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Article

Evaluating the Impact of Airport Design and Operations on the Efficiency of Part 139 Certificated Airports in the South and Southeast United States

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Abstract.

Several studies in the past have explored the relationship between various airport related variables and operations (Javanmard et al., 2024; Khireldin & Law, Li & Trani, 2017; Mott et al., 2016). This study delves into the impacts of airport design, runway characteristics, services, classifications, and comprehensive data sets on the operational volume of Part 139 certificated airports in the United States. Employing a hierarchical multivariate regression model, the research addresses the influence of various airport-related factors on operational volumes. Initial findings indicated significant associations between several key variables such as and operational volume, with runway length and the scale of air carrier and general aviation operations being particularly influential. The research also critically evaluated and refined the selection of variables based on statistical significance and multicollinearity, leading to a focused analysis on the most impactful factors. Despite initial assumptions that all proposed variables would be significant, the study refined these inputs to better align with observed data, enhancing the model's predictive accuracy and reliability. This paper provides valuable insights into airport operational dynamics, supporting future policy decisions and strategic planning in airport management.

Keywords: Airport Operational Regression Analysis, Part 139 Certification Operational Volume, Prediction Model of Part 139 Operation.

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1. Introduction

Integrating intelligent technologies and utilizing comprehensive data from multiple sources is crucial for effective airport management and strategic decision-making [1]. While aviation often brings to mind the image of an airplane, the airport is the core of aviation operations—a critical hub that coordinates various aspects of commercial and general aviation (GA) activities. Airports are the epicenter of aviation, providing essential points of departure and arrival for all aircraft. The operation of an airport is complex, reflecting the intricate nature of the aviation industry. Each facility uniquely contributes to the seamless execution of flight operations, and understanding these complexities is vital to comprehending the broader dynamics of the aviation sector.

Airports are intricate systems where design and capacity intersect with regional demographics and economic trends. The infrastructure of an airport—particularly the number and configuration of runways—plays a foundational role in managing air traffic and maximizing operational efficiency. At their most straightforward classification, runway configurations (e.g., single runway, parallel runways, or intersecting runways) significantly affect an airport's operational capacity as they determine how many aircraft can take off or land within a given period. Specific runway characteristics, such as length and uniformity of declared distances, further influence the variety of aircraft an airport can accommodate, which in turn directly impacts its operational volume. For instance, longer runways can support larger aircraft, enabling higher capacity operations, while more complex runway configurations can facilitate more efficient aircraft movement, reducing delays and enhancing overall throughput.

Beyond infrastructure, services provided by airports are essential to day-to-day operations. These include air traffic control, marked by towers' presence and operational hours, and fixed-base operators (FBOs) availability. These services ensure operational efficiency and safety, allowing the airport to support various aviation-related activities. Regulatory classifications, such as those from the National Plan of Integrated Airport Systems (NPIAS), Part 139 Certification, and the Aircraft Rescue and Firefighting (ARFF) index, further define an airport's scope of operations. These classifications reflect the regulatory and operational capacities that each airport is expected to handle.

This study uses a hierarchical multivariate regression model to examine the relationship between airport design, runway characteristics, and operational volume at Part 139 certificated airports. However, future research should explore additional methods to offer deeper insights into airport operations' temporal and spatial complexities. Time-series analysis, for example, could identify patterns in operational volumes over time, which would be valuable for understanding seasonal demand fluctuations or long-term changes. This approach would enable researchers to track how operational volumes evolve over different periods, which is critical for strategic airport capacity management.

Additionally, spatial models could account for geographic dependencies between airports, as airports within the same region may share similar operational patterns influenced by factors like regional economic conditions, weather, or proximity to transportation hubs. By incorporating spatial analysis, future studies could identify clusters of airports that exhibit comparable operational characteristics, providing deeper insights into how regional dynamics affect airport efficiency.

Finally, future research should consider using the Durbin-Watson test to detect autocorrelation in the residuals of the regression model. This test would ensure that the data's independence assumptions are met, improving the accuracy of predictive models. By combining time-series analysis, spatial models, and tests for autocorrelation, future studies could provide a more holistic view of the factors influencing airport operational volume across both temporal and geographic dimensions.

1.1 Purpose Statement

Several studies in the past have explored the relationship between various airport-related variables and operations [2-4]. However, a limited amount of research focused on understanding the Part 139 airports in the U.S. Therefore, the primary purpose of the current study was to investigate the relationship between airport design, runway characteristics, airport services, airport classifications, airport operations, and operational volume of Part 139 certificated airports.

1.2 Research Question

The primary research question for the current study is as follows:

What is the relationship between variables related to airport design, runway characteristics, airport services, airport classifications, airport operations and operational volume of Part 139 certificated airports?

1.3 Research Hypothesis:

The primary statistical hypothesis for the current studies are as follows:

- H1SetA. There will be a significant relationship between airport design and operational volume with respect to Part 139 certified airports.
- H1SetB. There will be a significant relationship between runway characteristics and operational volume with respect to Part 139 certified airports.
- H1SetC. There will be a significant relationship between airports services and operational volume with respect to Part 139 certified airports.
- H1SetD. There will be a significant relationship between airport classifications and operational volume with respect to Part 139 certified airports.
- H1SetE. There will be a significant relationship between airports operations and operational volume with respect to Part 139 certified airports.

2. Literature Review

2.1 Airport Operations in Research

In airport management, data is not just a tool but the cornerstone of effective decision-making. The ability to harness and interpret data—from airport design to daily operations—offers a narrative that reveals past performance, uncovers current trends, and, crucially, forecasts future developments. This dynamic and ever-evolving industry depends on precise data insights to navigate its complexities and anticipate its needs. As we delve into the intricacies of airport operations data analysis and modeling, it becomes evident how indispensable data is to the present and future of airport management. Airport operations encompass various activities, each requiring precise coordination and management. Effective airport management relies on understanding these operations thoroughly. Research in this area has utilized various models and methodologies to optimize different aspects of airport operations. Discrete event simulation models play a significant role in optimizing runway operations. These models help manage runway operations efficiently by simulating scenarios and predicting potential bottlenecks. A detailed case study on Cairo International Airport illustrates the benefits of these models in managing runway operations. This research highlights how simulation can improve operational efficiency and reduce delays by accurately modeling the complexities of runway use and aircraft movements [3].

Statistical approaches are also crucial in understanding and managing airport operations. The least-square model, for instance, is employed to estimate historical percentages of itinerant general aviation operations by aircraft types and flight rules [3]. This methodology provides valuable insights into airport operations, allowing for more informed decision-making. By analyzing past data, airport managers can better predict future trends and adjust their strategies accordingly [5]. Furthermore, automated data collection methods, such as crowd-sourced ADS-B data, offer innovative solutions for accurately counting airport operational data. This approach reduces reliance on traditional methods and improves data accuracy, facilitating better operational planning. The use of ADS-B data allows for real-time monitoring and analysis, providing a comprehensive overview of airport activities and helping to identify areas for improvement [6].

2.2 Managing Through Data Analysis and Forecasting

Building on an understanding of airport operations research, effective management hinges on robust data analysis and forecasting techniques. By leveraging advanced data analysis techniques, airports can enhance operational efficiency and improve customer experience. Data analytics is increasingly used to enhance operational efficiency and the customer experience in airport operations. The integration of big data analytics is highlighted in a comprehensive review, emphasizing their impact on intelligent airport management and their development [1]. Nontraditional statistical methodologies provide alternative methods for estimating aircraft operations. These approaches are compared to traditional methods, showcasing their effectiveness in different scenarios. For instance, nontraditional statistical approaches are more effective in specific contexts than traditional methods [4]. Simulation and modeling techniques, such as discrete event simulation, are essential for understanding various aspects of an airport's operations, such as operational flow, capacity constraints, and planning and development. Statistical forecasting models, including Seasonal Autoregressive Integrated Moving Average and Exponential Smoothing models, are evaluated for accuracy and applicability in predicting airport operation indicators. These models provide valuable insights for short-term and long-term planning in airport management [7].

2.3 Predicting the Future Through Data

As data analysis and forecasting become more sophisticated, predictive analytics allows airport managers to anticipate future trends and make proactive decisions. By leveraging advanced forecasting models, airports can better prepare for future challenges and opportunities.

Hybrid prediction models, which integrate machine learning techniques, are explored for their effectiveness in forecasting air transportation demand. These models provide a comprehensive framework for predicting future demands and their impacts on energy consumption and emissions [2]. The performance comparison between SARIMA and ETS models is crucial for understanding their respective advantages in forecasting airport operations. Detailed analysis reveals the strengths and limitations of each model [7]. Pairwise, machine learning algorithms offer a robust approach for enhancing prediction accuracy in air transportation demand. The hybrid approach is discussed, providing insights into its application and benefits by optimizing the reduction in mistakes [2].

Case studies and practical applications provide concrete examples of these methodologies in action. For instance, the discrete event simulation for runway operations at Cairo International Airport is a prime example of optimizing airport efficiency. The case study results and implications are thoroughly examined [3]. Forecasting models are also evaluated for their effectiveness in predicting operational indicators at Polish airports. The study comprehensively reviews different models and their applications [7]. Furthermore, demand forecasting for Canadian air transportation is explored, focusing on its implications for energy consumption and emissions. The findings highlight the importance of accurate forecasting in sustainable aviation practices [2].

2.4 Future of Airport Management Decision-Making

This literature review underscores the pivotal role of operational data in airport management, from understanding complex operations to forecasting future trends. Integrating discrete event simulation models, advanced statistical methodologies, and innovative data collection techniques has proven instrumental in enhancing operational efficiency and decision-making capabilities. Big data analytics and machine learning algorithms extend these capabilities, enabling airports to react to current trends and proactively anticipate and prepare for future challenges. The findings from case studies, such as those conducted at Cairo International Airport and various Polish airports, illustrate these advanced data techniques' practical applications and significant benefits. These studies highlight the importance of accurate data collection and sophisticated analysis in optimizing airport operations and improving overall efficiency. However, the review also identifies gaps and limitations that warrant further research. More comprehensive models are needed to integrate various data sources and forecasting techniques. Future research could also focus on developing sustainable practices that can effectively implement in airport management. This includes exploring the environmental impacts of airport operations and identifying strategies to mitigate these effects through improved forecasting and operational adjustments.

This literature review reveals operational data's indispensable role in shaping airport management's future. Through the lens of various advanced methodologies, we see how data reflects past performance and provides actionable insights for current and future operations. Despite the significant advancements, gaps and opportunities remain for further research, particularly in developing more comprehensive models and sustainable practices. As the industry evolves, embracing the intricacies of airport operations, data analysis, and modeling will be critical for the present and future of airport management decision-making.

3. Methodology

3.1 Research Design

The current study has multiple independent variables (IVs) divided into five functional sets and a single dependent variable (DV), as listed in Table 1. The dependent variable, the operational volume, is the total annual aircraft movements gathered from the respective airports and submitted to the FAA. Therefore, the current study employed an exploratory correlation research design. The current design is appropriate as the objective was to determine the relationship between multiple measures and a single group.

Table 1. Functional Sets and Independent Variables in the Current Study

Sets/Independent Variables	Operational Definitions
Set A = Airport Design	
X_1 = Number of Runways	X_1 is a continuous variable, number of runways at each airport.
X_2 = Runway Configuration	X_2 is a categorical variable Single Runway, Parallel Runways, Open/Close V Runways, Intersecting Near Mid-Point Runways, and Other.
Set B = Runway Characteristics	
X_3 = Length of Longest Runway.	X_3 is a continuous variable, runway's total length.
X_4 = Same Declared Distances.	X_4 is a categorical variable, declared distances same as the length of the longest runway (Yes or No).
Set C = Services	
X_5 = Tower	X_5 is a categorical variable, if the airport has a manned tower. The categories are Yes and No.
X_6 = Tower Hours	X_6 is a categorical variable denotes a tower's hours of operation: 24/7 Operations, Partial Operations, and No Tower.
X_7 = Number of FBOs	X_7 is a continuous variable, number of fixed-base operators (FBOs) operate at each airport.
Set D = Airport Classifications	
X_8 = NPIAS Classification	X_8 is a categorical variable, Federal Aviation Administration (FAA) categories are Small hub, Non hub, National, and Regional.
X_9 = Part 139 Classification	X_9 is a categorical variable is based on an airport's Part 139 certification type. These categories are Class I, Class II, Class III, and Class IV.
X_{10} = ARFF Index	X_{10} is a categorical variable is based on an airport's aircraft rescue firefighting (ARFF) index. These categories are Index A, Index B, Index C, Index D, and Index E).
Set E = Airport Operational Data	
X_{11} = Air Carrier Operations	X_{11} is a continuous variable, is the total annual air carrier operations.
X_{12} = GA Operations	X_{12} is a continuous variable, is the total annual GA operations.
X_{13} = Based Aircrafts	X_{13} is a continuous variable, is the total number of based aircrafts.
Dependent Variables	
Y = Operational Volume	Y is a continuous variable, total number of aircraft movements.

3.2 Population and Sample

3.2.1 Population

This current study focused on Part 139 certificated airports within the United States, which meet specific regulatory standards for operational and safety criteria. These airports constitute the population of interest due to their standardized operational frameworks and comprehensive data reporting to regulatory bodies like the FAA.

3.2.2 Sample

The sample is drawn from this population and includes airports with similar operational capacities, characterized by metrics such as air traffic volume, types of aircraft, passenger numbers, and service offerings. The sample was limited to Small Hub, Nonhub, National, and Regional airports. The selection criteria, informed by professional experience, ensure the inclusion of airports with comparable levels of activity and service provision.

Initially, the sample was geographically limited to the southern United States, including states like Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, and Texas. To enhance the study's scope, the sample was expanded to encompass a more diverse range of states, including Arizona, Delaware, Maryland, New Mexico, and Virginia. This expansion enables a comprehensive examination of airports across varied economic and demographic contexts while maintaining a common thread of operational characteristics. By selecting a representative sample, this research aims to deliver an in-depth analysis of operational performance and service efficiency across a diverse and comprehensive subset of U.S. airports.

3.2.3 Sample Size Planning

Table 2 outlines the results of an a priori power analysis conducted to determine the necessary sample size for our study to ensure an adequate power level to detect a medium effect size. According to Faul et al. [8], for a desired effect size (ES) of 0.15 and an alpha level (α) of 0.05, a minimum sample size of 150 is required to achieve a power of approximately 0.80 for the overall model R2. This provides an 80% chance of correctly rejecting the null hypothesis for the combined effect of all independent variables on the dependent variable. For individual sets of variables labeled sRA2 through sRE2, the estimated sample sizes range from 69 to 78 to achieve a similar power level.

Table 2. A priori Power Analysis

Parameter Being Tested	α	*ES*	Estimated Same Size (*N*)	Power Based on Estimated *N*
R^2	0.05	0.15	150	0.803
$sR_A{}^2$	0.05	0.15	69	0.805
$sR_B{}^2$	0.05	0.15	69	0.805
$sR_C{}^2$	0.05	0.15	78	0.802
$sR_D{}^2$	0.05	0.15	78	0.802
$sR_E{}^2$	0.05	0.15	78	0.802

3.3 Data Collection and Analysis

The current study's data was from established archival databases. The dependent variable, the operational volume, is the total annual aircraft movements gathered from the respective airports and submitted to the FAA. The independent variables were meticulously sourced from authoritative aviation databases, such as the Federal Aviation Administration (FAA), which provide extensive data pertinent to airport operations.

The current study used hierarchical multivariate regression analysis to examine Operational Volume factors at Part 139 certificated airports. The sets were entered in the following order for the hierarchical analysis: Set A – Set B – Set C – Set D – Set E. This model aligns with industry practices by introducing variables in stages, mirroring the complexity of airport operations. Upon collection, the data were imported into the statistical software JMP® [9], facilitating descriptive and inferential analyses. This robust platform allows for comprehensive statistical evaluation, including correlation analysis and hierarchical multiple regression, to predict how different variables impact airport operational volume.

The use of dummy variables in this study enables the inclusion of categorical data, such as airport classification and runway configuration, in a linear regression model. Since categorical variables lack a numerical relationship between their categories, converting them into dummy variables allows the model to treat each category as a distinct factor. For instance, the difference between a small hub and a non-hub airport cannot be quantified numerically, but both may have distinct impacts on operational volume. Assigning a value of 0 or 1 to each category ensures that the model can estimate the unique effect of these classifications while keeping other variables constant.

This method is essential for isolating the specific influence of each category. For example, a non-hub airport's impact on operational volume can be compared directly to a small hub, allowing for a more unambiguous interpretation of how different airport classifications or runway configurations affect outcomes. By employing dummy variables, the model captures the independent effects of these categories on the dependent variable—operational volume.

This study operationalized NPIAS classification using a reference category (small hub) with other classifications coded into distinct dummy variables. This approach ensured that the regression model could accurately assess non-numerical variables. Additionally, multicollinearity diagnostics, particularly the Variance Inflation Factor (VIF), were used to check for potential overlap between predictor variables. All VIF values were within acceptable ranges, confirming that multicollinearity was not a concern and affirming the robustness of the model.

4. Results

4.1 Preliminary Analysis

This study did not perform cross-validation or holdout sample validation, representing a limitation. These techniques are commonly employed in predictive modeling to evaluate how well a model performs on unseen data. Cross-validation involves dividing the dataset into multiple parts and training the model on some sections while testing it on others to ensure it generalizes effectively to new data. In contrast, holdout sample validation sets aside a portion of the data exclusively for testing the final model, indicating how the model would perform in real-world applications. Implementing either of these techniques in future research would significantly enhance the robustness and reliability of the model's predictive accuracy.

Similarly, this study did not conduct a sensitivity analysis, though it is recommended for future research. Sensitivity analysis involves re-running the regression model after removing potential outliers to assess how these extreme data points influence the results. This process helps determine whether the findings are stable or if they are being unduly affected by unusual values. Given that this study identified outliers using jackknife distances, conducting a sensitivity analysis that compares results with and without these outliers would increase the credibility of the conclusions.

Interaction terms were also not included in this analysis, but they should be explored in future research to identify more complex relationships between key variables. For example, it is plausible that the effect of runway length on operational volume may differ based on airport classification. A small hub airport might experience a greater increase in operational volume from a runway extension than a non-hub airport. Testing for these interaction effects in future models could provide a deeper understanding of the intricate dynamics between different operational factors.

4.1.1 Data Set Modification

For the data analysis in this study, the categorical variables were systematically coded using dummy variables to facilitate quantitative assessment, as detailed in the provided tables. The NPIAS Classification (X1) used Small Hub as a reference group, with National, Nonhub, and Regional classifications assigned codes as per Table 3.

Table 3. Small Hub as the Reference Group

	Coded Variables		
X_8: NPIAS Classification	C_1	C_2	C_3
National	1	0	0
Nonhub	0	1	0
Regional	0	0	1
Small Hub	0	0	0

Tower Hours (X5) were simplified using Partial Operations as the reference, and alternative operational hours were coded as indicated in Table 4. Runway Configuration (X1) followed the pattern, with Single Runway as the baseline and other configurations coded according to Table 5.

Table 4. Partial Operations as the Reference Group

	Coded Variables		
X_5: Tower Hours	C_1	C_2	C_3
24/7 Operations	1	0	0
No Tower	0	1	0
Partial Operations	0	0	0

Table 5. Single Runway as the Reference Group

	Coded Variables			
X_1: Runway Configuration	C_1	C_2	C_3	C_4
Intersection Near Mid-Point Runways	1	0	0	0
Open/Close V Runways	0	1	0	0
Other	0	0	1	0
Parallel Runways	0	0	0	1
Single Runway	0	0	0	0

4.1.2 Missing Data Analysis

The dataset underwent a thorough examination for missing data, which revealed that all variables were complete with no omissions. This comprehensive data availability has allowed retaining all variables in their original form, ensuring a robust and uninterrupted analysis process.

4.1.3 Outlier Analysis

The outlier analysis using jackknife distances identified 20 cases that exceeded the upper control limit (UCL) of 6.90 within the dataset. These cases underwent a thorough review, confirming that they were not errors or miscoding's but accurate reflections of rare events in the operational volume of the airports studied. Since these outliers represented legitimate data from reliable sources, the decision was made to retain them in the analysis. Excluding these valid cases could have skewed the results by omitting significant variations in airport operations, as the dataset aims to reflect the full spectrum of airport activities. Therefore, retaining these outliers was crucial in accurately representing rare but valid operational scenarios.

4.1.4 Multicollinearity

Upon reviewing the Variance Inflation Factor (VIF) in Figure 0, a few variables show signs of multicollinearity and exceed the VIF threshold of 10. X1: Runway Configuration C3 (Other) registers a VIF of 11.989, slightly above the usual cutoff [9]. Despite this, based on the minor increment, it has been decided to retain this variable in the dataset for its potential unique contribution to the model. For the other variable sets, most show acceptable VIF levels and will be kept. However, for Set C, there is an overlap between X4: Tower and X5: Tower Hours C2 (No Tower), indicating redundancy; hence, X4: Tower will be excluded as its data is captured within X5: Tower Hours [9].

Regarding Set D, although X3: ARFF Index C1, X3: ARFF Index C2, and X3: ARFF Index C3 display high VIFs, and X3: ARFF Index C4 does not, the entire variable group will be removed [9]. This is informed by the industry observation of a consistent relationship between the size of airports in X1: NPIAS Classifications and their corresponding ARFF Index, where smaller airports like Regional often have an Index A and larger ones like Small Hub have higher indices such as Index C. This observed trend and regulatory requirements that tie ARFF levels to airport classifications support this decision. The VIFs for the remaining variable sets are within acceptable limits, so no further exclusions are necessary from these sets.

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	355.79947	29440.03	0.01	0.9904	.
X1: Number of Runways	4968.6375	6017.77	0.83	0.4105	7.2819725
X2: Runway Configuration C1	-11792.84	8452.636	-1.40	0.1654	4.2371659
X2: Runway Configuration C2	-8666.053	8352.803	-1.04	0.3014	3.8673496
X2: Runway Configuration C3	-7015.008	15091.54	-0.46	0.6428	10.853823
X2: Runway Configuration C4	-9380.474	11270.68	-0.83	0.4068	2.345987
X3: Length of Longest Runway	5.2105003	1.359123	3.83	0.0002*	1.8827169
X4: Same Declared Distances	-4542.34	4076.5	-1.11	0.2672	1.2108692
X5: Tower Cno	-7304.992	6879.553	-1.06	0.2903	1.6943489
X6: Tower Hours C1	4542.3254	5628.472	0.81	0.4211	1.5473617
X7: Number of FBOs	3647.226	4035.366	0.90	0.3678	1.8124315
X8: NPIAS Classification C1	-6068.449	10925	-0.56	0.5795	2.9996798
X8: NPIAS Classification C2	9354.6546	7104.203	1.32	0.1902	3.8104725
X8: NPIAS Classification C3	6646.7667	9798.597	0.68	0.4988	4.4589923
X9: Part 139 Classification C1	-634.1538	8145.715	-0.08	0.9381	2.9992709
X9: Part 139 Classification C2	1335.9171	13523.99	0.10	0.9215	1.4078132
X9: Part 139 Classification C3	8429.4747	12595.42	0.67	0.5045	1.5161638
X10: ARFF Index C1	-42784.69	24095.17	-1.78	0.0781	42.708972
X10: ARFF Index C2	-37561.4	23796.92	-1.58	0.1169	39.420278
X10: ARFF Index C3	-39881.81	24371.3	-1.64	0.1042	29.011375
X10: ARFF Index C4	-49766.55	28605.43	-1.74	0.0843	3.1914877
X11: Air Carrier Operations	0.9372659	0.172555	5.43	<.0001*	2.2068249
X12: GA Operations	1.1654227	0.065921	17.68	<.0001*	2.1260481
X13: Based Aircraft	-6.287586	35.97262	-0.17	0.8615	2.5878581

Figure 1. Multicollinearity Using VIF Demonstration

4.1.5 Regression Assumptions

Before conducting the hierarchical multivariate regression analysis to assess operational volume at Part 139 certificated airports, validating the underlying regression assumptions was essential. Linearity was confirmed, and variables with p-values above 0.2 were excluded. Key assumptions such as measurement error, homoscedasticity, and independence of residuals were also satisfied. A QQ plot and Shapiro-Wilk test ($p < 0.0001$*) indicated non-normality, but the model remained robust due to the large sample size (N = 153). Although log transformation was considered, it was deemed unnecessary given the model's overall reliability.

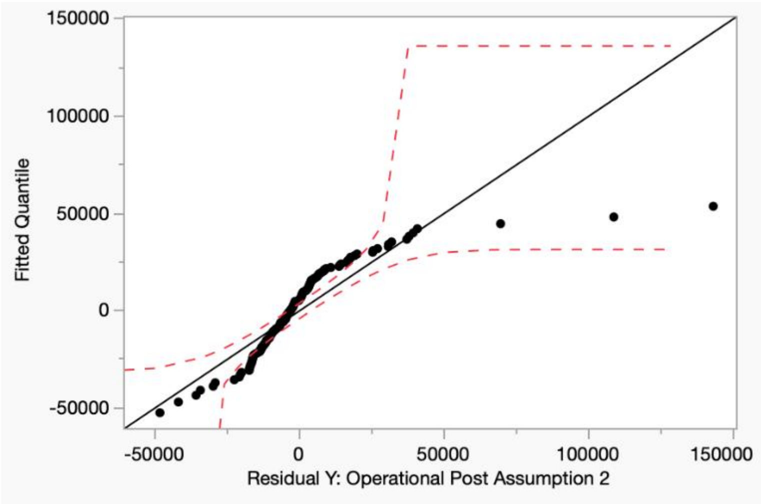

Figure 2. Q-Q Plot for Normality Assumption

4.2 Primary Analysis

4.2.1 Descriptive Statistics

The descriptive statistics for the 153 Part 139 certificated airports present a diverse operational landscape, as reported in Table 6. Operational Volume (Y) has a mean (M) of 66,773.118, showcasing a wide operational range indicative of varied airport activities. Service availability, represented by the average Number of FBOs (X7) of 1.340 and the Number of Runways (X1) with a mean of 2.039, suggests standard service provision across the airports with slight variation in airfield capacity. Infrastructure-wise, the Length of Longest Runway (X3) averages 8,110.556 feet, pointing to diverse capacities catering to various aircraft sizes. Operational metrics, like Air Carrier Operations (X11) and GA Operations (X12), have high means but even higher variations, reflecting the different scales of commercial and general aviation activity. The Based Aircraft (X13) average indicates that some airports are significant hubs.

Table 6. Summary of Continuous Factors

Factors	*M*	*SD*	*Range*
Y: Operational Volume	66,773	56,056	5,888-382,739
X_6: Number of FBOs	1.340	0.609	0-4
X_7: Number of Runways	2.039	0.818	1-6
X_9: Length of Longest Runway	8,110	1,842	4,803-13,502
X_{11}: Air Carrier Operations	8,015	15,7081	0-148,086
X_{12}: GA Operations	39,943	40,360	0-257,721
X_{13}: Based Aircraft	103	81.59	0-416

Note. N = 153

4.2.2 Inferential Statistics

The detailed results analysis of the hierarchical multivariate regression model, presented in Table 7, provides a granular examination of how various independent variables influence the operational volume at Part 139 certificated airports. The analysis is structured across five sets, each focusing on different airport operations and features. When Set A = Airport Design comes into the model with one variable X1 = Runway Configuration, R2 = .0162, F (1,151) = 2.4970, p = .1162, the overall model was not significant at this stage. Set A focused on Runway Configuration, examining one specific type of Intersection Near Mid-Point Runways with single runways. As the omnibus was not significant, further exploration of the regression coefficient was not deemed necessary. When Set B = Runway Characteristics variables come into the model in the presence of Set A = Airport Design, the overall model was R2 = .158, F (2,150) = 14.11, p < .0001. Set A and Set B collectively account for 15.8% variance in operational volume. In addition to that, Set B = runway Characteristics uniquely accounted for 14.2% of the variance in the operational volume; this increment was significant at a p < .0001. Set B focused on the Length of Longest Runway, B3 = 11.82, for every one-unit increase in runway length on average, operational volume increased by 11.816 units (p < 0.001), reflecting the critical role of runway length in accommodating larger aircraft and more frequent operations.

Table 7. Hierarchical Regression Analysis with a Set Entry Order A-B-C-D-E

Variables	*B*	95% CI		*SE*	β	R^2	Δ R^2
		LL	*UL*				
Set A						0.016	0.016
Constant	71,084***	60,670	81,499	5,270	0.00		
X_1 = Runway Configuration C_1	-16,089	-36,207	4,028	10,1852	-0.13		
Set B						0.158*	0.142***
Constant	-27,894	-67,937	12,148	20,265	0.000		
X_1 = Runway Configuration C_1	-4,353	-23,584	14,877	9,732	-0.04		
X_3 = Length of Longest Runway	11.82***	7.18	16.46	2.36	0.39		
Set C						0.178	0.020***
Constant	-22,266	-62,406	17,874	20,313	0.000		
X_1 = Runway Configuration C_1	-3,332	-22,432	16,766	9,665	-0.03		
X_3 = Length of Longest Runway	10.58***	5.78	15.357	2.42	0.35		
X_6 = Tower Hours C_1	20,418	-932	41,768	10,804	0.15		
Set D						0.186	0.008
Constant	-16,511	-57,752	24,729	20,869	0.00		
X_1 = Runway Configuration C_1	2,249	-21,411	16,913	9,697	-0.02		
X_3 = Length of Longest Runway	10.47***	5.692	15.245	2.417	0.34		
X_6 = Tower Hours C_1	18,698	-2,820	40,218	10,889	0.14		
X_8 = NPIAS Classification C_2	-9,945	-26,660	6,769	8,458	-0.09		
Set E						0.851*	0.665
Constant	-37,955***	-56,279	-19,631	9,271	0.00		
X_1 = Runway Configuration C_1	-4,678	-12,949	3,592	4,185	-0.04		
X_3 = Length of Longest Runway	5.88***	3.67	8.09	1.12	0.19		
X_6 = Tower Hours C_1	3,858	-5,996	13,714	4,986	0.03		
X_8 = NPIAS Classification C_2	9,169*	1,613	16,726	3,823	0.09		
X_{11} = Air Carrier Operations	0.96***	0.68	1.23	0.14	0.27		
X_{12} = GA Operations	1.14***	1.05	1.23	0.05	0.82		

Note. N = 153. * p < 0.05. *** p < 0.001.

While some variables, such as tower hours and airport classification, showed lower statistical significance, their retention in the model was purposeful to provide a comprehensive understanding of airport operations. Though not individually significant, these variables may exert influence when combined with other factors. For example, tower hours, despite showing low direct impact, may play a more nuanced role when examined in interaction with runway configurations or airport classifications. Retaining these variables ensures the model captures the broader operational environment, offering a holistic analysis of airport efficiency.

When Set C = Services comes into the model in the presence of Set A = Airport Design and Set B = Runway Characteristic variables, the overall model was R2 = .178, F (3,149) = 10.761, $p < .0001$. Set A, Set B, and Set C collectively account for a 17.8% variance in operational volume. In addition to that, Set C = Services uniquely accounted for 2% of the variance in the operational volume; this increment was significant at a $p < .0001$. No additional factors were significant at this stage.

When Set D = Airport Classification variables come into the model in the presence of Set A = Airport Design, Set B = Runway Characteristics variables, and Set C = Services, the overall model was R2 = .185, F (4,148) = 8.43, $p < .0001$. Set A, Set B, Set C, and Set D collectively account for an 18.5% variance in operational volume. In addition, Set D = Airport Classification uniquely accounted for 0.8 % of the variance in the operational volume; this increment was not significant at a $p < .0001$. No additional factors were significant at this stage.

When Set E = Airport Operational Data variables come into the model in the presence of Set A = Airport Design, Set B = Runway Characteristics variables, Set C = Services, and Set D = Airport Classification, the overall model was R2 = .851, F (6,146) = 138.48, $p < .0001$. Set A, Set B, Set C, Set D, and Set E collectively account for 85.1% variance in operational volume. In addition, Set E = Airport Operational Data uniquely accounted for 66.5 % of the variance in the operational volume; this increment was not significant at a $p < .0001$. B8 = 9169; on average, non-hub airports had 9169 more operational volume than small airports ($p = .017$). B11 = .96, for every one-unit increase in air carrier operations on average, operational volume increased by 1 unit ($p < 0.001$). B12 = 1.14, for every one-unit increase in GA operations on average, operational volume increased by 1 unit ($p < 0.001$).

The comprehensive analysis across these sets highlights the specific contributions of each variable to the operational dynamics of airports and validates the robustness of the hierarchical regression model. The incremental R2 values for each set demonstrate these variables' varying degrees of impact, with Set E showing the most substantial influence. This detailed examination allows for targeted insights into the factors most significantly affect airport operations, providing a valuable framework for policy-making and strategic planning in airport management.

4.2.3 Research Model Equation

In this research on the impact of various factors on the operational volume at Part 139 certificated airports, it is crucial to present both a comprehensive and a reduced model to address the research question accurately. The full model includes all the variables initially considered, represented by the equation Y = -4,678.474X8C1 + 5.878X9 +

3,858.896X5C1 + 9,169.945X1C2 + 0.955X11 + 1.138X12 - 37,955.480. This version incorporates all the predictors irrespective of their statistical significance, providing a holistic view of the potential influences on operational volume.

5. Discussion

The conclusion drawn from the hierarchical multivariate regression analysis underscored that operational volume at Part 139 certificated airports is intricately associated with specific airport characteristics and operations. Notably, runway configurations and the scale of air carrier and general aviation operations are significant predictors of airport activity. The pronounced effect size in the model illustrates that a substantial proportion of variability in operational volume can be attributed to these identified factors. This robust correlation paves the way for a more granular examination of how each variable within sets A through E contributes to the overall operational dynamics. In moving forward, the analysis will delve deeper into the individual impact of these variables, seeking to unravel the nuances of airport functionality and management. This continued exploration aims to refine the understanding of operational volume drivers, thereby informing strategic decisions and policy formulations in the aviation industry.

5.1 Effect Size

For the RQ, the effect size as a measure of explained variance is $\eta 2 = 0.8505$. This means that the impacts of airport design, runway characteristics, services, airport classifications, and 5010 data explain 85.05% of the variance in the operational volume of Part 139 Certificated airports. The effect size as a measure of standard deviation is Cohen's f = 2.3852 (Cohen's f = $\sqrt{(\eta 2 / (1 - \eta 2))}$). This means the effect size is more significant than Cohen's operational definition of a large effect (0.40).

5.2 Post-hoc Power Analysis

The provided post-hoc power analysis detailed in Table 8 evaluates the ability of the study to correctly identify significant effects based on the sample size of 153 and varying effect sizes for different regression parameters. With an alpha level of 0.05 and an impressively high effect size of 5.711, the overall model power surpasses 0.99 [8]. This indicates a near-certain probability of correctly rejecting the null hypothesis, asserting that the model explains approximately 85.2 % of the variance in the dependent variable effectively.

Table 8. Post-hoc Power Analysis

Parameter Being Tested	α	*ES*	Size (*N*)	Power Based on Estimated *N*
$R^2 = 0.851$	0.05	5.711	153	> 0.99
$sR_A^2 = 0.016$	0.05	0.016	153	0.343
$sR_B^2 = 0.158$	0.05	0.166	153	0.999
$sR_C^2 = 0.178$	0.05	0.020	153	0.412
$sR_D^2 = 0.186$	0.05	0.008	153	0.196
$sR_E^2 = 0.851$	0.05	1.985	153	> 0.99

Note. Reference Data in Appendix G – Post-hoc Data from G*Power 3.1 (Faul et al., 2009)

5.3 Plausible Explanations

The comprehensive analysis of Part 139 certificated airports underscores the influence of airport design, runway characteristics, services, classifications, and various data sets on operational volumes. Initially, the outlier analysis validated the inclusion of 28 cases that deviated from the UCL due to their reflection of rare operational scenarios, affirming their necessity for a robust model ($R^2 = 0.851$). This decision validated the alternate hypothesis as operational activity at all airports can be normal for one but an outlier to others.

Addressing multicollinearity revealed the complex interdependencies among the variables, especially those related to runway configurations and airport classifications. Despite high VIF scores, specific variables like Open/Close V Runways were retained for their unique contributions. This decision aligns with the hypothesis that operational volumes are influenced by detailed airport characteristics, necessitating a plausible explanation of the impact of each variable retained despite high multicollinearity. Critical evaluation led to the exclusion of several variables due to insufficient statistical leverage, sharpening the focus on factors demonstrably impacting operational volumes. This step directly addresses the research question by confirming the measurable relationships suggested by the alternative hypotheses. Explaining why certain variables were excluded based on leverage plots will further clarify their lack of impact.

Finally, the post-hoc power analysis demonstrated substantial statistical power, affirming the study's capability to detect significant effects. This robust validation of the regression model's effectiveness calls for a plausible explanation of how the model remains sensitive to the subtleties of operational volume influences across various airport configurations. The research supports the alternative hypotheses across multiple dimensions, enhancing the understanding of how specific airport characteristics influence operational volumes. Each significant finding prompts the need for plausible explanations to elucidate the complex interactions and impacts observed, guiding future policy and management strategies in the aviation sector.

6. Conclusion

The findings of this research hold significant implications for airport management and policy formulation, with potential positive economic impacts. The results highlight the importance of crucial airport characteristics, such as runway length, air carrier operations, and general aviation activities, in driving operational volumes. The strong correlation between these variables and airport activity suggests that investments in infrastructure, particularly extending runway lengths, can enhance operational efficiency and capacity.

Such improvements are likely to yield broader economic benefits. Increased airport capacity and efficiency can attract more airlines and flights, resulting in higher passenger traffic and cargo throughput. This can stimulate local economies by creating jobs, boosting tourism, and fostering business investments. For example, regions with well-developed airports may see growth in the hospitality and retail sectors due to increased passenger flow. Moreover, maintaining and expanding airport capacity can promote long-term economic growth and stability. The insights from this research provide valuable guidance for strategic planning and resource allocation, ensuring that airports are equipped to meet current and future demands while contributing to regional economic development. Policymakers and airport managers can use these findings to make informed, data-driven decisions that support broader economic goals.

Additionally, this study offers a robust framework for understanding the factors influencing operational volumes at Part 139 certificated airports. Future research should explore interaction terms—such as between runway characteristics and airport classifications—to uncover how these factors jointly impact operational volumes. Interactions between services, like tower hours and runway configurations, could further clarify how these variables influence operational capacity, providing deeper insights into airport management.

7. Recommendations

Based on the findings of this study, several recommendations can be made to improve airport operational efficiency and capacity. First, extending runway lengths where feasible is a critical step, as the analysis shows that runway length significantly influences operational volume, especially for airports accommodating larger aircraft. By extending runways, airports can increase their capacity to manage air carrier and general aviation operations, improving overall efficiency. This is particularly important for smaller and non-hub airports looking to expand their services.

Additionally, investing in infrastructure improvements is essential. Upgrading operational services such as lighting systems and air traffic control tower hours and increasing the number of fixed-base operators (FBOs) can further enhance efficiency, improve safety, and support higher air traffic volumes. For airports with limited tower hours, transitioning to 24/7 operations may significantly reduce delays and streamline operations.

Furthermore, airports and policymakers should conduct detailed economic impact studies to better understand how infrastructure improvements can stimulate local and regional economies. Investments in airport facilities improve operational efficiency and contribute to economic growth through job creation, tourism, and business development. A thorough analysis of these benefits can provide a strong case for further investment in airport infrastructure.

Another key recommendation is adopting advanced predictive modeling tools, such as ARIMA or SARIMA models, to forecast future operational volumes. By integrating these models, airports can better anticipate changes in demand and allocate resources effectively, ensuring they are prepared for both short-term fluctuations and long-term growth. Finally, future research should include field studies, such as direct observations and interviews with airport personnel. These qualitative insights would complement the quantitative data, offering a more complete understanding of operational challenges and informing strategic decision-making.

8. Limitations and Delimitations

This study acknowledges several limitations and delimitations. One limitation of this study is its reliance on data from existing datasets, which may have restricted the depth of analysis. While the data allowed for comprehensive statistical modeling, it lacked the depth that field research could provide. Incorporating field research, such as interviews with airport managers or on-site observations, would offer additional context and potentially enhance the findings. Field research could also uncover operational nuances not captured in quantitative data, such as staffing patterns, logistical challenges, or local economic factors affecting airport operations.

Another limitation is that the research primarily focused on Part 139 Certificated airports, encompassing commercial and non-commercial service airports. This scope may limit the generalizability of the findings to exclusively commercial airports. Furthermore, the sample initially focused on the southern United States before expanding to other states, and while this expanded the diversity of data, regional characteristics such as economic, demographic, and geographic factors may still influence the results in ways not fully accounted for.

Additionally, some variables, such as operational data and service classifications, were derived independently, which may have introduced inconsistencies in the data. These inconsistencies could affect the reliability of the findings, as uniform data collection methods were not used across all variables. Variables that exhibited high multicollinearity or insufficient statistical leverage were excluded from the final analysis, which, while necessary to ensure the robustness of the model, may have omitted potentially relevant factors. Future studies should explore these excluded variables in greater detail to better understand their influence on airport operations.

Lastly, future research should consider the variability in data quality across different sources. Although efforts were made to use authoritative aviation databases, inconsistencies in data reporting practices across airports could introduce bias. Field research could also serve as a valuable tool in validating or supplementing the existing data, enhancing the overall reliability of the findings.

9. Future Research

Future research should address the limitations identified in this study while exploring new avenues to deepen understanding. Expanding the sample to include airports from all U.S. states would enhance the generalizability of the findings. A more comprehensive national sample would provide a clearer view of airport operations across different regions, each with unique operational challenges.

At the same time, narrowing the focus to exclusively commercial service airports, particularly high-traffic hubs, could yield targeted insights. These airports are critical to the national transportation network, and understanding their operational dynamics is essential for strategic planning and infrastructure optimization. Additionally, future studies should explore variables excluded due to multicollinearity or insufficient statistical leverage. Techniques such as Principal Component Analysis or Ridge Regression could be employed to reveal the true impact of these factors and refine the overall analysis.

A fundamental limitation of this study was the reliance on existing datasets, which may have constrained the depth of analysis. While the data enabled robust statistical modeling, it lacked the qualitative insights that field research could provide. Future research could incorporate interviews with airport managers or on-site observations to add context and enrich the findings. This approach would uncover operational nuances not captured in quantitative data, such as staffing patterns, logistical challenges, or local economic factors affecting airport operations.

Moreover, variability in data quality across different sources remains a concern. Although efforts were made to use authoritative aviation databases, inconsistencies in reporting practices may introduce bias. Field research could help validate or supplement existing data, enhancing the reliability and accuracy of future findings.

Additionally, future studies should explore interaction terms to capture more complex relationships between variables. For example, the effect of runway length on operational volume may vary depending on airport classification, with smaller hubs potentially benefiting more from extended runways than non-hub airports. Testing for these interactions could uncover subtler dynamics and improve our understanding of how different airport characteristics influence operational performance.

To move beyond current operational volumes, future research should integrate time-series models such as Autoregressive Integrated Moving Average and Seasonal Autoregressive Integrated Moving Average to forecast trends. This approach would allow airports to anticipate future operational volumes under various scenarios, such as increased general aviation (GA) operations or infrastructure expansions. Dynamic forecasting could provide valuable insights for long-term capacity planning and resource allocation, making the model more applicable to strategic airport management.

While this study did not implement cross-validation or holdout sample validation, future research should consider these techniques to enhance predictive reliability. Cross-validation would allow for more robust testing of the model's generalizability by splitting the dataset into training and testing sets, thereby reducing concerns about overfitting. Similarly, holdout sample validation would offer further insights into how well the model performs on unseen data, strengthening its applicability to real-world airport operations.

This study chose hierarchical regression for its ability to introduce variables based on their theoretical relevance sequentially. However, future research could benefit from exploring alternative modeling techniques such as stepwise regression or penalized regression methods, including the Least Absolute Shrinkage and Selection Operator or Ridge Regression. These methods are particularly useful for handling multicollinearity and reducing overfitting in complex models. These approaches are particularly useful for handling multicollinearity and reducing overfitting in complex models. Comparing hierarchical regression with penalized techniques would offer a more nuanced understanding of which variables are significant while improving model parsimony and predictive accuracy.

This study did not address autocorrelation or spatial dependencies between airports, as the focus was on the hierarchical multivariate model. Future research should consider conducting tests for autocorrelation, such as the Durbin-Watson Test, to ensure that operational volumes are independent over time. Additionally, spatial dependencies between airports in the same geographic region could be explored using Spatial Lag Model. Airports nearby may share similar operational patterns driven by regional factors, and incorporating these models would provide a more comprehensive view of airport dynamics.

Finally, recognizing the potential for outliers to skew results, future studies should consider robust regression techniques like Huber or Tukey's Biweight Regression. These methods would offer a more nuanced analysis if traditional regression methods fail to account for the impact of outliers. Conducting a sensitivity analysis by comparing results with and without outliers could provide further insights into the model's robustness, ensuring that outliers do not disproportionately influence the results and reinforcing the reliability of the conclusions.

10. Summary

Throughout this comprehensive study, the primary aim was to investigate the multifaceted impact of various factors such as airport design, runway characteristics, services, classifications, and 5010 data, on the operational volume at Part 139 certificated airports. Leveraging a hierarchical multivariate regression model, the research meticulously evaluated the significance of each variable, resulting in a refined understanding that not all hypothesized factors maintained their presumed influence. Notably, while some variables were expected to be pivotal based on industry experience, the statistical analysis excluded certain variables due to insufficient significance, refining the predictive model to focus only on the most impactful factors. This paper's findings underscore the importance of empirical evidence in shaping our understanding of airport operations, highlighting how data-driven insights can lead to more informed decision-making and policy formulation in the aviation industry. This project advances academic knowledge and aligns with practical realities, offering a robust framework for future research and operational strategy development in airport management.

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