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An evaluation of the impact of wake vortex re-categorization: The case of Charlotte Douglas International airport (CLT)

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ABSTRACT

This study compared departures before and after wake recat implementation at CLT. In both periods, departure counts and departure demand loaded highly onto Factor 1, arrival demand and gate departure delays onto Factor 2, and taxi-out time onto Factor 3. A two-level negative binomial mixed-effects model considered the random effects of approach conditions on operations. Only gate departure delay was significant within and across both samples. NextGen capabilities including wake recat appeared to minimize the random effects of instrument approach conditions (IAC) on operations in both samples. Wake recat increased departure throughputs in IAC and enabled multiple departure pushes throughout the day.

1. Introduction

The success of wake re-categorization or 'wake recat' at Atlanta (ATL), Houston (IAH), Cincinnati (CVG), and Memphis (MEM) has encouraged the Federal Aviation Administration (FAA) to pursue its implementation at other airports in a phased approach, which is highlighted in the NextGen Joint Implementation Plan.[1] The Next Generation Air Transportation System or 'NextGen' is a set of programs including complex technologies and procedures to transition the present radar-based, air-traffic-controlled system into a satellite-based, air-traffic-managed system.

This analysis focuses on the case of Charlotte Douglas International airport (CLT) where wake vortex re-categorization or 'wake recat' was implemented in March 2015. This study refers to Phase 1 of the wake recategorization program at CLT. Wake recat is part of the Separation Management portfolio of NextGen capabilities designed to enhance aircraft separation assurance. To prevent wake vortex turbulence, aircraft are separated at takeoff and landing based on their weight category (i.e., super, heavy, Boeing 757, large, and small aircraft). The redefinition and reduction in separation criteria have allowed air traffic controllers to take advantage of reduced inter-departure times to maximize available airport capacity. The separation distances between aircraft categories are specified in the Appendix A.

Besides wake vortex re-categorization, the FAA implemented other NextGen-related capabilities at CLT such as area navigation (RNAV), optimized profile descent (OPD), automated terminal proximity alert (APTA), and adjacent center metering (ACM). It also expanded low-visibility operations using lower runway visual range (RVR) minima. These capabilities have enabled air traffic controllers to manage arrival and departure flows into the airport through precision approach (utilizing area navigation or RNAV) and continuous descent to the airport, which contributes to saving fuel burn and minimizing carbon emission footprint. Both APTA and adjacent center metering enable air traffic control to regulate separation in the terminal and enroute environment, respectively about 40 and 100 nautical miles from the airport. While these capabilities may improve airport capacity management, reduce fuel

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[1] See the NextGen Performance Snapshots website for detailed on the NextGen Priorities at http://www.faa.gov/nextgen/snapshots/priorities and performance success story on wake recat at https://www.faa.gov/nextgen/snapshots/stories/?slide=34.

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burn, and minimize delays by pacing traffic flows in and out of CLT, this analysis focuses on departure throughputs defined as the counts of departures per hour.

This case study is of interest to aviation practitioners for several reasons. First, it examines how some key operational variables such as arrival and departure demand, gate departure delays, and taxi-out times may cluster into a few unobserved factors (factor analysis). It also evaluates how these variables may influence the counts of departures (through incidence rate ratios), before and after the implementation of wake recat, when data are grouped by runway configuration and type of approach conditions. Second, it illustrates how a negative binomial mixed-effects regression model can help identify the impact of random and fixed effects on departure counts before and after the implementation of a NextGen capability. Hilbe (2011) provided an extensive treatment of negative binomial regression models. Third, it evaluates whether the variance of departure counts and the incidence rate ratios had significantly changed in the post-implementation period. Finally, other airports may learn from the Charlotte case study where limited space between gates and taxiways is likely to present some challenges at peak times in the form of increased departure and arrival demand, gate departure delays, and longer taxi-out times.

2. Literature review

Wake recat is not a new concept. However, its recent implementation as part of the NextGen portfolio implementation may explain the paucity of case studies using actual data. Most of the literature on wake recat pertains to the outcomes of simulations and tests in a controlled environment to measure the effects of separation on airport capacity utilization.

Diana (2015) used actual traffic data at Hartsfield-Jackson Atlanta International airport (ATL) and applied a Markov regime-switching model to assess changes in periods of higher (unconstrained) versus lower (constrained) departure outputs and to determine how fast the regimes would alternate. One of the key assumptions was that wake recat would allow airports to sustain longer periods of high departure throughputs because of shorter inter-departure times and more homogeneous traffic mix. In the post implementation period, Diana determined that there was a 91 percent chance departure throughputs would remain unconstrained (up from 86 percent before implementation) compared with a 37 percent chance departure throughputs would become constrained (up from 35 percent before implementation). The author argued that the marginal benefits of separation reduction were likely to decrease as the volume of departures increased during periods of unconstrained departures. Diana's research assumed that there were two regimes, whereas this study expects throughputs to vary with the random effects of instrument approach conditions on total operations (arrivals and departures). As wake recat reduces inter-departure times, we expect fewer intense peak departure throughputs and multiple departure pushes throughout the days, which improves arrival and departure demand management and taxi-out times.

In a *News and Updates* release, the FAA estimated that the capacity of Memphis International Airport (MEM) increased more than 15 percent after wake recategorization was implemented on November 1, 2012.[2] This was made possible by closer spacing at takeoff, which allowed controllers to add nine flights per hour on average. Wake recat also enabled FedEx to reduce taxi-out times by three minutes as aircraft of same categories were less likely to spend less time in the takeoff queue. Based on the outcomes at MEM, we expect departure counts and departure demand to load high on the same factor in the case of CLT.

According to Borener et al. (2016), since NextGen programs have been implemented recently, it was difficult to measure their impact on safety through traditional metrics such as the number of accidents and/or incidents. To anticipate what may lead to unsafe operations, the authors evaluated how changes in separation standards through wake vortex classification may lead to unsafe outcomes based on historical data such as the counts of wake, proximity, and anomalous trajectory events in two 30-day samples, respectively in the pre- and post-implementation of wake recat at MEM.

This case study is original since it utilized actual data. Gate departure times were compared with the last filed flight plans submitted before takeoff to avoid the issue of schedule padding (Wu, 2005). Padding refers to extra minutes added to the scheduled gate arrival time to provide for unpredictable enroute and surface delays.

3. Methodology

As a first step, we used factor analysis to reduce the selected variables into a few meaningful factors. Factor analysis provides a means of explaining variations among relatively many original variables. Then, a negative binomial mixed-effects model described the relationship between the counts of departures as the response variable and some operational independent variables such as gate departure delays, arrival and departure demand, as well as taxi-out times. The mixed-effects models provided the benefit of evaluating the relationship between independent and response variables at two levels: by approach condition and by runway configuration. These levels mostly explain variations in departure throughputs, available airport capacity, and, eventually, delays.

The model outputs utilized the incidence rate ratios (IRR) instead of coefficients. The IRR represents the rate at which events (departures) occur by hour. IRR reports estimated coefficients transformed to incidence-rate ratios, that is, $e^{\beta i}$ instead of β_i. Nevertheless, ratios do not provide an overall understanding of the underlying unobservable (latent) variables reflected in the observed variables (manifest variables), which motivated the use of factor analysis.

[2] Federal Aviation Administration, "Memphis RECAT Increases Capacity Significantly", January 30, 2013, https://www.faa.gov/news/updates/?newsId=70,804&omniRss=news_updatesAoc&cid=101_N_U.

3.1. The data sample and variables

All the variables originated from the Aviation System Performance Metrics[3] (ASPM) data warehouse, which includes data from the Traffic Flow Management System (TFMS), ARINC's Out-Off-On-In (OOOI) messages, and U.S. Department of Transportation's Aviation Service Performance Quality (ASQP). The variables were measured by day and by core operations hour (from 07:00 to 21:59, local time). A comparison of the Akaike Information Criteria (AIC) values helped identify which variables were to be included in the model—a lower AIC value for a specific model determined the choice of the variables.[4]

Each of the two samples included 1380 hourly observations for all days of the week. The pre-implementation sample covered the period from March to May 2014, whereas the post-implementation one included the months of March to May 2015. The periods under consideration did not contain peak season traffic, such as summer months when convective weather may affect the variability of operations, or peak holiday traffic.

- *Departure Counts* represent the response variable. Departure counts refer to hourly departures recorded in ASPM. The counts are based on DZ (departure) messages from the Traffic Flow Management System (TFMS), as well as gate-out, wheels-off, wheels-on, and gate-in (OOOI) data from ARINC. The departure counts consist of commercial air carrier, general aviation, and military operations, as well as foreign and domestic flights.
- *Gate Departure Delays* account for flights that leave the gates one minute or more past the times specified in the last flight plan submitted before takeoff. The variable refers to the duration in minutes between actual departure times and flight plan departure times. Delays compared with flight plan information minimize the possibility to skew delay metrics through schedule padding. Filed departure times also internalize airlines expectations for surface and enroute delays due to weather conditions or congestion.
- *Taxi-Out Times* represent the number of minutes elapsed from gate-out to wheels-off times. They are an indicator of airport congestion. Taxi-out times increase as the volume of aircraft waiting for departure increases.
- *Departure Demand* accounts for the number of aircraft ready to depart CLT. Based on ASPM's variable definitions, the start of demand is calculated as gate-out time plus unimpeded taxi-out time. Departure demand ends at wheels-off time. "When expected departure clearance time (EDCT) delays are implemented, the duration of EDCT delay is excluded from departure demand calculations and added to the arrival side. This adjustment is made because in the case of ground delay programs (GDP) with EDCT's, excess departure demand may be caused by capacity restrictions at the arrival airport."[5] Unimpeded taxi-out time represents the nominal time for an aircraft to travel from gate to takeoff, taking into account seasonality and the average taxi-out times of the large carriers reporting in the Aviation Service Quality Product (ASQP) of the U.S. Department of Transportation.
- *Arrival Demand* refers to the number of aircraft that left the origin airport and are expected to land at CLT. The start of demand corresponds to actual wheels-off time plus estimated time enroute. Actual wheels-on time marks the end of arrival demand. If a flight has an expected departure clearance time, then the start of arrival demand is equal to wheels-off time plus estimated time enroute minus the EDCT delay.
- *Weather* is a dummy variable labelled as '1' for instrument approach conditions (IAC) and '0' for visual approach conditions (VAC). Flights operate in instrument approach conditions at CLT when the ceiling is below 3600 feet and visibility is less than five nautical miles.
- *Runway Configuration.* This study considered the two most frequently used configurations and all the others as a separate group. These configuration are 18C, 18R, 23|18C, 18L and 36C, 36L, 36R|36C, 36R. The Appendix A includes the CLT runway layout.

3.2. The assumptions of the negative binomial mixed-effects model

Negative binomial regression usually models over-dispersed count variables. Over-dispersion occurs when the conditional variance exceeds the conditional mean, a violation of a Poisson distribution. The chi-square value of the goodness-of-fit test for Poisson distribution was less than $\alpha = 0.05$ for the counts of departures before and after the implementation of wake recat. Therefore, we rejected the hypothesis, at a 95 percent level, that the counts of departures in both samples followed a Poisson distribution.

The dependent variable represents the counts of departures by hour, from 07:00 to 21:59 (local time). A mixed-effects model contains fixed-effects and random-effects terms. While fixed effects are constant across the selected variables, random effects assume that the individual specific effects are uncorrelated with the independent variables. The random effects can be modeled by prior distributions, which is not the case for fixed effects. "Random effects are useful for modeling intra-cluster correlation; that is, observations in the same cluster are correlated because they share common cluster-level random effects," (Stata, 2015). Readers interested in multilevel and longitudinal negative binomial models are referred to Rabe-Hesketh et al. (2008) and to Zuur et al. (2009).

The negative binomial distribution can be written as follows:

$$\mathrm{F}(\mathrm{y_i}|\mathbf{x}_\mathrm{i}) = \frac{\Gamma(y_i+\alpha^{-1})}{y_i!\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu_i}\right)^{\alpha^{-1}}\left(\frac{\mu_i}{\alpha^{-1}+\mu_i}\right)^{y_i}, \quad y_i = 0,1,2,\ldots,\mathrm{n} \tag{1}$$

[3] The website is https://aspm.faa.gov.

[4] The Akaike Information Criterion is defined for samples larger than 40 observations as AIC = −2(log-likelihood) + 2K where K represents the number of parameters and the log-likelihood is a measure of model fit. See Akaike (1974).

[5] See ASPM definitions at http://aspmhelp.faa.gov/index.php/ASPM_Efficiency:_Definitions_of_Variables.

with $\alpha > 0$. The conditional mean and variance are respectively

$$E[Y_i|\mathbf{x}_i] = e^{X_i^T\beta} \tag{2}$$

$$Var[Y_i|\mathbf{x}_i] = \mu_i(1 + \mu_i/\theta) = \mu_i(1 + \alpha\mu_i) > E[Y_i|\mathbf{x}_i] \tag{3}$$

The present hierarchical model consists of two levels:

- Three possible runway configurations (18C, 18R, 23|18C, 18L; 36C, 36L, 36R|36C, 36R, and all others),
- Instrument versus visual approach conditions.

Level-1 Model (within observations)

$$\log(departures_{ij}) = b_{0i} + b_{1i}\ taxi\text{–}out\ time + b_{2i}\ departure\ demand + b_{3i}\ arrival\ demand + b_{4i}\ departure\ delays + \epsilon_i \tag{4}$$

where i is the count response of the ith observation, $j = 1, \ldots, n_j$ from the jth cluster$j = 1, \ldots, M$.

Level-2 Model (between observations)

$$\begin{aligned} b_{0i} &= \beta_0 + \nu_{0i} \\ b_{1i} &= \beta_1 + \nu_{1i} \\ b_{2i} &= \beta_2 + \nu_{2i} \\ b_{3i} &= \beta_3 + \nu_{3i} \\ b_{4i} &= \beta_4 + \nu_{4i} \end{aligned} \tag{5}$$

with ν_i as the random effects.

4. Results of analyses

Before reducing the variables to a few factors and deriving the incidence rate ratios, we tested the hypothesis that departure counts before and after the introduction of wake recat had the same variance. Then, we assessed whether environmental factors such as time of the day, season, weather conditions, volume of operations, and traffic mix, may explain differences in the variance between the two samples.

4.1. Descriptive statistics

Since the p-value of the Anderson-Darling test of normality was less than $\alpha = 0.05$, we concluded at a 95 percent level that the distribution of departure counts in the pre- and post-sample was not normal. Using the Levene's test of equal variance for non-normal variables, we rejected the null hypothesis that departure counts before and after the introduction of wake recat had the same variance (p-value = 0.018).

At first sight, it was difficult to explain differences in the variance. A comparison of traffic mix data showed no significance difference in the categories of aircraft that flew during the selected pre- and post-implementation periods: Two percent of the departing aircraft during the core hours were categorized as 'heavy'; one percent as 'Boeing 757's; 39 percent as 'large jets'; and 58 percent as 'small' equipment. The data originated from the Traffic Flow Management System available in ASPM. The categories of equipment and maximum takeoff weights are indicated in the Appendix A.

The number of departures only increased 0.31 percent, that is, from 69,339 in the pre-sample to 69,559 departures in the post-sample. Finally, the percent on-time gate departures compared with flight plans did not significantly change: In the pre-implementation sample, 82.71 percent of the flights departed on time with reference to filed flight plans compared with 81.70 percent in the post-implementation period. The average minutes of gate departure delays declined from 8.48 to 7.98 min after the implementation of wake recat.

However, a further consideration of environmental data may explain the difference in variation. In the post-implementation sample, 81.96 percent of the departures operated in visual approach conditions compared with 76.52 percent in the pre-implementation sample during core hours (source: ASPM). According to data from the Operations Network (OPSNET), the number of delay counts increased 13.49 percent in the post-implementation period, mainly driven by weather events (10.64 percent increase) and traffic volume (17.31 percent increase).

The introduction of wake recat may have reduced inter-departure times and enabled more frequent departure pushes than before. This, in turn, may explain why the variance in departure throughputs was different between the pre- and post-implementation periods.

Fig. 1 shows how departures changed during core hours, before and after the introduction of wake recat. A comparison of the bar graph of departure throughputs by hour revealed more peaks scattered during the core operations hours in the post-implementation sample: As inter-departure times decreased, more departures were 'pushed' out of the airport.

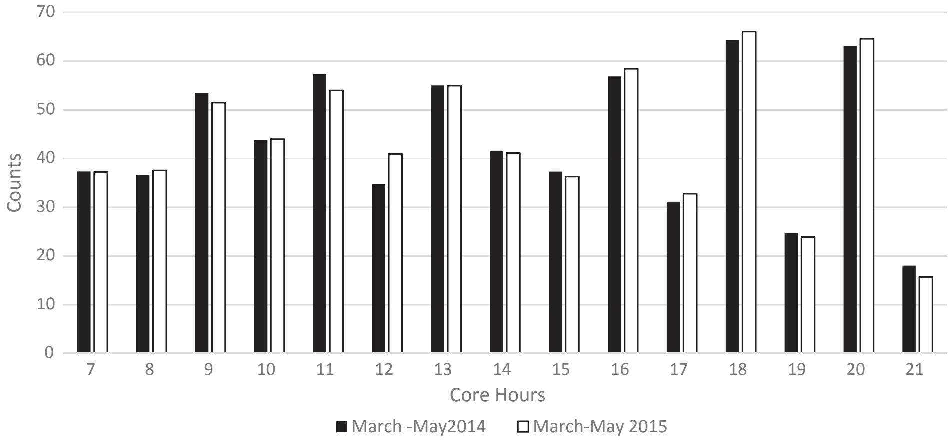


Fig. 1. Departure throughputs by core hour in all approach conditions.

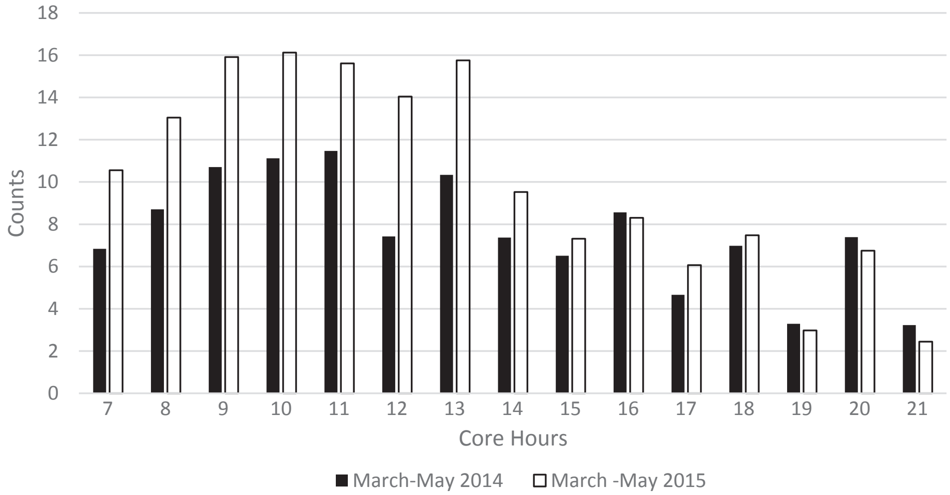


Fig. 2. Departure throughputs by core hour in instrument approach conditions.

Fig. 2 shows the differences in departure throughputs by core hour between the two samples in instrument approach conditions. It highlights an increase in departure throughputs during the morning peak hours in the post-implementation sample—despite an increase in the percentage of periods in instrument approach conditions from 18.04 percent in the pre-sample to 23.48 percent in the post-sample.

4.2. Factor analysis

Factor analysis makes it possible to summarize the data covariance structure into a smaller number of dimensions. Factor analysis describes the covariance among the selected variables in terms of a few underlying unobservable random quantities or factors. In the present case, the iterated principal axis methodology made it possible to identify three factors—regardless of runway configuration and approach conditions under consideration. The iterated principal axis methodology is a least-squares estimation of the common factor model, without makings any assumption about the type of error. Varimax rotation imposed the restriction that the factors could not be correlated. The communality for a given variable represents the proportion of variation in that variable explained by the three factors. Communality values close to 1 indicate that the model explains most of the variation for those variables. For a discussion on factor analysis applied to operational and delay variables, see Diana (2014).

In Tables 1 and 2, departure counts and departure demand loaded highly onto Factor 1, arrival demand and gate departure delays onto Factor 2, and taxi-out time onto Factor 3. The factor analysis provides an overall picture of how the variables reduce to a few factors regardless of approach conditions and runway configurations used. This implies that the variance in departure throughputs

Table 1
Factor analysis (pre-implementation sample).

Variable	Factor 1	Factor 2	Factor 3	Communality
Departure counts	**0.972**	−0.007	0.084	0.952
Departure demand	**0.958**	0.05	0.208	0.964
Arrival demand	0.283	**0.824**	−0.077	0.765
Gate departure delays	−0.288	**0.727**	0.253	0.676
Taxi-out time	0.204	0.086	**0.943**	0.939
Variance	2.0681	1.2168	1.0102	4.2951
% Variance	0.414	0.243	0.202	0.859

Table 2
Factor analysis (post-implementation sample).

Variable	Factor 1	Factor 2	Factor 3	Communality
Departure counts	**0.926**	−0.16	−0.223	0.933
Departure demand	**0.969**	−0.066	−0.075	0.949
Arrival demand	0.332	**0.714**	−0.392	0.774
Gate departure delays	−0.151	**0.839**	0.11	0.739
Taxi-out time	0.544	0.187	**0.784**	0.945
Variance	2.2253	1.2795	0.8357	4.3405
% Variance	0.445	0.256	0.167	0.868

was strongly related to the variance in departure demand, while a high level of demand for arrivals was likely to delay departures. Finally, surface congestion in the form of longer taxi-out times may affect departure throughputs, as it takes longer for aircraft to move from gate to takeoff.

While the individual communalities indicate how well the model is working for the individual variables, the total communality gives an overall assessment of performance.

The proportion of the total variation explained by the three factors was not significantly different: 0.859 and 0.868, respectively in the pre- and post-implementation sample. The bolded areas provide the grouping of the variables by factor. The information in Tables 1 and 2 does not take into account multiple levels and the random effects of instrument approach conditions on operations volume.

4.3. The outcomes of the mixed-effects models

Tables 3 and 4 provide the respective outputs of the pre- and post-implementation negative binomial mixed-effects models. The estimates are organized by runway configuration in instrument approach condition. The random effects (volume of operations in instrument approach conditions) are also indicated. At a 95 percent level, we rejected the null hypothesis that all the parameters in both mixed-effects models were equal to zero (the p-value of Wald chi-square < 0.000).

Table 3
Mixed-effects model outputs before wake recat implementation.

Counts of departures	18C, 18R, 23|18C, 18L n = 289		36C, 36L, 36R|36C, 36R n = 565		All other configurations n = 526	
	IRR	P > |z|	IRR	P > |z|	IRR	P > |z|
Taxi-out time	1.017	0.021	1.035	0.000	0.995	0.337
Departure demand	1.022	0.000	1.031	0.000	1.018	0.000
Arrival demand	0.997	0.002	0.999	0.545	1.000	0.617
Gate departure delays	0.987	0.000	0.984	0.000	0.983	0.000
Intercept	1.172	0.220	0.928	0.599	1.713	0.000
/lnalpha	−2.387		−2.375		−2.600	
Random effects						
Meteorological Approach Conditions (IAC = 1)						
var(tot_ops)	8.53E−38		4.02E−05		2.09E−37	
var(_cons)	1.29E−36		4.02E-32		4.56E-33	

Table 4
Mixed-effects model outputs after wake recat implementation.

Counts of departures	18C, 18R, 23|18C, 18L n = 386		36C, 36L, 36R|36C, 36R n = 420		All Other Configurations n = 574	
	IRR	P > |z|	IRR	P > |z|	IRR	P > |z|
Taxi-out time	0.995	0.337	1.037	0.000	1.032	0.000
Departure demand	1.018	0.000	1.004	0.241	1.017	0.000
Arrival demand	1.000	0.617	0.975	0.967	0.995	0.000
Gate departure delays	0.983	0.000	0.979	0.000	0.988	0.000
Intercept	1.713	0.000	0.950	0.659	1.238	0.099
/lnalpha	−2.284		−2.365		−2.359	
Random effects						
Meteorological Approach Conditions (IAC = 1)						
var(tot_ops)	2.78E−38		6.14E−05		1.69E−34	
var(_cons)	0.016459		1.36E−32		1.93E−03	

The Stata algorithm allows for over-dispersion (variance greater than the mean) when using the negative binomial procedures. The parameter '/lnalpha' represents the log-transformed over-dispersion parameter. The alpha value is always positive and it is derived from the maximum likelihood estimate of the log of alpha. In a Poisson model, the alpha value is constrained to zero. In the pre-sample, the conditional over-dispersion α is parametrized on the log scale and its estimate is computed as $\exp(-2.6) = 0.07$. The unconditional over-dispersion is derived as $\exp(-2.6) * (1 + 4.56E - 33) - 1 = -0.92$. Overall, there was less over-dispersion in the data than predicted, given the low values of the random-effects variables in both samples (Tables 3 and 4).

Except for the magnitude and significance of the gate departure delay estimates, there was no consistency in the significance patterns of the incidence rate ratios (IRR) when comparing both samples. This implies that the impact of the variables on the counts of departures was likely to depend on random effects such the choice of runway configurations and approach conditions.

Incidence rate ratios facilitate the interpretation of the estimates. For instance, in the case of the '18C, 18R, 23|18C, 18L' runway configuration, the incidence rate ratio (IRR) value of 1.017 in the pre-sample represented the estimated rate ratio for a one-minute increase in taxi-out time, during core hours, in instrument approach conditions, holding other variables constant. If taxi-out time were to increase by one minute, then the counts of departures would be expected to decrease by a factor of 0.983, during core hours, in instrument approach conditions, holding all other variables constant. In the post-implementation sample, if taxi-out times were to decrease by one minute, then the counts of departures would be expected to increase by a factor of 0.005, in instrument approach conditions, during core hours, holding other factors constant.

There was no significant difference between the pre- and post-implementation sample as far as the incidence of gate departure delays is concerned: If gate departure delays were to decrease by one minute, then the counts of departures would be expected to increase by a factor of 0.02 during core hours, in instrument approach conditions, holding other factors constant.

Tables 3 and 4 also show a shift in the significance of arrival demand for the busiest runway during core hours in instrument approach conditions. Whereas it was significant at a 95 percent level in the pre-implementation sample, arrival demand was not in the post-implementation one. This may be explained by the regulation of traffic flows through optimized profile descent (implemented in January 2013), automated terminal proximity alert (June 2013), and the deployment of time-base flow management (August 2013). Automated terminal proximity alert allows controllers to reduce the required space between aircraft on their final approach. In the post-implementation sample, the implementation of expanded low-visibility operations using lower runway visual range minima in April 2015 may have further reduced the variability of operations in instrument approach conditions.

5. Final comments

This study compared departure throughputs before and after the implementation of wake vortex recat. The mixed-effects model provided the benefits of evaluating the fixed effects of selected operational variables at two levels (i.e. instrument approach conditions and specific runway configurations), while taking into account the random effects of instrument approach conditions on total operations.

As a first analytical step, factor analysis facilitated the reduction of the selected observable variables (departures, taxi-out time, departure and arrival demand, and gate departure delays) into three latent variables called factors. The outcomes of factor analysis suggested that departure demand and taxi-out times would have a strong incidence on departure throughputs in the negative binomial mixed-effects model.

The estimates were expressed as incidence rate ratios (IRR) to facilitate the interpretation and comparison of the variables impact on departure counts, pre- and post-implementation. Except for the magnitude and significance of the gate departure delay estimates in the pre- and post-implementation mixed-effects models, there was no consistency in the significance of the incidence rate ratios.

The incidence rate ratio of departure demand was not significant at a 95 percent level in the post-implementation sample for the most frequently used runway configuration.

Finally, the impact of instrument approach conditions on total operations as a random effect was not substantial in both pre- and post-implementation samples. This may be explained by the implementation of NextGen technologies such as lower runway visual range minima, which optimizes operations in poor weather conditions, as well the compression of departures through shorter inter-departure times throughout the day.

The reduction in inter-departure times explained why departure demand and departure counts loaded high onto Factor 1. However, in the mixed-effects models, the incident rate ratios of arrival demand and gate departure delays were not significant across the three selected configurations, in instrument approach conditions. Finally, the fact that taxi-out time represented a factor in itself emphasized the importance of surface congestion if an airport is to benefit by reduced inter-departure times.

The study underlined the challenge for airport analysts to isolate the individual impact of initiatives such as wake recat when several other NextGen initiatives have been deployed at the same airport. Although factor analysis provided some insight on how observed variables loaded onto several factors, the study also indicated that the relationship between the incidence of departures and the selected independent variables would vary with respect to approach conditions and runway configurations. As a result, airport operators are able to anticipate the impact of specific configuration selection on departure throughputs, which can help plan and manage available airport capacity management accordingly.

It is also important to recognize that the effectiveness of wake recat may depend, not only on the selected variables when evaluated at multiple levels (i.e. runway configuration and specific approach conditions). It is also contingent upon the random effects of human factors related to controller and pilot training, as well as their willingness to utilize reduced separations.

On November 29, 2017, the FAA and the National Aeronautics and Space Administration (NASA) launched a joint demonstration (Airspace Technology Demonstration 2/Integrated Arrival/Departure/Surface).[6] The ATD-2/IADS system is designed to meter flights departing CLT in order to alleviate demand/capacity imbalances on airport surface. Controllers will be able to hold some departing flights at the gates to avoid long departure queues. It will be of interest to replicate this study after Phase 1C is implemented to measure the impact of the demonstration capabilities on taxi-out time, departure demand, and departure throughputs in various weather conditions and runway configuration uses.

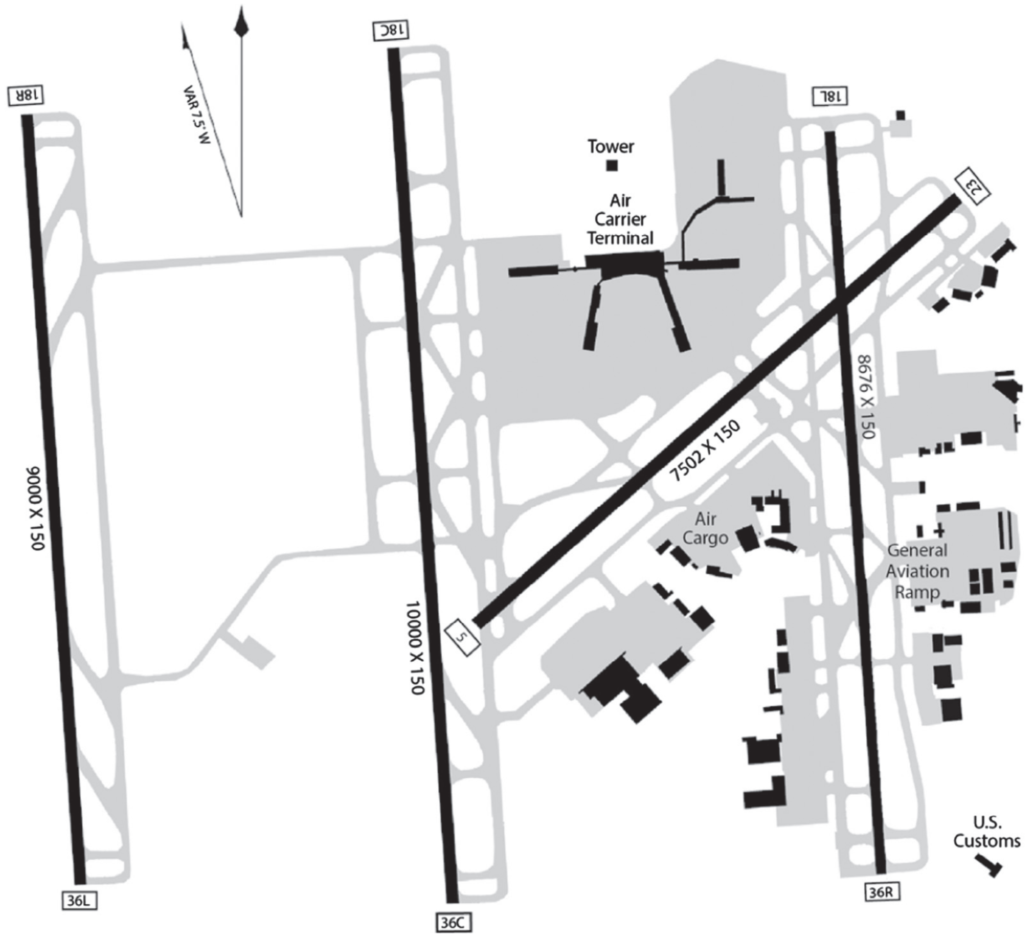
Appendix A. FAA wake separation standards (at the threshold)

Leader/follower	Super	Heavy	B757	Large	Small	Maximum takeoff weight (lbs.)
Super	MRS	6	7	7	8	> 1,200,000
Heavy	MRS	4	5	5	6	300,000–1,199,000
B757	MRS	4	4	4	5	115,600
Large	MRS	MRS	MRS	MRS	4	299,000–31,000
Small	MRS	MRS	MRS	MRS	MRS	< 31,000

Note: MRS means minimum radar separation.
Source: Federal Aviation Administration, Advisory Circular 90-23G, February 10, 2014.

[6] NASA, "ATD-2 Field Demonstration Commences Surface Departure Metering", Aviation System Division, December 6, 2017, https://www.aviationsystemsdivision.arc.nasa.gov/news/index.shtml.6.

CLT Runway Layout



Source: Federal Aviation Administration, NextGen Performance Snapshots (http://www.faa.gov/nextgen/snapshots).

Note

The conclusions of this study do not reflect the official opinion of the Federal Aviation Administration.

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