MINIMIZING AIRPORT PASSENGER TRAFFIC AT SECURITY CHECKPOINTS WITH QUEUEING MODELS AND DISCRETE-EVENT SIMULATION

By Jonathan Sax
Northwestern University
MSDS 460 - Decision Analytics
27 August 2022

Abstract

Passenger volume forecasts, time of day, time of year, weather conditions, and flight data are just a handful of the parameters that decision managers at airport security checkpoints take into account on a daily basis. This paper will apply queueing optimization techniques in order to minimize passenger wait time and maximize the rate of flow through security checkpoints. As well, this paper will present a hypothetical discrete-event simulation of a typical slow month at San Francisco International Airport's (SFO) Terminal 3 security checkpoints, followed by a typical busy month. Sensitivity analysis will be performed on the results of the simulation. Lastly, several improvements to the current system will be proposed, ranging from queueing enhancements, to increased access to TSA PreCheck lanes, to the circulation of live wait time data.

Keywords: TSA PreCheck, airport security screening, queueing models, discrete-event simulation, terminal checkpoints.

- **Introduction and Research Question**

Waiting in line at airport security checkpoints is a requirement for every air traveler. With each trip, there is opportunity to improve the trek from the curb to the jetbridge. While there are hundreds of parameters to consider when modeling wait times at each security checkpoint, this paper will address six key components to each passenger experience: queue length, number of security lanes, loading time, screening time, retrieval time, and if necessary, secondary screening time.

San Francisco International Airport (SFO) is my home airport. I nearly always fly out of Terminal 3 on United Airlines. Averaging over 60,000 miles per year and over half a million total travel miles to date, I am always finding ways to improve my airport experience. One of the most beneficial improvements has been enrolling in the U.S. Customs and Border Protection's Global Entry program, which grants me access to TSA PreCheck lanes. In July 2022, 95% of TSA PreCheck passengers waited less than five minutes at security checkpoints (TSA 2022). In scenarios where I do not have access to TSA PreCheck (lane closures, foreign airports, etc), I tend to wait in much longer queues. This is not only because of the larger calling population in the regular lanes, but also due to the added loading and retrieval times as a result of passengers having to remove their laptops/electronics and take off their shoes in these regular lanes. Using the above statistic about PreCheck wait times, along with pre-pandemic passenger data from 2010-2019 at SFO, I will create a queuing model that will simulate the flow rate of passengers through the two Terminal 3 checkpoints in two scenarios: a typical busy month (December), and a typical slow month (February) over the next 10 years, from 2023 to 2032. Then, I will use the results of the 10-year simulation to calculate average server utilization, average number of passengers in each queue, average number of passengers in each system (checkpoint), average waiting time in the queue, and average time in the system.

In addition to calculating the above results of the queing system, there are two research questions this paper will answer. Firstly, what is the average hourly flow rate of passengers in February (slow month) and December (busy month)? Secondly, how can we minimize wait times at both TSA PreCheck and regular security checkpoints?

Referencing Appendix A, the first map of SFO, Security Checkpoint F1 is the main checkpoint servicing Terminal 3. It has a CLEAR/Pre-Check lane, and a regular lane. Security Checkpoint F3 also services Terminal 3, but F3 does not have a TSA Pre-Check lane (it only has one regular lane). It is important to note that F3 is only open in busy months; in Appendix B, a map also presented on FlySFO.com, Checkpoint F3 is not even listed (it would have been located just beyond Door 13). Lastly, Security Checkpoint G services the International Terminal, but passengers can walk freely between the two terminals after going through security. In the past, when I have observed very long lines at the F1 checkpoint, I have walked over to the G Checkpoint (the International Terminal Checkpoint), cleared security, and then used the walkway in between the two terminals to walk to my gate at Terminal 3. I will begin building the simulation by focusing on February, when only the F1 checkpoint is active.

- **Assumptions**

- Daily passenger flow is a normally distributed variable centered around their means, located below in Figure 1.

- Passenger interarrival times (the time between consecutive arrivals) will follow a Poisson distribution.

- Over the next 10 years, from 2023-2032, there will be no construction, maintenance, or updates to Terminal 3 that would affect the model's input variables.

- When each checkpoint opens at 3:30am every morning, the starting queue value will be 10 passengers.

- The queue discipline (the order in which members of the queue are selected for service) will follow a first-come, first-serve policy.

- 27% of all travelers are eligible for the TSA PreCheck lane (US Congress 2018), so I will round down to 25% to account for eligible TSA PreCheck travelers using the regular lane. I will refer to this percentage as the TSA PreCheck *access parameter*.

- One of Terminal 3's two security screening checkpoints, Checkpoint F3, only opens in the busiest times of year. This paper will assume that Checkpoint F3 is open in December, but closed in February.

- 5% of passengers with flights departing from Terminal 3 will enter the International Terminal G checkpoint and walk back to Terminal 3 after clearing security (leaving 25% using PreCheck lane, and remaining 70% using regular lanes).

- The maximum capable service rate (denoted by μ) is 10,000 passengers per day in PreCheck lanes and 15,000 per day in regular lanes.

- There are two servers in each security checkpoint lane (see rendering on cover page for visualization).

- Input variables in the regular security lanes at each checkpoint – loading time, screening time, retrieval time, and secondary screening time – will take on values 10-20% larger than the TSA PreCheck lanes at each checkpoint. This percentage will be randomly distributed between 10-20% in each simulation. This added time accounts for passengers removing/retying shoes, laptops/electronics, and the assumption that secondary screening time takes longer on passengers in these lanes vs. TSA PreCheck lanes, due to higher probability of security violations by less frequent flyers and/or those who did not enroll in TSA PreCheck.

- **Methodology**

There are a total of 119 gates at SFO. Terminal 3 has the largest amount of gates at 35, or 29.4% (FlySFO.com). To best approximate the amount of travelers with flights departing from Terminal 3, I divided the total number of travelers by two (to hypothesize a roughly equal amount of travelers departing from SFO and arriving at SFO), since I am only interested in the departing population. From there, I multiplied that number by 0.294, so that only 29.4% of departing passengers at SFO are in our Terminal 3 data set. The below table shows that in a slow month like February, on average, there are roughly 15,841 travelers departing from Terminal 3. In a busy month like December, on average, there are roughly 19,060 travelers departing from Terminal 3.

Year	February	Daily Avg.	Term. 3 Departures Avg.	December	Daily Avg.	Term. 3 Departures Avg.
2010	2525392	90192.57	13258.31	3177096	102486.97	15065.58
2011	2619193	93542.61	13750.76	3450820	111316.77	16363.57
2012	3005764	103647.03	15236.11	3448766	111250.52	16353.83
2013	2142313	76511.18	11247.14	3819276	123202.45	18110.76
2014	2194751	78383.96	11522.44	3856908	124416.39	18289.21
2015	3248534	116019.07	17054.80	4129462	133208.45	19581.64
2016	3543751	122198.31	17963.15	4343971	140128.10	20598.83
2017	3481480	124338.57	18277.77	4660693	150344.94	22100.71
2018	3882605	138664.46	20383.68	4580901	147771.00	21722.34
2019	3755973	134141.89	19718.86	4726513	152468.16	22412.82
Mean	3039976	107763.97	15841.30	4019441	129659.37	19059.93
Std. Dev.	639281	22533.24	3312.39	554662	17892.31	2630.17

Figure 1: San Francisco International Airport Passenger Data 2010-2019 (FlySFO.com)

The F1 checkpoint operates 21 hours a day, opening at 3:30am and closing at 12:30am. In times of year when the F3 checkpoint is open, it also has these hours of operation. Figure 2 below demonstrates the structure of both of these queueing systems, and the four possible states of each passenger in each system: loading, screening, retrieval, and if ncessary, secondary screening. The wait times in each state of the system have been approximated based on data from a 2018 hearing before the Subcommittee on Transportation and Protective Security (U.S. House of Representatives 2018).

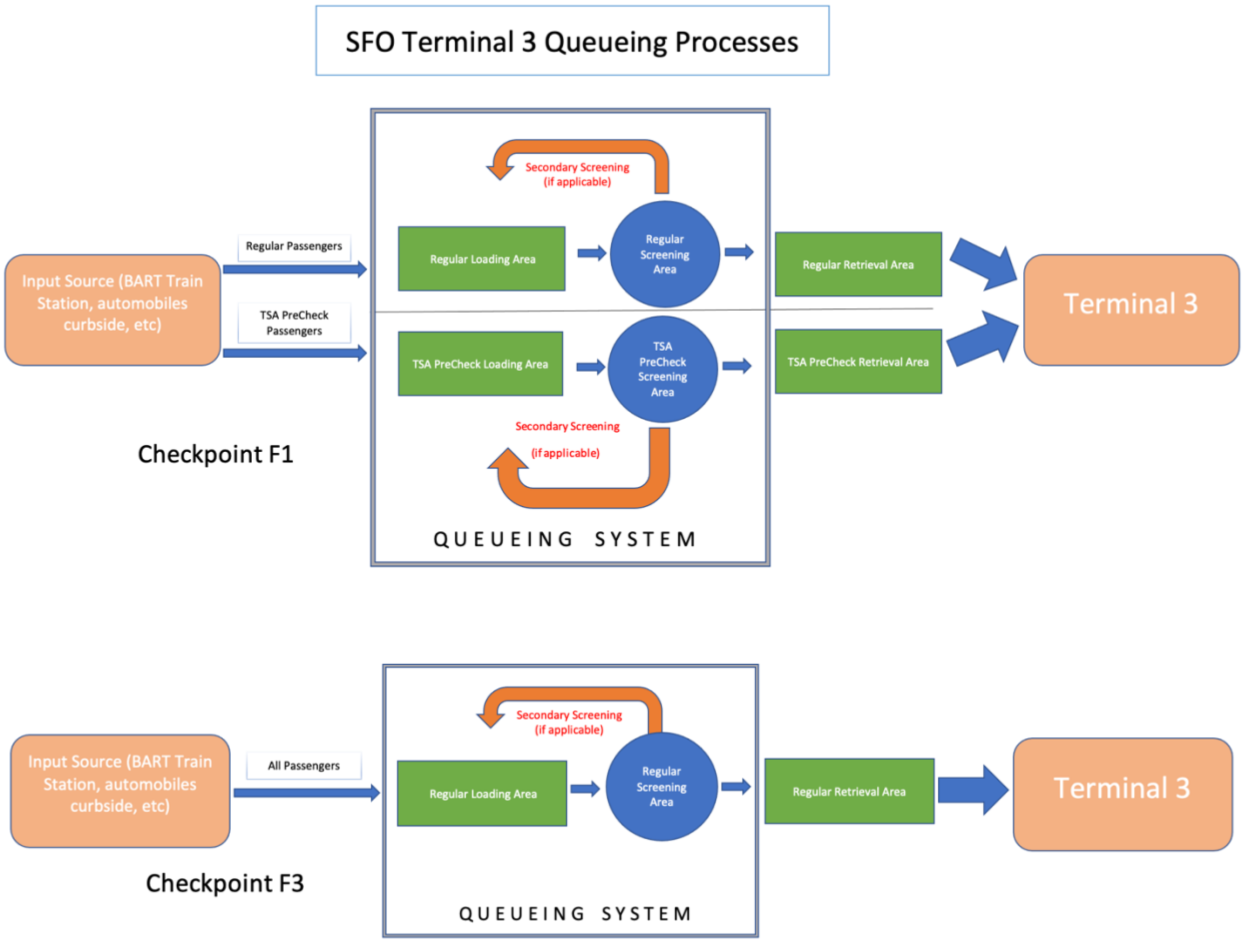

Figure 2: The structure of the queueing systems and retrieval areas at both Terminal 3 checkpoints.

As Figure 2 suggests, the first three queue states – loading, screening, and secondary screening – are all contributing factors toward time elapsed in the queue. The retrieval area is considered part of the overall system, but the time spent by each passenger in the retrieval area will not contribute to their overall wait time in the queue.

All four states in the simulation are random numbers with varying ranges of time (in minutes) elapsed in each state. The range is dependent on whether or not the passenger is traveling through a TSA PreCheck lane or a regular lane. For example, in February 2023, the first month of the 10-year simulation, the average secondary screening time of a TSA PreCheck passenger at Checkpoint F1 (Cell M20) is a random integer between 0 (no wait) to 15 (15 minutes of time waiting in secondary screening). In order to mimic rush periods when both TSA PreCheck and regular lanes are busy, the corresponding regular lane waiting time (Cell M21) will take on a randomly-assigned value between 10-20% higher than that of the TSA PreCheck lane. Here is the Excel code demonstrating this time difference:

Cell M20 (the TSA PreCheck lane at checkpoint F1) → =RANDBETWEEN(0,15)
Cell M21 (the regular lane at checkpoint F1) → =M20*RANDBETWEEN(1.1,1.2)

The daily arrival rate of passengers, denoted by λ_t, takes into account all passenger arrival data from 2010-2019 at time. From there, a random integer is generated to hypothesize future passenger arrival numbers at time *t*. This value must be an integer for each simulation, as it is not possible to have any fraction of a passenger pass through the system. These randomly-generated numbers are normally distributed around the corresponding 2010-2019 mean value. The Excel code for calculating the first randomly-generated arrival in February 2023 at the TSA PreCheck lane at Checkpoint F1, λ_1 is:

Cell F20 → λ_1 → =INT(MAX(NORMINV(RAND(),D$13,D$14),0)*0.25)

Recall for February (slow month), the overall daily number of passengers to pass through each lane is hypothetical split as 25% TSA PreCheck, 70% regular, and 5% Terminal G. For December (busy month), the arrivals are split as 25% TSA PreCheck F1, 35% regular F1, 35% regular F3, and 5% Terminal G.

The service rates per day are denoted by μ_t, and are consistent throughout the simulation: TSA PreCheck lanes can service up to 10,000 passengers per day, and regular lanes can service up to 15,000 passengers per day. Average server utilization percentages (ρ_t) denote the percentage probability that the checkpoint lane will be busy. For each lane, the formula for calculating ρ_t is

$$\rho_t = \frac{\lambda_t}{\mu_t * \# \, of \; servers} * 100$$

- **Simulation**

Now that the relationship between all the airport's prior data points and the new hypothetical ones are clearly laid out, I begin the simulation with the first instance, February 2023, and iterate over an additional 49 instances, for a total of 50 security lanes of average daily passenger traffic flowing into SFO Terminal 3 (5 lanes of security checkpoints over 10 years). The results of the simulation are as follows:

Operating Characteristics		
Average server utilization (ρ)	31.21532801	%
Avg. number of passengers in the queue (L_q)	32.74011479	in queue
Avg. number of passengers in the system (L)	34.30011479	in system
Average waiting time in the queue (W_q)	12.44	minutes per passenger
Average time in the system (W)	14	minutes per passenger
Starting queue length	10	passengers
Average flow rate	5.256380952	passengers per minute

Figure 3: Overall Operating Characteristics of the Simulation

The hypothetical amounts of time I assigned in each state yielded moderately accurate results relative to my real-life empirical observations. Firstly, at any given moment, if combining both TSA PreCheck and regular averages, somewhere around 32 passengers are in my simulation's queuing system, and 34 are within the entire system, including the retrieval area. Secondly, a little less accurate result of my simulation was the approximate 30-minute average time spent at a security checkpoint at SFO Terminal 3 for a randomly-selected passenger. I would give SFO Terminal 3 (especially the PreCheck lane) a little bit more credit than that. Here is how these numbers change when isolating only the PreCheck Lane simulation:

Operating Characteristics	PreCheck Lane (only)	
Average server utilization (ρ)	11.24175	%
Avg. number of passengers in the queue (L_q)	21.51552406	in queue
Avg. number of passengers in the system (L)	22.9789387	in system
Average waiting time in the queue (W_q)	10	minutes per passenger
Average time in the system (W)	11.8	minutes per passenger
Starting queue length	10	passengers
Average flow rate	3.62124183	passengers per minute

Figure 4: Operating Characteristics of the PreCheck Lane Simulation

While PreCheck passengers on average spent a couple of minutes less in the system than regular passengers, at any given moment, roughly the same number of passengers were in the PreCheck queue and system as the regular queue and system. Another interesting observation when comparing PreCheck vs. overall operating characteristics is that the average flow rate is actually slower in the PreCheck lane versus the regular lange. This is against my intution; one might assume that less time in the system indicates a faster average flow rate. In actuality, the slower average flow rate is an indication that only 25% of the overall population has access to this lane. Consequently, its average server utilization is significantly lower, at just 11.24%.

- **Sensitivity Analysis and Parameter Tuning**

In this model, the average minute-by-minute flow rates at each security lane are a function of arrival rates per day divided by total minutes each checkpoint is open per day (21 hours = 1,260 minutes). Therefore, in order to increase flow rates at each security lane, each security lane would need to see a higher arrival rate λ. In order to accomplish this, keeping all other things equal, SFO would have to reduce the number of available security lanes. This is not a viable solution.

Instead, using intel from the previous section's commentary on average server utilization %, a much more viable solution would be to <u>increase access to TSA PreCheck lanes</u>. I will elaborate on ways to increase PreCheck access from an organizational standpoint in the next section. Quantitatively speaking, for the sake of sensitivity analysis, I will autocratically tune our *access parameter* for TSA PreCheck lanes from 25% to 50% in both February and December periods. By doubling the amount of eligible passengers in TSA PreCheck lanes, keeping all else equal, and re-running the simulation, SFO's new operating characteristics of both Terminal 3 overall *and* the F1 PreCheck Lane (only) have improved dramatically:

Operating Characteristics	Overall System	w parameter tuning
Average server utilization (ρ)	37.72887411	%
Avg. number of passengers in the queue (L_q)	36.17477717	in queue
Avg. number of passengers in the system (L)	37.91477717	in system
Average waiting time in the queue (W_q)	4.174893617	minutes per passenger
Average time in the system (W)	5.914893617	minutes per passenger
Starting queue length	10	passengers
Average flow rate	5.692253968	passengers per minute
Operating Characteristics	**PreCheck Lane (only)**	**w parameter tuning**
Average server utilization (ρ)	56.674375	%
Avg. number of passengers in the queue (L_q)	29.69019616	in queue
Avg. number of passengers in the system (L)	31.59263518	in system
Average waiting time in the queue (W_q)	4.4	minutes per passenger
Average time in the system (W)	5.8	minutes per passenger
Starting queue length	10	passengers
Average flow rate	7.207422969	passengers per minute

Figure 5: Improved operating characteristics of the system with increased access to TSA PreCheck lanes.

Expanded access to TSA PreCheck means more travelers using lanes with consistently lower loading times, screening times, retrieval times, and secondary screening times* (*if necessary). With 25% more people entering this accelerated system, the end result of the new simulation is significantly reduced average waiting time in the system in all scenarios. By increasing PreCheck access by 25%, SFO has reduced overall average waiting times in the system by over eight minutes per passenger, from 14 minutes to 5.91 minutes. Meanwhile, average number of passengers in the queue (L_q) and average number of passengers in the system (L) increased slightly. Overall, this is a nominal burden of the model's sensitivity that decision managers at SFO should be willing to take on; a longer line has resulted in a faster overall security experience for all passengers in the aggregate.

- **Recommended Policy Changes**

There are several adjustments to be made outside of these queuing systems that will improve passenger experiences within them.

It is clear that increased usage at TSA PreCheck lanes will improve overall waiting times. Reducing the price of PreCheck enrollment to civilians would increase higher demand. Additionally, increased cooperation between TSA PreCheck and all government agencies requiring security clearance would be very beneficial. As of 2017, only service members and civilian employees of the Department of Defense with security clearance have automatic access to TSA PreCheck (Elias 2017).

Next, airlines could reduce or remove checked bag fees. This measure will reduce carry-on luggage, subsequently reducing loading and retrieval times at security checkpoints. That said, increased checked luggage may result in the need for more baggage handlers, and may create a different type of traffic within the internal baggage handling system of SFO. This would create an entirely different decision sciences problem within the airport.

Additionally, the Transportation Security Administration could enhance the technology to reduce wait times at all security checkpoints (this is easier said than done). For example, if there was a new technology that eliminated the need for regular-screening passengers to remove their shoes and/or remove their laptops from their bags, that would greatly reduce wait times in two of the four passenger states in my model: loading stage, and retrieval stage. And perhaps one day, all passengers will be able to walk through a screener with luggage in hand, instead of putting electronics, etc onto a slow conveyor belt and requiring a trained TSA eye to rigorously surveil the majority of passenger luggage.

Lastly, granting free public access of estimated wait times via wireless signal tracking would greatly improve the simulation. There is a phone app called "SFO Copilot" that provides flight status, parking metrics, and checkpoint wait times, but it is only accessible to SFO employees. It is surprising that this is not publically available. If more people went through security at International Terminal G, it would reduce congestion at Terminal 3, and increase the 5% access parameter (the amount of Terminal 3 passengers going through the Terminal G checkpoint) that I originally estimated in my simulation.

- **Literature Review**

Until now, this paper has exclusively focused on one goal: reducing wait times at TSA security checkpoints. In reality, airports take a more multi-objective approach, introducing other optimizations like passenger safety and workforce allocation of TSA security officers.

Two years ago, an article appeared in Institute of Industrial and Systems Engineers called "Demand Prediction and Dynamic Workforce Allocation to Improve Airport Screening Operations," which presented a real-world multi-objective programming model at Orange Regional Airport in New South Wales, Australia. Instead of solely focusing on wait time reduction, the model they proposed gave optimal security checkpoint configurations based on two diverging objectives: minimizing workforce allocation (staff and overall pay minimization) while maximizing passenger flow (Hanumantha et al. 2020).

They were also interested in server utilization percentages (ρ_t), but instead of increasing the TSA PreCheck access parameter, as I have, they increased the total number of servers. After I played with my simulation via several Excel iterations, this was not effective based on my model's parameters. Whereas, in their model, increasing the number of servers improved overall performance. That said, their overall impact depended on the exact location of each additional server and the time of day (Hanumantha et al. 2020). In contrast, interarrival passenger times in my model followed a standard Poisson distribution. Their model went a step further and actually forecasted passenger arrival times based on flight departure schedules.

Taking this extra step to better forecast passenger interarrival times would create a more robust model. Additionally, taking into account other improvements like granting free public access of estimated wait times via wireless signal tracking would take this model to the next level.

- **Conclusion**

Using a decade of pre-pandemic data from 2010-2019 to forecast the next decade of passenger traffic flying out of San Francisco International Airport's Terminal 3, I have effectively created a discrete-event simulation to forecast the next decade of departures at this terminal from 2023-2032. With the results of the simulation, I conducted sensitivity analysis and parameter tuning. The most effective improvement to my model was to increase the access parameter of TSA PreCheck lanes from the current estimation of 25% up to 50%, and re-running the simulation. Additionally, I have prescribed three other viable 21st-century solutions to minimize wait times at these security checkpoints: reduce or remove checked bag fees, provide checkpoint wait times (in real-time) online, and enhance the screening technology.

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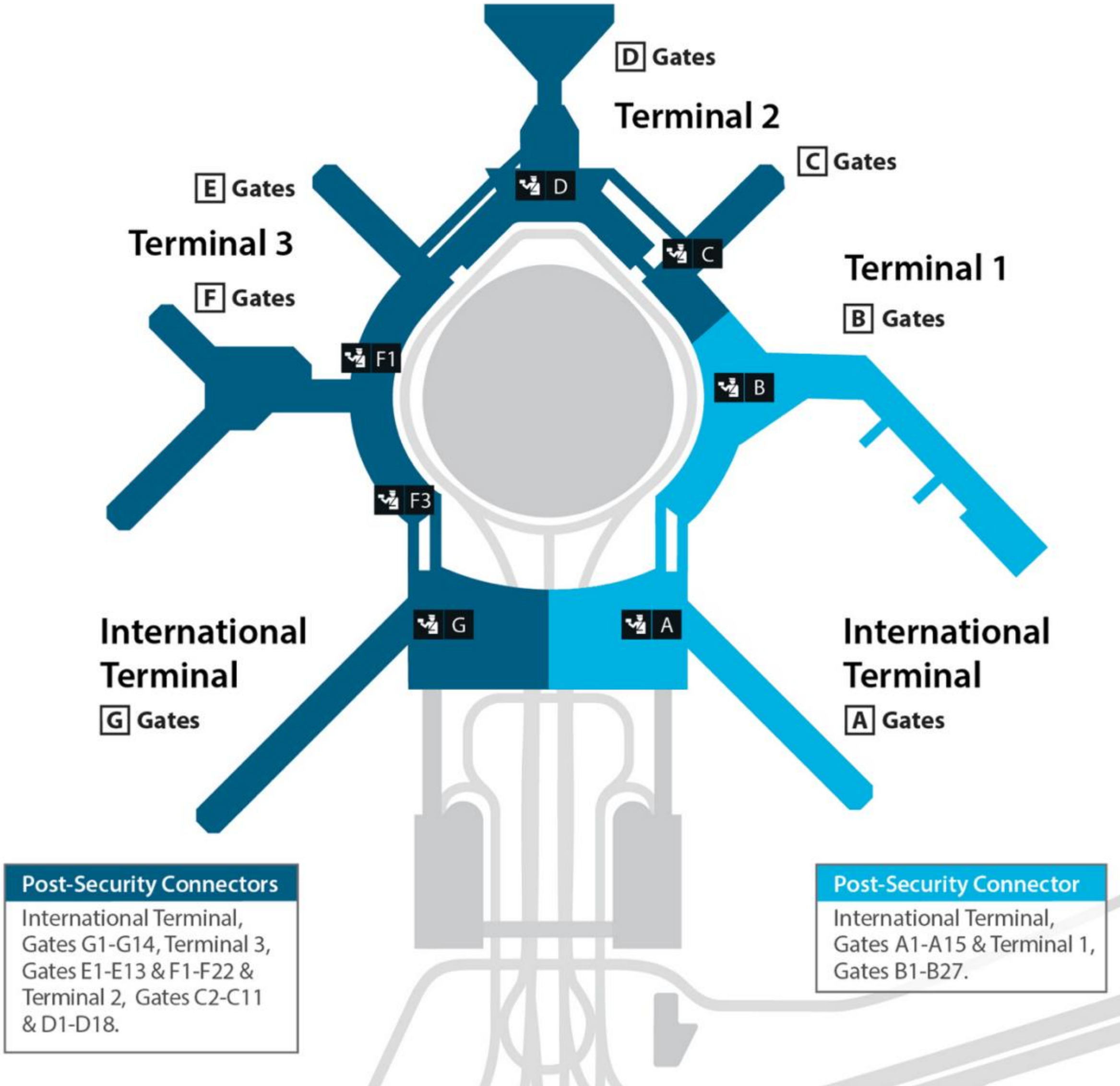
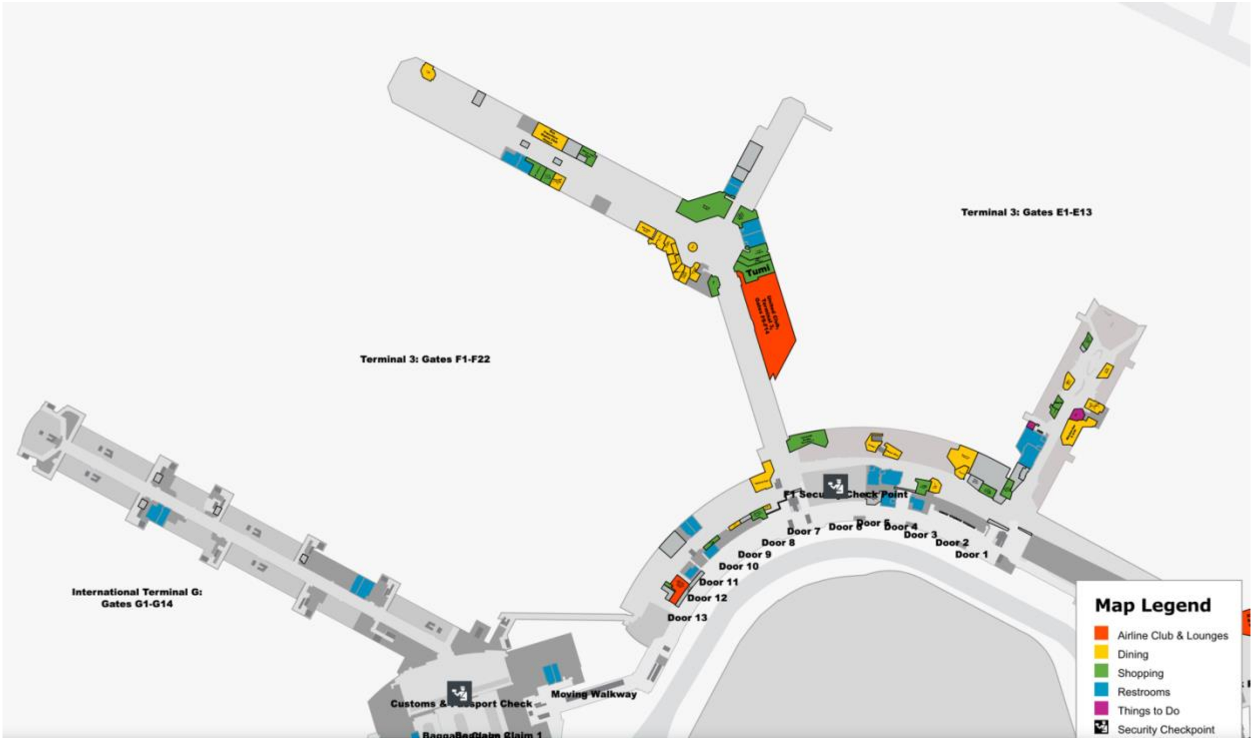
Appendix



Appendix A: Map of San Francisco International Airport (FlySFO.com)



Appendix B: Map of Terminal 3 and International Terminal G (FlySFO.com)

Appendix C: The Simulation and Flow Chart

Year	February	Feb Daily Avg.	Term. 3 Departures Avg.	December	Dec Daily Avg.	Term. 3 Departures Avg.
2010	2525392	90192.57	13258.31	3177096	102486.97	15065.58
2011	2619193	93542.61	13750.76	3450820	111316.77	16363.57
2012	3005764	103647.03	15236.11	3448766	111250.52	16353.83
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2018	3882605	138664.46	20383.68	4580901	147771.00	21722.34
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Mean	3039976	107763.97	15841.30	4019441	129659.37	19059.93
Std. Dev.	639281	22533.24	3312.39	554662	17892.31	2630.17

Operating Characteristics	Overall System	w parameter tuning
Average server utilization (r)	38.76911348	%
Avg. number of passengers in the queue (L	37.69342212	in queue
Avg. number of passengers in the system (L	39.31342212	in system
Average waiting time in the queue (W_q)	12.97574468	minutes per passenger
Average time in the system (W)	14.59574468	minutes per passenger
Starting queue length	10	passengers
Average flow rate	5.818190476	passengers per minute

Operating Characteristics	PreCheck Lane (only)	w parameter tuning
Average server utilization (r)	59.1853125	%
Avg. number of passengers in the queue (L	30.29371075	in queue
Avg. number of passengers in the system (L	31.70834489	in system
Average waiting time in the queue (W_q)	9.2	minutes per passenger
Average time in the system (W)	11.2	minutes per passenger
Starting queue length	10	passengers
Average flow rate	7.53225957	passengers per minute

									Part of queue:	Part of queue:	Not part of queue:	Part of queue:			
Year	**Month**	**Checkpoint**	**Lane**	**Starting Queue**	**Arrival rate (λ) per da**	**Service rate (μ) per da**	**P(Interarrival<1 mi**	**Number of Server**	**Avg. Loading Time (minutes)**	**Avg. Screening Time**	**Avg. Retrieval Time**	**Avg. Secondary Screening Ti**	**Utilization %**	**Flow rate per minute**	**Average Time at Checkpoint (per passenger, in minutes)**
2023	February	F1	TSA PreCheck	10	8127	8000	0.93591259	2	1	2	2	3	50.7938	6.45	8
		F1	Regular	10	8229	12000	0.931420373	2	1	4	4	6	34.2875	6.530952381	15
	December	F1	TSA PreCheck	10	11483	8000	0.692448789	2	1	2	2	8	71.7688	9.113492063	13
		F1	Regular	10	3980	12000	0.99955279	2	2	4	4	16	16.5833	3.158730159	26
		F3	Regular	10	4888	12000	0.997743401	2	1	2	2	9	20.3667	3.879365079	14
2024	February	F1	TSA PreCheck	10	8141	8000	0.935307641	2	1	4	4	0	50.8813	6.461111111	9
		F1	Regular	10	9880	12000	0.831322941	2	1	1	1	0	41.1667	7.841269841	3
	December	F1	TSA PreCheck	10	10038	8000	0.819180667	2	1	2	2	8	62.7375	7.966666667	13
		F1	Regular	10	4169	12000	0.999348444	2	2	3	2	16	17.3708	3.308730159	23
		F3	Regular	10	4973	12000	0.99743065	2	1	6	4	15	20.7208	3.946825397	26
2025	February	F1	TSA PreCheck	10	6488	8000	0.983391359	2	1	3	0	9	40.55	5.149206349	13
		F1	Regular	10	8489	12000	0.919074093	2	0	6	0	18	35.3708	6.737301587	24
	December	F1	TSA PreCheck	10	10002	8000	0.821982641	2	1	2	0	6	62.5125	7.938095238	9
		F1	Regular	10	5297	12000	0.995903111	2	0	4	0	12	22.0708	4.203968254	16
		F3	Regular	10	5902	12000	0.991185056	2	2	1	2	3	24.5917	4.684126984	8
2026	February	F1	TSA PreCheck	10	7920	8000	0.94442952	2	0	2	4	14	49.5	6.285714286	20
		F1	Regular	10	6159	12000	0.988222886	2	0	2	2	28	25.6625	4.888095238	32
	December	F1	TSA PreCheck	10	8533	8000	0.916856592	2	1	4	4	7	53.3313	6.772222222	16
		F1	Regular	10	5318	12000	0.995783463	2	1	2	0	14	22.1583	4.220634921	17
		F3	Regular	10	5490	12000	0.994695494	2	1	4	0	6	22.875	4.357142857	11
2027	February	F1	TSA PreCheck	10	11296	8000	0.710121085	2	0	3	0	4	70.6	8.965079365	7
		F1	Regular	10	8991	12000	0.891566335	2	0	6	0	8	37.4625	7.135714286	14
	December	F1	TSA PreCheck	10	12017	8000	0.640717192	2	1	3	2	6	75.1063	9.537301587	12
		F1	Regular	10	3632	12000	0.999790695	2	2	6	4	12	15.1333	2.882539683	24
		F3	Regular	10	4352	12000	0.999081854	2	2	2	1	11	18.1333	3.453968254	16
2028	February	F1	TSA PreCheck	10	9061	8000	0.887347961	2	1	4	2	2	56.6313	7.191269841	9
		F1	Regular	10	6004	12000	0.990087704	2	0	3	1	4	25.0167	4.765079365	8
	December	F1	TSA PreCheck	10	7480	8000	0.959946292	2	0	6	2	6	46.75	5.936507937	14
		F1	Regular	10	4536	12000	0.998728705	2	2	3	1	12	18.9	3.6	18
		F3	Regular	10	6097	12000	0.988998388	2	2	6	2	5	25.4042	4.838888889	15
2029	February	F1	TSA PreCheck	10	11395	8000	0.700799836	2	1	2	1	6	71.2188	9.043650794	10
		F1	Regular	10	8408	12000	0.923059109	2	2	4	2	12	35.0333	6.673015873	20
	December	F1	TSA PreCheck	10	10132	8000	0.811768262	2	1	3	1	1	63.325	8.041269841	6
		F1	Regular	10	5089	12000	0.996948328	2	2	6	2	2	21.2042	4.038888889	12
		F3	Regular	10	4778	12000	0.998101625	2	0	3	1	15	19.9083	3.792063492	19
2030	February	F1	TSA PreCheck	10	11090	8000	0.729239722	2	1	6	2	4	69.3125	8.801587302	13
		F1	Regular	10	9390	12000	0.866292605	2	0	2	1	8	39.125	7.452380952	11
	December	F1	TSA PreCheck	10	11173	8000	0.721584068	2	1	4	2	8	69.8313	8.867460317	15
		F1	Regular	10	5110	12000	0.996853709	2	1	2	2	16	21.2917	4.055555556	21
		F3	Regular	10	4205	12000	0.999301846	2	0	4	4	6	17.5208	3.337301587	14
2031	February	F1	TSA PreCheck	10	6965	8000	0.973947316	2	0	3	0	9	43.5313	5.527777778	12
		F1	Regular	10	7850	12000	0.947130332	2	2	6	0	18	32.7083	6.23015873	26
	December	F1	TSA PreCheck	10	11131	8000	0.725466329	2	0	1	2	1	69.5688	8.834126984	4
		F1	Regular	10	4702	15000	0.998320965	2	2	2	4	2	15.6733	3.731746032	10
		F3	Regular	10	4977	12000	0.997415112	2	2	3	1	12	20.7375	3.95	18
2032	February	F1	TSA PreCheck	10	7446	8000	0.96100419	2	1	6	2	3	46.5375	5.90952381	12
		F1	Regular	10	7484	12000	0.95982054	2	1	3	0	6	31.1833	5.93968254	10
	December	F1	TSA PreCheck	10	9475	8000	0.860529376	2	1	6	0	11	59.2188	7.51984127	18
		F1	Regular	10	5343	12000	0.995637419	2	1	2	0	22	22.2625	4.24047619	25
		F3	Regular	10	3431	12000	0.999870893	2	0	4	0	3	14.2958	2.723015873	7