International Journal of Aviation, Aeronautics, and Aerospace

Volume 7 | Issue 1 Article 10

2020

Increasing Airports' On-Time Arrival Performance Through Airport Capacity and Efficiency Indicators

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Scholarly Commons Citation
Dinler, N., & Rankin, W. B. (2020). Increasing Airports' On-Time Arrival Performance Through Airport Capacity and Efficiency Indicators. *International Journal of Aviation, Aeronautics, and Aerospace, 7*(1). https://doi.org/10.15394/ijaaa.2020.1444

Air travel always does not offer smooth operations given that flight delays might occur. A flight can be canceled or delayed due to various reasons such as late arrivals, extreme weather, the National Airspace System, and security concerns (BTS, 2019a). Delays can also be attributable to the lack of airport capacity (Bai, 2006). As such, flight delays are a critical factor for airport operators. To accommodate unavoidable flight delays, airport operators strive to make more efficient use of existing runways, taxiways, and gates (U.S. Congress, 1984). In other words, airport operators believe that the operational efficiency of airports is a critical factor in on-time airport operations.

Nevertheless, it is not easy to increase airports' operational effectiveness given that airports are complex and dynamic organizations (Humphreys & Francis, 2002). Diana (2017), however, posits that the implementation of the Next Generation Air Transportation System (NextGen) programs, which are designed to increase airport capacity and to reduce delays, improved airports' on-time performance. As part of NextGen programs, the Federal Aviation Administration (FAA) continuously measures U.S. airports' operational efficiencies by using on-time performance metrics (i.e., effective gate-to-gate time, taxi-in time, and taxi-out time). Thusly, with increasing pressures for improving efficiency, airport executives need to identify key performance dimensions (Bezerra & Gomes, 2018).

Given these considerations, the purpose of this paper was to create a prediction model for the airport annual on-time arrival rates by identifying the factors that affect an airport's efficiency and capacity analyzing the period of 2009 through 2017. Using a correlational design methodology which includes a hierarchical regression analysis, we have attempted to build a prediction model. Data used in the study were archival data derived from the U.S. Bureau of Transportation Statistics and the FAA.

Background

The literature review considered two specific subjects, (a) airport efficiency and (b) airport performance. Previous studies addressed several aspects of airport efficiency and performance factors, such as service quality, safety, security, financial, and environmental. Ha, Wan, Yoshida, and Zhang (2013) measured the efficiency of airports using both data envelopment analysis and stochastic frontier analysis based on a sample of eleven major airports in Northeast Asia throughout 1994 and 2011. The resulting efficiency scores saw a slight decrease because of events such as the September-11 terrorist attack, SARS outbreak, and the recent US financial crisis. Ha et al. (2013) also suggested that the decentralization of airport ownership and operations negatively affected the airport's efficiency scores, while intense airport competition resulted in higher airport efficiency. Kutlu and McCarthy (2016) examined the effects of airport ownership on airport efficiency based on a sample of all U.S. medium and large hub airports. The authors suggested that while form of ownership could be important for cost efficiency, its effect was relatively small. The authors go on to explain that type of public sector ownership had cost efficiency implications in certain environments.

Other studies investigated and analyzed airport efficiency providing prediction models. For example, Tsui, Gilbey and Balli (2014) examined the operational efficiency of New Zealand airports by identifying several variables (i.e. population around the airport, airport hub status, airport operating hours, airport ownership, Christchurch earthquakes, and the Rugby World Cup) that explain variations in airport efficiency among the sampled New Zealand airports. The estimated results for their regression analysis revealed that four explanatory variables were statistically significant in explaining of airport efficiency, including the airport's hub status, airport operating hours, airport ownership, and the Rugby World Cup 2011. Their findings suggested that there was a positive impact between the operational efficiency of New Zealand airports and the variables of airport operating hours, airport ownership, and Rugby World Cup 2011. More specifically, for the variable of airport operating hours, the positive impact suggested that the extension of airport operating hours increased the efficiency of the New Zealand airports. Similarly, sports tournaments such as the Rugby World Cup increased airport demand and improved the efficiency of New Zealand airports. Their finding on airport ownership implied that privately managed or owned airports had better efficiency than airports controlled or owned by local government or joint ventures. On the other hand, Tsui et al. (2014) found that the airport hub status had a negative impact on the operational efficiency of the New Zealand airports, suggesting that airports in New Zealand that operate as an international airport are less efficient than those that operate as a regional or non-hub airport. In another study providing a prediction model, Orkcu, Balikci, Dogan, and Genc (2016) examined the operational efficiency of Turkey's airport industry by focusing on the predictor variables identified in the study of Tsui et al. Orkcu et al. (2016) argue that airport operating hours and percentage of international traffic were statistically significant factors in explaining the variance in airport efficiency among the sampled Turkish airports. Orkcu et al. (2016) suggest that the growth of operating hours influenced favorably in the operational efficiency of airports, whereas the increase in the ratios of the international traffic would reduce the airports' operational efficiency.

Airports' performance has also become the focus of other studies. Different methodologies have been used to show airports' performance. For example, Bai (2006) investigated the delay performance of U.S. airports and found that the daily average arrival delays at airports were related to the departure delays at other airports. Bai (2006) also argued that the precipitation and wind speed around the airports negatively affected airports' arrival performance, and that airport capacity had no significant effect on arrival performance. In another study focusing on the airports' performance, Diana (2017) investigated whether airline market concentration and NextGen programs had a significant effect on on-time performance of airports at prioritized and non-prioritized metroplexes before and after the 2008 recession. The results of the study published by Diana (2017) indicated that the degree of market concentration and the introduction of NextGen programs improved airports' on-time performance, especially at prioritized metroplexes. Eshtaiwi, Badi, Abdulshahed, and Erkan (2018) identified a set of key performance indicators to measure and monitor airports' performance over time. The findings of their analysis revealed that safety and security, passenger services, and airside capacity were the most important indicators for monitoring and evaluating airport performance.

Although airports' on-time performance and efficiency have always received much attention, the researchers are unaware of any other research that measures the effects of airports' efficiency and capacity indicators as provided by FAA on the airports' on-time arrival rates. Hence, we have tried to develop a prediction model that can be used to observe the effects of airport efficiency and capacity indicators on the airports on-time arrival rates.

Methodology

The purpose of the present study was to create a prediction model for the airports' annual on-time arrival rates based on the factors affecting airports' efficiency and capacity over the period between 2009 and 2017. For the statistical analysis, the current study utilized a correlational design with a hierarchical regression analysis. A correlation methodology was appropriate because the focus of this research was to determine the relationship between airport efficiency and capacity indicators and the airport's on-time arrival rates. Conducting the hierarchical regression analysis, we found the factors influencing the airports' on-time arrival rates and how they related to the airports' on-time arrival rates. Data used in this research was archival data derived from the U.S. Bureau of Transportation Statistics (BTS) (2019b) and Federal Aviation Administration (FAA) (FAA, 2018a).

Population and Sample

The target population was all U.S. airports' on-time arrival rates over the period from 2009 to 2017. The accessible population was 30 U.S. major airports' on-time arrival rates that were reported in the Bureau of Transportation Statistics' (2019b) annual on-time arrival rankings for major airports database. The database is publicly accessible and contains the U.S. major airports' on-time arrival rates over the period from 2003 through 2018. The sampling strategy for the study was a purposive sampling strategy (non-probability sampling). By using the purposive sampling strategy, 20 U.S. commercial airports listed in the appendix were selected as the sample of the study. As a result, the current study used a sample size of N = 180, keeping the outliers in the model.

The dependent variable was the U.S. airports' on-time arrival rates, whereas the predictor variables were airport efficiency and capacity indicators, namely (1)Average daily capacity, (2) Average gate arrival delay, (3) Average number of level-offs per flight, and (4) Distance in level flight from top of descent to runway threshold, (5) Effective gate-to-gate time, (6) Taxi-in time, and (7) Taxi-out time. Besides, the predictor variables in the data set were portioned into two sets as one of the multiple regression data-analytic strategies: Set A= Airport Capacity Indicator and Set B= Airport Efficiency Indicators. (1)Average daily capacity was placed in Set A, while the other predictor variables, (2) Average gate arrival delay, (3) Average number of level-offs per flight, and (4) Distance in level flight from top of descent to runway threshold, (5) Effective gate-to-gate time, (6) Taxi-in time, and (7) Taxi-out time were assigned to Set B.

Research Question and Hypotheses

The primary research question for this study is:

When examined using set entry order of A-B in hierarchical perspective, what is the anticipating incremental gains at each step of the analysis within the relationship of airports' on-time arrival rates?

The corresponding hypotheses are as follows:

H_0: $\rho^2_{YA} = 0$. Set A alone, without any influence from Set B, will not have anticipated gains within the relationship of airports' on-time arrival rates when examined using set entry order of A-B in hierarchical perspective.

H_1: $\rho^2_{YA} \neq 0$. Set A alone, without any influence from Set B, will have anticipated gains within the relationship of airports' on-time arrival rates when examined using set entry order of A-B in hierarchical perspective.

H_0: $\rho^2_{YB \cdot A} = 0$. Set B will not have anticipated gains within the relationship of airports' on-time arrival rates in the presence of Set A when examined using set entry order of A-B in hierarchical perspective.

H_1: $\rho^2_{YB \cdot A} \neq 0$. Set B will have anticipated gains within the relationship of airports' on-time arrival rates in the presence of Set A when examined using set entry order of A-B in hierarchical perspective.

To answer the research question, our analysis was conducted using a hierarchical regression analysis with the set entry order A-B. The entry order of the sets variable entry was determined by the scope of the study.

A Summary of Preliminary Analysis

Prior to performing the primary analysis, we tested regression assumptions and curvilinearity and ran an outlier analysis using Jackknife distances to see if there were any extreme scores relative to the data set. After testing the regression assumptions, the three predictor variables in Set B, (2) Average gate arrival delay, (3) Average number of level-offs per flight, and (4) Distance in level flight from top of descent to runway threshold were removed from the data set because of violation of multicollinearity which is the existence of substantial correlation among independent variables. Table 1 provides a definition of the criterion variable and the remaining predictor variables in the study.

Table 1
Definition of Independent and Dependent Variables in the Data Set

Variables	Description
Criterion variable	
Annual On-Time Arrival Rates for the U.S. Major Airports	A continuous variable represented by the major airports' on-time arrival rates in the United States throughout 2009 and 2017.
Explanatory variables	
Average Daily Capacity	A discrete variable represented by the average daily sum of the Airport Departure Rate (ADR) and Airport Arrival Rate (AAR) reported by fiscal year (FY).
Effective Gate-to-Gate Time (Minutes per Flight)	A continuous variable represented by the difference between the Actual Gate-In Time at the destination airport and the Scheduled Gate-Out Time at the origin airport.
Taxi-In Time (Minutes per Flight)	A continuous variable represented by the yearly average of the difference between Wheels-On Time and Gate-In Time for flights arriving at the selected airport from any of the Aviation System Performance Metrics (ASPM) airports.
Taxi-Out Time (Minutes per Flight)	A continuous variable represented by the yearly average of the difference between Gate-Out Time and Wheels-Off Time for flights from the selected airport to any of the ASPM airports.

After we had tested if each respective independent variable had a curvilinear relationship with the airports' on-time arrival rates, we suggested that (1) Average daily capacity had a curvilinear relationship within the first three powers of a polynomial function. We, therefore, conducted a hierarchical regression analysis using the variable entry order of X–X^2–X^3 to observe if the overall R^2s at each step of the investigation were statistically significant. The results are summarized in Table 2.

Table 2
Bivariate Fit of Y = Airports On-Time Arrival Rates by X_1 = Average Daily Capacity

Variable in Model	R^2	*df*	*F*	$I = sr_I^2$	df_I	F_I
X_1	.143	1, 178	29.87	.143	1, 178	29.87*
X_1^2	.144	2, 177	14.92	.001	1, 177	0.2
X_1^3	.214	3,176	16.03	.07	1,176	15.67*

*$p < .05$

Based on the results above, the cubic model of (1) Average daily capacity was determined as the best model because the increment associated with the cubic aspect of X_1 was significant. Nonetheless, when the cubic aspect of X_1 was used in the final model, it was observed that each respective regression coefficient had no practical effect on airports' on-time arrival rates. As a result, the single aspect of average daily capacity was used in the final model even though it was suggested to have a curvilinear relationship with the airports' on-time arrival rates. Following that the outlier analysis flagged eight outliers in the data set, we conducted two separate bivariate regression analyses: one in the presence of outliers and one in the absence of outliers. Because both analyses yielded similar statistical results and outliers reflected real-world fluctuations in the airports' on-time arrival rates, we decided to keep the outliers in the final model. Finally, to assure if a sample size of N = 180 provided statistically significant results, a priori power analysis was conducted considering these parameters: $\alpha = .05$, $\beta = .20$ (minimum power of .80), a population effect size of ES = .15, and the number of predictors k = 4. These parameters were consulted with G*Power package and yielded a minimum sample size of N =85 needed for the overall model to be significant.

Primary Analysis

To answer the research question associated with the purpose of the study, we ran a hierarchical regression analysis (Fit Model) in *JMP* which is a computer program for statistical analysis. By conducting the hierarchical regression analysis with the set entry order of A-B, we were able to generate a regression equation with a regression coefficient. As noted earlier, the sets entry order was determined by the research' purpose.

Estimating and Discussion of the Results

In the first stage of the primary analysis, we summarized individual variables in the data set. A summary of the descriptive statistics relating to the variables in the data set is presented in Table 3. As reported in Table 3, the mean of the criterion variable, Y = Airports' On-Time Arrivals Rates, was M = 79.65 (SD = 4.29), the median was Mdn = 80.41, and it ranged from 65.76 to 88.55. Regarding the explanatory variables, X_1= Average Daily Capacity had the mean of 1788.85 (*SD* = 619.42), the median of 1591.5, and the range was from 787 to 3,450 aircraft operation per day. X_2= Effective gate-to-gate time with the mean M = 156.14 (SD = 25.01) had a median of 154.35, and the range was from117.2 to 224.9 minutes per flight. The mean of X_3= Taxi-in Time was M = 7.22 minutes per flight (SD = 1.82 minutes), the median was 7.05, and the range was from 3.6 to 14.2 minutes per flight. The mean of X_4 = Taxi-out Time was 17.55 (SD = 3,74), the median was 17l.15, and it ranged from 11.9 to 33.1 minutes per flight.

Table 3
A Summary of Descriptive Statistics

Factors	***M***	***Mdn***	***SD***	***Range***
X_1 = Average daily capacity	1,788.85	1,591.5	619.42	787 – 3450
X_2 = Effective gate-to-gate time	156.15	154.35	25.01	117.2 – 225
X_3 = Taxi-in time	7.23	7.05	1.83	3.6 – 14.2
X_4 = Taxi-out time	17.55	17.15	3.75	11.9 – 33.1
Y = Airports' on-time arrivals rates	79.65	80.41	4.29	65.76 – 88.55

***Note*. *N* = 180.**

As a reminder, the purpose of the study was to create a prediction model for the airports' on-time arrival rates by determining the variations in the airports' on-time arrival rates through airport efficiency indicators provided by the FAA. The hierarchical regression analysis with the set entry order A-B analysis provided all of this information. The estimated results for the hierarchical analysis are included in Figures 1 and 2 in the appendix. A summary of the findings relating to the hierarchical regression analysis is reported in Table 4 below.

Table 4
Summary of Hierarchical Multiple Regression Analysis

	Model 1 B_a	Model 2 B_b	95% CI
Constant	74.95	89.76	[85.39, 94.13]
X_1= Average Daily Capacity	0.0026*	0.0029*	[0.0018, 0.004]
X_2 = Effective gate-to-gate time		-0.045*	[-0.068, -0.0219]
X_3= Taxi-in time		-0.627*	[-1.046, -0.207]
X_4 = Taxi-out time		-0.214*	[-0.376, -0.052]
Statistical Results			
R^2	.144	.436	
F	29.87*	33.8*	
ΔR^2		.29	
ΔF		29.99*	

Note. N = 180. Set entry order was A-B
[a]Model 1 corresponded to the first stage of the hierarchical regression analysis when the airports' on-time arrival rates were regressed on Set A = Airport Capacity Factor. [b]Model 2 corresponded to the final stage of the hierarchical regression analysis when the airports' on-time arrival rates were regressed on Set B = Airport efficiency factors in the presence of Set A.
*p < .05.

Set A: Airport Capacity Factor. As reported in Table 4, the first step of the analysis involved regressing of Y= Airport's on-time arrival rates on airport capacity factor, which contains X_1=Average Daily Capacity. When Y was regressed on Set A, it was found that Set A accounted for about 14% of the variance in Y=Airports' on-time arrival rates. Consequently, the set of airport capacity alone, without any influence from the other sets, accounted for 14% of the variance in the airports' on-time arrival rates, which was statistically significant, R^2Y.A = .144, F (1, 178) = 29.87, p < .0001*.

An inspection of the individual factor within Set A revealed that X_1=Average Daily Capacity was statistically significant: B_1= 0.0026, t (178) = 5.47, p < .0001*. Interpreting this regression coefficient, for every 1000 increases in airports' average daily capacity, the airports' on-time arrival rates increased on average by 3%.

Set B: Airport Efficiency Factors. As reported in Table 4, when the three factors of Set B including X_2= Effective gate-to-gate time, X_3=Taxi-in time, and X_4= Taxi-out time entered to the analysis in the presence of Set A, it yielded $R^2_{Y.AB}$ of 0.436. As a result, the collective contribution of the sets, airport capacity, and airport efficiency factors accounted for almost 44 % of the variability in the

https://commons.erau.edu/ijaaa/vol7/iss1/10
DOI: https://doi.org/10.15394/ijaaa.2020.1444

airports' on-time arrival rates; this was statistically significant, F (4, 175) = 33.8, p < .0001 *. Furthermore, the increment of Set B was $sR^2_B = .29$. Thus, Set B= Airport efficiency factors accounted for about 30% additional variation of airports' on-time arrival rates when analyzed in the presence of the Set A. This was also statistically significant, F (3, 176) = 29.99, p < .05 *.

Within an omnibus test, an analysis of the effects of the individual factors within Set B in the presence of Set A showed that all variables in Set B were statistically significant. With respect to X_2 = Effective gate-to-gate time, holding X_1 = Average daily capacity, X_3 = Taxi-in time, and X_4 = Taxi-out time constant, for every 10 minutes increase in effective gate-to-gate time, the airport's on-time arrival rates decreased on average 0.5 %. This was statistically significant, B_2 = -0.045, t (176) = -3.86, p = .0002*. Regarding X_3 = Taxi-in time, holding X_1 = Average daily capacity, X_2 = Effective gate-to-gate time, and X_4 = Taxi-out time constant, for every 10 minutes increase in taxi-in time, the airport's on-time arrival rates decreased on average 6 %. This was statistically significant, B_3 = -0.627, t (176) = -2.95, p = .0036*. With respect to X_4 = Taxi-out time, holding X_1 = Average daily capacity, X_2 = Effective gate-to-gate time, and X_3 = Taxi-in time constant, for every 10 minutes increase in taxi-out time, the airport's on-time arrival rates decreased on average 2 %. This was statistically significant, B_4 = -0.214, t (176) = -2.61, p = .0098*.

When the three factors of Set B were individually examined in the absence of Set A, the factors in Set B, collectively explained about 35% of the variance in the airports 'on-time arrival rates, which was statistically significant R^2 = .346, F(3, 176) = 31.11, p < .0001*. The estimated results of Set B is included in Figure 3 in the appendix.

The corresponding 95% confidence intervals reported in Table 4 for the final analysis (Model 2) were fairly narrow, which implied that the accuracy in parameter estimation for each of the corresponding regression coefficients was probably high. For example, the 95% CI of X_1 = Average Daily Capacity was [0.0018, 0.004]. This points out that 95% of the time the airports' on-time arrival rates in the population is expected to increase on average anywhere between 0.0018 to 0.004 for every aircraft operation increases in the airports' average daily capacity when considered in the absence of the other variables.

Overall, from a variance perspective, the explanatory variables in the final model explained 43.6% of the variability in the airports' on-time arrival rates. From a prediction, the four explanatory variables in the final model collectively provided 43.6% of the information needed to correctly predict the airports' on-time arrival rates.

Results of Hypotheses Testing

As reported in Table 4, there was a significant predictive gain when Set A = Airport Capacity entered the model alone, $R^2_{Y \cdot A}$ = .144, F (1, 178) = 29.87, p <

.0001*. As a result, H_0***:*** $\rho^2_{Y \cdot A} = 0$ was rejected. Instead, the study accepted that Set A alone, without any influence from Set B, will have anticipated gains within the relationship of airports' on-time arrival rates.

As reported in Table 4, there was a significant predictive gain when Set B= Airport Efficiency entered the model in the presence of Set A. $sR^2_{YA \cdot B} = .29$, F (3, 176) = 29.99, $p < .05$*. As a result, **H_0: $\rho^2_{YA \cdot B} = 0$** was rejected. Instead, the study accepted that Set B will have anticipated gains within the relationship of airports' on-time arrival rates in the presence of Set A.

Precision Analysis of the Overall Model

To determine the precision of the coefficient of determination (R^2), we first calculated the standard errors (*SE*s) of R^2 by using Cohen, Cohen, West and Aiken's (2003, p. 88) equation, then determined the corresponding (t) value to the 95% confidence intervals (CIs). Table 5 summarizes the results of the precision analysis for R^2.

$$\widehat{SE}R2 = \sqrt{\frac{4(.436)(1-.436)^2(180-4-1)^2}{(180^2-1)\,(180+3)}} = \sqrt{\frac{16,996}{5,929,017}} = 0.053$$

95% CI = .436 +/- 0.053 (1.976)
= .436 +/- 0.105
=.331 - .541

Table 5
Precision Analysis for Overall Model(R^2)

Model	Actual Value	Standard Error (*SE*)	t_{critical}	Lower 95%	Upper 95%
Overall Model[b]	$R^2_{Y \cdot AB} = .436$	.053	t (175) = 1.976	.331	.541

Note. N = 180. [a]The overall model consisted of four independent variables that were partitioned into two functional sets A and B. Set A = Airport Capacity, which consisted of X_1 = Average Daily Capacity. SetB = Airport Efficiency, which consisted of X_2 = Effective gate-to-gate time, X_3= Taxi-in time, and X_4 = Taxi-out time.

As a result, the CIs for $R^2_{Y \cdot AB}$ was [.331, .541]. This indicates that approximately 95% of the CIs will include the true population $R^2_{Y \cdot AB}$ between 33.1 and 54.1. Put another way, if we were to randomly select 100 samples of size 180, then in the 95 of these samples, the collective contribution of the four explanatory variables in the model in explaining the variability in the airports' on-time arrival rates would be between 33.1% and 54.1%. Note that the standard error was small and that the resulting 95% CI = [.331, .541] was fairly narrow, which indicates that accuracy in parameter estimation (AIPE) of the overall R^2 was probably high.

DOI: https://doi.org/10.15394/ijaaa.2020.1444

Post Hoc Power Analysis

To assess the power for the multiple correlation coefficient squared (R^2), we consulted with *G*Power* software program by inputting parameters such as the sample size $N = 180$, the significance criterion $\alpha = .05$, and the number of predictor variables =4. The effect size of the overall R^2 was calculated by using Cohen et al.'s (2003, p. 92) equation. The results are summarized in Table 6.

Table 6
Power Analysis and Calculated Powers for $\alpha = .05$ Based on $N = 180$

Model	Actual Value	Actual Effect Size	Number of Predictors (k)	Approximate Power
Overall Model[a]	$R^2_{Y \cdot AB} = .436$	.773	4	> .99

Note. $N = 180$. Set entry order was A-B.
[a]The overall model consisted of four independent variables that were partitioned into two functional sets A and B. Set A = Airport Capacity, which consisted of X_1 = Average Daily Capacity. SetB = Airport Efficiency, which consisted of X_2 = Effective gate-to-gate time, X_2= Taxi-in time, and X_4 = Taxi-out time.

With respect to the overall $R^2_{Y \cdot AB}$, the power was greater than .99, which means that we have more than 99% chance of correctly rejecting the null hypothesis involving $R^{2.}$ with the effect size of 0.773.

Discussion of the Results

As presented in Figure 2 of the appendix, all explanatory variables in the model were found to be significant factors that explain variations in airports' on-time arrival rates. The equation of the final multiple regression analysis is:

$\hat{Y} = 0.0029(B_1) - 0.045(B_2) - 0.627(B_3) - 0.214(B_4) + 89.76$

B_1(0.0029) = Average Daily Capacity. The sign of the average daily capacity's coefficient indicated the direction of the effect was positive. More specifically, holding all other variables constant in the model, for every 1,000 aircraft operation increases in the airports' average daily capacity, we can expect an average 3% increase in the airports' on-time arrival rates. This was statistically significant: $t(175) = 5.21$, $p < .0001$*. Our analysis suggested that airports' capacity was a significant factor in the airport on-time arrival rates. Therefore, airport planners should invest in the airport infrastructures in such a way that it leads to an increase in the average daily capacity. As a quick reminder, in the preliminary analysis, a curvilinear relationship was determined between X_1 = average daily capacity and the airports' on-time arrival rates at the polynomial degree 3. Readers, therefore, should be careful about the average daily capacity's interpretation.

B_2(-0.045) = Effective gate-to-gate time. The sign of the effective gate-to-gate time's coefficient indicated the direction of the effect was negative. Holding all other variables constant in the model, for every 100 minutes increases in the effective gate-to-gate time, we can expect an average 4.5% decreases in the airports' on-time arrival rates. This was statistically significant: t (175) =-3.86, p = .0002*. According to the FAA (2018b), effective gate-to-gate time is a time difference between the actual gate-in time at the destination (selected) airport and the scheduled gate-out time at the origin airport during reportable hours. Additionally, the calculation of effective-gate-to gate time includes the time that aircraft spends in a non-movement area; therefore, changes made to the airlines 'operations at an airport may impact effective-gate-gate time. Based on the results in the given study, we concluded that making frequent changes in the airlines' scheduled operations increases airlines' effective gate-to-gate time, leading to decrease in airports' on-time arrival rates.

B_3(-0.627) = Taxi-in time. The sign of the taxi-in time's coefficient indicated the direction of the effect was negative. Holding all other variables constant in the model, for every 10 minutes increases in the taxi-in time, we can expect an average 6.3% decreases in the airports' on-time arrival rates. This was statistically significant: t (175) =-2.95, p = .0036*. According to the FAA (2018b), taxi-in time is the yearly average of the difference between wheels-on time and gate-in time for flights arriving at the selected airport. Additionally, the desired trend for the taxi-in time should be downward. Our analysis also confirmed that there was an inverse relationship between taxi-in time and the airports' on-time arrival rates.

B_4(-0.214) = Taxi-out time. The sign of the taxi-out time's coefficient indicated the direction of the effect was negative. Holding all other variables constant in the model, for every 10 minutes increases in the taxi-out time, we can expect an average 2.1% decreases in the airports' on-time arrival rates. This was statistically significant: t (175) =-2.61, p = .0098*. According to the FAA (2018b), taxi-out time is the yearly average of the difference between wheels-off time and the actual gate-out time for departures at the selected airport. Our analysis suggested that airlines which have long taxi-out times made airports 'on-time arrival rates decreased. Thus, airport planners are advised to design direct accesses between an apron and a runway given that direct accesses may decrease the taxi-out time at an airport.

Conclusion

Airport operators can increase their on-time arrival rates by improving the efficiency at their airports. The purpose of this paper was to create a prediction model for the airports' annual on-time arrival rates by identifying airport efficiency indicators. For the estimation of the airports' on-time arrival rates, this paper used a hierarchical regression analysis that provided us with cumulative increments in each set including predictor variables. Our study revealed that all predictors in the sets, namely the average daily capacity, the effective gate-to-gate time, the taxi-in time, and the taxi-out time were statistically significant for the identified variations

DOI: https://doi.org/10.15394/ijaaa.2020.1444

in airports' on-time arrival rates : (1) the airports that could increase their average daily capacity had higher on-time arrival rates than the airports that failed to increase their average daily capacity . (2) the decrease in airlines' effective-gate-to-gate time led to better airports' on-time arrival rates. (3) the decrease in airlines' taxi-in time led to better airports' on-time arrival rates, and (4) the decrease in airlines' taxi-out time led to better airports' on-time arrival rates. Thus, the present study suggests that four variables analyzed could provide a useful model for the airport planners and forecasters in the estimation of airports' on-time arrival rates.

In addition to concluding comments related to the results, the current study raises a number of issues for future research. For example, regarding the applicability of the study, we believed that it would be difficult to generalize the current study's results outside of the United State. This is because the U.S. airport industry has its unique characteristics. Future research can address this limitation by focusing on different geographic areas, such as the Asia and Pacific regions. Furthermore, the study assumed that there was a relationship between the airports' on-time arrival rates and the four explanatory variables in the model. The primary data sources for the current study was the Bureau of Transportation Statistics' database, meaning that we did not have direct control of the variables in the study. Due to the lack of control, it is not true to say there is a genuine relationship between IVs and airports' on-time arrival rates. However, future studies may be conducted to minimize the effect of this limitation by directly taking consistent data from airlines. Finally, as we pointed out in the summary of the preliminary analysis section, the outliers in the data were not removed from the data set. Thus, a recommendation for future research is to use different outlier analysis strategies.

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Appendix

Effect Summary

Summary of Fit

RSquare	0.143729
RSquare Adj	0.138918
Root Mean Square Error	3.985654
Mean of Response	79.6535
Observations (or Sum Wgts)	180

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	474.6264	474.626	29.8781
Error	178	2827.6079	15.885	Prob > F
C. Total	179	3302.2343		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	74.950895	0.91017	82.35	<.0001*	.
X1= Average Daily Capacity (Number of Operations)	0.0026288	0.000481	5.47	<.0001*	1

Figure 1. **Estimation Results for Set A=Airport Capacity Factor**

Effect Summary

Summary of Fit

RSquare	0.435896
RSquare Adj	0.423003
Root Mean Square Error	3.262604
Mean of Response	79.6535
Observations (or Sum Wgts)	180

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	1439.4318	359.858	33.8067
Error	175	1862.8025	10.645	Prob > F
C. Total	179	3302.2343		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	Lower 95%	Upper 95%	VIF
Intercept	89.764263	2.212348	40.57	<.0001*	85.397945	94.130582	.
X1= Average Daily Capacity (Number of Operations)	0.0029169	0.000554	5.27	<.0001*	0.0018236	0.0040103	1.9802086
X2= Effective Gate-to-gate time (Minutes per flight)	-0.045023	0.011678	-3.86	0.0002*	-0.06807	-0.021975	1.4347828
X3= Taxi-in Time (Minutes per flight)	-0.62705	0.212477	-2.95	0.0036*	-1.046398	-0.207703	2.5409075
X4= Taxi-out Time (Minutes Per Flight)	-0.214637	0.082202	-2.61	0.0098*	-0.376871	-0.052402	1.5940159

Figure 2. **Estimation Results for Set B=Airport Efficiency Factor in the Presence of Set A= Airport Capacity (Overall Model)**

Summary of Fit

RSquare	0.346533
RSquare Adj	0.335395
Root Mean Square Error	3.501542
Mean of Response	79.6535
Observations (or Sum Wgts)	180

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	1144.3341	381.445	31.1109
Error	176	2157.9002	12.261	**Prob > F**
C. Total	179	3302.2343		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	97.016999	1.857984	52.22	<.0001*	.
X2= Effective Gate-to-gate time (Minutes per flight)	-0.073099	0.01115	-6.56	<.0001*	1.1356271
X3= Taxi-in Time (Minutes per flight)	0.1338194	0.167177	0.80	0.4245	1.3656093
X4= Taxi-out Time (Minutes Per Flight)	-0.394076	0.080283	-4.91	<.0001*	1.3200287

Figure 3. **Estimation Results of Set B=Airport Efficiency in the absence of Set A= Airport Capacity**

A List of the U.S. Airports Selected as The Sample of the Study

Salt Lake City	UT (SLC)
Minneapolis/St. Paul	MN (MSP)
Detroit	MI (DTW)
Seattle	WA (SEA)
Phoenix	AZ (PHX)
Charlotte	NC (CLT)
Washington	DC (DCA)
San Diego	CA (SAN)
Denver	CO (DEN)
Philadelphia	PA (PHL)
Tampa	FL (TPA)
Baltimore	MD (BWI)
Orlando	FL (MCO)
Las Vegas	NV (LAS)
Boston	MA (BOS)
Los Angeles	CA (LAX)
New York	NY (JFK)
San Francisco	CA (SFO)
Fort Lauderdale	FL (FLL)
Newark	NJ (EWR)