Advancing Airport Security through Optimization and Simulation

Michelle R. Livesey
Carlos A. Diaz
Terrence K. Williams
Humboldt State University
Arcata, CA

Advisor: Eileen M. Cashman

Summary

Our design team was tasked with developing optimization and simulation models to:

- help the airlines optimally schedule all flight departures within peak hours at two large airports in the Midwest; and
- predict the number of explosives detection systems (EDSs) and explosives trace detection (ETD) machines required at the two airports to examine all passengers' bags departing during a peak hour.

Our optimization model is linked with a genetic algorithm to schedule flight departures optimally for each airport. We use Monte Carlo simulation to generate random data sets for use in a transient stochastic simulation model developed to predict EDS and ETD needs.

The optimization model yields near-optimal flight schedules for peak hours at the two airports. These flight schedules, along with various probabilities associated with passenger arrival, machine processing speeds, and flight seat distributions, were used by the simulation model to predict the number of EDS and ETD machines required: Airport A requires 30 EDS and 12 ETD machines, and airport B requires 34 EDS and 13 ETD machines. More machines would be needed to accommodate multiple peak hours in succession or increased travel in peak seasons.

The UMAP Journal 24 (2) (2003) 141–152.

Review of Literature

Queueing Theory

A queueing model is essentially concerned with the input process and service mechanism of the system [Takacs 1962]. The input process at an airport is a combination of the time when passengers arrive before their departure and the number of bags that a passenger checks. The service mechanism is "first-come, first-served," so the order of bags checked is conserved through the screening process.

Markov Chains

A Markov chain is concerned with discrete time and has the property that "if the present state of the system is known, the future of the system is independent of its past" [Kulkarni 1995]. The state of the system at time $(n+1)$ depends on the system at time n, which depends on the system at time $(n-1)$, and so on until at time zero, the starting point of the system.

Arrival Distributions

Queueing models allow the input process to follow any probabilistic distribution. However, many examples in texts describe the arrival of people as a Poisson process [Takacs 1962; Devore 1995]. The assumption that people arrive following a Poisson process is widely used [Heyman and Sobel 1982]. When the arrival density parameter of the Poisson process is large, the distribution is approximately normal [Devore 1995].

Simulation Models

Simulation queueing models can show the behavior of systems over time [Solomon 1983]. They have been used in the airport industry recently to determine the number of instruments and staff for effective security [Crites 2003]. Simulation models can also take into account the variability of stochastic events, such as passenger arrival distributions and security-screening device operational reliability.

Genetic Algorithms

A genetic algorithm (GA), through its stochastic nature, provides a robust and efficient method for solving difficult optimization problems with large nonlinear search spaces; it generally finds extremely good solutions since it is able to simultaneously search various points of the solution space [Dandy 2001].

Based on the mechanics of natural selection and genetics, GAs randomly generate solutions which are checked for fitness and then utilize genetic processes such as selection, crossover, and mutation to combine the most fit solutions into a new population of solutions. In this manner, highly fit and desirable traits are passed from one generation to the next, supplanting unfit traits in the process. The GA iteratively repeats this process over a number of generations until a near global optimum is achieved.

Methodology and Application

To predict the number of EDS and ETD machines to deploy, we must understand the flow of passengers into the airport. To do so, we develop flight schedules discretizing the peak hour into time steps. Flight scheduling can then be achieved using an optimization model, whose objective is to minimize the variance between the total numbers of passengers departing in each time step while meeting the constraints of departing the correct number of flights of each type within the peak hour.

Scheduling Model

We develop an optimization model to determine flight schedules. We discretize the peak hour into 20 time steps, thereby scheduling flights in 3-min intervals. The configuration and development of the model was tailored to a genetic algorithm software called Generator [New Light Industries 2001]. The multiobjective function, which minimizes the variance between the numbers of passengers departing in each time step and also assigns the correct number of flights of each flight type during the peak hour, is of the form

$$\min z = \sum \frac{(x_i - \bar{x})^2}{n-1} + \sum P_j (y_j - b_j),$$

where

x_i = the number of passengers departing in time step i,

$\bar{x}$ = the average number of passengers departing per time step,

n = the total number of time steps in the peak hour,

P_j = the penalty associated with not meeting constraint for flight type j,

y_j = the number of flights being scheduled for flight type j, and

b_j = actual number of flights leaving airport of flight type j.

The genetic algorithm and optimization model provide near-optimal flight schedules for both airports A and B, so that approximately the same number of passengers depart in any given time interval. The airport security simulation model incorporates the optimization model's output (the flight schedule) to predict the number of EDS and ETD machines required.

Simulation Model

The simulation model requires various data sets (randomly generated via random number generator) to simulate peak hours at each airport:

- normally distributed passenger arrival times, varying from 45 to 120 min prior to departure of peak hour flights;
- normally distributed random variable consisting of the number of filled seats on each flight leaving in the peak hour;
- normally distributed random variable consisting of the EDS and ETD instantaneous machine processing rates;
- uniformly distributed discrete random variable that describes the number of checked bags per passenger;
- uniformly distributed discrete random variable that is used to determine which bags are selected for additional ETD screening.

The simulation model accesses a vector containing the flight schedule to determine the number of each type of flight leaving per time step during the peak hour. It then accesses random variables associated with the filled seat distribution for each flight and sums these values:

$$P_{ij} = \sum_{k=1}^{\text{Sched}_i} \text{FS}_i,$$

where

P_{ij} = number of passengers on all flights of type i leaving in time step j,

Sched_i = the number of flights of flight type i leaving in time step j,

FS = filled seat random variable,

i = flight type, and

j = time step.

The total number of passengers departing during the time step is then calculated by summing the number of passengers on each flight type during that time period:

$$P_{\mathrm{TOT},j} = \sum_i P_{ij},$$

where

P = number of passengers departing in time step,

i = flight type, and

j = time step.

The simulation model then randomly assigns passenger arrival times to all passengers leaving during the peak hour. Assuming that 99.7% of passengers arrive between 45 and 120 min before their departure, the approximate normal distribution of arrival of passengers has a mean of 82.5 min before departure time and a standard deviation of 12.5 min.

Each passenger is assigned a uniformly distributed discrete random variable between 1 and 5. A passenger who receives a 1 is checking zero bags, a passenger who receives a 2 is carrying one bag, and the rest are carrying two bags. The result is a random bag rate at each time step.

For each time step, normally distributed random variables are generated to represent the EDS machine processing speed; this is multiplied by the number of machines to predict the number of bags processed. If that number is greater than the number of bags arriving during that time step, then the bags are processed and the residual is zero bags. Otherwise, the residual is calculated and added to the number of bags arriving in the following time period.

The residual variable represents the number of bags queued by the security machines. A maximum allowable number of bags queued is established using the number of machines, the mean EDS bag-processing speed, and the maximum time allowed for processing a bag. A maximum time of 15 min was used in the simulation. If the number of bags queued ever exceeds the maximum allowable bags queued, a flight could be delayed.

The simulation model was run with ten data sets to produce the effects of ten independent peak hours, and then run in series to simulate ten consecutive peak hours. In the independent peak-hour simulation, the number of bags queued is initially set to zero, assuming that peak hours are scheduled between periods of zero flight departures. In the multiple peak-hour simulation, the passenger and bag arrival phenomena are assumed to follow a Markov process.

ETD Simulation

The independent peak hour simulation was modified to incorporate ETD machines; 20% of the bags processed by the EDSs are flagged for ETD scrutiny. The ETD machine processing speeds, bags queueing, and maximum bags queued are all calculated as described earlier for EDS machines. A maximum allowable queue time of 9 min was used; this implies that bags have 21 min to reach their flights after ETD scanning.

We had hoped to develop the Markov model to incorporate the ETD machines, but time constraints and coding requirements proved prohibitive.

Model Assumptions

- Normal distribution of:
  - passenger arrival time before departure,
  - seats occupied on a plane (unless all full planes were specifically simulated), and
  - detection systems processing rates.
- Bags are processed on a first-come first-served basis.
- EDSs are accessible to all bag check-in locations.
- People who arrive less than 45 min before their plane departure time are turned away and their baggage is not checked.
- For people who arrive more than 120 min before their departure, their bags are not checked until exactly 120 min before their departure.
- The time needed to transfer EDS-screened bags to planes is less than 30 min.
- The time needed to transfer ETD-screened bags to planes is less than 21 min.
- The optimally scheduled time steps within the peak hour are interchangeable, and reorganizing these time steps will not change the outcome of the simulation.
- If the number of bags received during a time step is less than the processing rate for that time period, all of those bags are processed during that time period.
- Flight cancellation is not considered in this simulation; this is justified by the fact that some baggage destined for a canceled flight will have already been checked. This assumption also adds a conservative element.

Results and Discussion

Flight Schedules

Using the genetic algorithm, we determined optimal flight schedules for airports A and B. [EDITOR'S NOTE: We omit the details of the schedules.]

Number of Machines

We used the optimization and simulation models to determine the number of EDS and ETD machines required at airports A and B (see **Table 1**).

Table 1.
Model prediction summary for EDS and ETD machines.

Airport	Flight Status	Machines Required	
A	100% full	37	15
	Varying % full	30	12
B	100% full	40	15
	Varying % full	34	32

Passenger Arrivals

Simulations of the various peak-hour data sets showed slight variations in passenger and checked baggage arrival distributions. **Figure 1** shows superimposed passenger arrival distributions at airport A for all 10 peak hour data sets used in the simulation.

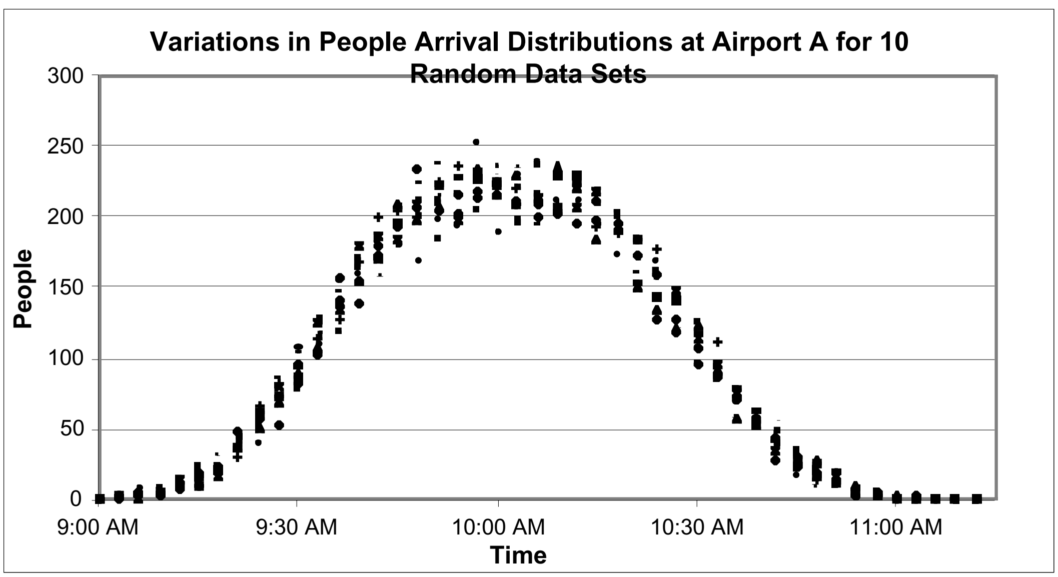

Figure 1. Variations in people arrival distributions at airport A for 10 random data sets.

The peak hour begins at 11:00 A.M., and passengers arrive between 45 and 120 min before their flight according to an approximately normal distribution.

The same normal passenger arrival distribution was observed for airport B. Passenger arrival rates were also normally distributed for airport B, with a slightly higher mean and standard deviation, which explains assigning more machines to airport B.

The simulation model uses passenger and bag arrival probabilities, and EDS and ETD machine processing rate probabilities, to simulate the operational performance of each machine type under peak-hour passenger flows at both airports. **Figure 2** shows some operational performance characteristics of airport A's EDS machines for all ten data sets.

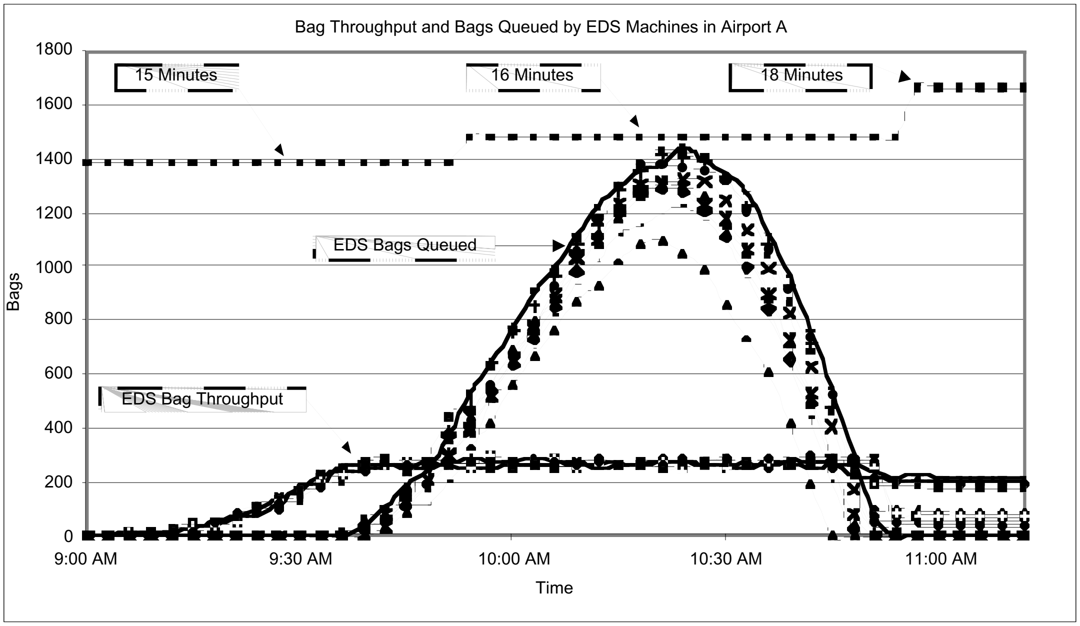

Figure 2. Variability of model response to ten data sets with respect to bag throughput and bags queued by EDS machines in airport A.

EDS BAG Throughput

EDS bag throughput is the number of bags examined and passed by all EDS machines in one time step. The bag throughput increases steadily as more passengers begin to arrive for peak-hour flights, until the machine's operational speed is overcome, at which point bags begin to queue up awaiting examination. The number of bags queued increases steadily as passenger and bag arrivals continue to exceed the processing rate of the EDS machines, but the queue never exceeds the upper limit, denoted by the 15-, 16-, and 18-minute lines **Figure 2**. These lines correspond to the maximum allowable bags queued so that all arrive on time to their planes. When more time is allowed for bag queueing, then the total number of bags allowed to queue increases, apparent in the stepwise increases shown in the graph. Therefore, by requiring passengers to arrive slightly earlier than the current 45 min deadline, the number of EDS and ETD machines required could be reduced.

The simulation model also generates system characteristics for the ETD machines at airport A. These results are shown in **Figure 3**.

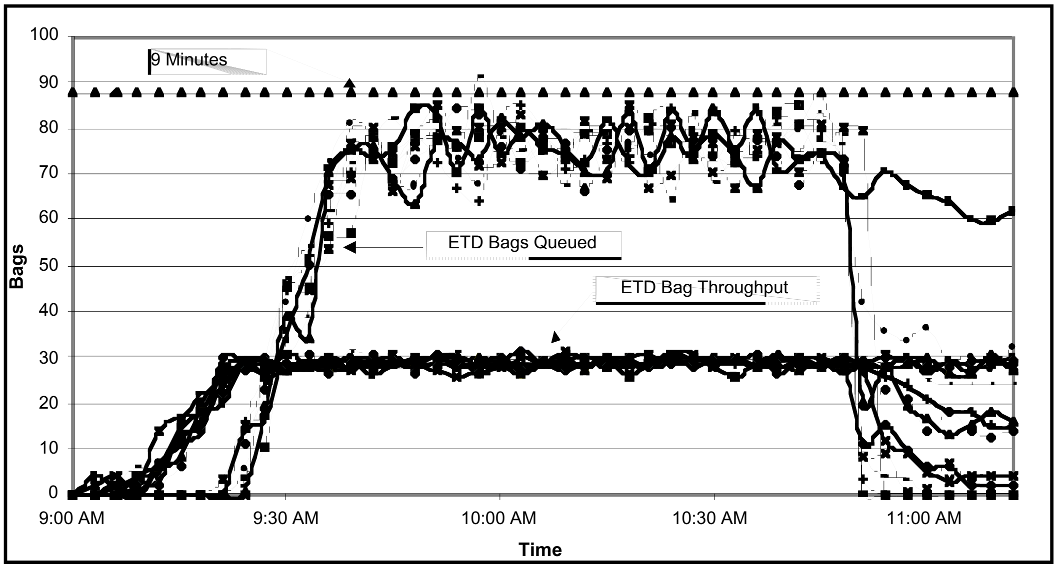

Figure 3. Bag throughput and bags queued by ETD machines in airport A.

The simulation model also predicted the number of EDS and ETD machines required at airport B, with similar results. Since all queued bags are processed within the 15-min allowed time period, no delays will occur with this system, assuming bags can arrive to their planes within 30 min. Bags passing through ETD examination have only 21 min to arrive to their planes.

If time is an issue, passengers could be required to arrive earlier for flights, or additional personnel could be employed to ensure ETD examined bags arrive to their respective planes without delay.

Multiple Peak Hours

In addition to simulating single peak-hour events at both airports A and B, we evaluated the effects of combining 10 peak-hour events in succession. This simulation is representative of days when air traffic does not slow down but remains heavy throughout the day. Since passenger arrivals do not slow down, as in the single peak-hour simulation, we expect to need more machines. Our simulation of multiple peak hours predicts only the number of EDS machines required and does not consider ETD machines. **Table 2** shows the results.

The EDS system performance for multiple peak hours, in which planes' seating capacities vary, is shown in **Figure 4**.

The bag arrival distribution seems to approach a steady-state value that is maintained throughout most of the day. Although the queued bags steadily increase throughout the day, none of these bags exceed the maximum allowable time in queue. Similar results were also obtained for airport B.

Table 2.
Model results for EDS machines for 10 consecutive peak hours.

Airport	Flight Status	EDS Machines Required
A	100% full	38
	Varying % full	31
B	100% full	43
	Varying % full	35

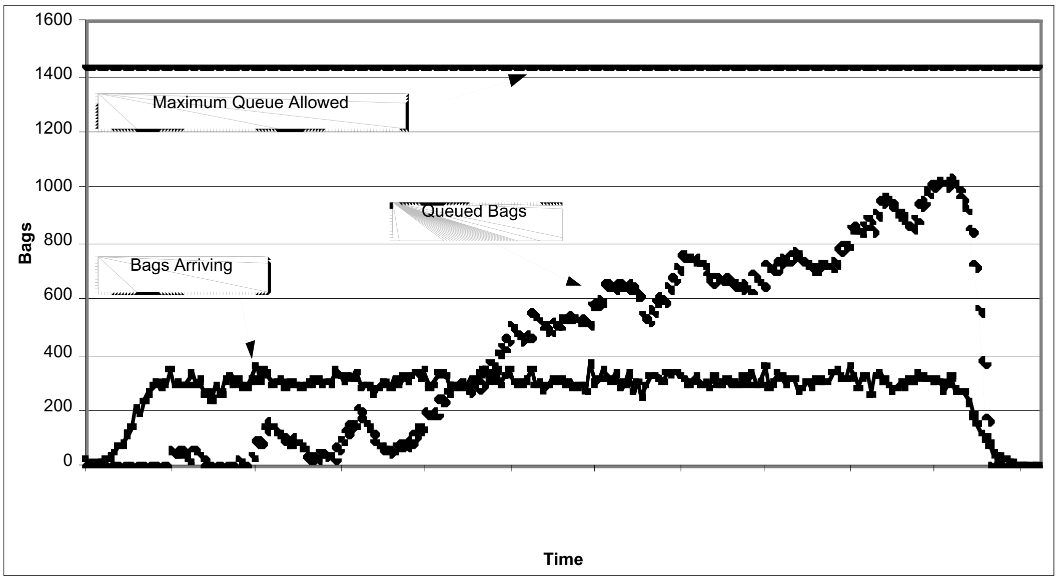

Figure 4. Bag arrival and queued bag distributions over 10 peak hour period in airport A.

Conclusions and Recommendations

- Our optimization model, in conjunction with a genetic algorithm, proved invaluable in developing optimal flight schedules for airports.
- Increasing the number of successive peak hours requires an increase in the number of EDS machines required to prevent flight delays.
- Our simulation model analyzes tradeoffs between changes in technology and their effects on airport security.
- Both EDS and ETD technologies should be employed to provide improved airport security.
- Our optimization and simulation models could easily be applied to the remaining 193 airports in the Midwest region and elsewhere.

References

Cai, X., D.C. McKinney, and L.S. Lasdon. 2001. Solving nonlinear water management models using a combined genetic algorithm and linear programming approach. *Advances in Water Resources* 24 (2001): 667–676.

Crites, Jim, et al. 2003. Simulation modeling plays critical role in designing security. *World Airport Week* 14 (2) (29 January 2003); `http://archives.californiaaviation.org/airport/msg24923.html` .

Dandy, G. C., and M. Engelhardt. 2001. Optimal scheduling of water pipe replacement using genetic algorithms. *Journal of Water Resources Planning and Management* 127 (4): 214–223.

Devore, Jay L. 1995. *Probability and Statistics for Engineering and the Sciences*. 4th ed. Pacific Grove, CA: Brooks/Cole.

Heyman, Daniel P., and Matthew J. Sobel. 1982. *Stochastic Models in Operations Research, Volume I: Stochastic Processes and Operating Characteristics*. New York: McGraw-Hill.

Karp, Aaron. 2002. USA admits it cannot meet 100% explosives screening deadline. *Flight International* (19 November 2002); available through Lexis-Nexis.

Kirby, Mary. 2002. TSA claims success in meeting checked baggage deadline. *Air Transport Intelligence*; available through Lexis-Nexis.

Kulkarni, Vidyadhar G. 1995. *Modeling and Analysis of Stochastic Systems*. London, UK: Chapman and Hall.

Loucks, Daniel P., Jerry R. Stedinger, and Douglas A. Haith. 1981. *Water Resource Systems Planning and Analysis*. Englewood Cliffs, NJ: Prentice-Hall.

New Light Industries. 2001. Generator. `http://www.nli-ltd/products/genetic_algorithms/generator.htm` .

Nyhoff, Larry and Sanford Leestma. 1997. *Fortran 90 for Engineers and Scientists*. Upper Saddle River, NJ: Prentice-Hall.

Osaki, Shunji. 1985. *Stochastic System Reliability Modeling*. Philadelphia, PA: World Scientific Publishing.

Pagas, Alain, and Michel Gondran (E. Griffin, trans.). 1986. *System Reliability: Evaluation and Predictability in Engineering*. London, UK: North Oxford Academic Publishers.

Properties Energetic Materials. TNO Prins Maurits Laboratory Website. `http://www.pml.tno.nl/en/em/detection.html` .

Rade, Lennart. 1994. The art of simulation. *European Journal of Engineering Education*. 19 (1): 7–14.

Sohn, So Young. 2002. Robust design of server capability in $M/M/1$ queues with both partly random arrival and service rates. *Computers and Operations Research* 29 (5) 433–440; available through Dialog.

Solomon, Susan L. 1983. *Simulation of Waiting-Line Systems*. Englewood Cliffs, NJ: Prentice-Hall.

Takacs, Lajos. 1962. *Introduction to the Theory of Queues*. New York: Oxford University Press.

Willis, Robert, and Brad A. Finney. 2000. *Environmental Systems Engineering and Economics*. Unpublished.