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RESEARCH ARTICLE

Modelling Airline Operations at Major Commercial Airports for Strategic Decision Support

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ABSTRACT

The authors discuss an integrated modelling approach for improving flight operations at major commercial airports. Statistical models, built with microdata from hundreds of thousands of flights, are embedded in a process-oriented discrete-event simulation model with two-dimensional geo-spatial characteristics and logical structures based on the concept of staged queues. With results from three application settings, the authors illustrate the wealth of information that this modelling framework can provide for collaborative planning of airport infrastructure and flight operations. Novel about this work are (1) the use of microdata to construct multivariate statistical models for delay propagation at the focal airport and their use to provide time-dependent and situation-dependent parameters for stochastic behaviour in the simulation model, (2) rigorous validation of the simulation model against historical performance, and (3) creation of an integrated analytical platform for strategic decision support.

1. Introduction

The efficiency with which flight operations occur at commercial airports is determined by physical infrastructure (runways, taxiways, ramps, passenger terminals, gates), resources available for ground service (such as tractors for pushbacks and de-icing equipment), and interdependent activities in three major spheres: air traffic control (ATC), airport operations control (AOC), and maintenance services. ATC personnel coordinate flights between airports. ATC ground controllers control aircraft movements through networks of taxiways between runways and parking positions. AOC personnel assign parking gates or remote parking stands for passenger aircraft and re-assign parking spots (gates) as necessary if designated parking spots are occupied when an aircraft arrives. Maintenance

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personnel service aircraft and prepare them for departure.

Investments in airport infrastructure (e.g., new runways and terminal modifications) cost billions of dollars, and years are required to perform environmental assessments, design physical facilities and complete construction. Airport planning thus requires a long-term strategic view and collaborative engagement of major stakeholders is required to encourage the best use of airport facilities. Analytical models are required to assess how changes in airport infrastructure, supporting resources, and operating practices may affect scheduled airline service, air cargo operations and general aviation [1-3]. Questions frequently encountered in the planning and management of airport operations include:

1) What is the operating capacity of an airport with a particular physical configuration, supporting resources, and operating practices?

2) What are the major constraints in accommodating future growth in traffic?

3) How would flight delays be affected by altering scheduled arrival and departure times for existing flights or adding new flights to the schedule?

4) How might pushbacks (departures from gates) be regulated to reduce taxi times, fuel burned by planes on the ground and resulting air pollution?

5) What is the consequence of changing how runways are used for arrivals and departures?

6) How does performance depend on the positioning and range of activity of tractors used to push back aircraft that are parked at gates or parking stands and require such service?

7) What would happen if a runway were closed for major repairs and traffic must be diverted to other runways?

8) How would operating performance be affected by using remote parking stands for aircraft and bussing passengers to the airport terminal?

9) How vulnerable is an airport's performance to delays or airspace restrictions at connected hub airports?

10) How would performance depend on alternative assignments of preferred parking positions (gates) to individual flights and on rules for selecting alternative parking sections if preferred spots are unavailable when an aircraft arrives?

In this paper, we demonstrate a unique melding of statistical modelling and discrete-event simulation to address these questions. With microdata from transponder readings that track aircraft movements on the ground as well as in the air, we construct multivariate statistical models for delay propagation at the focal airport. We use these statistical models to provide time-dependent and situation-dependent parameters for stochastic behaviour in the simulation model. We discuss the simulation model's development and validation for flight operations at Charlotte Douglas Airport (CLT), a major U.S. hub for the world's largest airline. Then, with simulation results addressing questions 3-5 at CLT and in two other settings, we demonstrate the type of insight that this modelling approach can provide.

2. Related Research

Mathematical optimization, queueing models, statistical models and computer simulation have been applied widely in airport planning and operational research. Mathematical optimizing models have been applied to problems involving the timing of pushbacks, sequencing arrivals or departures, performing services such as de-icing aircraft, and optimizing movements through taxiways [4-10]. These operational research (OR) models, however, tend to ignore stochastic aspects of system behaviour and interactions that must occur with other parts of the system [11-14].

Sophisticated three-dimensional simulation models such as SIMMOD, which the Federal Aviation Administration maintains, the Total Airspace and Airport Modeller (TAAM), and the Multi-Agent Transport Simulation (MATSim) represent aircraft movements with remarkable realism, and have been used for decades to study air traffic control procedures and airport capacity [15-31]. Effectively, these models take a set of flight plans for individual aircraft, with a stipulated departure time, starting position and ending position; determine shortest paths in taxi networks; simulate the movement of the airplanes through taxiway systems to the assigned runway for take-off; simulate the flight in three dimensions from waypoint to waypoint; simulate the approach to an assigned runway; and simulate movements on taxiways to the destination gate. There is some provision in these models for random variation in departure times and in the time required for specific simulated activities. These models are excellent for studying system behaviour in microscopic detail but they carry enormous overhead for studies that are more strategic in nature. Multiple runs to test alternative operating practices can take many hours to complete. Further, they do not consider external factors that contribute to systematic delays in arrivals and work involved in servicing aircraft as they are prepared for departure.

To consider stochastic effects when estimating outbound taxi times, Simaiakis and Balakrishnan [32] used analytical queueing models to predict aggregate taxi-out times and departure queues by time of day. Ravizza et al. [33] used regression to demonstrate systematic variance in taxi times depending on whether the aircraft is arriving or departing, distances involved, and number of planes ahead taxiing to the same position. Lordan et al. [34] similarly used a log-linear regression model to predict inbound and outbound taxi times depending on the day of the week and the number of aircraft taxiing inbound and outbound.

Bubalo et al. [35] investigated the impact of allowing a 15-minute window around scheduled departure times when releasing planes for departures. They generated pushback sequences with a neighbourhood search heuristic and tested the efficacy of their revised sequences by driving their solutions through multiple replications of the SIMMOD model with some stochastic variation in ramp and pushback times. They discarded replications in which SIMMOD failed to complete a full day's schedule because of gridlock at intersections (which would require refinement in the model's logic to resolve). Despite possible bias from rejecting replications with gridlock, the authors demonstrated that substantial reductions in emissions might occur with careful staging of pushbacks when taxiways are congested. They did not consider interactions between arriving and departing aircraft.

Another stream of research deals with the propagation of delays in airline service networks. AhmadBeygi et al. [36] consider downstream itineraries for crew and pilots, along with slack in turnaround schedules, to generate estimates of the extent to which individual flights pose a risk of propagating delays. Campanelli et al. [37] used agent-based simulation to represent the flow of aircraft through their schedules for a day to compare slot-allocation procedures in the U.S. and Europe. Pyrgiotis et al. [38] mapped downstream itineraries of aircraft departing from an airport and, considering slack between subsequent scheduled arrival and departure times, used analytical queueing methods (with airports treated as having single servers for arrivals and departures respectively) to estimate how delays would propagate under different service rates in each airport. Du et al. [39] used a casualty network to study flight delays. They found that the causes of delay vary considerably among airports, and that to understand fully the reasons for departure delays, the operations at individual airports need to be modelled deliberately. Each of these studies relies on exogenous estimates of throughput capacity at individual airports. None provides mechanisms for assessing the impact of specific changes to airport infrastructures and operating practices.

Seeking a productive balance between realism and analytical efficiency, Smith et al. [40,41] have simulated flight and ground operations at individual airports as processes involving entities (aircraft) in networks of staged queues with two-dimensional geo-spatial characteristics. They take into account the ways that aircraft can be maneuvered in tight areas on the airport surface and procedures employed by air traffic control (ATC) to regulate traffic flows. Embedded in the simulation models are statistical models that incorporate systematic (time-dependent and entity-dependent) variation in simulation parameters. We employ this approach in the present setting and organize our presentation as follows. In Section 3, we describe features of the discrete-event simulation model constructed for prescriptive analysis. In Section 4, we describe how microdata from hundreds of thousands of individual flights were used to construct statistical models used in the simulation model for estimating likelihood of flight delays, lengths of delay when they occur, and times required to prepare aircraft for subsequent departures. In Section 5, we describe the model validation process and present related statistics that demonstrate the efficacy of the model to represent actual flight operations at Charlotte Douglas Airport. Section 6 provides illustrations of insight from simulation experiments in several settings. Section 7 contains concluding remarks.

3. Research Method

A discrete-event simulation model [41] represents flight operations at a focal airport including the final approach of aircraft to assigned runways, their movements on the airport's surface, and departures from assigned runways. The model is constructed in Arena 14.7 as a process-oriented simulation with two-dimensional geo-spatial dimension. Aircraft are the simulated entities. Simulated aircraft taxi inbound from the point of landing to a designated parking location (terminal gate or parking stand). They are prepared for their next scheduled departure, are pushed back from their parking location, and then they taxi to their assigned runway for departure. Finally, with stipulated separation for safety, the aircraft take off and are removed from the model. They are processed through networks of staged queues which realistically represent actual airport operations. In the CLT setting, for example, there are 368 queues for 313 resources and 55 logical holding conditions in which entities (aircraft) may be placed as they proceed through the simulation logic [42].

Dozens of attributes associated with the aircraft (flight schedules, aircraft characteristics, critical event times, assigned runways, parking locations, etc.) are used to moderate the process flow. Resources used by the aircraft include segments of airspace, runways, taxiways, intersections, and staging areas on the field where aircraft may be positioned pending clearance to advance further; ramp areas near terminal gates, passenger gates, remote parking stands from which passengers might alternatively be bussed to the terminal; and tractors and tractor operators required to push back the aircraft when they are ready to depart.

The model is superimposed on the airport diagram used by ATC and pilots with proper scale (see Figure 1). We identify points on the airport surface where aircraft may be staged as they progress from runways to gates and vice versa. Routes between staging points across ramps and along taxiways are mapped, and aircraft are directed to the next staging point depending on the runways to be used for landings and take-offs of individual flights and which staging points between their current position and airport destination (gate or runway) can accommodate them. Stipulated separations are imposed by controlled releases of aircraft about to approach and depart from the airport. Landing aircraft receive priority in runway use over departing aircraft. Departing aircraft cannot enter a runway for take-off if an arriving aircraft is on "short final approach" to that runway.

Parking sections at airport terminals are designated that have common staging points for arrivals and departures at a group of gates (blue dots in Figure 1). Arriving aircraft are staged in queues in one area of the ramp pending the availability of a gate (and clear path to it). Departing aircraft (which may be held on the ground by ATC for weather or the control of traffic flow in congested areas) are staged at another area if they must clear a gate to accommodate arriving aircraft. Standard routings are used through taxiways between parking sections and runways.

We simulate operations for a full 24-hour day beginning at midnight. Aircraft scheduled to have arrived "yesterday" and departed "today" are placed in parking positions as part of the initial setup. Arrivals "today" are generated externally by SAS with systematic and random components of variation and placed on a flat file in order of their simulated arrival times at the "final approach fix" for the designated runway specific to the flight. The externally generated arrivals are read, with all the flight details, by the Arena model and then proceed through the process-oriented simulation logic. Non-scheduled flights such as general aviation and some air cargo activity are generated within the Arena model using nonstationary exponential inter-arrival times. They are generated at the maximum rates that occur in any hour of the day and "thinned" randomly to create proper time-of-day patterns and assigned to parking areas randomly with stipulated frequencies.

Simulated traffic movements are controlled by signals that indicate the direction of flow and the capacities of resources such as ramps, runways and taxiways to accommodate aircraft. We use lognormal distributions for elemental activity times involving physical movements of aircraft. Simulated times for aircraft to move between points on the field are determined by the physical distance involved and the taxi speed of the aircraft.

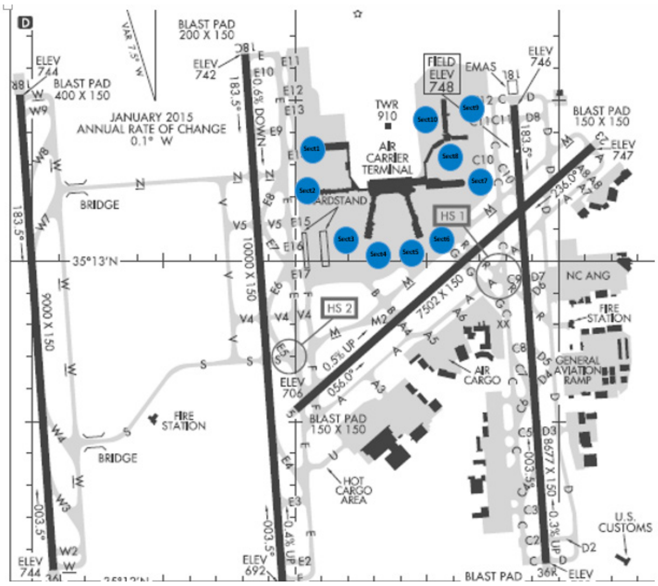

Figure 1. Airport template for simulation at Charlotte, NC.

The model is animated with activity dashboards that show, at any point in simulated time:

- the current and cumulative use of runways (Figure 2)
- the number of planes taxiing into, parked, and taxiing out of each parking section (Figure 3)
- the number of planes in various designated "hotspots" on the airfield, current directional status for each runway, etc.
- aircraft movements on runways and taxiways (Figure 4)
- aircraft parked and moving in gate areas

A single run with animation is performed to ensure that the day's schedule can be completed without gridlock with given capacities of ramps and taxiways and stipulated rules for traffic flow. Once effective (stable) performance is demonstrated with a particular configuration, the model is then run in batch mode without animation for multiple replications to generate the necessary data for statistical analysis of system performance. Flight restrictions such as those caused by extreme weather in a flight sector are able to be imposed and alternative strategies for coping with stressful conditions can be tested with consideration of the interacting effects of arrival and departure activity.

Ten (10) replications generally give good estimates of "average" statistics for performance on various dimensions. One hundred (100) replications are performed for a more refined analysis of the stochastic effects of changing infrastructure and operating practices.

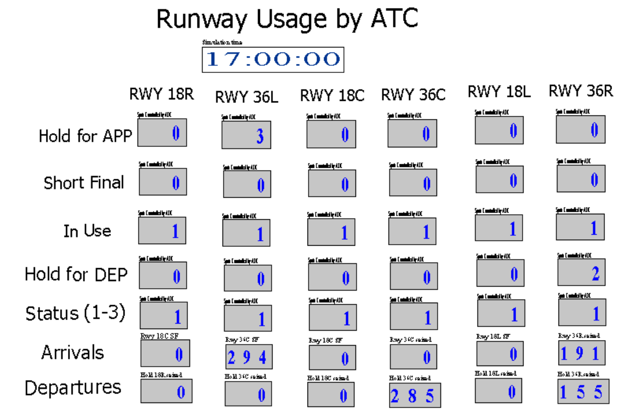

Figure 2. Dashboard for runway activity.

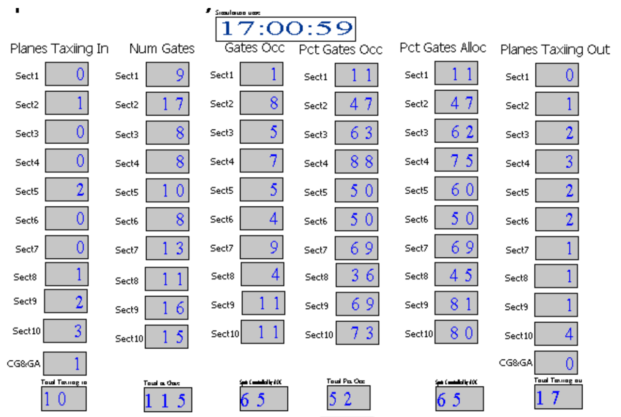

Figure 3. Status for parking sections.

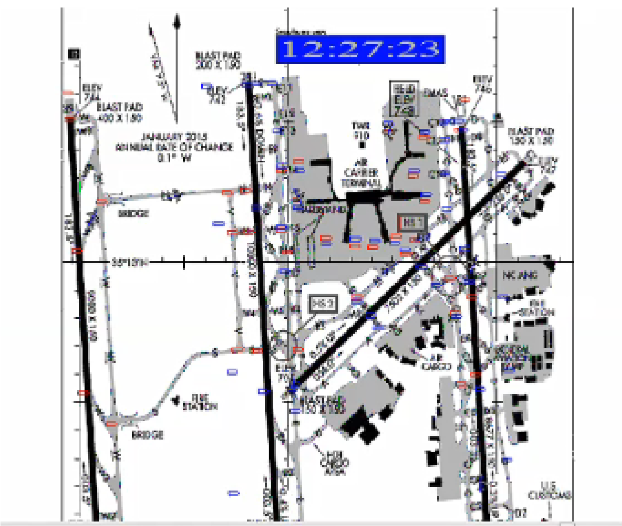

Figure 4. Animated aircraft movements.

A detailed log (Figure 5) is created to capture each simulated key event (approach, touchdown, origination, arrival at the gate, pushback, release tractor, and liftoff). This allows in-depth study of delays, taxi times, and resource usage according to time of day, airline, etc.

Obs	nrep	Event Time	Event	Airline	Flight	RWY	PKG Spot	Prev Arpt	Cont. Flight	Next Arpt	Sched Arr Time	Sched Dep Time
2409	1	1521	0: Approach	American	AAL861	36L	C6	IAH	Yes	BOS	1535	1625
2410	1	1521	3: Pushback	American	AAL955	36R	B14	DFW	Yes	BOS	1354	1454
2411	1	1521	2: Arrival	AAEagle	JIA5522	36L	E17	OMA	Yes	YYZ	1531	1612
2412	1	1522	3: Pushback	Delta	DAL2597	36C	A08	ATL	Yes	ATL	1410	1445
2413	1	1522	5: Liftoff	AAEagle	ASQ2862	36C	E21	SBN	Yes	HSV	1010	1315
2414	1	1522	5: Liftoff	AAEagle	JIA5447	36R	E12	ORF	Yes	ORF	1415	1450
2415	1	1522	0: Approach	AAEagle	JIA5106	36L	E38C	AVP	Yes	TYS	1535	1848
2416	1	1522	0: Approach	American	AAL2084	36L	C4	MEM	Yes	ALB	1542	1638
2417	1	1522	RT	AAEagle	PDT4874	36C	E36	ROA	Yes	ROA	1405	1440

Figure 5. Excerpt from a simulation event log.

4. Multivariate Models for Time-dependent and Situation Dependent Simulation Parameters

Commercial flights operate according to published schedules for arrivals and departures. For scheduled airline flights, we first model arrival delays and then model proneness to departure delays contingent on the amount of time available to "turn around" the airplane for its next scheduled departure. To construct the multivariate statistical models for CLT, we used Aerobahn microdata that track the movement of each aircraft in the air and on the ground to the nearest second. Appended to the flight-tracking data from Aerobahn were the aircraft tail (registration) number, airline and flight number, the scheduled arrival or departure time, the type of aircraft, previous airport for each arrival, next airport for each departure, parking location (gate assigned) and taxiway routes and runways used. With the tail number, we were able to match arrivals and departures for an aircraft and consider the time available to "turn around" the aircraft when estimating the likelihood and length of departure delays for departing flights. From the longitudes and latitudes of the respective airports, we determined the distance and bearing for direct flights between the relevant cities and whether the flight was international. Arriving flights were assigned to one of four airspace sectors (NE, SE, SW, or NW) according to the inbound direction. From the runway used, we determined whether the flight would have a "straight-in" approach, or, alternatively, require a reversal of course on approach that would add time to the flight. Indicator (0-1) variables for month of the year are used to account for seasonal variation in weather and passenger activity. Indicator variables for hour of day capture the effects of variation in flight activity that occurs systematically each day.

First, we produced a regression equation for arrival delays. Factors contributing to the expected (average) delay include scheduled hour of arrival (to capture the effect of concentration of flight activity and tendency for prior delays to propagate), airline indicator, whether the previous airport is a particular hub airport prone to departure delays, whether the inbound direction of flight involves a reversal in direction for final approach (therefore adding time), airspace sector for the arriving flight, inbound flight distance (nm), whether the flight is international, size of aircraft, and month of the year (to capture seasonal weather effects). Random effects are imposed according to the distribution of the residuals of the regression model. We created models with each parameter statistically significant by using backward elimination at a 0.05 level of statistical significance.

The model for arrival delays (estimating the logarithm of arrival delay plus 30 minutes) is used to create a file of "arrivals", which effectively queues each airplane at the "final approach fix" for its designated runway. The "arrival" time at the FAF is the scheduled arrival time at the gate plus the expected delay from the regression equation, plus a random (residual) delay (which may be negative, for an early arrival) less the average time required for an aircraft to complete its approach from the final approach fix, and then land and taxi to the gate. We use another regression model to impose time-of-day effects when estimating inbound taxi times (similarly to Lordan et al. [38]) and we offset the arrivals for queueing at the FAF accordingly.

Departure delays are generated differently for planes requiring an "immediate turnaround" than for planes not requiring an immediate turnaround. An immediate turnaround is defined as having less than 30 minutes between arrival time and next scheduled departure if there are up to 100 seats in the aircraft and less than 45 minutes otherwise. For immediate turnarounds, a log-regression model is used to generate the time required to turn around the aircraft and its readiness for pushback is "delayed" by that amount of time. For non-immediate turnarounds, a logistic model is first used to determine the likelihood that a delay relative to the scheduled departure time will occur. Delays occur randomly according to that probability. Then, for a plane that experiences a delay, a log-regression model is used to generate the expected amount of time after scheduled departure that the plane will be ready for its pushback. Residual variation is added randomly to the expected delay using an offset lognormal distribution consistently with the residuals from the regression model.

Together, these statistical models provide time and situation-dependent parameters for generating key events that occur throughout the day. Times for incremental movements of aircraft from point to point were generated from measured distance of the respective segments and standard speeds for aircraft using lognormal distributions (with constant coefficients of variation). We used lognormal distributions with average ground speed for approaches (140 knots considering true air speed on approach and assuming slight headwind) from the FAF to the runway for the approach segment and lognormal distributions with customary taxi speeds (15 knots) for ground movements on taxiway segments.

5. Model Validation

To calibrate and validate the simulation model, we compare statistics from the simulation event logs with those from historical event logs where the same schedules were in effect and where the same runways were in use (dictated by wind direction). We compare inbound and outbound aircraft movements (counts and average taxi times) by hour of day for all runway and parking-area combinations. Adjustments are made, as necessary, to means and coefficients of variation of the elemental activities to bring statistics in line with the operating conditions to be simulated. Simulated and actual activity for 2018 summer operations with northerly traffic at CLT, for example, corresponded to this degree:

- Correlation = 0.90 for the average number of planes taxiing inbound by hour of day
- Correlation = 0.86 for the average number of planes taxiing outbound by hour of day
- Correlation = 0.89 for the total number of flight operations by hour of day
- Correlation = 0.94 for average inbound taxi times for different runway-parking section combinations
- Correlation = 0.92 for the average ramp and taxi time of inbound and outbound flights by hour of day
- Correlation = 0.82 for the average length of delay for inbound and outbound flight by hour of day
- Correlation = 0.75 for the proportion of flights experiencing delays in excess of 15 minutes for inbound and outbound flights by hour of day
- Correlation = 0.43 for the average outbound ramp and taxi times for runway-taxiway combinations by outbound traffic

Outbound taxi times are correlated less than inbound taxi times (as expected) because many outbound flights converge at the same runways for take-off and they spend a greater amount of time queued for take-off versus taxiing in motion. (Taxiing time includes time in motion and time at rest.) Inbound flights, in contrast, exhibit a reverse funnelling effect. They scatter to a large number of gates and their taxi times are therefore more strongly related to the distance taxied. The model accurately represented this phenomenon.

Airlines constantly adjust their schedules and crew assignments to deal with systematic issues. We therefore allow *ad hoc* offsets to be imposed as we generate arrival times of individual flights to accommodate possible changes in flight schedules (such as scheduling arrivals earlier to provide additional turnaround time, which can dramatically reduce the incidence of delays). We allow scaling of residual variance or compression of arrival or departure delays, if necessary, to create a simulation base case with the percentage of delays over 15 minutes that are consistent with their chosen reference period or conditions.

6. Illustrated Applications for Strategic Use of Airport Assets

When the simulation model is validated to represent the operating environment with sufficient precision, a base level of performance is provided against which the effects of changes in infrastructure, supporting resources or operating practices may be measured. We provide, in this section, just a few examples of such analyses performed in different settings.

Runway usage: At St. Louis Lambert International Airport, a question was posed about the effects of using a cross runway (RWY 06-24) for small aircraft operated by a regional carrier and general aviation in peak periods instead of the dominant runways (36R and 29) which are used by the major air carriers. Potential benefits from such a strategy (seen in comparisons of Table 6 with Table 7) were revealed even at prevailing traffic levels, which were much below the design capacity of the airport. When higher traffic scenarios were tested (not shown here), the potential benefits were magnified considerably. Savings of just a minute or two for inbound and outbound taxi times can have significant effects on delay propagation, fuel burned, and air pollution at an airport. Guépet et al. [8] cite statistics that indicate that hundreds of thousands of tonnes of CO_2 emissions would be eliminated by a one-minute reduction in taxi times at European airports.

Deployment of ground resources: In an Asian setting, where ground services were provided by the airport for multiple carriers, we used the model to demonstrate the effect of different deployment strategies for tractors used to pushback aircraft for departures. In initial meetings with personnel from ATC, AOC and ground services, it was asserted that shortage of tractors would be the most inhibiting factor in improving airside performance. Maintenance personnel gave us an initial proposal for locations from which the tractors would be deployed and range of service from each deployment point. Simulation results with the initial settings revealed times of day when delays in pushbacks would occur. These were able to be mitigated by changing the positioning and range of service for individual tractors (Table 8) and led to discussions of how tractor resources could be deployed dynamically in response to changing concentrations of gate activity during the day. In practice, the maintenance department did use the tractors with range of service adjusted as needed and tractor utilization inferred from the simulation model was consistent with actual tractor utilization.

Table 6. Simulated STL performance with use of dominant runways only.

		Av. delays (min.)		Flights with delay > 15 min.		Ramp and taxi time
Airline	**Event**	**No of flights**	**Av. delay**	**No of flights over 15 min.**	**P (>15 min.)**	**Av. (min.)**
American	**2: Arrival**	2,598	1.4	727	0.280	6.2
	4: Departure	2,600	5.9	279	0.107	13.1
Cape Air	**2: Arrival**	2,500	-6.4	49	0.020	6.5
	4: Departure	2,499	3.7	219	0.088	8.4
Delta	**2: Arrival**	1,876	-5.7	302	0.161	6.1
	4: Departure	1,600	4.7	121	0.076	14.9
GA	**2: Arrival**	0	-	0	0.000	7.2
	4: Departure	0	-	0	0.000	5.0
United	**2: Arrival**	3,280	8.3	1,260	0.384	6.1
	4: Departure	3,300	5.9	375	0.114	15.2
US Air	**2: Arrival**	1,400	0.6	367	0.262	6.0
	4: Departure	1,400	2.8	77	0.055	13.6
Southwest	**2: Arrival**	9,495	0.5	2,229	0.235	7.4
	4: Departure	9,500	10.0	1,258	0.132	12.1
Overall		42,048	3.8	7,263	0.134	8.9

Table 7. Simulated STL performance with diversion of small aircraft to RWY 06-24.

		Av. delays (min.)		Flights with delay > 15 min.		Ramp and taxi time
Airline	**Event**	**No of flights**	**Av. delay**	**No of flights over 15 min.**	**P (>15 min.)**	**Av. (min.)**
American	**2: Arrival**	260	0.4	67	0.258	5.9
	4: Departure	260	5.5	21	0.081	10.4
Cape Air	**2: Arrival**	250	-7.6	3	0.012	6.0
	4: Departure	250	3.5	21	0.084	6.8
Delta	**2: Arrival**	185	-5.3	26	0.141	5.8
	4: Departure	160	3.6	7	0.044	10.3
GA	**2: Arrival**	0	-	0	0.000	7.6
	4: Departure	0	-	0	0.000	6.1
United	**2: Arrival**	327	9.7	135	0.413	5.9
	4: Departure	330	4.9	30	0.091	10.3
US Air	**2: Arrival**	140	0.0	34	0.243	5.8
	4: Departure	140	2.6	9	0.064	12.7
Southwest	**2: Arrival**	947	0.1	210	0.222	7.1
	4: Departure	950	9.4	112	0.118	10.1
Overall		4,199	3.4	675	0.124	7.9

Schedule Adjustments: For our third application of the model, we shall examine the potential impact of adjustments to some flight schedules of American Airlines (AAL) as derived from activity at CLT on July 12, 2018. We provide a scheduling cushion of 20 additional minutes for the inbound flight (i.e., departing 20 minutes earlier from the previous airport) for each AAL flight that has a scheduled turnaround time of less than 60 minutes, and shifted arrival times at the FAF accordingly. Results with the original schedule are presented in Table 9; results with the revised schedule are in Table 10. In this case, the AAL arrival and departure delays are reduced with no spillover effects on the other carriers.

Runway assignments for reducing taxiing time: In a second illustrative experiment for CLT, we explore the potential benefits that could accrue if runway use were altered with a goal of reducing inbound and outbound taxi times by assigning runways according to taxi distances between runways and parking locations. All the previous results (and delay statistics provided in Table 9) are based on the actual runways used for the flights on July 12, 2018. In Table 11, we present the results of a simple experiment where all arriving flights destined for Parking Sections 9-10 use RWY 36R and all flights departing from Sections 9-10 use 36R for departures. In that experiment, all arriving flights destined for Parking Sections 1-6 use RWY 36L and all flights departing from Sections 1-6 use 36C for departures. Arriving and departing flights for Sections 7 and 8 used the actual runways used for flights on July 12, 2018. The results suggest that potential reductions both in arrival and departure delays and total taxi times would occur and the delays would be more uniform among the carriers. In this experiment, we ignored issues that would be confronted when integrating arriving and departing traffic from different sectors of airspace. Extending this analysis would involve simulation of strategies intended to maximize the efficiency of arrivals and departures in the air and then jointly considering strategies for air traffic control in the air and on the ground.

Experiments involving growth in traffic: Simulations with adjustments to schedules of individual flights and changes in traffic levels at the focal airport are easily performed, but such experiments need to be crafted to reflect market realities (passengers' preferences for travel times), noise abatement constraints, competitive positioning of carriers, scheduling of aircraft and crews, and patterns of congestion at previous airports for arrivals and next airports for departures [43-45]. Smith and Bilir [42] recognize that hub airports inevitably have bunches of arrivals followed by bunches of departures. One must fully consider daily flight patterns when intensifying schedules to simulate the effects of growth in traffic. To create new schedules that continue to exhibit similar patterns to those that have evolved through time, we again rely on multivariate statistical models derived from historical data.. New flights for scheduled airline service were generated as follows to perform experiments on the effects of higher traffic levels on gate-hold strategies to reduce taxi times at CLT:

1) The hour of day for a new inbound flight was assigned randomly using the same distribution as in the current schedule and minute of the scheduled flight was set randomly between 00 and 59 using a uniform distribution.

2) The airline operating the flight was set with probabilities from a multinomial logistic model having hour of day as the sole independent variable.

3) The binary variable for whether the flight was international was set with probability from a logistic model based on airline and hour of day. The binary variable for whether the outbound (departing) flight is international was set with probability from a logistic model based on airline, hour of day, and whether the inbound flight was international.

4) The airspace sector for the inbound flight was set with probabilities from a multinomial logistic model de-

Table 8. Effects of different deployments of tractors for pushbacks.

With original tractor deployment

Hour of tractor request	No. of tractors engaged	Av. wait (min.)	Percent engaged after wait > 5 min.
7	1	0.0	0.0
9	11	6.6	36.4
10	9	0.0	0.0
11	14	3.1	35.7
12	9	0.0	0.0
13	13	5.5	30.8
14	8	11.3	62.5
15	11	12.4	81.8
16	14	10.1	64.3
17	11	1.4	18.2
18	10	4.3	50.0
19	10	0.0	0.0
20	14	4.0	42.9
21	7	3.4	42.9
22	9	6.4	55.6
23	11	1.6	9.1
	162		

With adjusted tractor deployment

Hour of tractor request	No. of tractors engaged	Av. wait (min.)	Percent engaged after wait > 5 min.
7	1	0.0	0.0
9	11	5.1	36.4
10	9	0.0	0.0
11	14	2.9	21.4
12	8	0.0	0.0
13	13	1.4	7.7
14	9	2.2	11.1
15	11	2.8	36.4
16	13	1.4	15.4
17	12	0.0	0.0
18	10	0.0	0.0
19	10	0.0	0.0
20	14	1.0	7.1
21	7	0.0	0.0
22	10	1.7	20.0
23	10	1.5	10.0
	162		

Table 9. CLT delays by airline in 100 simulation replications of July 12, 2018 schedule.

		Av. delays (min.)		**Flights with delay > 15 min.**		**Ramp and taxi time**
Airline	**Event**	**No of flights**	**Av. delay**	**No of flights over 15 min.**	**P (> 15 min.)**	**Av. (min.)**
AAEagle	**2: Arrival**	36,000	13.9	10,581	0.294	13.8
	4: Departure	36,323	14.2	10,715	0.295	20.5
American	**2: Arrival**	28,270	11.0	6,733	0.238	10.5
	4: Departure	29,454	11.9	7,328	0.249	18.8
Delta	**2: Arrival**	2,021	7.8	314	0.155	9.0
	4: Departure	2,234	9.2	452	0.202	20.9
Other	**2: Arrival**	7,256	12.6	1,868	0.257	7.9
	4: Departure	6,684	6.2	820	0.123	13.5
Southwest	**2: Arrival**	874	26.0	411	0.470	8.9
	4: Departure	938	20.7	326	0.348	17.8
United	**2: Arrival**	483	14.2	149	0.308	8.8
	4: Departure	500	3.6	42	0.084	25.8
Overall		151,037	12.6	39,739	0.263	15.6

pending on airline, hour of day and whether the inbound flight was international.

5) The airspace sector for the outbound flight was assigned with probabilities from a multinomial logistic model that depends on airline, hour of day, and whether the flight is an international departure.

6) Whether the arrival was from another hub airport was set with probability given by a binary logistic model depending on airline.

7) Whether the departure is to another hub airport was set with probability from a binary logistic model depending on airline, hour of day, whether inbound flight was from another hub and whether inbound flight was international.

8) The number of seats in the aircraft was assigned with a regression model depending on airline, hour of day, whether arriving flight is international and whether flight is from another major hub.

9) Inbound flight distance was set with a regression model depending on airline, hour of day, whether flight is international and whether from a major hub.

10) Whether the flight is an immediate turnaround was set with probability from a binary logistic model depending on scheduled hour of day of the arriving aircraft.

11) The turnaround time for immediate turnarounds was set at 45 minutes if aircraft seats were more than 100; otherwise it was set 30 minutes.

12) Turnaround time for nonimmediate turnarounds was set with a regression model depending on airline, hour of day, number of seats and whether the flight is an international departure.

13) Scheduled departure time was set to scheduled arrival time plus turnaround time.

14) The desired terminal gate (and therefore parking section) was set randomly according to historical gate usage by the particular airline.

Having developed the new schedules with the desired number of total flights per day and distribution through the day consistently with historical patterns, we were able to perform experiments that demonstrate the effects of airport congestion and operating rules on system performance. Table 12 (with information from Smith and Bilir [42]) illustrates, for example, how the simulation model revealed the impact of different "gate-hold" strategies under higher traffic levels and demonstrates the design capacity of the airport in the process. It also reveals how intolerable delays would occur under any regime with a 30% increase in flight operations.

Table 10. Delays in 100 replications with arrival cushion for selected AAL flights.

		Av. delays (min.)		Flights with delay > 15 min.		Ramp and taxi time
Airline	**Event**	**No of flights**	**Av. delay**	**No of flights over 15 min.**	**P (>15 min.)**	**Av. (min.)**
AAEagle	**2: Arrival**	36,000	13.9	10,579	0.294	13.9
	4: Departure	36,324	14.2	10,781	0.297	21.0
American	**2: Arrival**	28,270	8.8	5,352	0.189	10.6
	4: Departure	29,491	9.9	5,975	0.203	19.1
Delta	**2: Arrival**	2,021	7.6	311	0.153	9.0
	4: Departure	2,241	8.8	425	0.190	21.1
Other	**2: Arrival**	7,288	12.5	1,839	0.252	7.8
	4: Departure	6,680	6.3	843	0.126	13.7
Southwest	**2: Arrival**	873	26.1	418	0.479	8.9
	4: Departure	933	21.4	348	0.373	18.1
United	**2: Arrival**	485	14.1	146	0.301	8.8
	4: Departure	500	3.2	33	0.066	25.9
Overall		151,113	11.8	37,068	0.245	15.8

Table 11. Simulated performance with runway selections intended to reduce taxi times.

		Av. Delays (min.)		Flights with Delay > 15 min.		Ramp and taxi time
Airline	**Event**	**No of flights**	**Av. delay**	**No of flights over 15 min.**	**P (> 15 min.)**	**Av. (min.)**
AAEagle	**2: Arrival**	36,000	10.7	7,830	0.218	10.2
	4: Departure	36,358	12.1	8,982	0.247	20.8
American	**2: Arrival**	28,264	10.3	6,280	0.222	11.4
	4: Departure	29,448	11.3	6,969	0.237	19.2
Delta	**2: Arrival**	1,995	6.8	273	0.137	8.9
	4: Departure	2,226	7.8	369	0.166	19.7
Other	**2: Arrival**	7,211	11.7	1,583	0.220	7.7
	4: Departure	6,634	6.0	786	0.118	13.0
Southwest	**2: Arrival**	856	24.2	392	0.458	9.0
	4: Departure	920	19.2	325	0.353	16.6
United	**2: Arrival**	469	13.8	132	0.281	8.8
	4: Departure	500	3.3	34	0.068	25.1
Overall		150,881	11.0	33,955	0.225	15.0

Table 12. Effects of gate-hold strategies under increased traffic levels.

with 10% increase in daily flights

Gate-hold strategy (Max no. planes taxiing to runways)	Effects on Outbound Flights						Effects on Inbound Flights				
	Av. Pushback Delay (min.)	**Pushback Delays > 15 min.**	**Av. taxi-out time (min.)**	**Av. taxi-out time - peak hours (min.)**	**Av. Liftoff Delay (min.)**	**Liftoff Delays > 15 min.**	**Av. Arrival Delay (min.)**	**Arrival Delays > 15 min.**	**Av. taxi-in time (min.)**	**Av. taxi-in time - peak hours (min.)**	**Parking Section Changes**
Without limits	**15.5**	**30.9%**	**19.4**	**22.5**	**16.9**	**34.1%**	**14.8**	**30.6%**	**13.8**	**15.4**	**9.8%**
R36C: 20 - R36R:12	15.7	31.1%	19.2	21.6	16.8	34.1%	14.8	30.6%	13.8	15.4	9.6%
R36C: 15 - R36R:9	16.9	33.3%	18.0	19.3	16.9	34.4%	14.8	30.6%	13.8	15.4	10.0%
R36C: 10 - R36R:6	21.6	44.6%	15.9	16.2	19.5	40.4%	15.0	31.0%	14.2	16.0	14.0%

with 30% increase in daily flights

Gate-hold strategy (Max no. planes taxiing to runways)	Effects on Outbound Flights						Effects on Inbound Flights				
	Av. Pushback Delay (min.)	**Pushback Delays > 15 min.**	**Av. taxi-out time (min.)**	**Av. taxi-out time - peak hours (min.)**	**Av. Liftoff Delay (min.)**	**Liftoff Delays > 15 min.**	**Av. Arrival Delay (min.)**	**Arrival Delays > 15 min.**	**Av. taxi-in time (min.)**	**Av. taxi-in time - peak hours (min.)**	**Parking Section Changes**
Without limits	**25.8**	**43.6%**	**21.4**	**25.9**	**28.5**	**47.7%**	**30.9**	**53.4%**	**20.3**	**19.8**	**27.0%**
R36C: 20 - R36R:12	26.4	44.2%	20.8	24.8	28.6	48.2%	31.2	53.7%	20.8	20.0	28.0%
R36C: 15 - R36R:9	28.7	47.4%	19.1	21.1	29.4	49.2%	32.3	54.7%	22.4	21.6	29.0%
R36C: 10 - R36R:6	46.4	70.9%	16.6	16.4	44.6	67.2%	44.5	64.9%	40.1	27.4	28.0%

7. Discussion and Conclusions

We have illustrated how multivariate statistical models constructed from flight-tracking microdata can be used to create time-dependent and situation-dependent parameters in simulation models of flight operations at commercial airports and thereby properly represent stochastic behavior of the system. The statistical models for arrival delays, time to turn around aircraft for departures, likelihood of departure days for originating flights and lengths of departure delays that occur for originating flights, reflect factors found to be statistically significant in other published studies and known by operations personnel to influence such delays. Agreement in detailed statistics for simulated and historical activity at the focal airport (considering time of day, season of the year, airline, parking section, arrival and departure runway, etc.) validates the simulation model's ability to represent the complex interactions of airside activity with a process-oriented framework involving staged queues in a two-dimensional geo-spatial framework. The simulation model generates valuable information for both long-term strategic planning and improvement of daily operations. The model runs very efficiently. To investigate the stochastic effects of changes in physical infrastructure and operating practice with 20% intensification of traffic at CLT, for example, one can perform 100 replications of a day's flight operations in 13 minutes of processing time on a laptop computer with an Intel Core i5 processor.

Features of airside activity follow the same general principles at airports worldwide and we have configured the model successfully for other airports in the U.S. and Asia. While the construction of a model of this scope might seem like a formidable undertaking, analysts familiar with airport and flight operations (and the model itself) can adapt the model to a new setting in a matter of a few months. Much of the effort (about 50%) is in building the statistical components for arrivals and flight turnarounds and fine-tuning the parameters to bring model performance in alignment with historical performance before conducting experiments with alternative configurations of resources and operating practices. Local operating practices such as gate-sharing arrangements among carriers, traffic-separation rules for landings and takeoffs, gate-reassignment rules to resolve conflicts between early arrivals and late departures, and centralized provision of ground services, are incorporated as modifications to resource sets and process logic.

The effects of implementing a change in available resources or operating practice may depend upon time period, airport setting, or even operations of a particular carrier in a specific section of an airport. Detailed event logs from the simulation model are used to create a data warehouse for meta-analysis as advocated by Ehmke et al. [46] to study the impact of different operational strategies on individual stakeholders (individual airlines, air cargo operators, general aviation, users of particular group of gates, flights scheduled at a particular time of day), etc. The analysis is done with sufficient granularity to avoid the "flaw of averages" to which so many comparable studies are prone.

Our research to date has focused on modelling airside activity alone. We ignore the "groundside" effects of gate assignments, for example, which affect the ease with which passengers and crews can make connections among flights and the concentration of passengers in airport concourses and security checkpoints that result from gate assignments and reassignments. Optimizing airplane movements cannot occur without consideration of the groundside effects. On the groundside, it is desirable to have flight with connecting passengers and crew operate in adjacent gates but not to the extent that congestion causes interference with smooth boarding processes. With complementary data about passenger and crew connections, it would be possible to augment the statistical models for turnaround times and departure delays to consider those factors. That would enable airline operations personnel to refine their analysis of the effects of alternative practices in flight scheduling and gate assignments to consider both the airside and groundside effects.

Author Contributions

The authors have no conflict of interest. The authors confirm contribution to the paper as follows:

- Study conception and design: L. D. Smith, C. Bilir.
- Data collection: L. D. Smith, C. Bilir.
- Analysis and interpretation of results: L. D. Smith, C. Bilir.
- Manuscript preparation: L. D. Smith, C. Bilir.

Conflict of Interest

There is no conflict of interest.

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