passenger numbers (17–88) and baggage times (5–85 minutes) exhibited wide spreads and right-skewed distributions, while customs times (≈15 minutes) and flight delays (≈6–10 minutes) were much more stable (Fig. 3).

After standardization, all variables had mean ≈ 0 and standard deviation = 1, ensuring equal contribution to the analysis. This step was crucial, since without scaling, variance-based methods such as PCA and clustering would have been dominated by passenger and baggage variables.

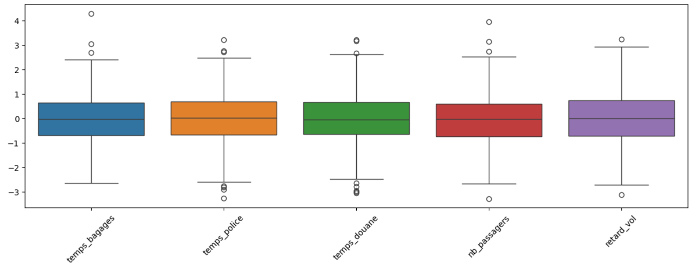

Fig. 3. Box plot showing variable values after standardization. Source: statistical results.

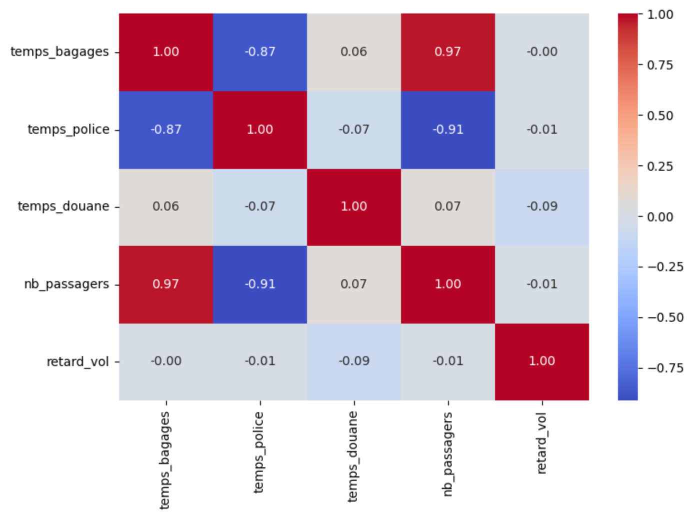

Fig. 4. Correlation matrix of standardized variables. Source: statistical results.

B. Correlation and Covariance Matrix

The correlation matrix revealed strong dependencies between certain variables (Fig. 4):

• High positive correlation between baggage time and passenger load (≈ +0.97), confirming that heavier flights require longer baggage handling.

• High negative correlation between police screening and both passenger load (≈ –0.91) and baggage time (≈ –0.87), suggesting that heavily loaded flights paradoxically move faster through police checks, perhaps due to streamlined screening procedures.

• Near-zero correlations between customs and delays with other variables, indicating that these processes operate relatively independently.

Because the data were standardized, the covariance matrix was numerically equivalent to the correlation matrix.

C. Eigenvalues, Eigenvectors and Explained Inertia

The eigenvalue decomposition of the correlation matrix yielded five principal components (Fig. 5). The first three explained 96.7% of total inertia:

• PC1 (56.8%) – associated with passenger load and baggage (positive loadings) versus police screening (negative loading).

• PC2 (21.7%) – driven by the opposition between flight delays (positive) and customs time (negative).

• PC3 (18.2%) – capturing the joint effect of customs and delays, highlighting cases where long customs checks directly translate into longer delays.

The eigenvectors confirmed these structures: PC1 was mainly defined by nb_passagers (+0.586), temps_bagages (+0.577), and temps_police (–0.565), while PC2 was dominated by retard_vol (+0.721) and temps_douane (–0.692).

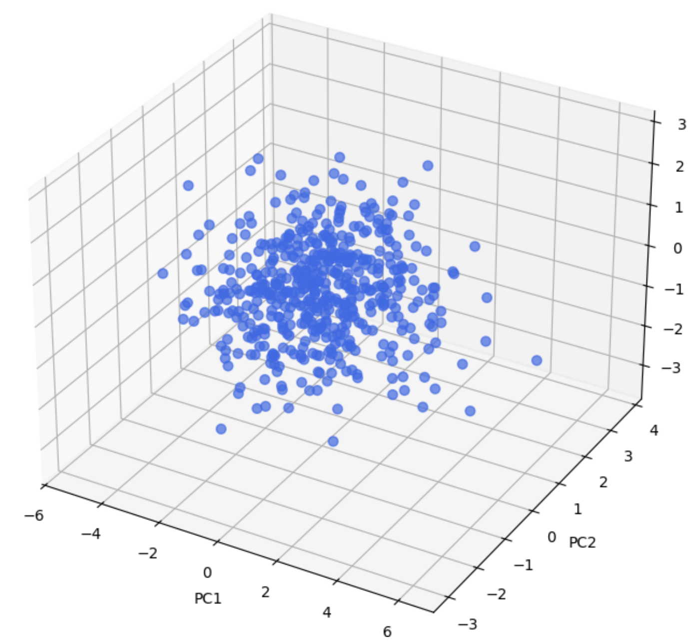

Fig. 5. 3D Projection of observations onto the first three components. Source: statistical results.

D. Principal Axes and 2D Projection

Flights were projected into the new PCA coordinate system (PC1, PC2). The first two axes explained 78.5% of total variance, making them suitable for 2D visualization (Fig. 6).

• Along PC1: flights on the right corresponded to high passenger loads and long baggage times, but short police checks; flights on the left showed the opposite profile.

• Along PC2: flights higher on the axis experienced long delays despite smooth customs, while those lower had slow customs but minimal delays.

Most flights clustered near the origin, representing average operations, but a few outliers occupied extreme positions, corresponding to unusual operational profiles.

E. Correlation Circle

The correlation circle of variables confirmed the interpretation of axes (Fig. 7):

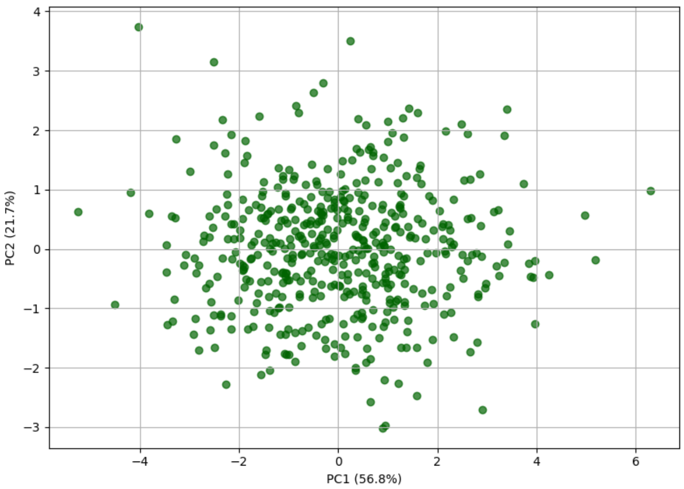

Fig. 6. 2D Projection of data onto the PC1–PC2 Plane. Source: statistical results.

• PC1 aligned with nb_passagers and temps_bagages (positive) versus temps_police (negative).

• PC2 opposed retard_vol and temps_douane.

• Customs and delays were almost orthogonal to the passenger–baggage–police dimension, confirming their independence.

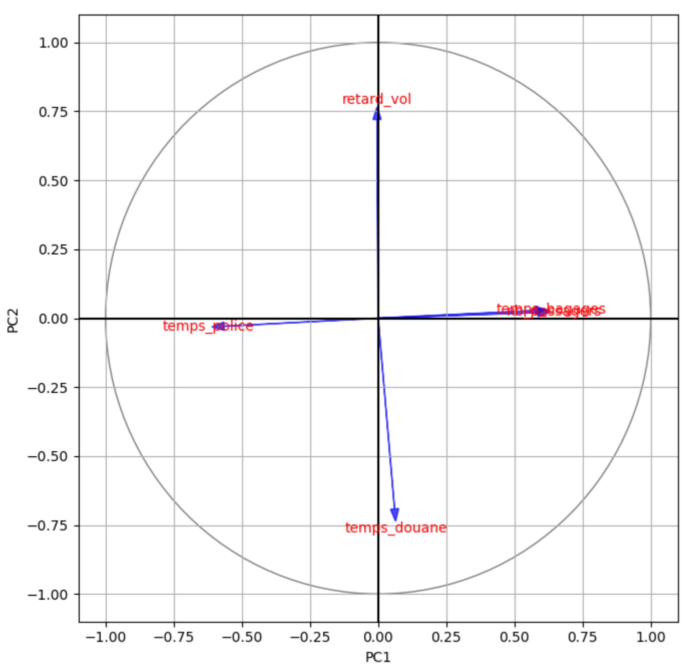

Fig. 7. Correlation circle. Source: statistical results

This visualization highlights two main operational logics: 1. Load-driven dynamics (passengers, baggage, police),

2. Time-driven dynamics (customs vs. delays).

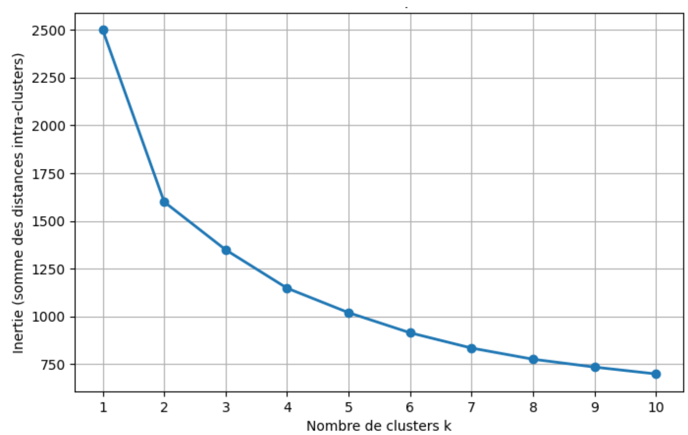

Fig. 8. Elbow method for K-Means. Source: statistical results.

F. Clustering of Flights

To complement the PCA, K-means clustering was applied to the standardized data (Fig. 8). The elbow method suggested k = 3 as optimal, though a two-cluster partition was particularly interpretable.
• Cluster 0 – "Light-load, Heavy Screening": ≈42 passengers, ≈23 minutes baggage, ≈31 minutes police.
• Cluster 1 – "High-volume, Streamlined Screening": ≈58 passengers, ≈41 minutes baggage, ≈0 minutes police.
• Customs (≈15 min) and delays (≈7 min) were nearly identical across both clusters.

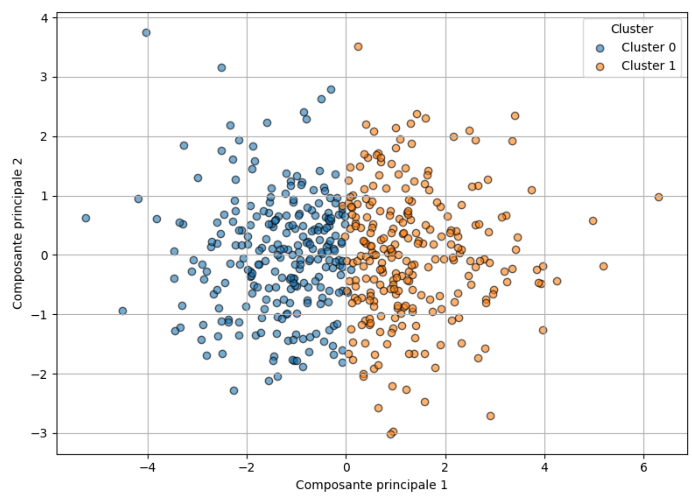

Fig. 9. K-Means clusters visualization in PCA space. Source: statistical results.

In PCA space, the two clusters were well separated along PC1, confirming that passenger load and baggage vs. police screening are the dominant factors driving operational segmentation (Fig. 9). PC2 added nuance by capturing customs–delay interactions within each cluster.

IV. Discussion

The PCA results provide new insights into the operational dynamics of Moroccan airports. By reducing the complexity of five correlated variables into a few principal components, the analysis highlights patterns that are not immediately visible in raw data.

A. Passenger and Baggage vs. Police Screening

The dominant dimension (PC1) shows that flights with high passenger volumes and long baggage handling times tend to experience shorter police screening. This counterintuitive relationship suggests that resource allocation for security may be adjusted depending on expected load. In practice, heavily loaded flights may benefit from dedicated or fast-track lanes, ensuring that passenger flow is not disproportionately delayed by police checks.

This finding has managerial implications:

• For flights with low passenger volumes, police screening becomes the main bottleneck, requiring additional staffing or process adjustments.

• For high-volume flights, the main constraint shifts to baggage handling, where more staff or technological solutions (e.g., automated conveyors, sorting systems) could reduce processing time.

B. Customs and Flight Delays as Independent Dimensions

PC2 and PC3 demonstrated that customs clearance and flight delays are largely independent from passenger load. This independence highlights that delays cannot simply be explained by the number of passengers or baggage. Instead, they reflect operational inefficiencies at later stages of turnaround—such as ground-handling or coordination between airport services.

The clustering confirmed this interpretation: while clusters differed strongly in passenger load, baggage, and police times, flight delays remained similar across groups. This suggests that delay management is governed by different mechanisms than screening or baggage.

For airport managers, this result calls for a targeted monitoring of customs throughput and ground operations, as improvements in these areas are more likely to reduce delays than simply increasing police or baggage capacity.

C. Operational Segmentation of Flights

The K-means segmentation into two dominant clusters—"Light-load, Heavy Screening" versus "High-volume, Streamlined Screening"—offers a practical typology of flights. This typology enables managers to anticipate where resources should be allocated depending on flight profile:

• Cluster 0 flights should trigger reinforcement of police screening staff, as this stage disproportionately slows low-volume flights.

• Cluster 1 flights should trigger reinforcement of baggage handling resources, as baggage is the main bottleneck.

By projecting these clusters into PCA space, airports can design real-time dashboards that classify incoming flights by operational profile, thus enabling proactive resource planning.

D. Comparison with International Literature

The observed patterns align with findings in airport management literature, where baggage handling is often identified as the primary bottleneck in large passenger flows, while security screening dominates smaller flows. However, the strong independence of delays from passenger volumes appears distinctive, possibly reflecting the organizational characteristics of Moroccan airports, where customs and ground-handling practices may play a larger role.

Future comparative studies could investigate whether this independence is consistent across other regional airports, or whether it is context-specific.

E. Managerial and Theoretical Implications

From a managerial perspective, this research demonstrates that PCA combined with clustering can serve as a diagnostic tool for airport operations. It identifies hidden structures in operational data, enabling managers to anticipate bottlenecks and tailor staffing strategies accordingly.

From a theoretical standpoint, the results contribute to the growing literature on multivariate analysis in transport systems. They show how dimensionality reduction techniques can be used not only for descriptive analysis but also for actionable decision support, bridging the gap between quantitative modeling and operational management.

V. Conclusion

In this paper, we propose a multivariate statistical methodology based on PCA and clustering techniques to be applied on the operational data collected from Moroccan airports. The application of PCA resulted in a parsimonious two-component solution, accounting for a considerable amount of the total variance across the three main dimensions of the investigated airport operation. The interpretative meaning of the first principal axis is a forming a bipolar dimension around "passenger and baggage flow throughput" and the time used in police screening. Hence, this axis is representing the essential trade-off between serving passengers as fast as possible and fulfilling the very strict requirements of passenger security and regulatory satisfaction. The second component can be termed a delay vs. customs dimension and relates how flight delays are associated with the efficiency of customs clearance. The third dimension identifies a correlated custom-delay axis and forecasts the association between customs procedures and flight scheduling. Using these derived factors, we find that flights can indeed be grouped into two major operational clusters. The light-load flights have longer police screening time and shorter baggage processing time, which indicates that fewer passengers facilitates more thorough security checks and less complexity is introduced in baggage handling. In contrast, baggage handling takes longer on the high-volume flights, but they have quicker police checks, implying that airports introduce fast-track security on busy flights to facilitate the flow of passengers at peak-period.

These are good news for the airport administrators. Depending on the flight operations profile, discom resources should be orient to strengthen police-screening (in case of low-volume flights) or baggage process (in case of high-volume flights). Interestingly, delays seemed to have little to do with the load of passengers and bags, but rather with the efficiency of customs and ground handling, which proved to be the two major blind spots in punctuality. This article contributes to the literature as it represents the first empirical multivariate analysis of airport operations in a North African country, venturing into a significant research gap in the region's transport studies as well as the scarcely researched topic of operational efficiency drivers in developing market environments. For airport staff, this research can provide a real-time practical decision tool for detecting bottlenecks in the operations that potentially would provide managers with an opportunity to concentrate interventions and resources in one or more of the three process areas of security, baggage handling, and customs.

There are a few limitations in the present study. The dataset contains information on few variables and airports in Morocco. On the other hand, on qualitative side, flight type (domestic/international), airline policies or passengers profiles (tourists, business, students, etc.) were considered. Additionally, delays were only quantified in minutes and without differentiating causes. Future research may be able to further generalize the analysis by adding more airports, qualitative factors, and real-time operation information. Comparative studies with other regions could also shed light on whether the independence of delays from passenger load is a general result or one only valid in the Moroccan context. In short, this study has shown that the use of multivariate analysis enables potential complex operational data to be simplified to provide clear managerial implications. By integrating PCA with clustering, the airport administrators have a diagnostic instrument for predicting bottlenecks and for the understanding of how to deploy the resources in the most effective manner so as to improve the passengers' experience.

REFERENCES

[1] da Cruz, A. L. M. (2024). THE TRANSFORMATION OF AIR TRAFFIC MANAGEMENT WITH BIG DATA. https://revistaft.com.br/the-transformation-of-air-traffic-management-with-big-data/ . DOI: 10.69849/revistaft/cl10202012010958

[2] Dimitriou, Dimitrios & Sartzetaki, Maria & Karagkouni, Aristi. (2024). Airport Operators Performance Management in the Era of Business Intelligence. 10.1016/B978-0-443-29109-8.00001-3.

[3] Ma, W., T. Yuan and N. Liu, (2023). An Application of Operations Research in Airport Ground Path AI Decision for Apron Operation Control. 2023 IEEE 5th International Conference on Civil Aviation Safety and Information Technology (ICCASIT), Dali, China, pp. 659-663, doi: 10.1109/ICCASIT58768.2023.10351633.

[4] Weiqing J. & Han K. (2023). Airport ground operation optimization based on two region macroscopic fundamental diagrams, Proc. SPIE 12790, Eighth International Conference on Electromechanical Control Technology and Transportation (ICECTT 2023), 127906R (7 September 2023); https://doi.org/10.1117/12.2689776

[5] Chakrabarti, S., & Vela, A. (2023). Optimal Sequencing and Scheduling of Airport Operations. In AIAA AVIATION 2023 Forum (p. 3257).

[6] Aziz, A., Brohi, M. N., Soomro, T. R., Ghazal, T. M., Alzoubi, H. M., & Alshurideh, M. (2023). Aircraft turnaround manager (atm): a solution to airport operations. In The Effect of Information Technology on Business and Marketing Intelligence Systems (pp. 679-702). Cham: Springer International Publishing.

[7] Lee, C., Lee, J., Park, J., & Baik, H. (2022). An analysis on the utilization of STAR (Standard Terminal Arrival Route) and CDO (Continuous Descent Operation) flight ratio in the domestic airport. Journal of the Korean Society for Aviation and Aeronautics, 30(4), 132-144.

[8] Porouhan, P., & Premchaiswadi, W. (2022). Improving efficiency of international flight operations with process mining. In 2022 20th International Conference on ICT and Knowledge Engineering (ICT&KE) (pp. 1-9). IEEE.

[9] Tian, L., Liu, B., & Cheng, H. (2022). Establishment of Flight Operation Risk Model Based on Entropy Method and FAHP. In 2022 IEEE 4th International Conference on Civil Aviation Safety and Information Technology (ICCASIT) (pp. 555-559). IEEE.

[10] Wang, X., Chen, Z., & Li, K. (2022). Quantifying the Resilience Performance of Airport Flight Operation to Severe Weather. Aerospace, 9(7), 344.

[11] Chen, T., & Hanaoka, S. (2022). Improvement of airport surface operation at Tokyo international airport using optimization approach. Aerospace, 9(3), 145.

[12] Stroe, G. L., Costea, M. L., Costache, F., Semenescu, A., & Andrei, I. C. (2022). Modelling and analysis of the air traffic control systems. In AIP Conference Proceedings. Vol. 2425, No. 1. AIP Publishing LLC.

[13] Goncharenko, V. I., Lebedev, G. N., Martynkevich, D. S., & Rumakina, A. V. (2021). Operational planning of aircraft routes when servicing a random stream of requests arriving during the flight. In Journal of Physics: Conference Series. Vol. 1958, No. 1. IOP Publishing.

[14] Katsigiannis, F. A., & Zografos, K. G. (2021). Optimising airport slot allocation considering flight-scheduling flexibility and total airport capacity constraints. Transportation Research Part B: Methodological, 146, 50-87.

[15] Zhang, J., Zou, X., Wu, Q., Xie, F., & Liu, W. (2020). Empirical study of airport geofencing for unmanned aircraft operation based on flight track distribution. Transportation Research Part C: Emerging Technologies, 121, 102881.

[16] Mao, Y., Chen, X., Chen, P., Yan, Y., Sheng, Y., & Yang, Y. (2020). Flight delay-oriented airport group flight arrangement optimization method.

[17] Chen, X., Yu, H., Cao, K., Zhou, J., Wei, T., & Hu, S. (2019). Uncertainty-aware flight scheduling for airport throughput and flight delay optimization. IEEE Transactions on Aerospace and Electronic Systems, 56(2), 853-862.

[18] Price, J. C., & Forrest, J. S. (2016). Airport Emergency Planning, Part II: Emergency Management Functions. Practical airport operations, safety, and emergency management, 427.

[19] Amiri, M. A., & Kusakci, A. O. (2024). A scoping review of artificial intelligence applications in airports. Comput. Res. Prog. Appl. Sci. Eng. Trans. Ind. Eng, 10, 2900.

[20] Chandra, A., Hazra, S., Verma, A., & Sooraj, K. P. (2025). On the Possibilities of Efficient Air Traffic Monitoring through Complex Network Clustering Based Airspace Sub-Sectorization: A Multi-Objective Discrete Particle Swarm Optimization Approach. Transportation Research Record, 2679(2), 2127-2143.

[21] Swinney, C. J., & Woods, J. C. (2022). K-means clustering approach to UAS classification via graphical signal representation of radio frequency signals for air traffic early warning. IEEE transactions on intelligent transportation systems, 23(12), 24957-24965.