Airport Baggage Screening: Optimizing the Implementation of EDS Machines

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Summary

As analysts for the Transportation Security Administration, we explore the effects of the new 100% baggage screening law. Our first goal is to find the optimal number of Explosive Detection Systems (EDS) that an airport will require to meet the new federal mandates. In addition, we develop a scheduling algorithm to minimize airport congestion. Lastly, we use an analysis of cutting-edge technology, including Explosive Trace Detection (ETD), for recommendations concerning the future of airport security.

We develop three models to estimate the optimal number of EDS machines required for the two largest airports in our region. Our first model is a simple approximation; we then develop a more accurate multichannel queuing system model. Finally, we create an influx simulation to analyze minute-by-minute baggage arrivals. This model accurately examines passenger arrival dynamics, including the build-up of baggage throughout peak hours of operation.

For an optimum peak-hour schedule, we arrange the flights so that passengers are equally distributed among evenly spaced time intervals. This arrangement minimizes congestion in the airport and turmoil if delays occur. We find this optimal schedule for any given set of flights. Finally, by combining this model with our influx simulation, we find that airport A requires 23 EDS machines at a cost of $25.3 million and airport B requires 24 EDS at $25.9 million.

We formulate recommendations for security decision-makers and address their concerns, including our dismissal of ETDs as a supplement to EDSs.

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EDS Modeling

Model 1: The Hasty Model

To find a quick approximation for the number of EDSs needed, we first determine the total number of people who use the airport during the given peak hours.

The problem statement provides a range of probabilities for passenger turnout for each flight. Because the ranges are broad, we assume that:

- 85% of people show up for flights with 85 or fewer seats;
- 80% of people show up for flights with between 128 and 215 seats; and
- 75% of people show up for flights with 350 seats.

The expected number of passengers who show up for a flight, μ_x, is the number n of passengers scheduled to be on the flight times the probability p of showing up:

$$\mu_x = np.$$

An EDS can scan between 160 and 210 bags per hour; to account for the worst case, we assume 160 bags per hour. Let B be the number of bags to be scanned and x be the number of EDS scanners needed at the airport. Then

$$x = \frac{B}{160t},$$

where t is the number of hours of operation of the scanners.

We assume that all passengers arrive and check their bags 2 hours before departure, so that $t = 2$.

Each EDS scanner costs \$1 million plus an installation cost I (dependent on the airport), for a total cost of

$$\text{Cost} = (1{,}000{,}000 + I)x.$$

The number of bags to be scanned for a flight is the expected number of passengers times the average number of bags per person. According to the problem statement, the distribution is 0 bags: 20%, 1 bag: 20%, and 2 bags: 60%. The average is 1.4 bags per passenger, the *bag rate*. We have

$$B = 1.4\mu_x.$$

We assume that all bags are present at the beginning of the peak hour and that the scanners have the complete time to work on them at a constant rate, so that each scanner can process a total of 320 bags over the two-hour period.

Table 1.
Flights at airport A and their expected numbers of passengers.

Type	Seats/flight	Flights	Occupancy	Expected passengers
1	34	10	70–100%—	289
2	46	4	use 85%	156
3	85	3		217
4	128	3	60–100%—	307
5	142	19	use 80%	2158
6	194	5		776
7	215	1		172
8	350	1	50–100%—	
			use 75%	263
	Totals	46		4338

Airport A

Table 1 shows a breakdown of the flights at airport A and the expected number of passengers for each flight.

From the table, we can determine that in the peak hour, airport A will see about 4,338 people leave on 46 flights. We estimate the total number of bags to be $4,338 \times 1.4 \approx 6,072$, hence approximately $\lceil 6100/320 \rceil \approx 19$ scanners are needed. For airport A, we have $I = \$100,000$; so the total cost of the scanners is $20.9 million.

Airport B

The calculations for airport B are similar. At the peak hour, 4,665 people leave on 48 flights with 6,531 bags, requiring 21 scanners. For airport B, we have $I = \$80,000$; the total cost of the scanners is $22.68 million.

The Extremes of Being Hasty

Our calculations are based on an average probability of passenger arrival. What about the extreme days of operation? Analysis of the highs and the lows of our model can yield both interesting and useful information as to the robustness and resilience of the model.

To estimate for low traffic, we arbitrarily reduce the probabilities of arriving to 70%, 60%, and 50% for small, medium, and large planes, instead of 85%, 80%, and 75%. Our high extreme is, of course, 100%.

We find the numbers of machines corresponding to low, mean, and high traffic to be:

Airport A: 15, 19, 24;
Airport B: 16, 21, 26.

Model 2: Multi-Channel Queuing Model

Background Analysis

The arrival of airport passengers and baggage can be modeled by queuing theory. Because the EDS machines are not at the ticket counters, two queues form:

- People waiting to check in at the ticket counter. We assume that they arrive at a uniform rate according to a Poisson process.
- People waiting to have their bags checked. To determine how the bags arrive at each EDS machine, we analyze the layout of the airport and the logistics of placing the machines in the building. Since each EDS machine is approximately 20 ft long and 4 ft wide, there will not be sufficient space to install the machines at the ticket counters [Domestic Flights Usage Guide 2003]. The most viable option is to install the machines in open lobby areas throughout the airport, evenly spacing them so passengers find close EDS machines regardless of where they enter the airport.

Airports have two options of dealing with baggage at the EDS machine.

- Require all passengers to remain with their baggage until it has passed through the EDS. This method would result in longer queues, as people would pile up in the queue along with baggage.
- Have the ticket agent stamp the luggage at check-in, allowing passengers simply to drop off baggage at the EDS machine. Passengers could then leave and allow the attendants to finish processing the bags. The baggage would then form a queue of its own as bags piled up waiting to be put through the machine.

We use the second option.

The baggage queue follows the same Poisson process as the queue for the counter: As people leave the counter queue, they arrive in the baggage queue. Baggage dropped off becomes the calling unit waiting in the queue and is serviced according to how fast the EDS machines can handle baggage [Render 1997, 662]. The input process for the baggage queue is a first-come-first-serve process.

Logistics of the Queue

To perform our queuing analysis, we first define parameters:

- λ = average arrival rate (bags/h),
- μ = average service rate at each channel (bags/h), and
- M = number of channels open (EDS machines).

Average Arrival Rate

For this model, we examine each flight type separately. For each flight type, we used Mathematica to generate a random number in the given range of percentages of people that show up. We multiplied this value by the total number of seats in that flight type. We then determine the total number of passengers and the corresponding number of bags. From this we deduce the average arrival rate λ of bags per hour.

Mean Service Rate

The average service rate μ at each channel depends on:

- the number of people staffing the machine and their experience with it,
- the protocol for dealing with flagged baggage (which slows down the processing),
- locked bags (they will have to be cut open and searched),
- machine reliability (a breakdown will temporarily stop the queue and create a backlog; according to the problem statement, each machine is operational 92% of the time).

We assume an average of 185 bags/h for an operating machine; taking into account that a machine is operational 92% of the time, the mean service rate is $185 \times .92 = 170.2$ bags/h.

Number of Channels Open

We want to determine the number M of open channels that optimize the system and allow all of the baggage to be checked in time to prevent any delays in flight departures.

Advantages of the Queuing Model

A queuing model allows us to determine the average number of units in the system at any given time and the average time that a unit spends in the waiting line or being serviced. Perhaps the most important advantage is the fact that we can also determine a utilization rate for the servers [Ecker 1988, 379]. From this information, we can aim to increase utilization in order to decrease costs and optimize our solution.

Airport A

For each day of simulation, we determine the total number of bags and run them through our queue simulation in Mathematica. We also estimate the number of servers needed to process all of the bags within a 2-hour period.

After a few guess-and-check trials, we determined that $M = 19$ servers will be adequate. Bags arrive at approximately $\lambda = 2{,}999$ bags/hour, each bag spends about 0.52 min in the scanner, and with 19 EDS scanners an average of 9 bags are waiting in the queue at one time. On average, a bag waits 0.17 min in the queue, and the total time to get all of the bags scanned is 1.85 h—well within the limit of 2 h. The utilization rate is 93%, so each EDS machine is being used almost the entire time.

Airport B

One run produces 6633 bags, for which 20 machines will do. Approximately $\lambda = 3317$ bags arrive per hour, and the average time spent scanning each bag is 0.95 min. The average number of bags waiting to be scanned is 33, while the average waiting time is 0.59 min. The entire queue takes approximately 1.95 h to run, with a utilization factor of 97%.

Comparison

The results from this model (19 machines at A, 20 at B, at costs of \$20.9 million and \$23.6 million) agree closely with those of the Hasty Model (19 and 21 machines, at \$20.9 million and \$22.7 million).

Model 3: Influx Simulation Model

In our previous models, we assumed a constant flow of arrivals. Realistically, different numbers of people arrive at the airport every minute, either dashing to the counter (if they are late) or walking patiently towards the EDS machine (if they are on time). The main drawback in our queueing model is that it handles arrivals as a whole and does not separate them into separate flights and departure times. However, our Influx Simulation Model will account for this by using a separate Poisson process, to simulate people arriving, for each flight. The flights will be analyzed individually, resulting in a minute-by-minute distribution.

Arrival Rate

To account for peak traffic, we assume that 100% of passengers show up for their flights, over the 1.25 h-period between 120 min and 45 min before departure. Therefore, we estimate that a flight with 128 passengers will have an arrival rate equal to the number of passengers divided by the time interval in which those passengers arrive. For example, this flight will have an arrival rate of 128/1.25 or approximately 102.4 passengers/h.

Scanning Rate, Bag Rate

The scanning rate is 185 bags/h, and passengers average 1.4 bags/person.

The Influx Simulation Model

We split the peak hour into 10 six-minute intervals, to provide a decent buffer between flights and give people an opportunity to have a couple of minutes leeway in case a flight is slightly delayed. We also chose this size interval to provide a small number of flights departing in an interval, which helps reduce possible waiting-line congestion. Our model can deal with multiple planes in large airports; however, smaller airports would have to choose a different process for scheduling, because they might not have the runway capacity to support multiple flights.

At airport B, with 100% of passengers showing up for full flights, a total of 5781 passengers arrive. We divide them into 10 "platoons" of 578 each according to the six-minute interval in which their plane departs. With approximately the same number of people departing in each time interval, we even out the congestion.

For a Poisson process, the following properties must hold [Lapin 1997, 229]:

- The number of events in one interval is independent from any other interval.
- The mean process rate λ must remain constant at all times.
- The number of events in any interval of length t is Poisson distributed with mean λt.
- As the interval size goes to zero, the probability of 2 or more occurrences in an interval approaches 0.

Under these conditions, the probability of x arrivals in a single interval is

$$P(x) = \frac{e^{-\lambda t}(\lambda t)^x}{x!}, \qquad x = 0, 1, 2, \dots .$$

The 578 people in a platoon arrive over a 1.25 h-period. **Figure 1** displays the graph of a continuous approximation to the discrete probability mass function of a Poisson process with arrival rate *per minute* of $\lambda = 578/(1.25 \times 60) = 7.7$ people/min.

We use the graph in **Figure 1** to simulate the arrival of passengers. We start by generating random ordered pairs. The first coordinate is a random integer between 0 and 15, representing the number of passengers that arrive in one minute, and the second coordinate is a random number between 0 and 0.2 (above the peak of the curve in the figure). We check each ordered pair to determine whether or not it falls under the curve of the graph. If so, we consider the pair to represent passengers arriving into the queue. We repeat this process until we generate 75 points that fit under the curve. These 75 points

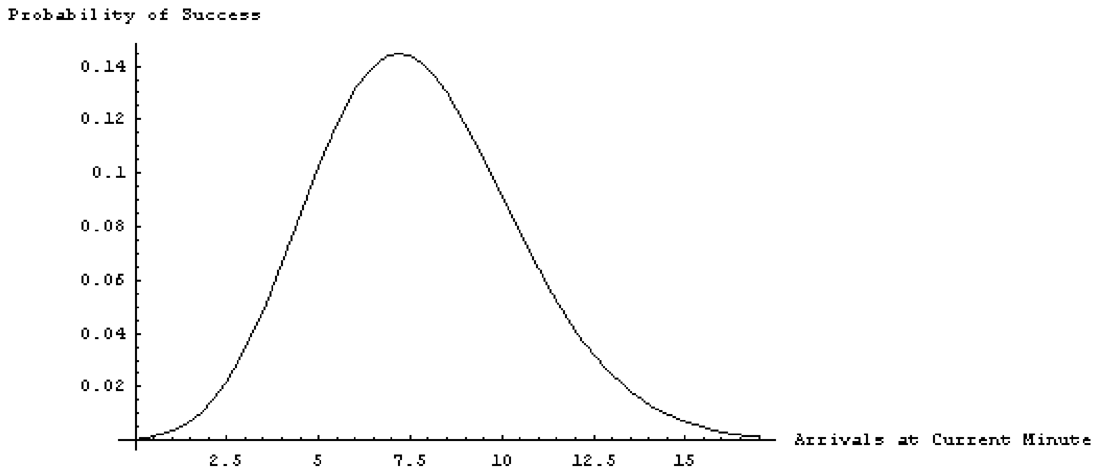

Figure 1. Graph of continuous approximation to a Poisson distribution with arrival rate $\lambda = 7.7$ people/min. The peak of the curve is at approximately $(7.5, 0.15)$

represent how passengers for departures in this six-minute interval arrived at the airport in each minute of the 75 min in the 1.25 h arrival period. We also put a stipulation in the program to hit the target number of people arriving, i.e., 578 for airport B. For each airport, we generated a list of Poisson values for each of the 10 different time intervals of departure times. We organize the Poisson sequences in **Figure 2**.

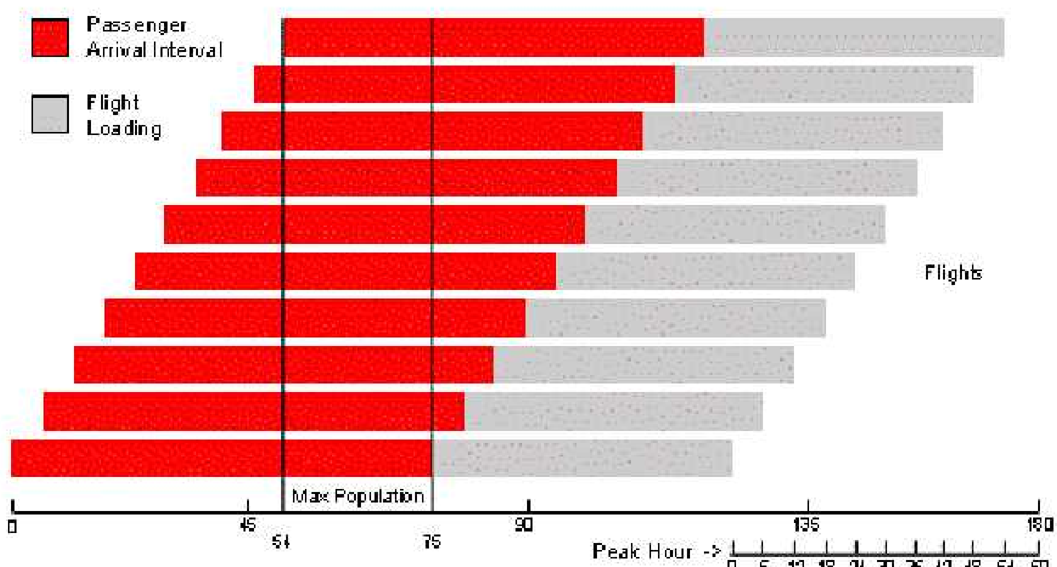

Figure 2. Results of 10 simulations.

The dark bars represent intervals of 75 min; each corresponds to arrivals for a six-minute time interval of flight departures. The gray bars correspond to the remaining 45 min when the plane is loading luggage and passengers.

We analyzed the minute-to-minute data in a spreadsheet, with a column for each six-minute departure interval and a row for each minute from 0 down to

180. The spreadsheet processes the rows from top to bottom. The spreadsheet

- sums a row to yield the number of passengers arriving in a particular minute,
- multiplies that total by the baggage rate (1.4 bags/passenger) to get the number of arriving bags,
- adds those bags to any leftover from the previous minute to get Bag Total, and
- subtracts Bag Total from the number of scanners times 3.083 (the scanner rate in bags per minute).

If the difference is positive, the number of scanners was sufficient for that minute. If the difference is negative, not all bags in the queue could be scanned through; these bags are carried over to the next minute and the system begins to get behind. As long as the machines can stay close to keeping up, flights will not be delayed.

Passengers cannot arrive for their flights less than 45 min before departure. However, baggage dropped off at the EDS can be processed and loaded on the plane up to 15 min after this cutoff, since planes start loading passengers approximately 30 min before departure. The extra 15-min leeway allows time for the EDS machines to catch up and for baggage to get loaded.

From the column for the number of bags in the queue, we can determine whether or not the machines keep up. If 15 min after passengers are no longer allowed to board, the number of bags in the queue equals the total of the bags arriving for flights departing after the current flights, then all of the bags for the current flights have already been scanned. Therefore, when the flight leaves, the scanner may still be behind but any backed up bags are from flights not yet set to depart.

Figure 3 is a plot of every minute of the peak hours of airport A. The graph accentuates the maximum population in the interval 54–75. The optimal number of scanners to use at airport A is 23, for a total cost of $25.3 million. Airport B displays similar results, yielding 24 scanners at a cost of $25.9 million.

Developing a Flight Schedule

During the peak hour, 46 flights depart from airport A and 48 from airport B. We need optimal schedules for all passengers to have their baggage scanned in time for their departures.

Scheduling too many flights to depart around the same time leads to congestion in the EDS queue; additional machines would be needed to handle these extreme times but would be underutilized the rest of the day.

A hasty approach might be to schedule approximately the same number of flights to leave at the same time. However, because the flights have different numbers of passengers, there could still be massive congestion.

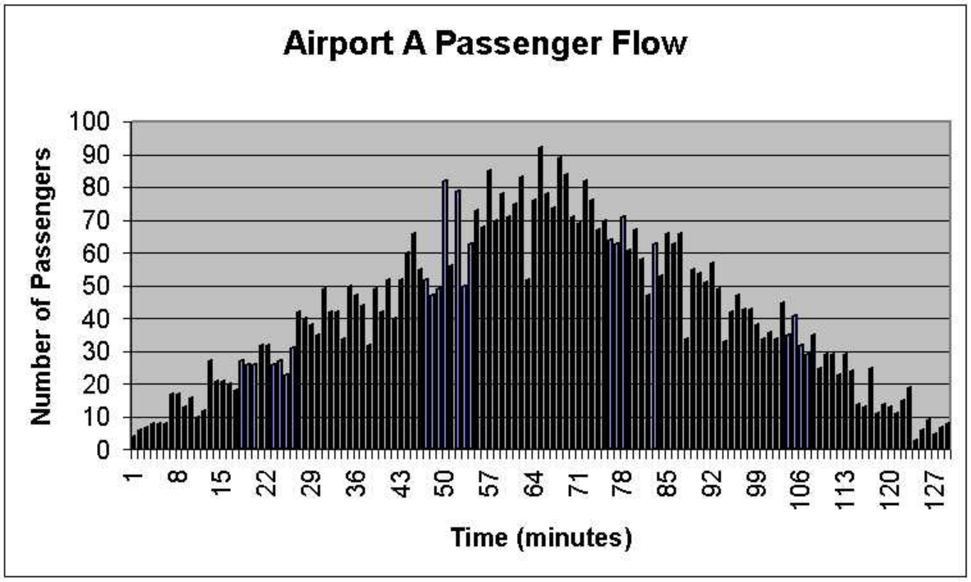

Figure 3. Minute-by-minute passenger report at airport A.

Assumptions

- All passengers arrive in a Poisson process no more than 2 hours before, and no less than 45 min before, their departure.
- Passengers arriving later than 45 min before the flight cannot board.
- All baggage must be checked before passengers are allowed to board the plane.
- Passengers start boarding 30 min before gate departure.
- In relation to the previous two assumptions, all baggage for any given flight must be scanned 30 min prior to departure.
- Checked baggage is scanned at a uniform rate.
- Carry-ons are not scanned by EDS.

Equally Distributed Passengers

One way to avoid congestion is to ensure that large numbers of people are not required to arrive at the airport during the same time period. This is accomplished in the model by splitting the peak hour into 10 six-minute intervals, with the goal to space out the passengers equally in these 10 intervals.

We use the range of passengers per flight (given in the problem statement) to calculate the number of passengers departing during the hour. Assuming all flights are full and all passengers arrive for their flights, 5,396 passengers arrive for airport A (540 per interval) and 5,781 for airport B (578 per interval).

We distribute the flights into the 10 intervals so that approximately the desired number of passengers depart in each interval. Our algorithm (as implemented in a Mathematica program) works for any desired interval and provides a listing of which flights should be scheduled to depart in the same time intervals. After arranging the flights into intervals, scheduling becomes a matter of determining the order of departures of the small number of flights in an interval. **Table 2** shows the schedule for airport A.

Table 2.

Flight schedule for airport A.

	Flight interval									
	:00	:06	:12	:18	:24	:30	:36	:42	:48	:54
Specific flight capacity	142	142	142	142	142	142	194	194	215	350
	142	142	142	142	142	142	142	194	194	194
	142	142	142	142	85	128	142	142	128	
	46	46	46	46	85	128	34			
	34	34	34	34	85		34			
	34	34	34	142						
Totals	540	540	540	540	539	540	546	530	537	544

During peak hours, the rate of passengers coming in continues to grow until the middle of the peak period. If delays were to occur during this time, large flights might be delayed, which could eventually also delay smaller flights because of runway congestion. To avoid this problem, we place the time periods that contain the larger flights near the end of our flight interval. This allows the passengers for the smaller planes to get on their planes and depart on time. If there is a delay or unexpected congestion towards the end of the peak hour, it mainly affects just the two larger flights.

Recommendations

Install 23 EDS machines in airport A and 24 machines in airport B. With these numbers, during the peak hours 100% baggage screening can be accomplished without delaying any departures while also maintaining high utilization rates.

Implement an optimal form of flight scheduling by distributing passengers evenly among a set number of time intervals. This type of a schedule will reduce passenger congestion, help prevent takeoff delays, and reduce the additional congestion if a plane gets delayed.

Device Technology

New technologies are accurate enough to warrant research to perfect their technologies. X-ray diffraction would equal the accuracy of EDS, and increasing research intensity should prove useful, and quadrupole resonance is specialized in detecting potentially explosive materials such as phosphorous.

Cost

Currently, the EDS can scan 3.1 bags per minute. If we could up the rate to 4 bags per minute, the number of required scanners will decrease by at least one. The new technologies would obviously be expensive, but a decrease of even one scanner could decrease the total cost by over $1 million.

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