Modeling Airside Operations at Major Airports for Strategic Decision Support

Final Report
November 2015

Sponsored by
Lambert – St. Louis International Airport
Midwest Transportation Center
U.S. Department of Transportation
Office of the Assistant Secretary for
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Technical Report Documentation Page

1. Report No.	**2. Government Accession No.**	**3. Recipient's Catalog No.**
4. Title and Subtitle Modeling Airside Operations at Major Airports for Strategic Decision Support		**5. Report Date** November 2015
		6. Performing Organization Code
7. Author(s) L. Douglas Smith, Liang Xu, Ziyi Wang, and Deng Pan		**8. Performing Organization Report No.**
9. Performing Organization Name and Address Center for Business and Industrial Studies in collaboration with Center for Transportation Studies University of Missouri-St. Louis One University Blvd. St. Louis, MO 63121		**10. Work Unit No. (TRAIS)**
		11. Contract or Grant No. Part of DTRT13-G-UTC37
12. Sponsoring Organization Name and Address Midwest Transportation Center 2711 S. Loop Drive, Suite 4700 Ames, IA 50010-8664 Lambert - St. Louis International Airport 10701 Lambert International Blvd. St. Louis, MO 63145	U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology 1200 New Jersey Avenue, SE Washington, DC 20590	**13. Type of Report and Period Covered** Final Report
		14. Sponsoring Agency Code
15. Supplementary Notes Visit www.intrans.iastate.edu for color pdfs of this and other research reports.		

16. Abstract

Tens of billions of dollars are spent each year worldwide on airport infrastructure to promote safe, efficient, and environmentally friendly operations. Airport layouts, allocations of gates to carriers, and the manner of deploying ground equipment or personnel can dramatically affect passenger delays, fuel consumption, and air and noise pollution. Airport planners require reliable information about how different spheres of airport activity interact and how system performance would change with alterations to physical infrastructure or operating practices.

We developed a discrete-event simulation model that can be used for strategic decisions regarding the provision and effective utilization of infrastructure needed for airside operations at major airports. We calibrated the model with detailed activity data for an entire year, verified its ability to represent essential spheres of activity, and illustrated its application to study system performance under several operating scenarios.

17. Key Words airport operations—decision support—simulation modeling		**18. Distribution Statement** No restrictions.	
19. Security Classification (of this report) Unclassified.	**20. Security Classification (of this page)** Unclassified.	**21. No. of Pages** 40	**22. Price** NA

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized**

Modeling Airside Operations at Major Airports for Strategic Decision Support

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Sponsored by
Lambert - St. Louis International Airport,
Midwest Transportation Center, and
U.S. Department of Transportation
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Preparation of this report was financed in part
through funds provided by the Iowa Department of Transportation
through its Research Management Agreement with the
Institute for Transportation

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ACKNOWLEDGMENTS

The authors would like to thank the Midwest Transportation Center and the U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology for sponsoring this research. They also thank Dana Ryan, the planning manager at Lambert - St. Louis International Airport, and his staff for their help in executing this project and ensuring the model's relevance.

EXECUTIVE SUMMARY

Major commercial airports rely on multiple parties for safe and efficient operations. Air traffic controllers coordinate approaches to the airport, aircraft movements on the ground, and departures from the airport. Airline personnel coordinate activities on the parking ramps and at passenger gates. Third parties may service aircraft at gates or at designated stations (e.g., for de-icing). System performance is affected by the concentration of airline flight schedules, activities of air express carriers, taxiway and ramp layouts, resources allocated for gate operations, air traffic control procedures, adverse weather conditions, and traffic backups at major connecting hubs.

Consolidation of major carriers and concentration of flight activity at a few mega-hubs have put some airports under stress while others experience dramatic reductions in flight operations. Strategic decision support is needed to provide ways of better utilizing existing assets in some environments, intelligently expanding them in others, and selectively removing assets from service where costly excess capacity exists.

For this project, we developed and calibrated a discrete-event simulation model that captures essential interactions of "airside" activity at commercial airports. Our model, calibrated with detailed flight and gate data for an entire year's activity at Lambert - St. Louis International Airport, represents the interactions of key system components with sufficient granularity to study the effects of different planning scenarios and operating rules.

We modeled airport operations using Arena software by moving simulated aircraft through a network of staged queues—some physical, others conceptual.

Ground movements are controlled by signals and routings that consider capacities of ramps and taxiway segments. Aircraft arrivals are generated by a Statistical Analysis System (SAS) pre-processor and placed in conceptual queues at the final approach fix (FAF) for an active runway. Scenarios are defined by active runways for takeoffs and arrivals, weather in airspace sectors through which arrivals and departures take place, and conditions at major hub airports. Movements of aircraft are simulated using lognormal distributions from point to point until the designated flight's activity at the airport is completed (with termination at the gate, or, if continuing to another destination, after turnaround and departure).

Statistical models for individual airlines are used to set the probability of delay and duration of delay at the gate dependent on time of day and whether the flight is originating or continuing. Entities for flights that terminate at the airport are removed from the simulation after reaching the gate and the gate is then made available for originating flights that are generated by the model according to schedule (with random perturbation if desired) or for a new arrival.

Dispatching strategies are imposed by routing aircraft among staging points on the airport surface and releasing them with dynamic priorities that reflect the decision rules in force.

Detailed logs are created of each simulated event and statistical analysis and reporting of simulated performance are accomplished externally using SAS.

We demonstrate the application of the model to investigate the effects of different operating conditions and dispatching strategies upon delays, ramp time, and taxi time for individual airlines.

INTRODUCTION

In recent years, major airlines in the US have altered their route structures and schedules to concentrate their flight activity at a few mega-hubs. Consolidation of this sort and hub operations of express freight carriers strain some airports while other airports now have excess capacity.

Airport planners in cities with congested facilities seek ways to better utilize existing assets and intelligently expand them. Planners in cities with idle capacity consider how to remove selective assets from service to reduce operating costs. In both situations, intelligent decision support can help to improve asset utilization.

Sophisticated simulation models such as Simmod, which the Federal Aviation Administration (FAA) maintains, the Total Airspace and Airport Modeller (TAAM), and the Multi-Agent Transport Simulation (MATSim) simulate air traffic with remarkable realism, and have been used for decades to study air traffic control procedures and airport capacity (Atkin et al. 2009 and 2010, Bazargan et al. 2002, Bertino et al. 2011, Offerman , 2001, Brentnall and Cheng 2009, Bubalo and Daduna 2011, Capozzi et al. 2013, FAA 1989, Fishburn et al. 1995, Gilbo 1993, Gotteland et al. 2001, Wei, G., and Siyuan 2010). These models are excellent for studying system behavior in microscopic detail but they carry enormous overhead for studies that are more strategic.

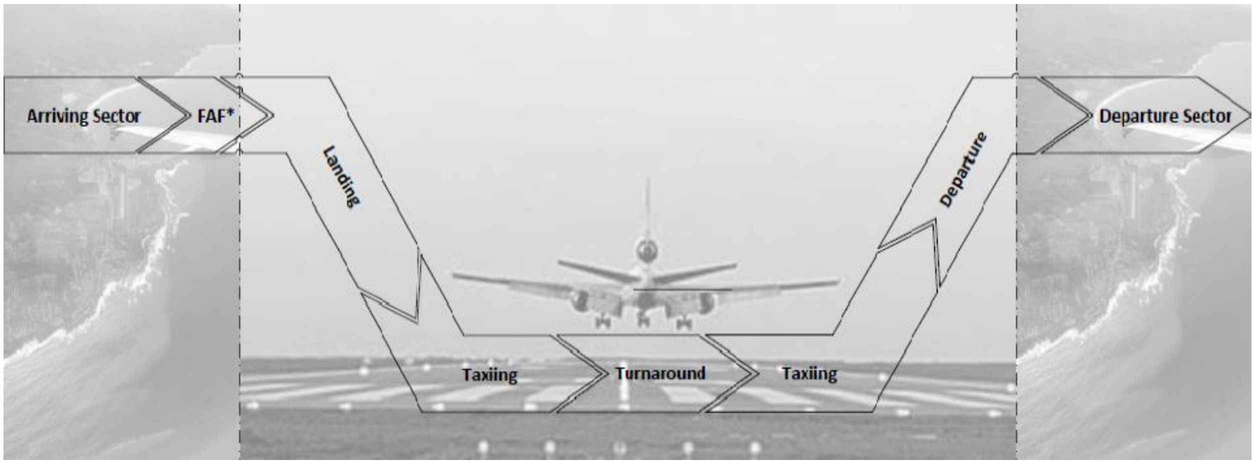
For strategic decision making, mathematical optimizing models have been employed for airport activities such as timing pushbacks, sequencing arrivals or departures, performing regular gate services, performing special services such as de-icing aircraft, or optimizing flows through the network of taxiways (Horstmeier and de Haan 2001, Khadilkar and Balakrishnan 2013, Ravizza et al. 2013, Sherali et al. 1992, Yan et al 2002, Herrero et al., 2005). These operational research (OR) models, however, tend to ignore stochastic aspects of system behavior or necessary interactions with other parts of the system (Bubalo and Daduna 2011, Odoni et al. 1997, Snowdon et al. 2000, Zografos and Madas 2014, Norin et al., 2009).

In developing our models, we strike a balance between these extremes. We capture the essential interactions of key system components, represent the system with sufficient granularity, and facilitate the efficient conduct of experiments with multiple replications of a wide range of planning scenarios and operating rules. To accomplish this, we represent the system as a network of staged queues (Gue and Kang 2001, Smith et al. 2011 and 2014).

For this project, we completed the development of a prototype constructed to represent airline movements for the dominant runway usage scenario at Lambert - St. Louis International Airport. We developed a new tool for integrating time-stamped data from different sources without a common matching key. We validated the simulation model's performance against historical flight activity and we applied the model to several planning and operational scenarios to illustrate its potential as a decision support tool for airport asset management.

AIRPORT OPERATIONS AS A SYSTEM OF STAGED QUEUES

Figure 1 represents the domain of our analysis.



FAF*=final approach fix

Figure 1. Scope of modeled activity for this project

Aircraft movements are considered from the time that aircraft reach local airspace for landing to the time that they depart after takeoff. Movements on the airport surface and turnaround activity on ramps and at terminal gates are included.

We move simulated aircraft through a system of staged queues—some physical, others conceptual. Aircraft arrivals are generated according to daily schedules of individual airlines but with random deviations appropriate for the scenario being simulated. The scenario is defined by local weather conditions, weather in airspace sectors through which arrivals and departures take place, and conditions at major hub airports, which may cause bunching of arrivals and traffic holds for departures.

Arriving aircraft are placed in conceptual queues at the final approach fix (FAF) for an active runway (Figure 2).

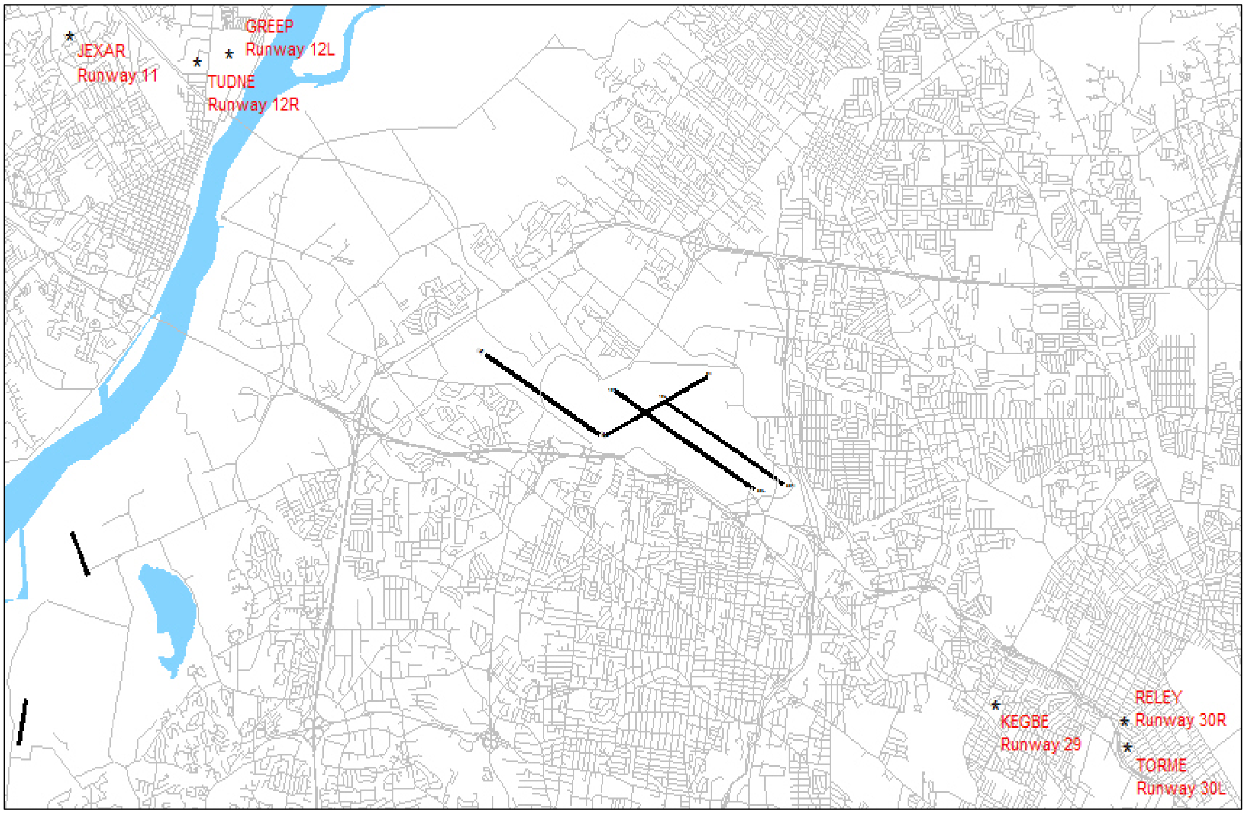


Figure 2. Final approach fixes for six arrivals at Lambert - St. Louis International Airport

Movements of each aircraft are simulated from the FAF until the designated flight's activity at the airport is completed (with termination at the gate, or, if continuing to another destination, after turnaround and departure).

Simulation entities for flights that terminate at the airport are removed from the simulation after reaching the gate and the gate is made available for originating flights that are generated by the model according to schedule (with random perturbation if desired) or for a new arrival.

Figure 3 shows the physical layout of runways, taxiways, and ramp areas at Lambert - St. Louis International Airport with key intersections that aircraft traverse from the points of touchdown to the gates and from the gates to the points of liftoff.

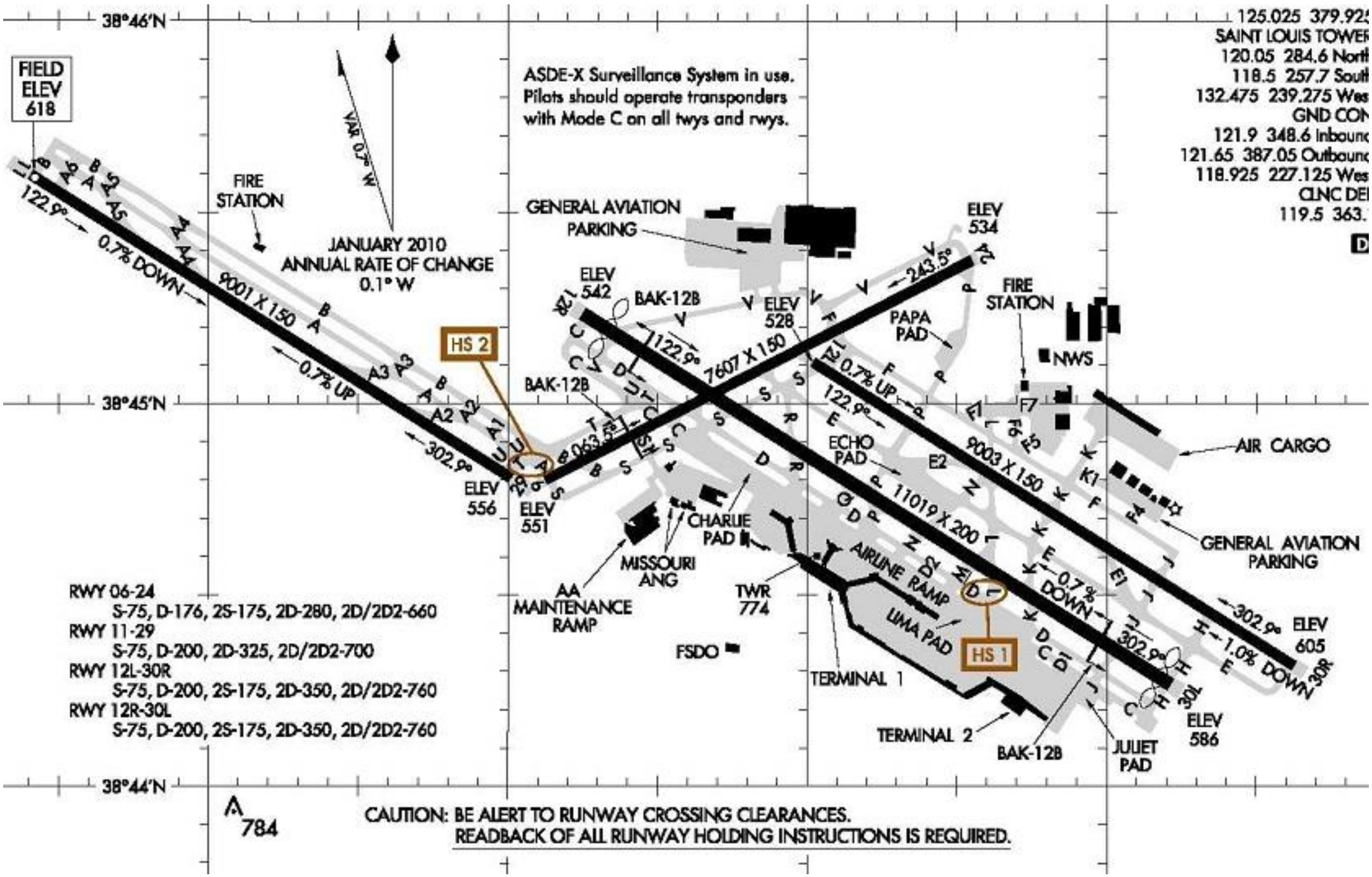


Figure 3. Physical layout at Lambert - St. Louis International Airport

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 which runways are in use for landings and takeoffs and which staging points between their current position and airport destination (gate or runway) can accommodate them.

Aircraft may be held at a staging point until the next segment of its route is available to traffic in the desired direction. Aircraft cannot enter a segment of a taxiway, for example, earlier than when it would be vacated by aircraft currently traversing it in the opposite direction.

Some staging points may have sufficient maneuvering space to allow re-sequencing of queued aircraft for the next segment of their taxi routes; others may require the aircraft to be processed in order of their arrival at that point.

Unlike Simmod and other highly realistic simulators for real-time simulation of ground operations, we do not indicate the specific physical locations of each aircraft waiting at staging points, nor do we regulate the speed of aircraft to maintain realistic physical separation while they are in motion.

To accommodate airlines' independent behavior in managing their own resources on the ground and dispatching their flights, we designate separate staging areas on the ramp for each airline's arrivals and departures. 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 air traffic control/ATC for either weather or traffic control) are staged at another area if they must clear a gate to accommodate arriving aircraft.

Figure 4 shows the gate staging areas and taxiing routes to the gates for four major airlines at Lambert - St. Louis International Airport with gates at Terminals 1 and 2.

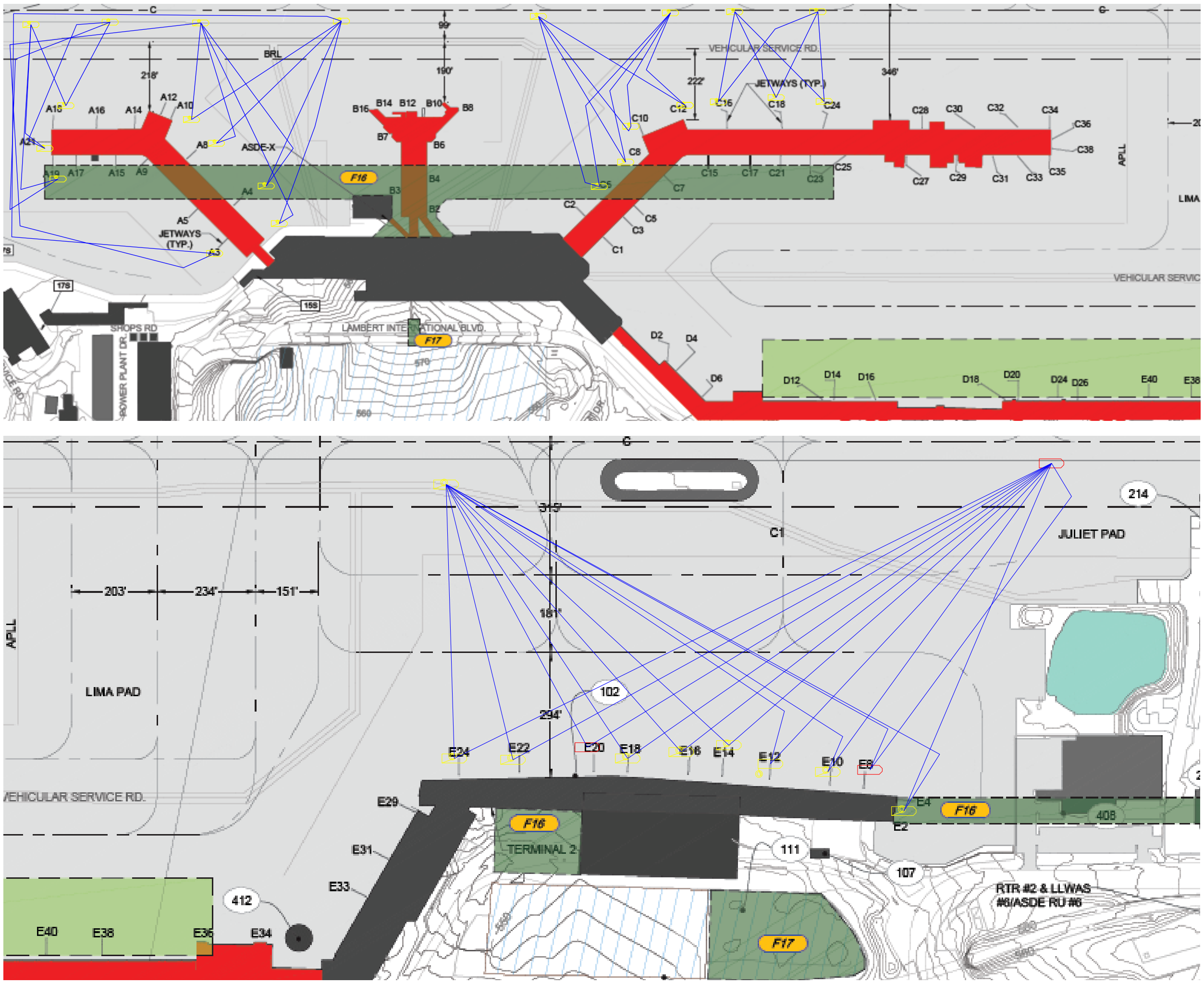


Figure 4. Staging points on ramps for arrivals and departures of individual airlines

Areas on the airfield may be designated for spillover when physical capacity is reached at the primary ramp locations for staging the airlines' arrivals and departures.

Other areas on the airfield are designated as staging points for departing aircraft when there is a backlog for takeoffs, traffic holds due to weather conditions in departure sectors, or holds due to weather or congestion at hub destinations. In addition to queues that are associated with physical positions on the airport property, aircraft are placed in conceptual queues to control the sequences of operations. Aircraft with routes that involve sectors of airspace temporarily restricted by severe weather, for example, may be held in a common queue and released in sequences determined by the simulated scheduling regime currently in effect.

PROCESSES FOR MODEL CALIBRATION AND VALIDATION

Calibration and validation of the model require integration of gate data maintained by individual airlines and flight data that are maintained by ATC systems for aircraft that operate under instrument flight rules (IFRs). The analytical process is illustrated in Figure 5.

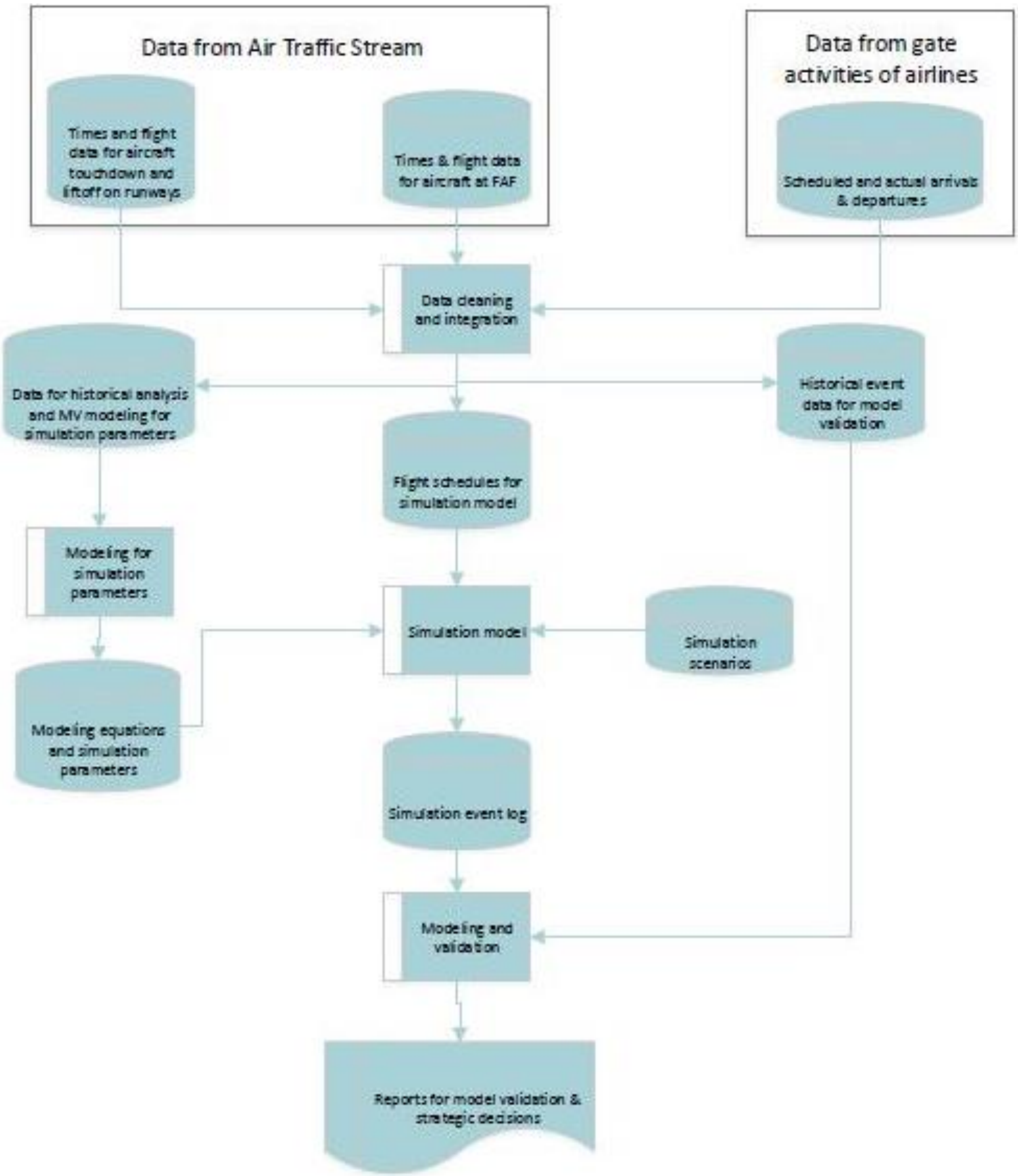


Figure 5. Analytical process flowchart

From airline data, we acquire information about aircraft type, origin and destination for the flight leg, and the scheduled and actual times of arrival or departure (pushback) at the gate. From ATC data, we obtain the time when an arriving flight reached the FAF and when it landed (touched down) on the runway. For departing flights, ATC data indicate the takeoff (liftoff) time. Merging these data, we are able to determine the itineraries of flights that arrive at the airport with continuing legs and generate the files used to activate arrivals and originating flights in the simulation model.

Taxiway routings and staging to coordinate aircraft traffic are directed by ATC ground controllers located in the airport control tower.. Direct observation of and interviews with ATC controllers were required to understand the combinations of runways, taxiways, and staging points used for arrivals and departures under different wind and weather conditions.

Release of arriving aircraft from the FAF occurs with consideration of the separation required for flight safety. Airports at the point of origin for inbound flights and airports at the destination of outbound flights are grouped according to ATC sectors. This enables schedule deviations to contain systematic elements related to wind and weather – which affect arrival itineraries and runways in use. Weather events at the airport, at connected hubs, and at airports in adjacent ATC sectors can be simulated by restricting the traffic flow accordingly.

THE DISCRETE EVENT SIMULATION MODEL

For the discrete-event simulation, we use Arena 14.7 software on a Windows platform. Heuristic scheduling and sequencing procedures can be written in C++ or Visual Basic and called by "event" blocks when the modeling logic requires them.

The simulation is run in replicating mode (suppressing animation) to allow statistical tests of the effects of factors or strategies covered in the experimental scenarios. Adverse weather conditions in airspace sectors and at hub airports that affect traffic movements into and out of the local airspace are simulated by blocking aircraft from entering designated sectors (using either user-defined schedules or exponential probability distributions for successive events and their duration) and placing affected aircraft in queues for orderly release when the traffic restrictions expire.

Arrivals for scheduled service in each simulation replication are generated with random variation imposed on their scheduled arrival times and stacked at the FAF. The file of arrivals is read by Arena, which creates a simulation entity (an aircraft) that progresses through the system depending on its scheduled activity and availability of required resources (taxiways, ramps, staging points, gates, personnel, and equipment) as simulated events occur.

Arrivals and departures for other (general aviation) aircraft are generated randomly through the day (using exponential distributions at the highest hourly rate and thinned randomly to create hourly intensity determined by historical patterns of flight activity or exogenous planning assumptions).

Airport locations (gates) for arrivals and departures of general-aviation aircraft are assigned randomly (as each flight is generated) in conformity with levels of activity at the respective fixed-base operations.

A subroutine assigns the aircraft to one of the active runways and the route to be followed from the point of landing to an available gate for the airline. Taxi-route segments are defined so that they have associated resources with capacity to hold a designated number of aircraft.

Originating flights (as opposed to continuing flights) are placed at an available gate for the airline at the later of its scheduled departure time or the time at which a gate becomes available for it (i.e., freed by a terminating flight). We assume that aircraft for originating flights are available. (The model, in its present form, does not force a reconciliation of inbound and outbound aircraft for each carrier. This could be done by artificially defining every arrival and departure as a continuing flight with a unique flight number, such as a combination of the inbound and outbound number.)

Parameters for the simulation model are estimated using logistic and regression models that are developed and maintained in the Statistical Analysis System (SAS). Likelihood (and length of) of an arrival delay for an airline's flight might, for example, be stated as a function of scheduled hour of day, total duration of the flight, whether the flight originated at a major hub, and an interaction term for arrival sector and runways in use.

SAS is also used to generate the files of arrivals for individual airlines (with some flights terminating and others continuing after turnaround at the gate) in conformity with historical airline schedules and imposition of random variation. SAS is used similarly to generate the file of originating flights for the simulated scenario.

Scheduled flight activity may be intensified or thinned by inserting new flights (indicating airline, flight number, origin, destination, aircraft type and scheduled time) or removing existing flights. Randomness in arrivals and departures of scheduled flights is imposed with daily and hourly time-varying means and standard deviations determined from historical airline gate data. Flows inbound from a sector or hub airport may be adjusted to simulate the effects of unusual conditions or events. Flows outbound from the airport may also be regulated to reflect flight restrictions in departure sectors or into destination airports.

We derive flight schedules from historical gate data on days without systematic disruptions. When considering scenarios involving greater traffic intensity, we generate new schedules by placing the desired number of new flights between existing flights at scheduled times halfway between the preceding and succeeding flights. Of course, we can also insert new flights at specified times.

METRICS FOR SYSTEM PERFORMANCE

Airport activity varies throughout the day, with a tendency for flights to concentrate during popular times. Table 1 shows an example of the statistics for departures that occurred over 364 consecutive days at Lambert - St. Louis International Airport.

Table 1. Sample departure delay statistics over 364 days at Lambert - St. Louis International Airport

Scheduled Flights and Delays		Airline					
		American	Delta	United	US Air	Southwest	Overall
Flights	Hour of Day						
	6AM to 8AM	797	19	18	6	1,509	2,349
	8AM to 10AM	659	1,437	1,026	835	5,616	9,573
	10AM to 12PM	1,860	1,352	588	470	3,085	7,355
	12PM to 2PM	1,360	982	939	913	3,768	7,962
	2PM to 4PM	2,108	1,054	731	1,077	3,604	8,574
	4PM to 6PM	2,376	1,394	1,472	661	3,997	9,900
	6PM to 8PM	1,547	183	1,413	666	5,154	8,963
	8PM to 10PM	1,353	823	1,277	539	3,537	7,529
	After 10PM	1,060	464	1,456	412	1,741	5,133
	Overall	13,120	7,708	8,920	5,579	32,011	67,338
Av. Delay	Hour of Day						
	6AM to 8AM	5.9	56.9	0.7	480.0	2.8	5.5
	8AM to 10AM	5.9	7.7	12.0	14.4	2.9	5.8
	10AM to 12PM	5.2	7.7	18.5	31.6	3.3	7.6
	12PM to 2PM	7.9	8.9	18.2	11.4	6.0	8.7
	2PM to 4PM	8.4	9.5	16.2	13.5	7.9	9.6
	4PM to 6PM	10.4	11.3	28.9	8.1	12.0	13.8
	6PM to 8PM	13.9	18.5	31.0	12.3	15.3	17.4
	8PM to 10PM	17.8	13.2	25.4	15.4	20.0	19.5
	After 10PM	22.7	11.3	22.7	7.2	20.5	19.7
	Overall	10.8	9.9	22.9	14.3	9.9	12.1

Note how delays propagate through the schedules as the day progresses. Some delays (such as weather) are highly correlated among carriers depending on schedules and routes flown (in our case, represented by airspace sectors and major connecting hubs). Others (such as equipment failure) are random.

Our performance statistics of airport activity include the following:

- Number of arrivals and departures for each hour of the day
- Distributions of delays (differences between actual and scheduled times for arrivals at the gate and departures (pushbacks) from the gate)
- Percentage of delays that constitute a significantly late arrival or departure (delays in excess of 15 minutes)
- Distributions of time required to taxi from touchdown on the runway to the designated arrival gate
- Distributions of time from pushback at the gate to liftoff
- Frequencies with which different runways are used for landings and departures
- Frequency, duration, and timing of ramp and gate holds for weather events
- Frequency, duration, and timing of ramp and gate holds for traffic congestion at destination hubs

To generate reports of simulation results, we create detailed logs of simulated activity (written to flat files) and perform the analysis with SAS. Table 2 illustrates information that is saved for individual aircraft.

Table 2. Excerpt from a simulation event log for aircraft movements

Obs	Replic. No.	Event time	Event	Airline	Flight Number	Lambert Gate	City	Continuing	Next City	Next Departure Time
450	1	1523	2: Arrival	WN	2544	E8	MCI	Yes	RSW	1545
451	1	1525	5: Liftoff	DL	2158	A2	ATL	Yes	ATL	1515
452	1	1525	4: Pushback	UA	5276	A9	CLE	Yes	CLE	1517
453	1	1527	2: Arrival	WN	1657	E16	BWI	Yes	HOU	1545
454	1	1528	3: Originate	UA	3820	A9	EWR	No	000	0000
455	1	1528	4: Pushback	UA	3820	A9	EWR	No	000	0000

Separating the simulation and analysis in this way, we can use data from multiple replications to investigate thoroughly how system performance varies over time. We can also assess the differential effects that physical or operational changes have on individual airlines or types of aircraft and estimate the extent to which variation is attributable to systematic versus random effects.

Likewise, by recording information as aircraft leave or arrive at key queuing points, we can retrospectively deduce the state of the system at any point in simulated time (e.g., gates in use, queues at various stages for arriving and departing flights, simulated aircraft in motion on the ground, aircraft holding on a ramp or taxiway, and aircraft in the simulated airspace).

MODEL CALIBRATION

In constructing the simulation model, we accommodate normal operating variation by adjusting for systematic effects with regression and logistics models (using combinations of indicator variables and partitioning of data with separate calibration for factors where there is significant interaction and sufficient data), impose randomness to reflect the residual variance, and impose further variation by creating disruptive scenarios.

From the detailed data for individual flight operations at Lambert - St. Louis International Airport, we examined the likelihood and length of delays and found, as expected, that delays tend to be greatest when traffic is most intense (depending on time of day and day of week), in times of inclement weather (depending on month of year), for carriers with flights from major hub airports, when direction of landing (into the wind) tends to involve longer approach paths or taxiing times for major carriers, or when flights involve busy airspace sectors.

In Table 3, we present results of fitting logistic regression models for the likelihood of departure delays considering time of day, month of year, and runway in use.

Table 3. Factors affecting the likelihood of Lambert - St. Louis International Airport flight delays

Logistic Variable	df	Parameter Estimate	Std. Error	Chi-Square	P > Chisq
Intercept	1	-2.5905	0.0673	1480.35	<.0001
Hourbef6	1	-1.0051	0.4241	5.6167	.0178
Hour6to8	1	-1.0904	0.1225	79.259	<.0001
Hour10to12	1	0.3371	0.0748	20.337	<.0001
Hour12to14	1	0.8410	0.0668	158.54	<.0001
Hour14to16	1	1.3742	0.0651	445.52	<.0001
Hour16to18	1	1.5742	0.0657	573.65	<.0001
Hour18to20	1	1.8975	0.0616	949.32	<.0001
Hour20to22	1	2.3613	0.0647	1331.3	<.0001
Houraft22	1	2.2326	0.7162	9.7180	.0018
January	1	0.2136	0.0625	11.690	0.0006
March	1	0.4805	0.0587	67.108	<.0001
April	1	0.3558	0.0646	30.324	<.0001
May	1	0.7305	0.0628	135.50	<.0001
June	1	0.7807	0.0641	148.52	<.0001
July	1	0.6103	0.0649	88.511	<.0001
August	1	0.7671	0.0656	136.80	<.0001
December	1	0.5861	0.0579	102.31	<.0001
RWY12L	1	-0.1837	0.0503	13.352	.0003
Rwy29	1	0.2785	0.0912	9.3373	0.0022
Rwy30L	1	0.1902	0.0517	13.553	0.0002

Each of these factors is highly statistically significant. The effects of these factors and others can vary among airlines. The factors are affected further by the scheduling practices of individual airlines, the physical resources that each airline employs, and the concentration of activity at each airline’s airport location. Some factors are interdependent (e.g., fleet mix, scheduled activity, and connecting cities for an airline). Hence, caution is always required when interpreting the coefficients of individual variables in logistics and regression models for delays.

Challenges include screening out exceptional cases when fitting the multivariate models, creating parameters for elemental operations (such as preparing a plane for departure or taxiing on a taxiway segment) that result in appropriate behavior cumulatively, and validating the model’s behavior under realistic scenarios (and overall) using higher-level statistics available from operating data. An iterative analytical process is required. This process involves continuous looping through the stages represented previously in Figure 5.

Constructing regression models from the simulated data and comparing their structure with those derived from historical data (for the base set of operating assumptions) helps to ensure that relevant factors are considered and that their influence is consistent with theory and operational history.

We encountered a particular challenge of matching time-stamped data with some missing observations and lack of a matching key for information maintained by different information systems.

A TOOL FOR MATCHING TIME-STAMPED DATA WITH MISSING ELEMENTS

For one regional carrier, we had to deal with the use of an identifier for the airplane in the flight plan (the source of information for the FAA data) instead of the published flight number (the practice of most major airlines). The gate data used the flight number. Many hours of manual review were required to match these data manually and attempts at matching them heuristically produced mixed results. To facilitate the matching of such data as new data became available each week, we developed a mixed integer programming (MIP) model. We report it here because we believe that the procedure has value for other data-cleansing applications. Table 4 illustrates the problem for activity on a particular day.

Table 4. Sequences of touchdowns and arrivals with missing data

Touch-down	ID	Sequence	Gate Arrival	Flight
05SEP13:06:25:03	KAP770	1	05SEP13:06:29:00	8341
05SEP13:06:31:03	KAP421	2	05SEP13:06:39:00	8302
05SEP13:06:44:34	KAP3212	3	05SEP13:06:46:00	8323
05SEP13:06:53:08	KAP721	4	05SEP13:07:01:00	8335
05SEP13:07:00:08	KAP280	5	05SEP13:07:19:00	8356
05SEP13:08:58:58	KAP310	6	05SEP13:08:55:00	8314
05SEP13:09:20:56	KAP421	7	05SEP13:09:31:00	8306
05SEP13:09:29:27	KAP16	8	05SEP13:09:34:00	8326
05SEP13:11:21:21	KAP3212	9	05SEP13:11:26:00	8327
05SEP13:11:30:13	KAP310	10	05SEP13:11:39:00	8350
05SEP13:11:35:55	KAP770	11	05SEP13:11:40:00	8316
05SEP13:11:41:55	KAP247	12	05SEP13:12:39:00	8308
05SEP13:12:29:54	KAP421	13	05SEP13:13:29:00	8337
05SEP13:13:24:39	KAP165	14	05SEP13:13:39:00	8358
05SEP13:13:30:40	KAP701	15	05SEP13:14:07:00	8329
05SEP13:14:05:07	KAP757	16	05SEP13:14:19:00	8320
05SEP13:14:09:23	KAP83	17	05SEP13:14:54:00	8352
05SEP13:14:47:45	KAP307	18	05SEP13:15:07:00	8310
05SEP13:14:49:11	KAP609	19	05SEP13:16:11:00	8332
05SEP13:15:07:55	KAP31	20	05SEP13:16:58:00	8321
05SEP13:16:06:18	KAP3212	21	05SEP13:17:03:00	8340
05SEP13:16:52:47	KAP701	22	05SEP13:17:42:00	8311
05SEP13:16:56:36	KAP165	23	05SEP13:17:49:00	8353
05SEP13:17:42:09	KAP307	24	05SEP13:18:00:00	8361
05SEP13:17:43:59	KAP609	25	05SEP13:18:21:00	8334
05SEP13:17:46:57	KAP31	26	05SEP13:20:50:00	8313
05SEP13:17:52:23	KAP83	27	.	.
05SEP13:18:13:03	KAP757	28	.	.
05SEP13:20:55:06	KAP31	29	.	.

Note how individual aircraft made several loops over the day for different scheduled flights.

In the MIP model, we use subscript i to represent the sequence of touchdowns for the airline. We use subscript j to represent the sequence of arrivals at the gate. There may be missing values for either. I=Max{i} may be larger or smaller than J=max{j}. The model is structured as follows.

X_{ij} = 1 if touchdown of flight i is matched to gate arrival j for the airplane
= 0 otherwise
t_i = time recorded for touchdown i by the airline
g_j = time recorded for gate arrival j by the airline
IBTU = upper bound on inbound taxi time (gj - ti) for an inferred match
IBTL = lower bound on inbound taxi time for an inferred match

$$Max \sum_{i=1}^{I} \sum_{j=1}^{J} X_{ij} = \text{MAXMATCHES}$$

Subject to the following:

We can match no more in total than maximum of total touchdowns or gate arrivals.

$$\sum_{i=1}^{I} \sum_{j=1}^{J} X_{ij} \leq \text{Min } \{I,J\}$$

Each touchdown can be assigned to at most one gate arrival:

$$\sum_{j=1}^{J} X_{ij} \leq 1 \text{ for each i} \tag{1}$$

Each gate arrival can be assigned to at most one touchdown:

$$\sum_{i=1}^{I} X_{ij} \leq 1 \text{ for each j} \tag{2}$$

$$(g_j - t_i) X_{ij} \leq \text{IBTU} \tag{3}$$

$$(g_j - t_i) X_{ij} \geq \text{IBTL} \tag{4}$$

$$X_{ij} = (0,1) \tag{5}$$

This formulation maximizes the number of matches while maintaining tolerance for each match.

Frequently, there are alternative solutions with the same number of "feasible" matches. In the next stage, we therefore minimize the sums (and average) of absolute deviations of (g_j - t_i) from the "target" value for taxi time while achieving the previously derived number of feasible matches. In a second stage we therefore:

$$Min \sum_{i=1}^{I} \sum_{j=1}^{J} \left| g_j - t_i - \text{target} \right| X_{ij}$$

Subject to the following:

$$\sum_{i=1}^{I} \sum_{j=1}^{J} X_{ij} = \text{MAXMATCHES} \tag{6}$$

and impose each of the other constraints as before.

Evolution of the matches is illustrated in Tables 5 and 6 with choices of (-5,15) for (IBTL, IBTU).

Table 5. Sample matches from the first phase of the optimal matching procedure

Obs	Flight Plan ID	Touchdown sequence	Time of Touchdown	Flight number	Time at Gate	Gate Arrival Sequence	Imputed Taxi Time	Dev from 5 min.	Abs dev
1	KAP770	1	05SEP13:06:25:03	8341	05SEP13:06:29:00	1	4.0	-1.0500	1.0500
2	KAP421	2	05SEP13:06:31:03	8302	05SEP13:06:39:00	2	8.0	2.9500	2.9500
3	KAP3212	3	05SEP13:06:44:34	8323	05SEP13:06:46:00	3	1.4	-3.5667	3.5667
4	KAP721	4	05SEP13:06:53:08	8335	05SEP13:07:01:00	4	7.9	2.8667	2.8667
5	KAP280	5	05SEP13:07:00:08		.	.	.	.	.
6	KAP310	6	05SEP13:08:58:58	8314	05SEP13:08:55:00	6	-4.0	-8.9667	8.9667
7	KAP421	7	05SEP13:09:20:56	8306	05SEP13:09:31:00	7	10.1	5.0667	5.0667
8	KAP16	8	05SEP13:09:29:27	8326	05SEP13:09:34:00	8	4.6	-0.4500	0.4500
9	KAP3212	9	05SEP13:11:21:21	8327	05SEP13:11:26:00	9	4.7	-0.3500	0.3500
10	KAP310	10	05SEP13:11:30:13	8350	05SEP13:11:39:00	10	8.8	3.7833	3.7833
11	KAP770	11	05SEP13:11:35:55	8316	05SEP13:11:40:00	11	4.1	-0.9167	0.9167
12	KAP247	12	05SEP13:11:41:55		.	.	.	.	.
13	KAP421	13	05SEP13:12:29:54	8308	05SEP13:12:39:00	12	9.1	4.1000	4.1000
14	KAP165	14	05SEP13:13:24:39	8337	05SEP13:13:29:00	13	4.4	-0.6500	0.6500
15	KAP701	15	05SEP13:13:30:40	8358	05SEP13:13:39:00	14	8.3	3.3333	3.3333
16	KAP757	16	05SEP13:14:05:07	8329	05SEP13:14:07:00	15	1.9	-3.1167	3.1167
17	KAP83	17	05SEP13:14:09:23	8320	05SEP13:14:19:00	16	9.6	4.6167	4.6167
18	KAP307	18	05SEP13:14:47:45	8352	05SEP13:14:54:00	17	6.3	1.2500	1.2500
19	KAP609	19	05SEP13:14:49:11		.	.	.	.	.
20	KAP31	20	05SEP13:15:07:55	8310	05SEP13:15:07:00	18	-0.9	-5.9167	5.9167
21	KAP3212	21	05SEP13:16:06:18	8332	05SEP13:16:11:00	19	4.7	-0.3000	0.3000
22	KAP701	22	05SEP13:16:52:47	8321	05SEP13:16:58:00	20	5.2	0.2167	0.2167
23	KAP165	23	05SEP13:16:56:36	8340	05SEP13:17:03:00	21	6.4	1.4000	1.4000
24	KAP307	24	05SEP13:17:42:09	8311	05SEP13:17:42:00	22	-0.2	-5.1500	5.1500
25	KAP609	25	05SEP13:17:43:59	8353	05SEP13:17:49:00	23	5.0	0.0167	0.0167
26	KAP31	26	05SEP13:17:46:57	8361	05SEP13:18:00:00	24	13.1	8.0500	8.0500
27	KAP83	27	05SEP13:17:52:23		.	.	.	.	.
28	KAP757	28	05SEP13:18:13:03	8334	05SEP13:18:21:00	25	8.0	2.9500	2.9500
29	KAP31	29	05SEP13:20:55:06		.	.	.	.	.
							130.2	10.1667	71.0333

24 matches for 29 recorded touchdowns and 25 recorded gate arrivals with average deviation = 0.42 minutes and average absolute deviation = 3.0 minutes from 5 minute target

Table 6. Sample matches from the second phase of the optimal matching procedure

Obs	Flight Plan ID	Touchdown sequence	Time of Touchdown	Flight number	Time at Gate	Gate Arrival Sequence	Imputed Taxi Time	Dev from 5 min.	Abs dev
1	KAP770	1	05SEP13:06:25:03	8341	05SEP13:06:29:00	1	4.0	-1.05000	1.0500
2	KAP421	2	05SEP13:06:31:03	8302	05SEP13:06:39:00	2	8.0	2.95000	2.9500
3	KAP3212	3	05SEP13:06:44:34	8323	05SEP13:06:46:00	3	1.4	-3.56667	3.5667
4	KAP721	4	05SEP13:06:53:08	8335	05SEP13:07:01:00	4	7.9	2.86667	2.8667
5	KAP280	5	05SEP13:07:00:08		.	.	.	.	.
6	KAP310	6	05SEP13:08:58:58	8314	05SEP13:08:55:00	6	-4.0	-8.96667	8.9667
7	KAP421	7	05SEP13:09:20:56	8306	05SEP13:09:31:00	7	10.1	5.06667	5.0667
8	KAP16	8	05SEP13:09:29:27	8326	05SEP13:09:34:00	8	4.6	-0.45000	0.4500
9	KAP3212	9	05SEP13:11:21:21	8327	05SEP13:11:26:00	9	4.7	-0.35000	0.3500
10	KAP310	10	05SEP13:11:30:13	8350	05SEP13:11:39:00	10	8.8	3.78333	3.7833
11	KAP770	11	05SEP13:11:35:55	8316	05SEP13:11:40:00	11	4.1	-0.91667	0.9167
12	KAP247	12	05SEP13:11:41:55		.	.	.	.	.
13	KAP421	13	05SEP13:12:29:54	8308	05SEP13:12:39:00	12	9.1	4.10000	4.1000
14	KAP165	14	05SEP13:13:24:39	8337	05SEP13:13:29:00	13	4.4	-0.65000	0.6500
15	KAP701	15	05SEP13:13:30:40	8358	05SEP13:13:39:00	14	8.3	3.33333	3.3333
16	KAP757	16	05SEP13:14:05:07	8329	05SEP13:14:07:00	15	1.9	-3.11667	3.1167
17	KAP83	17	05SEP13:14:09:23	8320	05SEP13:14:19:00	16	9.6	4.61667	4.6167
18	KAP307	18	05SEP13:14:47:45		.	.	.	.	.
19	KAP609	19	05SEP13:14:49:11	8352	05SEP13:14:54:00	17	4.8	-0.18333	0.1833
20	KAP31	20	05SEP13:15:07:55	8310	05SEP13:15:07:00	18	-0.9	-5.91667	5.9167
21	KAP3212	21	05SEP13:16:06:18	8332	05SEP13:16:11:00	19	4.7	-0.30000	0.3000
22	KAP701	22	05SEP13:16:52:47	8321	05SEP13:16:58:00	20	5.2	0.21667	0.2167
23	KAP165	23	05SEP13:16:56:36	8340	05SEP13:17:03:00	21	6.4	1.40000	1.4000
24	KAP307	24	05SEP13:17:42:09	8311	05SEP13:17:42:00	22	-0.2	-5.15000	5.1500
25	KAP609	25	05SEP13:17:43:59	8353	05SEP13:17:49:00	23	5.0	0.01667	0.0167
26	KAP31	26	05SEP13:17:46:57		.	.	.	.	.
27	KAP83	27	05SEP13:17:52:23	8361	05SEP13:18:00:00	24	7.6	2.61667	2.6167
28	KAP757	28	05SEP13:18:13:03	8334	05SEP13:18:21:00	25	8.0	2.95000	2.9500
29	KAP31	29	05SEP13:20:55:06		.	.	.	.	.
							123.3	3.30000	64.5333

24 matches for 29 recorded touchdowns and 25 recorded gate arrivals with average deviation = 0.14 minutes and average absolute deviation = 2.7 minutes from 5 minute target

In Table 5, we see the matches from the first phase of the optimizing process. This solution indicates it is possible to match 24 touchdowns and gate arrivals within the stipulated limits for imputed taxi times. In the second phase , the matches are refined (Table 6) and reduce the average absolute deviation from the target time of 5 minutes to 2.7 minutes from the 3.0 minutes in the first phase.

The matrix generator is written in a SAS data step. We impose the upper and lower bounds in times (groups of constraints 3 and 4) implicitly by defining variables for combinations of i and j only if they satisfy the constraints. The result is effectively a pair of assignment problems for which integer solutions emerge immediately. The SAS solution engine is used (Proc LP) and the results are merged with the original data to provide the incidental information in Tables 5 and 6.

MODEL VALIDATION

To show the correspondence between historical delays and those generated by the model for the most frequent operating practice, we present statistics for 364 days of actual airport activity in Table 7 and statistics for 100 days of simulated activity in Table 8.

Table 7. Actual delays computed from 364 days of gate activity

linecode	Recorded Arrivals	Av. Arrival Delay (min.)	Av. Arrival Delay (min.) Truncated	Prop. Arrival Delays >15 min.	Recorded Departures	Av. Departure Delay (min.)	Av. Departure Delay (min.) Truncated	Prop. Departure Delays >15 min.
AA	9,699	7.93	13.96	0.21	9,694	10.64	10.69	0.15
CP	3,421	0.44	1.72	0.02	7,737	1.12	1.38	0.02
DL	7,708	1.85	9.92	0.14	6,338	7.18	10.65	0.13
UA	8,920	17.73	22.86	0.29	8,318	15.54	19.15	0.25
US	5,579	8.34	14.26	0.18	5,600	6.82	10.24	0.14
WN	32,011	5.56	9.85	0.15	32,203	10.03	10.14	0.17

AA=American, CP=Cape Air, DL=Delta, UA=United, US=US Air, WN=Southwest

Table 8. Delays computed from 100 days of simulated activity

		Delays (av. min. delay)		Flights with Delay > 15 min.		Ramp and Taxi time
		Flights	Av. Delay	Number over 15 min.	P(>15 min.)	Av. Minutes
airline	event					
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

GA=Garuda Indonesia

This simulation scenario is a base case involving the use of these two runways: RWY 30R for arrivals and RWY 30L for departures. The assumed level of general aviation activity is similar to recent months. The average delay statistic in Table 7 includes negative values (early arrivals and departures). The truncated delays are computed by treating an early arrival or departure as having a delay = 0.

For this base case, we placed scheduled airline flights at their FAFs with random deviations based on a regression fitted with historical data. Deviations from schedule for gate arrivals are shifted back to the FAFs using average approach and taxi times for the runway in use. We defined 0-1 indicator variables for each hour of the day and used the resulting regression models to generate flight delays for each airline. For example, the equation for arrival delays of one airline took the following form:

$$\text{expminutesdelay} = 8.0 - 15.6 \times \text{hour7} - 7.8 \times \text{hour8} - 5.8 \times \text{hour9} - 5.7 \times \text{hour11} + 8.1 \times \text{hour16} + 10.0 \times \text{hour17} + 14.6 \times \text{hour18} + 3.6 \times \text{hour19} + 13.4 \times \text{hour20} + 3.5 \times \text{hour21} + 11.8 \times \text{hour22} + 2.2 \times \text{nesector} - 4.4 \times \text{swsector}$$

The residual standard error for that regression model was 36.0 minutes. The deviation from schedule for that airline's individual flights was set at max{-20,int(expminutesdelay + 36.0 × (standard normal deviate))}. In contrast, for general aviation, we generate arrivals and flight originations used exponential inter-arrival times at the highest hourly rate for the day and "thin" them to create the expected time-of-day variation.

Departure delays in the simulated activity for scheduled flights were the result of a two-step process involving pairs of logistic and regression models that were fitted separately for continuing flights and originating flights of individual carriers. For the former, we used a logistic regression model such as the following to determine the probability of a delay for an airline's flight:

$$\text{probpbdelay} = 1 \div (1 + \exp(0.54 + 1.48 \times \text{hour6} + 1.18 \times \text{hour7} + 1.11 \times \text{hour8} + 1.04 \times \text{hour9} + 0.89 \times \text{hour10} + 0.58 \times \text{hour11} + 0.34 \times \text{hour15} + 0.37\ \text{hour18} + 0.83 \times \text{hour20} - 0.28 \times \text{nesector} - 0.49 \times \text{swsector} + 0.84 \times \text{sesector}))$$

We then used regression equations calibrated with cases that experienced delays to estimate the lengths of delays, given they occur.

DEMONSTRATION SCENARIOS

Strategies for dealing with weather interruptions are employed by both airline operations and ATC. Our modeling framework readily allows an exploration of alternative actions from individual airlines, on one hand, and from ATC ground control on the other hand, if flights to some destinations need to be held. Ground controllers may hold an aircraft at the gate or direct it to a staging position elsewhere on the field if its departure would be delayed by weather or traffic on its planned route.

Given that delays are calculated as deviations from scheduled pushback rather than liftoff, the staged queuing strategy to cope with traffic holds have a significant impact on actual and reported performance for an airline. Moving an aircraft to free a gate may make it possible for an airline to accommodate incoming traffic without interruption and enable an "on-time" departure, but it may also create congestion elsewhere on the ground that interferes with other departures.

To distinguish random from systematic variation when comparing scenarios and procedures, we perform 100 replications of a day's activity and employ analysis of variance (for continuous performance measures). To perform 100 replications of a day's schedule with simple scheduling rules (first-come, first-served except for aircraft subject to gate and ramp holds) and pre-designated taxiing routes for active runways, less than two minutes of central processing unit (CPU) time were required on a workstation with an Intel Core2 Duo CPU E8400 processor at 3.0 gigahertz (GHz) and 3.5 gigabytes (GB) of random access memory (RAM).

To illustrate the process, we offer the results from a test of the effects of gate holds and ramp holds imposed in St. Louis for flights destined to Chicago airports because of severe weather. Flights to Chicago O'Hare International Airport (ORD) (served by American Airlines and United Airlines) and to Chicago Midway International Airport (MDW) (served by Southwest Airlines) were affected.

As ramp and taxiway capacities allowed, flights to other destinations were permitted. Random delays were imposed at departure gates using lognormal distributions with means and standard deviations determined from historical data considering time of day and whether the flight was continuing or originating. Other activity times (for taxiing, etc.) were generated using lognormal distributions with a 20% coefficient of variation. Arrivals were assumed to accrue at the FAF according to schedule (with no random variation).

Table 9 shows the simulated performance for a simulated extreme weather event that results in gate holds and ramp holds for flights in the morning between Lambert - St. Louis International Airport (STL) and ORD and MDW in Chicago.

Table 9. Stochastic simulation with 100 replications of severe weather scenario at major destination hub and affected aircraft held at gate and ramp

airline	event	Delay (minutes) Flights	Delay (minutes) Av. Delay	Flights with Pushback Delay Number	Flights with Pushback Delay P(>20 min.)	Ramp and Taxi time Av. Minutes
American	2: Arrival	3,000	7.1	0	0.000	7.1
	4: Departure	3,598	17.1	551	0.153	8.1
Delta	2: Arrival	1,800	7.0	0	0.000	7.0
	4: Departure	1,900	5.8	104	0.055	7.7
United	2: Arrival	2,500	7.4	22	0.009	7.4
	4: Departure	3,297	27.4	888	0.269	8.4
US Air	2: Arrival	1,500	7.0	0	0.000	7.0
	4: Departure	1,600	6.7	105	0.066	7.6
Southwest	2: Arrival	7,900	7.5	0	0.000	7.5
	4: Departure	7,899	8.9	859	0.109	8.2
Overall		34,994	10.5	3E3	0.072	7.7

Table 10 reflects the results of the same weather scenario without gate holds but imposition of holds on a ramp when the ramp capacity for flights staged for departure was reduced.

Table 10. Results of stochastic simulation with 100 replications for severe weather event with ramp hold, restricted ramp capacity, and no gate hold

airline	event	Delay (minutes) Flights	Delay (minutes) Av. Delay	Flights with Pushback Delay Number	Flights with Pushback Delay P(>20 min.)	Ramp and Taxi time Av. Minutes
American	2: Arrival	3,000	7.1	0	0.000	7.1
	4: Departure	3,599	9.4	389	0.108	20.7
Delta	2: Arrival	1,800	7.1	0	0.000	7.1
	4: Departure	1,900	5.7	96	0.051	13.3
United	2: Arrival	2,500	7.0	0	0.000	7.0
	4: Departure	3,297	14.7	584	0.177	24.0
US Air	2: Arrival	1,500	7.0	0	0.000	7.0
	4: Departure	1,600	5.9	79	0.049	10.6
Southwest	2: Arrival	7,900	7.5	0	0.000	7.5
	4: Departure	7,894	8.8	766	0.097	13.0
Overall		34,990	8.4	2E3	0.055	12.0

In the latter case, aircraft were pushed back when ready for departure but they were held at the staged queuing area on the ramp until the holds on flights to Chicago were lifted. The result is fewer flights registering pushback delays (i.e., better “on-time performance”) but longer resulting waits on taxiways and ramps (with higher fuel burn and emissions). Also, with reduced space for staging flights near the departure end of the runway, flights released from the gate cause interference with departures of airlines not destined to Chicago and the latter suffer delays that did not occur when the Chicago-bound flights were held at the gate. Without the reductions in ramp capacity, the flights not destined to Chicago did not suffer delays.

These results were generated using preliminary parameters estimated from the 364-day history and would not reflect actual experience over a year of flight activity. They simply verified that the modeled performance behaved as expected when the experimental changes to dispatching practices were imposed.

CONCLUSIONS AND FUTURE RESEARCH

Our simulation prototype was created to facilitate the analysis of airport ground operations with due consideration of the major intersecting spheres of activity and responsibility. It captures essential characteristics of the system in each operational sphere and links them with staged queues at the interfaces.

Optimizing heuristics may be embedded in portions of the Arena simulation model and the effects of their solutions may be tested with consideration of stochastic system behavior. Solutions from deterministic optimizing models may also be driven through the model to see their effects on other aspects of the operation and to examine whether promised gains from their use are achievable in a stochastic environment.

The simulation prototype was originally constructed to represent traffic in the dominant operating environment at Lambert - St. Louis International Airport (using runways 30L and 30R for departures and arrivals) and behavior was validated using complementary flight data for just a few weather scenarios. In the course of this project, the model was extended and calibrated for opposite traffic flows (using runways 12L and 12R), occasional traffic on runway 06-24 when strong crosswinds require such use, and use of runway 11-29 for occasional westerly departures from Terminal 1 and occasional easterly arrivals to Terminal 1. With these enhancements, we were able to address questions about the possible effects of using runways differently—namely segregating propeller traffic from turbine traffic for arrivals and directing the former to runway 06-24 while utilizing runway 11-29 for departures. This alternative was simulated while air traffic controllers experimented with these strategies in the actual operating environment.

Continued streaming of data for flight operations to the university and further experimentation with the model will enable us to estimate the effects of other changes to airport operations and to compare actual effects on performance with those predicted by the simulation model.

Models for fuel burn considering taxi time and idle times under power could be appended to the report generators to estimate fuel burned and emissions generated under alternative airport configurations and operating practices. Further refinements estimating stop-and-go behavior on runways and taxiways, depending on congestion levels, could provide better estimates.

In sum, our modeling approach provides a balance between the highly detailed engineering simulations of airspace and airports with microscopic detail, on one hand, and operations research models designed for strategic optimization of parts of the system, on the other hand. It incorporates necessary details of the operating environment and avoids the “flaw of averages” when studying system behavior. With extensions to the model, we can include complementary groundside operations (such as crossdocking facilities for cargo carriers). It is also possible to add details of flight activity at connected hub airports to examine the consequences of airline scheduling practices on individual airlines.

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