The UMAP Journal

Vol. 24, No. 2

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Editorial

Environmental Modeling: Not Just a Senior Elective Any More

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How much do you believe in the usefulness of mathematics? How well do your students concur? How much does their level of belief affect whether they choose to major in mathematics? How can you help up their level of belief?

Students who arrive at college already bent on a career in engineering or physical science need no further convincing—they have already been converted to the "religion" of applied mathematics. The faith of other students, including those fascinated with or intrigued by mathematics as an art, may be much weaker. Calculus, commonly taught as pure mathematics, by pure mathematicians, may weaken faith in applicability of mathematics rather than strengthen it.

Over the last 25 years, mathematics departments have introduced courses in mathematical modeling, usually as a senior elective and taken only by mathematics majors. Such courses tend to be annual tent revivals that attract the already-fervent. They are too little, too late; they miss major audiences whom we should strive to reach much earlier in their education, in particular

- students who take just one mathematics course in college,
- potential mathematics majors, and
- women.

COMAP's college text *For All Practical Purposes* [COMAP 2003] is aimed directly at the first group and has reached half a million students over the last 15 years. Meanwhile, over the entire 25 years, COMAP has developed an immense amount of material for demonstrating the applicability of mathematics and mathematical modeling at all levels, from grade school through college, including an entire high school mathematics text series. Much of that material has appeared in this *Journal* and been used by instructors with the second group above.

Yet the proportion of women in applied mathematics remains low. Why? A new longitudinal study suggests that "Girls shy away from careers in math not because they lack the skills. They just don't see math as useful." According to Jacquelynne Eccles, Professor of Psychology and Women's Studies at the University of Michigan's Institute for Research on Women and Gender,

> Girls do tend to underestimate their math ability in high school... But that's not what pushes them away from mathematically based majors. There are two key factors in that decision: how much they believe in the ultimate utility of mathematics, and how much they value working with, and for, people.... Boys' beliefs and values are pulling them toward [math-based majors and careers] while girls' are pushing them in other directions. [Becker 2003].

How can we "evangelize" this group?

- To show how mathematics works *for* people, focus on **environmental modeling.**

- To increase the experience of working *with* people, teach the course in a **"studio" format**: have students work in teams on projects, as in COMAP's Interdisciplinary and Mathematical Contests in Modeling.

- To emphasize the utility of mathematics, teach the mathematics involved in a **"just in time" spirit.** This is the opposite of the senior modeling elective, for which the students spend three year preparing before seeing where applications may lie.

- Teach mathematical modeling **earlier.** Courses in finite mathematics, liberal arts mathematics, and quantitative literacy can all be redirected toward a modeling spirit; and mathematics departments should consider a mainline mathematics course in modeling at the freshman or sophomore level. Apart from COMAP's own materials, there are now abundant others [Banks 1998, 1999; Fusaro and Kenschaft 2003; Giordano et al. 2003; Hadlock 1998; Kalman 1997; Mooney and Swift 1999]. With the help of dynamical modeling software, quite sophisticated modeling can be done without prior background in calculus or differential equations [Campbell 1996].

Mathematical modeling is a great way to show both that mathematics is useful and furthermore that *students themselves can use it to answer questions of interest to them*. Why deprive mathematics majors of this experience until their senior year and most other students altogether?

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About the Author

Paul Campbell graduated summa cum laude from the University of Dayton and received an M.S. in algebra and a Ph.D. in mathematical logic from Cornell University. He has been at Beloit College since 1977, where he served as Director of Academic Computing from 1987 to 1990. He is Reviews Editor for *Mathematics Magazine* and author of the annual articles on mathematics for the Encyclopædia Britannica yearbooks. He has been editor of *The UMAP Journal* since 1984.

Modeling Forum

Results of the 2003 Interdisciplinary Contest in Modeling

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Introduction

A total of 146 teams of undergraduates, from 84 institutions in 6 countries, spent the second weekend in February working on an applied mathematics problem in the 5th Interdisciplinary Contest in Modeling (ICM).

This year's contest began at 8:00 P.M. (EST) on Friday, Feb. 6, and ended at 8:00 P.M. (EST) on Monday, Feb. 10. During that time, the teams of up to three undergraduates or high-school students researched and submitted their solutions to an open-ended interdisciplinary modeling problem involving the coordination and management of airport security. After a weekend of hard work, solution papers were sent to COMAP.

The five papers judged to be Outstanding appear in this issue of *The UMAP Journal*. Results and winning papers from the first four contests were published in special issues of *The UMAP Journal* in 1999 through 2002.

In addition to the ICM, COMAP also sponsors the Mathematical Contest in Modeling (MCM), which runs concurrently with the ICM. Information about the two contests can be found at

`www.comap.com/undergraduate/contests/icm`
`www.comap.com/undergraduate/contests/mcm`

The ICM and the MCM are the only international modeling contests in which students work in teams to find a solution.

The UMAP Journal 24 (2) (2003) 97–110.

Centering its educational philosophy on mathematical modeling, COMAP uses mathematical tools to explore real-world problems. It serves the educational community as well as the world of work by preparing students to become better informed and better-prepared citizens, consumers, and workers.

This year's problem, the Airport Security Problem, which involved understanding, analyzing, and managing baggage screening and flight scheduling at U.S. airports, proved to be particularly challenging in that it contained various data sets to be analyzed, several challenging requirements needing scientific and mathematical connections, and also the ever-present requirements to use creativity, precision, and effective communication. The authors of the problem, operations research analysts and engineers Sheldon Jacobson and John Kobza, were members of the final judging team and their commentary appears in this issue.

All the competing teams are to be congratulated for their excellent work and dedication to scientific modeling and problem solving. This year's judges remarked that the quality of the papers was extremely high, making it difficult to choose the five Outstanding papers.

In 2003 the ICM continued to grow as an online contest, where teams registered, obtained contest instructions, and downloaded the problem through COMAP's ICM Website.

Problem: The Airport Security Problem

Aviation Baggage Screening Strategies: To Screen or Not to Screen, That Is the Question

You are an analysis team in the Office of Security Operations for the Transportation Security Administration (TSA), responsible for the Midwest Region of the United States. New laws will soon mandate 100% screening of all checked bags at the 429 passenger airports throughout the nation by explosive detection systems (EDSs; see Figure 1). EDSs use computed tomography (CT) technology to scan checked bags, similar to how CAT scans are used in hospitals. Using multiple x-rays of each bag, EDSs create three-dimensional images of a bag's content showing the density of each item. This information is utilized to determine whether an explosive device is present. Experimentation with EDSs indicate that each device is operational about 92% of the time and each device can examine between 160 and 210 bags per hour.

The TSA has been actively purchasing EDSs and deploying them at airports throughout the nation. Given that these devices cost nearly $1 million each, weigh as much as eight tons, and cost several thousand dollars to install in an airport, determining the correct number of devices to deploy at each airport and how best to use them (once operational) are important problems.

Currently, manufacturers are not able to produce the expected number of EDSs required to meet the federal mandate of 100% screening of checked luggage. Because of the limited number of EDS machines available, the Director of Airport Security for the Midwest Region (Mr. Sheldon) is not surprised that the TSA is requesting a detailed analysis on the estimated number of EDSs required at all airports. In addition, given the limited space and funds available for each airport, Mr. Sheldon believes that at some point a detailed analysis of emerging technologies will be needed. Promising technologies with more modest space and labor costs will emerge in the coming decade (e.g., x-ray diffraction; neutron-based detection; quadropole resonance; millimeter wave imaging; and microwave imaging).

Task 1

You have been tasked by your Director, Mr. Sheldon, to develop a model to determine the number of EDSs required at two of the largest facilities in the region, Airports A and B, which are described in the Technical Information Sheet (TIS) in **Appendix A**. Carefully describe the assumptions that you make in designing the model and then use your model to recommend the number of EDSs required using the data provided in **Table 1** of the TIS.

Task 2

Prepare a short (one-page) position paper to accompany your model that describes the security-related objectives of the airlines and the constraints that the airlines must work within for the sets of flights described in **Table 1** of the TIS.

Task 3

Since security screening takes time and might delay passengers, the airport managers at Airport A and B request that you develop a model that can help the airlines determine how to schedule the departure of different types of flights within the peak hour. Carefully describe all the assumptions that you make in designing the model and use your model to produce a schedule for the two airports with the data provided in **Table 1**.

Task 4

Based on your analysis, what can you recommend to Mr. Sheldon and the airlines about checked baggage screening for the flights during the peak hours at your two airports?

Task 5

Mr. Sheldon realizes that your work may have national impact and requests that you write a memo explaining how your models can be adapted to determine the number of EDSs and airline scheduling for all 193 airports in the

Midwest Region. He will send the memo along with the models and the analysis to the Director of the Office of Security Operations (his boss) at the TSA and to all security directors of other airports in the region for their comment and possible implementation.

Additional security measures associated with higher risks may require that up to 20% of the passengers will need to have all their checked bags screened through both an EDS and an explosive trace detection (ETD) machine, even though an EDS is 98.5% accurate in identifying explosive devices in checked bags. ETD machines use mass spectrometry technology to detect minute particles of explosive compounds. Each ETD machine costs $45,000 to purchase, however, the labor cost to operate the ETD machine is approximately 10 times that of the EDS. ETD can process 40 to 50 bags per hour; they are operational 98% of the time; and they are 99.7% accurate in identifying explosive materials on checked bags. At this time, ETD machines have not been federally certified, but Mr. Sheldon believes that they will soon be an integral part of national airport security systems.

Task 6

Modify your EDS models to incorporate the use of ETD machines and determine how many ETD machines are needed for Airports A and B and if the schedules need to be changed. Since this information may affect national level decisions, write a memo to the Director of Homeland Security and the Director of TSA with a technical analysis of this enhanced screening policy. Is the cost of such a policy justified in light of the value that it provides? Should the ETDs replace any of the EDS devices?

Task 7

The Director of Homeland Security must also decide how to best fund future scientific research programs. Use your EDS/ETD model to examine the possible effect of changes in the device technology, cost, accuracy, speed, and operational reliability. Include recommendations for the science, technology, engineering, and mathematics (STEM) research areas that will have the biggest impact on security system performance. Add your recommendation to the memo prepared in Task 6.

Appendix A: Technical Information Sheet (TIS)

Although all the flights in **Table 1** depart during a peak hour, their actual departure times are set by the airline when designing their flight schedule. A flight cannot depart until all its checked bags are screened using an EDS. The airline has the flexibility to schedule their flights during the peak hour to avoid undesirable flight delays due to unscreened bags.

Historical data indicates that flights with 85 or fewer seats typically fly with between 70% and 100% of their seats occupied. Flights with between 128 and

Table 1.
Peak-hour flight departures for airports A and B. Note: On average, 2% of flights are cancelled each day.

Type	Seats/flight	Airport A	Airport B
1	34	10	8
2	46	4	6
3	85	3	7
4	128	3	5
5	142	19	9
6	194	5	10
7	215	1	2
8	350	1	1

215 seats typically fly with between 60% and 100% of their seats occupied. Flights with 350 seats typically fly with between 50% and 100% of their seats occupied. Passengers typically arrive for their flight between forty-five minutes and two hours prior to their scheduled departure time. For flights other than shuttles service, airlines claim that 20% of the passengers do not check any luggage, 20% check one bag, and the remaining passengers check two bags.

Preliminary estimates indicate that it will cost $100,000 to modify existing infrastructure (reinforced flooring, etc.) to install each EDS at Airport A and $80,000 to install a device at Airport B.

Figure 1. Explosive Detection System (EDS).

The Results

Solution papers were coded at COMAP headquarters so that names and affiliations of authors would be unknown to the judges. Each paper was read preliminarily by two "triage" judges at the U.S. Military Academy at West Point, NY. At the triage stage, the summary and overall organization are the basis for judging a paper. If the judges' scores diverged for a paper, the judges conferred; if they still did not agree on a score, a third judge evaluated the paper.

Final judging took place at the United States Military Academy, West Point, NY. The judges classified the papers as follows:

	Outstanding	Meritorious	Honorable Mention	Successful Participation	Total
Airport Security	5	19	60	62	146

The five papers that the judges designated as Outstanding appear in this special issue of *The UMAP Journal*, together with commentaries by the authors and by one of the judges. We list those teams and the Meritorious teams (and advisors) below; the list of all participating schools, advisors, and results is in the **Appendix**.

Outstanding Teams

Institution and Advisor	**Team Members**
"Airport Baggage Screening: Optimizing the Implementation of EDS Machines"	
Carroll College	Gary Allen Olson
Helena, MT	Kylan Neal Johnson
Mark R. Parker	Joseph Paul Rasca
"How I Learned to Stop Worrying and Find the Bomb"	
Harvey Mudd College	Tara Martin
Claremont, CA	Gautam Thatte
Hank Krieger	Michael Vrable
"Advancing Airport Security through Optimization and Simulation"	
Humboldt State University	Michelle R. Livesey
Arcata, CA	Carlos A. Diaz
Eileen M. Cashman	Terrence K. Williams

"The Price of Security:
A Cost–Benefit Analysis of
100% Screening of Checked Baggage"
United States Military Academy
West Point, NY
Michael J. Johnson

Kyle Andrew Greenberg
Tate Alan Jarrow
Michael Alan Powell

"Feds with EDS: Searching for the
Optimal Explosive Scanning System"
Wake Forest University
Winston-Salem, NC
Bob Plemmons

Robert T. Haining
Dana M. Lindemann
Neal P. Richardson

Meritorious Teams (19 teams)

Asbury College, Wilmore, KY (Duk Lee)
Beijing Northern Jiaotong University, China (Yingdong Liu)
Beijing University of Posts and Telecommunications, China (Shoushan Luo)
Chongqing University, China (Xiaofan Yang)
Elon University, Elon, NC (Crista Coles)
Harbin Institute of Technology, China (Kean Liu)
Harvey Mudd College, Claremont, CA (Hank Krieger)
Jinan University, China (Daiqiang Hu)
Maggie Walker Governor's School, Richmond, VA (Martha Hicks)
Olin College of Engineering, Needham, MA (Michael Moody)
School of Peking University, China (Yulong Liu)
Trinity University, San Antonio, TX (Allen Holder)
United States Military Academy, West Point, NY (Elizabeth Schott)
United States Military Academy, West Point, NY (Christopher Farrell)
University College Dublin, Ireland (Rachel Quinlan)
University of Science and Technology of Hefei, China (Hong Zhang)
University of Virginia, VA (Julian Noble)
Wake Forest University, Winston-Salem, NC (Hugh Howards)
Zhejiang University, China (Yong He)

Awards and Contributions

Each participating ICM advisor and team member received a certificate signed by the Contest Directors and by the Head Judge. Additional awards were presented to the Humboldt State University team from Institute for Operations Research and the Management Sciences (INFORMS).

Judging

Director
Chris Arney, Dean of the School of Mathematics and Sciences,
The College of Saint Rose, Albany, NY

Associate Directors
Michael Kelley, Dept. of Mathematical Sciences, U.S. Military Academy,
West Point, NY
Gary W. Krahn, Dept. of Mathematical Sciences, U.S. Military Academy,
West Point, NY

Judges
Richard Cassidy, Dept. of Industrial Engineering, University of Arkansas,
Fayetteville, AR
John Kobza, Dept. of Industrial Engineering, Texas Tech University,
Lubbock, TX
Sheldon Jacobson, Dept. of Mechanical and Industrial Engineering,
University of Illinois, Urbana, IL
Frank Wattenberg, Dept. of Mathematical Sciences, U.S. Military Academy,
West Point, NY

Triage Judges
Mike Arcerio, Gabe Costa, Eric Drake, Bill Felhman, Jeff Flemming, Andy Glen, Paul Goethals, Alex Heidenberg, Denise Jacobs, Alan Johnson, Gary Krahn, Rich Laverty, Tom Lainis, Barb Melendez, Chris Moseley, Joe Myers, Mike Phillips, Bart Stewart, Frank Wattenberg, Brian Winkel, Robbie Williams, and Shaw Yoshitani, all of the U.S. Military Academy, West Point, NY.

Source of the Problem

The Airport Security Problem was contributed by Sheldon Jacobson (Dept. of Mechanical and Industrial Engineering, University of Illinois, Urbana, IL) and John Kobza (Dept. of Industrial Engineering, Texas Tech University, Lubbock, TX).

Acknowledgments

Major funding for the ICM is provided by a grant from the National Science Foundation through COMAP. Additional support is provided by the Institute for Operations Research and the Management Sciences (INFORMS).

We thank:

- the ICM judges and ICM Board members for their valuable and unflagging efforts, and
- the staff of the Dept. of Mathematical Sciences, U.S. Military Academy, West Point, NY, for hosting the triage judging and the final judging.

Cautions

To the reader of research journals:

Usually a published paper has been presented to an audience, shown to colleagues, rewritten, checked by referees, revised, and edited by a journal editor. Each of the student papers here is the result of undergraduates working on a problem over a weekend; allowing substantial revision by the authors could give a false impression of accomplishment. So these papers are essentially au naturel. Light editing has taken place: minor errors have been corrected, wording has been altered for clarity or economy, style has been adjusted to that of *The UMAP Journal*, and the papers have been edited for length. Please peruse these student efforts in that context.

To the potential ICM Advisor:

It might be overpowering to encounter such output from a weekend of work by a small team of undergraduates, but these solution papers are highly atypical. A team that prepares and participates will have an enriching learning experience, independent of what any other team does.

Editor's Note

As usual, some of the Outstanding papers were several times as long as we can accommodate in the *Journal*; so space considerations forced me to edit the Outstanding papers for length. The code and raw output of computer programs is omitted, the abstract is often combined with the summary, and usually it is not possible to include all of the many tables and figures.

For the Airport Security Problem, the memos of Tasks 2, 5, and 7 from most papers are largely omitted as such and their modeling content folded into the text. Although these memos provide valuable summaries, they do not contain modeling and tend to duplicate conclusions reached in other sections.

In all editing, I endeavor to preserve the substance and style of the paper, especially the approach to the modeling.

—Paul J. Campbell, Editor

Appendix: Successful Participants

KEY:
P = Successful Participation
H = Honorable Mention
M = Meritorious
O = Outstanding (published in this special issue)

INSTITUTION	CITY	ADVISOR	I
ALABAMA			
Athens State University	Athens	M. Leigh Lunsford	P
CALIFORNIA			
California State Polytechnic University	Pomona	Jennifer Switkes	P
Harvey Mudd College	Claremont	Arthur Benjamin	H
		Hank Krieger	O, M
Humboldt State University	Arcata	Eileen M. Cashman	O
Sonoma State University	Rohnert Park	Elaine T. McDonald	P
COLORADO			
Regis University	Denver	Jim Seibert	H, P
University of Colorado	Boulder	Bengt Fornberg	H
ILLINOIS			
Monmouth College	Monmouth	Christopher G. Fasano	P
INDIANA			
Earlham College	Richmond	Mic Jackson	P
KENTUCKY			
Asbury College	Wilmore	David L. Coulliette	H
		Duk Lee	M, H
Bellarmine University	Louisville	William J. Hardin	H
Northern Kentucky University	Highland Heights	Phillip H. Schmidt	H
MASSACHUSETTS			
Olin College of Engineering	Needham	Michael E. Moody	M
MICHIGAN			
East Grand Rapids Public Schools	Grand Rapids	Mary Elderkin	P
Lawrence Technological University	Southfield	Howard Whitston	H
		Ruth Favro	P
MINNESOTA			
Bemidji State University	Bemidji	Colleen G. Livingston	H
MISSOURI			
University of Missouri-Rolla	Rolla	Mohamed Ben Rhouma	M
MONTANA			
Carroll College	Helena	Holly S. Zullo	H
		Mark R. Parker	H

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Sierra Nevada College	Incline VIllage	Charles Levitan	P
NEW JERSEY			
Rowan University	Glassboro	Hieu D. Nguyen	P
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Concordia College	Bronxville	John Loase	H, H
Nazareth College	Rochester	Nelson G. Rich	P
Saint Bonaventure College	Olean	Albert G. White	P
U.S. Military Academy	West Point	Christopher M. Farrell	M
		Elizabeth W. Schott	M
		Michael J. Johnson	O
NORTH CAROLINA			
Appalachian State University	Boone	Eric S. Marland	H
Elon University	Elon	Crista Coles	M, P
N.C. School of Science and Mathematics	Durham	Dot Doyle	P
Wake Forest University	Winston-Salem	Bob Plemmons	O
		Edward E. Allen	P
		Hugh N. Howards	M
OHIO			
Ohio Wesleyan University	Delaware	Richard S. Linder	H
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		Michael Crescimanno	P
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Maggie Walker Governor's School	Richmond	Martha A. Hicks	M, H
University of Virginia	Charlottesville	Julian Victor Noble	M
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Washington State University	Pullman	V.S. Manoranjan	P
WISCONSIN			
Beloit College	Beloit	Paul J. Campbell	P

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		Zhang Bao Xue	P
Beijing Northern Jiaotong University	Beijing	Liu Yingdong	M
Beijing University of Chemical Technology	Beijing	Liu Damin	H
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		Zhao Xuanmmin	P
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Editor's Note

For team advisors from China, we have endeavored to list family name first.

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

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

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

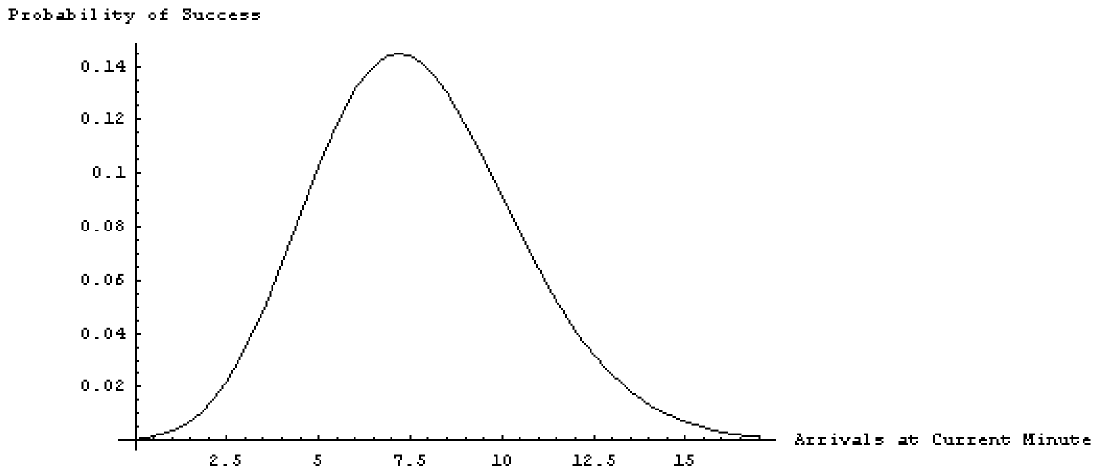

Figure 1. Graph of continuous approximation to a Poisson distribution with arrival rate $\lambda = 7.7$ people/min. The peak of the curve is at approximately $(7.5, 0.15)$

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**.

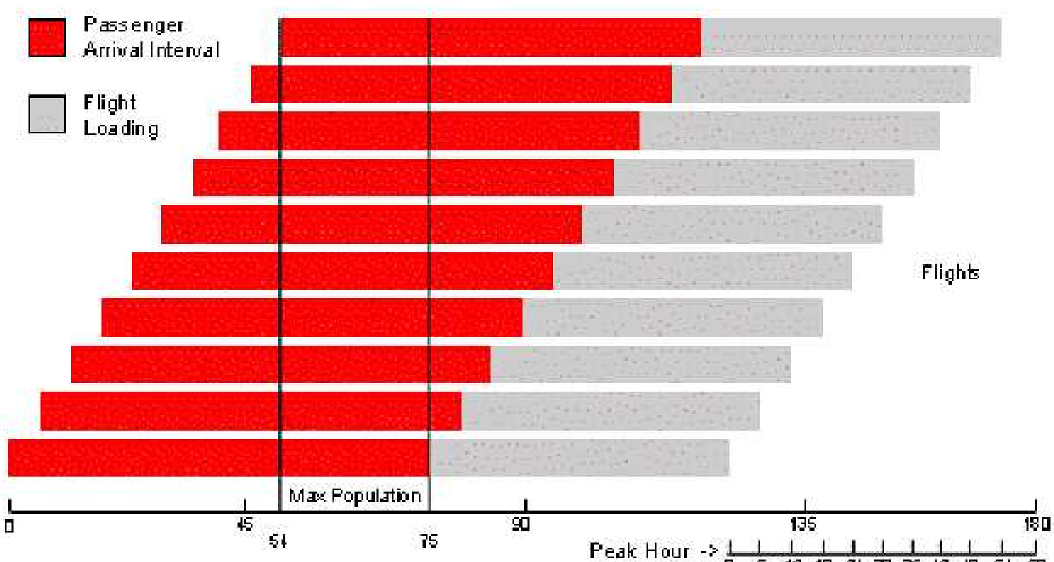

Figure 2. Results of 10 simulations.

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.

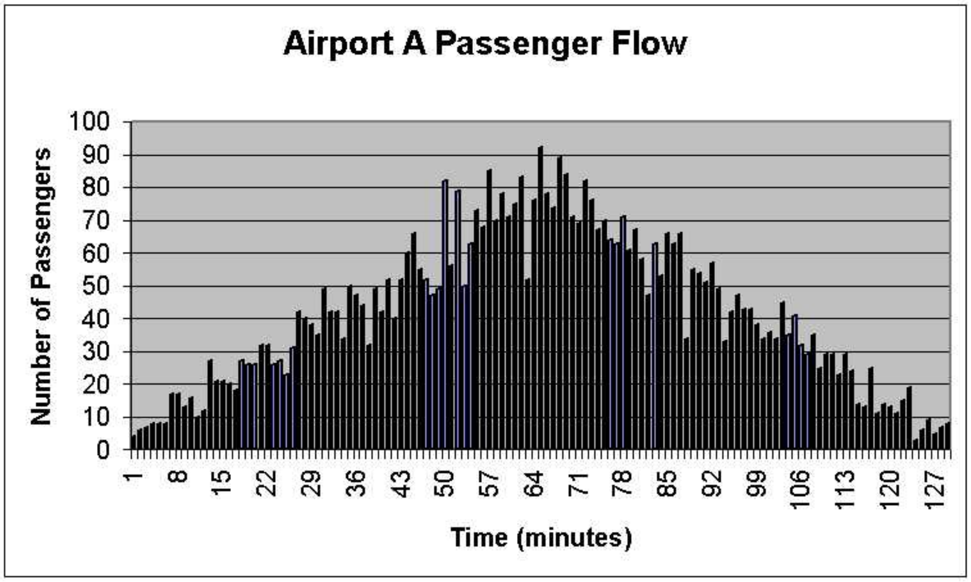

Figure 3. Minute-by-minute passenger report at airport A.

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
	142	142	142	142	142	142	194	194	215	350
Specific	142	142	142	142	142	142	142	194	194	194
flight	142	142	142	142	85	128	142	142	128	
capacity	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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How I Learned to Stop Worrying and Find the Bomb

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Summary

We develop a queueing system model to determine the optimal number of Explosive Detection System (EDS) and Explosive Trace Detection (ETD) machines to implement 100% baggage screening for airports A and B. We test the model with data from United Airlines at Denver International Airport.

The particular queue system implementation does not affect queue length but can affect the quantity of late bags and length of delay. Our two-queue system model is 92% as efficient as an optimal priority queue, so a complex queueing system is not required. If the system can handle peak-hour volumes, there will be no delays during the rest of the day.

We also compare three flight-scheduling algorithms for peak-hour flight departures and create flight schedules for airports A and B. Optimal scheduling of peak-hour flights does not significantly change the number of machines needed, although use of a greedy algorithm reduces late bags.

To meet the 100% baggage screening requirement using EDSs, we recommend 10 for airport A, 11 for B, and 48 for United Airlines at Denver. These conservative estimates account for breakdowns and a safety margin. To replace EDSs, four times as many ETDs are needed.

Initial cost of implementation at airports A and B is $22.9 million. This cost could be lowered by speeding the approval of cheaper and faster technologies such as dual-energy X-ray, multiview tomography, and quadrupole resonance.

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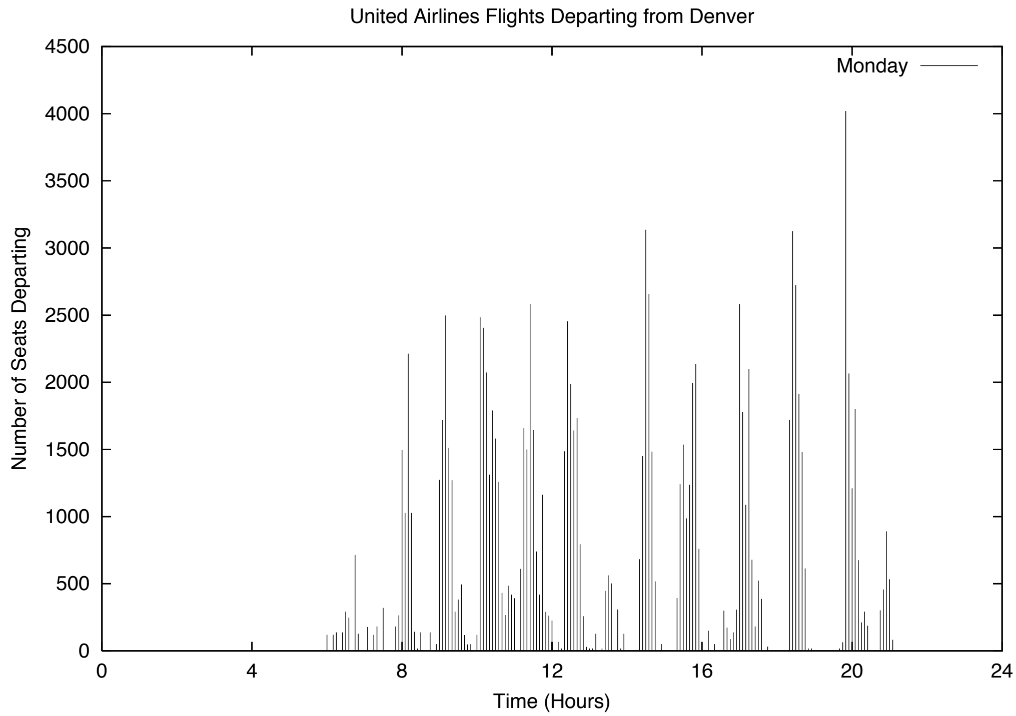

Figure 1. Flight departures from Denver by United Airlines during a single day.

Baggage Screening Queueing Models

We construct a queueing model of the screening baggage for explosives and test it with many more bags than it was designed to handle. Sample loads include peak-hour traffic at airport A and at airport B and a flight schedule modeled after traffic patterns at Denver International Airport. The raw data for the Denver simulation, summarized in **Figure 1**, consists of 991 nonstop flights on a typical Monday, as taken from a United Airlines timetable [United Airlines 2003].

Terminology

Queueing System. A system for storing bags that arrive before a screening machine can take them. The order in which the bags are removed depends on the type of queueing system. Queueing systems are described by their input, queue discipline, and service mechanism.

Queue. A system for storing bags which is first-in, first-out—that is, bags that arrive first are the first to be screened. A single queueing system might be composed of multiple queues.

Input. The *input* describes how the bags enter the system. In our model, the rate at which bags arrive varies during the day.

Queue discipline. The *queue discipline* describes how arriving bags are served, such as first-in, first-out.

Service mechanism. The *service mechanism* tells how the bags are assigned to *servers* (screening machines) as they leave the queue. Our model allows for many servers; in the case of multiple queues, the service mechanism specifies how machines are matched up with queues to process bags.

Formulation of the Model

We compute a schedule for the arrival of passengers and baggage. This baggage arrival schedule is left fixed irrespective of changes we make to the baggage queueing system to determine whether bags make it to flights on time. Our goal is a model that determines how long each bag is delayed and hence suggests an appropriate number of machines required for a specified load.

We make a number of simplifying assumptions:

- **The time required to screen a bag is short.** Any delay in delivery of the bag is due entirely to waiting for screening, not to the screening itself. This assumption allows us to disregard many distinctions among different screening machines; only the rate of screening is important.

- **Discretizing time does not introduce a large error.** Our simulation proceeds in small discrete time steps. This time step, denoted T (usually 2 min), is small in comparison to the time available for screening a bag, so rounding times to the nearest multiple of the time-step does not cause a large error.

- **Screening of a bag must be completed by some fixed time before its flight departs;** we use 10 min. A bag that does not meet this deadline is *late*.

- **Baggage screening, not check-in or other processes, is the only bottleneck.** Passengers do not encounter another bottleneck before baggage screening, such as a long line to check in, that affects the flow of bags into the screening system. This assumption allows us to consider the worst-case scenario of unlimited baggage inflow and to isolate the effects of the screening system from other airport influences.

- **It is not necessary to consider multiple separate screening systems at an airport;** if all are independent and approximately equally loaded, then the system behaves as a single system.

- **Baggage is processed at a constant rate.** We do not allow for oversized baggage or other variations that affect processing time of bags but assume these are included in the averages.

Our model is a *queueing system* [Prabhu 1997]. The input is a list of bags that arrive at each time step; the bags are grouped according to how much time they are allowed before they must be finished with the screening process. A fixed number of servers each can process a fixed number of bags in any time step.

General Analysis

Our queueing model can be described by several parameters:

- The *service rate* S (bags/time-step) is the rate at which machines can process bags at full efficiency.
- The *input rate* $\lambda(t)$ (bags/time step) is the number of bags added to the queueing system at time t.

Regardless of implementation, the number of bags in the queueing system at any time is determined only by S and $\lambda(t)$. The implementation of the queueing system can affect the order in which bags are removed from the queueing system, not the number in it.

The total number of bags in the queueing system at time t, denoted $Q(t)$, is determined by

$$Q(t+T) = \max\{0, Q(t) + \lambda(t) - S\}.$$

If $\lambda(t) > S$, the number of bags in the queueing system increases; if $\lambda(t) < S$, the number of bags shrinks. **Figure 2** shows the bag input rate $\lambda(t)$ at the Denver airport in our model. The dashed horizontal line shows the service rate S for 36 EDS machines operating at 180 bags/h. The solid line shows the number of bags in the queueing system $Q(t)$, which increases when $\lambda(t) > S$. Approximately 52 EDS machines would be required to prevent a backlog of bags from ever building up.

Queue Disciplines and Service Mechanisms

We analyze several mechanisms for controlling how bags are stored in the queueing system before screening and later removed from it. These mechanisms have a large impact on the timely screening of bags, so choosing an appropriate mechanism is important.

Naive Model

We first develop a simple model to give an upper bound estimate on the number of EDS machines we need, using the assumptions:

- The hour before the peak-hour has significant traffic.
- The minimum number of machines is the number to ensure that no flight is delayed.

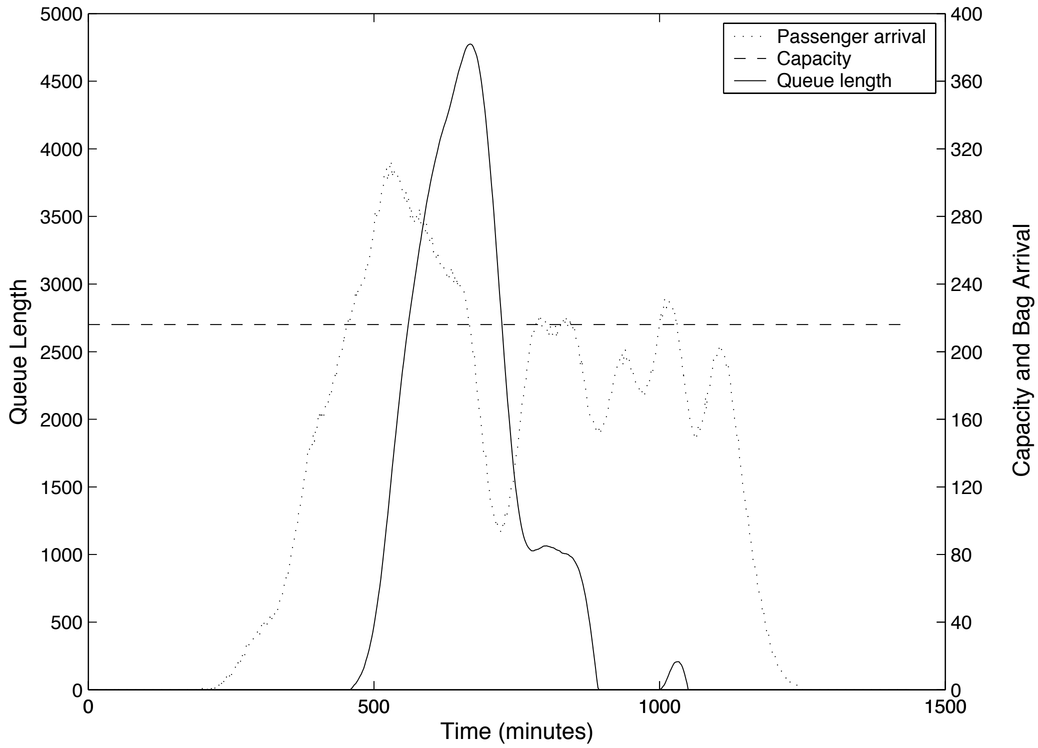

Figure 2. Bag arrival rate and number of bags in queueing system at Denver airport, assuming 36 EDS machines processing 180 bags/h.

- All bags arriving for a peak hour flight are processed in one hour.
- Bags for a flight are computed using parameters in the problem statement.

Bags arriving for peak-hour flights must be processed within a 1-h time period. Our model suggests that 34 and 37 EDS machines are required for airports A and B, respectively, and 55 for Denver International Airport. We believe that these are upper bounds. Any optimization in the passenger arrival model or the organization of people at the airport would probably achieve the same 100% success rate but with fewer machines.

Optimal Queueing

We develop an optimal queueing system that bounds the performance of any queueing system and compare various queueing models to this optimum.

We minimize the total amount of time by which bags are late.

Our optimal queueing system uses a priority queue: As bags arrive, they are added to a pile. When a bag is to be processed, we pick the bag that needs to be finished soonest.

In the Denver simulation with an optimal queue, 35 EDSs operating at 180 bags/min each are sufficient to process all bags before their deadlines. The queue fills with up to nearly 5,500 bags at one point (26 min of uninterrupted processing is required to screen all of these).

Practical implementation of such an optimal priority queue at an airport would be too complicated. Thus, we look at other less-complex queueing systems.

Single Queue

In a single first-in, first-out queue, bags that arrive earlier are screened earlier. This scheme could be implemented with a single conveyor belt carrying bags from check-in to machines.

As long as bags can be screened quickly enough that a significant line never develops, this scheme works well. We find that 47 EDS machines at Denver suffice to deliver all bags on time; this is 34% more than required by the optimal solution.

If bags must be finished screening at least 10 min before departure, then to guarantee that all bags arriving at least 30 min before the flight are processed in time, the wait must never grow to more than 20 min. In the Denver simulation, this can be done with 38 EDS machines; approximately 0.75% of all bags arrive within 30 min of departure and are delivered late.

This single-queue system does not perform very well under load. As the queue increases in length, the chance of processing a bag late rises quickly. Although most bags arrive with more than an hour that they could wait, the few bags with less time available forces the queue length to be kept small at all times. Many bags are processed much more quickly than necessary so that the few bags that need rapid processing are not late. This situation is not optimal, and it is improved by our next queueing model.

Double Queue Model

Giving preferential treatment to some bags can produce a better queueing system. In particular, bags that arrive late should be processed more quickly. We propose a two-queue system consisting of two first-in, first-out queues for bags of different priority: A normal queue is used for bags that arrive sufficiently early and a rush queue for bags that do not arrive as early.

The total throughput of the system is not increased, but bags are much more likely to be processed before their deadline. In effect, time is borrowed from bags that have it (by placing them in a slower queue) and given to those that need it (by allowing them to jump ahead of bags in the normal queue), approximating the optimal queue discipline. The number of machines can be decreased, resulting in longer lines but without causing bags to be processed late, and also in significant cost savings.

The double queue model requires several implementation decisions:

The method for sorting bags into the two queues (the queue discipline). The cutoff may be fixed (e.g., all bags with less than 40 min to departure go into the rush queue) or vary with the lengths of the queues.

The service mechanism. At each time step, the number of bags to remove from each queue must be determined. A fixed number of machines can be assigned to each queue; but if one queue empties, this leaves machines idle. It is better to adjust dynamically the number of machines processing bags from each queue. We suggest increasing the number of machines processing the rush queue as the rush queue increases in size.

In the Denver simulation, 42 EDS machines are sufficient to get all bags delivered on time. With 38 EDS machines, the only late bags are those that arrive late (only 0.05% of bags). This system requires 9% more machines than the optimal solution.

Evaluation

Adding more queues allows for more flexible scheduling of bag processing, which may help keep more bags from being late. However, more queues mean more parameters in the queue discipline and service mechanism, and a poor choice may harm performance. Additionally, adding queues adds complexity, with more potential for failures and higher labor cost. We believe that the benefits of a many-queue system are not worth the complexity incurred.

A double-queue system provides a performance competitive with the optimal system; we recommend its use. With only a few more machines than the 35 of the optimal queue, only a few bags are delivered late; and with only 20% more machines, no bags are late.

Validation of the Model

We account for

- unfilled seats (ranging from 0% to 50% and partially depending on the size of the flight),
- some of the passengers transfer from another flight and do not have bags rescreened (35%), and
- distribution of checked bags from 0 to 2 per passenger.

In the Denver simulation, a total of 82,500 bags are screened in a day.

We validate our model by comparing its predictions with numbers for EDS machines at actual airports. There are no statistics for the number of machines at Denver, but Dallas/Fort Worth processes 55,000 bags/day with 60 EDS machines [Douglas 2002]. If scaled to the same numbers of bags processed by Denver in our model, Dallas/Fort Worth would use 90 EDS machines. This is larger than the number we predict is necessary. However, on initial testing, EDS machines were less than half as fast as predicted (72 bags/min vs. 180 bags/min) [Clark County Department of Aviation 2002]; combined with a safety margin, our results are in agreement with the Dallas/Fort Worth figure.

Extensions to the Model

We present extensions to account for various modifications of the problem, with each change considered in isolation, not in combination with other extensions.

Accounting for Error Rates

EDS machines have a false positive rate of 30% [Butler and Poole 2002]. The result of a false positive is that the bag must be more closely examined, causing delay for that bag and some bags to be late that otherwise would not be—so more machines may be needed. We incorporate this false positive rate into our model by randomly adding a fixed time (6 min) to 30% of the bags.

At the Denver airport, the effect is to slow down screening enough that 40 EDS machines (instead of 38) are required to process all but late bags in a timely fashion. Doing so for all bags becomes nearly impossible, since some bags arrive with less than 16 min to departure.

Incorporating ETD Machines

Although we developed our model for EDS machines, it is generic enough to study other devices. We identify ways to incorporate ETD machines:

- **ETD Machines in series with EDS machines.** The problem statement relates that up to 20% of passengers may need to have bags screened through both an EDS and an ETD machine. We can account for this by giving 20% of bags an extra delay of 4 min.

  We assume that there is no queue between EDS and the ETD machines following them—appropriately many ETD machines are purchased to match the processing speed of EDS machines. In the Denver simulation, an increase to 39 EDS machines, instead of 38, allows all but late-arriving bags to be processed on time.

- **ETD machines replace EDS machines.** We can calculate the number of ETD machines necessary to obtain the same service rate as for EDS machines and compare the costs. Any mixture of the two machine types with the same overall service rate will behave the same in our model; but since the cost varies linearly as machines of one type are replaced with the other, the most cost-effective operation will occur at one of the extremes, either all EDS or all ETD machines.

  Assuming a rate of 45 bags/min for an ETD machine (one-fourth the rate of an EDS machine), four times as many ETDs will be needed. According to Butler and Poole [2002], ETD machines cost less than one fifth the amount of EDS machines to operate.

Strengths and Weaknesses of the Model

Our model succeeds in capturing the essence of the problem and allows for good predictions, as a result of its many strengths:

- **Our model is based on real-world data.** Use of data from Denver makes it much more likely that the results from our model are realistic and not artifacts of an artificial flight distribution, such as the isolated peak hour of flight at airports A and B. Additionally, agreement with figures for EDS and ETD machines currently installed at airports gives us confidence that our model is accurate.
- **Our model is flexible enough to handle other types of screening machines, passenger arrival schedules, etc.** Our model's parameters can be varied to account for changes in screening machinery, training of baggage screening personnel, and so on. Since our queueing simulation takes as input merely a list of arrival times for bags, it is also very easy to study airline flight schedules at any other location, or to modify the arrival behavior of passengers.
- **Our model can predict the screening capacity needed as well as predict how the system will fail.** Our model goes beyond merely predicting the number of baggage screening machines needed to process all bags on time to give a complete model for the flow of bags through the system. The model can thus be used to see exactly how the baggage screening system will begin to break down as it is pushed past its limits. This information will help airports evaluate what margin of safety they require.

At the same time, there are aspects of our model that could be improved:

- **More detailed data for machine operation could be incorporated.** Our model is rather simplistic in that all behavior is based only on the waiting time to process bags. Including the actual time to scan a bag (not just the queue wait time) may be better, especially for systems that are slower to screen bags.
- **Queue scheduling could be optimized further.** Our proposed two-queue system generally performs well, but we have not completed a detailed analysis of it nor systematically determined optimal values for its parameters.

Recommendations

Based on simulations and an analysis of our model, we are able to make a number of recommendations:

- **A safety margin can make a significant difference.**

  The loss of just a small percentage of the capacity of the system can make the difference between no late bags and a significant fraction of late bags.

This is shown in **Figures 3a** and **3b**. After the number of machines in use drops by about 10%, the number of late bags rises dramatically, regardless of queueing algorithm.

Seemingly paradoxically, the optimal queueing algorithm has the highest fraction of late bags for some values; this is because it sacrifices the percentage of bags on time for decreasing the average amount by which bags are late.

Since unpredictable slowdowns or large arrivals should be anticipated, planning to handle a larger than expected number of bags is necessary to avoid breakdown of the system. With EDS machines operational 92% of the time, at least 8% more EDS machines should be installed than predicted as necessary by our model. We recommend a further margin of safety, perhaps 10%, to account for any other unexpected circumstance, such as unusually high traffic.

Based on these considerations, we recommend 48 EDS machines for Denver, 10 for airport A, and 11 for airport B.

- **Backlogs should be avoided except at peak times.** The processing capacity (bags/min) should be set higher than the arrival rate of bags at all but peak times. Further, peak times must be fairly well isolated (to an hour or so), or queue lengths will grow quickly to unmanageable levels. When a line develops for scanning, it can then take a good deal of time to get back to a no-wait situation. While our model shows that a persistently long queue can sometimes be handled as long is it does not continue to grow, a long backlog of bags is unstable—any event that causes the queue to grow in length quickly causes many late bags. Thus, a persistently long queue indicates insufficient screening capacity safety margin.

- **Set stricter deadlines for passenger arrival before flights.** We assume that airlines are fairly lenient about accepting bags from passengers up to the final deadline for placing them on a flight. An airline could establish a policy wherein bags that are not checked by a certain time before the flight—say, 30 min—are not guaranteed to make the flight. With such a policy, any time we have identified a strategy as handling all but "late bags," all bags would be handled in time—the "late bags" would have been rejected by the airline outright and would not delay the flight.

- **Plan for future growth in aircraft travel.** Historical data shows a growth of about 6% per year in the number of airline passengers [Metropolitan Airports Commission 2003]. Since a screening system is a large investment, an airport should plan with an eye to future capacity. The dip in traffic since 2001 may be only temporary and airline traffic may return to its normal growth curve, with a corresponding larger-than-usual increase in traffic in the next year or two.

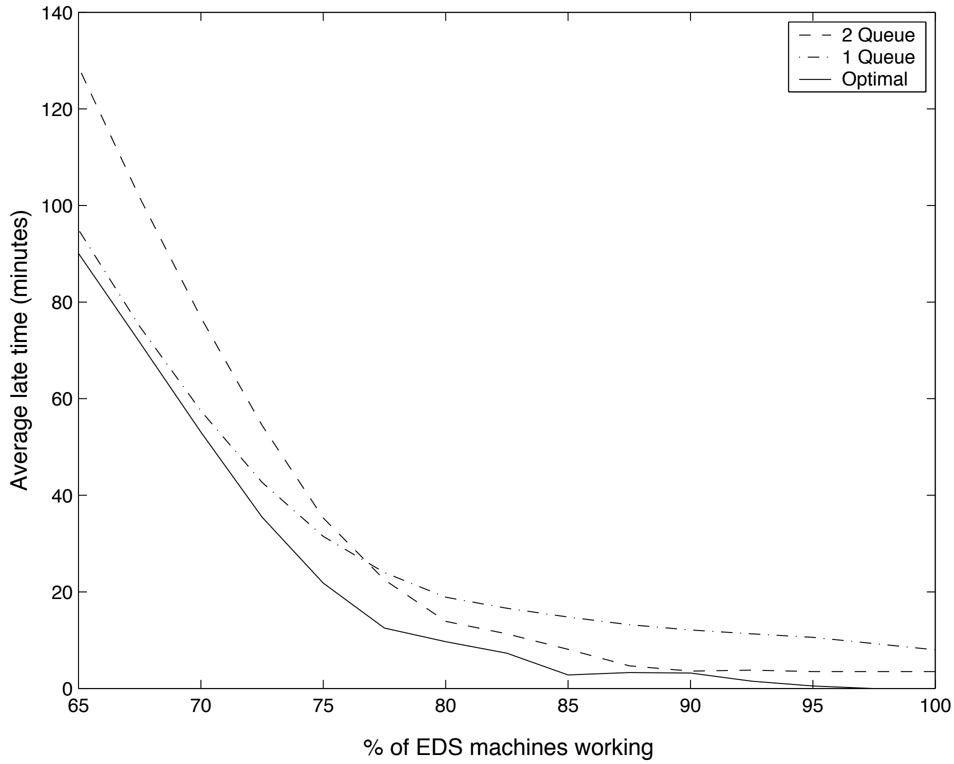

Figure 3a. Effects of the removal of baggage-screening capacity on the percentage of bags screened on schedule, for various queueing algorithms.

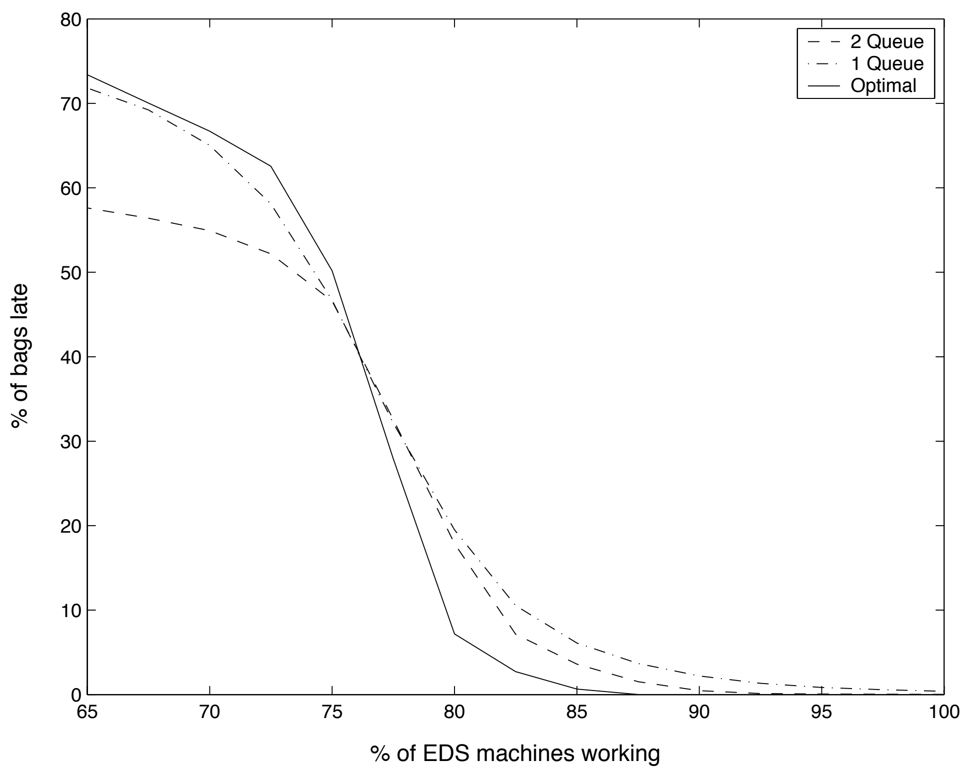

Figure 3b. Effects of the removal of baggage-screening capacity on the average delay for a bag, for various queueing algorithms.

- **Install a baggage screening system early, and ramp up use.** Unexpected difficulties may arise with a new screening system. In addition, machine operators need to become proficient. If an airport installs a baggage screening system in advance of the federally mandated deadline, screening can begin below 100% and increase to 100% by the deadline as problems are dealt with.

Optimal Peak-Hour Scheduling

We develop three passenger arrival models to schedule flights during the peak hour, with three distinct passenger arrival profiles and two arrival concentration distributions. The following assumptions simplify the model without reducing the validity of the simulations.

Assumptions

- **On average, passengers arrive 1.5 h before departure.** The problem statement says "between forty-five minutes and two hours"; although 1.5 h is not the middle of that range, it is close and makes for easier modeling.
- **Passengers arrive according to a Gaussian distribution.** We adopt a Gaussian arrival model from Clark County Department of Aviation [2002]; such a distribution encompasses realistic features, such as a peak in arrivals considerably before flight departure. We chose a mean of 90 min and tried standard deviations of 15 min and 30 min, implying that respectively 95% and 70% of passengers arrive between 2 h and 1 hour before their flights.
- **Flights scheduled to leave during the peak hour are uniformly spaced.** This assumption accommodates a generic runway structure.

Passenger Arrival Models

We apply three passenger arrival models to airports A and B. The peak-hour data given in the problem statement were processed both in isolation (no other flights during the day) and as part of a busier schedule that affects peak-hour departures.

Random Placement Algorithm

A random placement of flights within the peak hour, according to a uniform distribution, makes different parts of the hour look approximately the same. We regard this algorithm as a baseline.

Bimodal Distribution Algorithm

A bimodal distribution schedules the largest flights at the beginning and at the end of the hour in an attempt to reduce the peak in passenger arrival. This method is useful only when the standard deviation of arrival distributions is low (such as $\sigma = 15$ min). At higher standard deviations (such as $\sigma = 30$ min), the bimodal distribution converges to the distribution obtained with the greedy algorithm below.

Greedy Algorithm

A greedy algorithm always makes the optimal local choice in the hope that the final solution will be globally optimal [Cormen et al. 2001]. Our greedy algorithm attempts to minimize the peak in the arrival distribution and thus reduce a major peak in passenger arrival for peak hour flights. The following methodology is used:

- We consider the flights sequentially from largest flight to smallest.
- At each step, the center of the passenger arrival Gaussian distribution being considered is assigned to the minimum value among the possible centers of the distributions.
- Each center cannot be used for more than one distribution.

Simulation Results

We ran each of the passenger models through the optimal baggage screening model to determine which would be best suited for airports A and B. The $\sigma = 30$ cases outperformed the $\sigma = 15$ cases for all arrival distributions, which implies that having nearly all the passengers arrive for peak hour flights at the same time backs up the queue significantly.

The procedure used to combine the given peak-hour data and the Denver data involved:

- The peak-hour of the Denver data was identified as 10 A.M. to 11 A.M., with a maximum rate of baggage arrival of 160 bags/min.
- The peak-hour data for airports A and B were scaled up by a factor of 3.5 to approximate better the volume at Denver.
- The peak hour in the Denver data was entirely replaced by the airport A and B data in their respective simulation.

Both the embedded and the isolated peak data were processed using the optimal baggage screening algorithm.

The greedy algorithm creates a schedule that performs up to 50% better (in terms of total late time for bags) compared to the random schedule, when

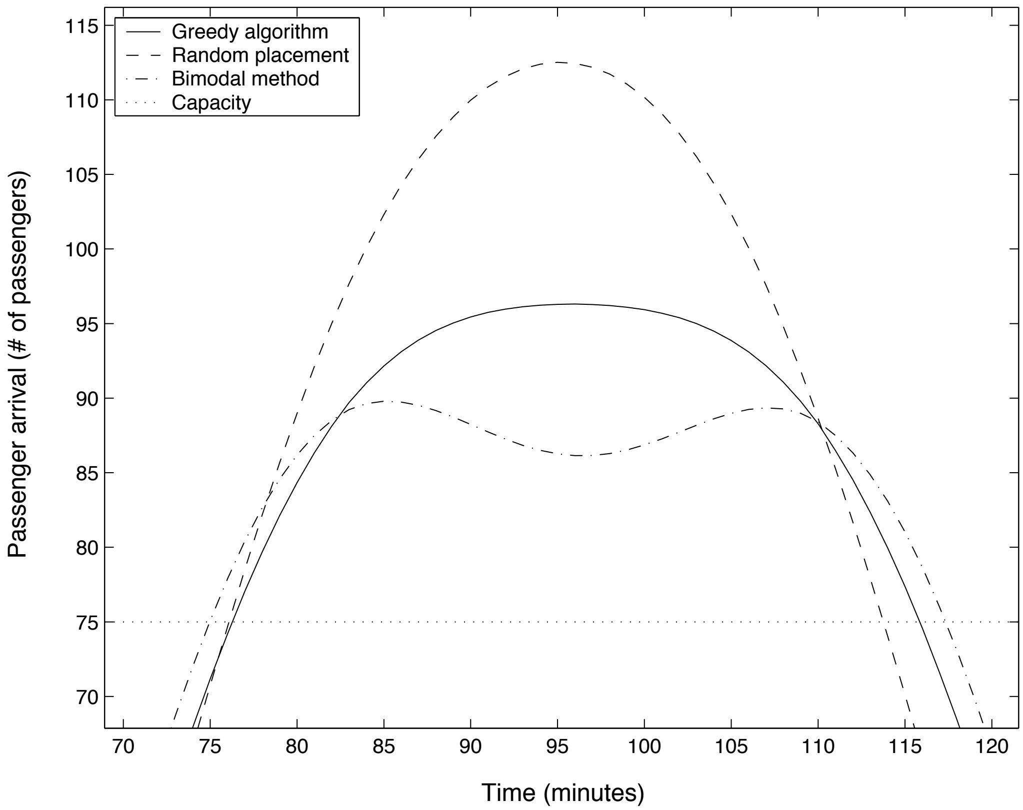

Figure 4. Comparison of peaks of passenger arrival profiles illustrating the superiority of the greedy schedule over the random and bi-modal distributions.

the peak hour is embedded in the relatively busy day; in isolation, a greedy algorithm schedule was about 30% superior. The bimodal algorithm produced a schedule that was worse than the baseline; we therefore eliminate it.

At a load below capacity of the machines, any scheduling algorithm will do. Above capacity, some methods perform better than others. The efficiency of a scheduling algorithm may be gauged by how long its operating capacity is exceeded and how backed up the queue becomes.

In **Figure 5**, notice that the bimodal profile exceeds its capacity first and continues to operate above capacity for the longest time. Even the intermediate decrease in queue backup is not enough to allow the bags to be processed faster than either the random or the greedy profiles. On the other hand, although the random placement profile exceeds its capacity latest and again drops below capacity earliest, its high peak leads to a significant queue backup that cannot be cleared as quickly as in the greedy profile. This latter profile balances both factors, giving the best result.

We used the two better algorithms to develop schedules for airports A and B. [EDITOR'S NOTE: We omit the details of the schedules.] For both airports, the greedy algorithm generated a better schedule. Both methods resulted in the use of the same number of EDS machines at the airports, although the greedy schedule results in fewer late bags. Airports A and B require 8 and 9 EDS machines, respectively, for 100% baggage screening and no delays due to the screening process.

Recommendations

With normal or above-normal traffic during pre-peak hours, the scheduling of flights during the peak hours does not matter much, because passenger arrivals are spread out over 3 hours, reducing the impact of changes within the peak hour.

If the peak hour has significantly more traffic than pre-peak hours, then the greedy algorithm is better than either the random or the bimodal distributions.

Review of Future Technologies

Current technology approved by the FAA is highly limited and extremely expensive.

EDS machines produce a three-dimensional image of the contents of a bag, allowing observation of hidden materials, zoom, and rotation of perspective to focus on suspicious objects. Unfortunately, EDSs use a powerful X-ray that requires screening to protect operators, is very expensive, and—due to the high sensor rotation rate required to resolve images—is limited in speed.

ETD machines use mass spectrometry to detect trace levels of explosives. The sample collection takes much longer and has much higher labor requirements than the EDS, with a critically high false-negative rate of 30% for a surface sample and 15% for an open-bag sample. This poor detection rate is due to the uneven concentration of explosive residues within a bag [Butler and Poole 2002].

Few alternatives have been developed as fully as EDSs and ETDs, but some appear very promising:

- **Coherent scatter** is slower than EDS (60–240 bags/h), but with a near perfect detection rate and an order of magnitude fewer false-positives, it is still relatively efficient [Butler and Poole 2002].

- **Dual-energy X-ray** has a high false alarm rate of 20% [Singh and Singh 2003] but can process 1,500 bags/h. These systems are being installed in London and other European airports and await certification in the U.S. [Butler and Poole 2002].

- **Stereoscopic tomography**, slightly different from the computed Tomography used in EDSs, scans 1,200–1,800 bags/h and is being tested for accuracy and false alarm rates [Singh and Singh 2003].

- **X-ray diffraction** uses unique diffraction patterns of scanned materials to determine their chemical composition. Current experiments show a nearly perfect detection rate and extremely small false-alarm rate [Singh and Singh 2003]. Throughput rates and cost will likely be similar to that of normal X-ray scanners, making this a promising technology.

- **Neutron-based detection** is used in several developing techniques:

  Thermal neutron analysis (TNA) can detect nitrogen levels particular to many plastic explosives but has limited sensitivity, a high false-alarm rate due to background nitrogen levels, and is at least as expensive as an EDS, making it a less promising candidate.

  Fast neutron analysis (FNA) is similar to TNA except that it can also detect oxygen, carbon, and hydrogen levels, allowing greater sensitivity and accuracy. However, the high-energy neutrons used create large amounts of noise, making information difficult to detect.

  Pulsed fast neutron analysis (PFNA) solves the noise problem but requires a collimated, pulsed energetic neutron beam, which is hard to make and tends to be unsafe and expensive.

  Pulsed fast thermal neutron analysis (PFTNA) uses a shorter pulse. It measures both thermal and fast neutron information. Portable models for landmine, unexploded ordinance, and narcotic detection have very high accuracy levels [Singh and Singh 2003].

- **Quadrupole resonance** uses magnetic resonance techniques to identify the composition of the scanned object. Every material releases a unique signal; those corresponding to explosive compounds can be isolated and identified. Machines using this technique are under construction; the manufacturer predicts that this technology will be faster (300 bags/h) and more accurate than both EDS and ETD [Quantum Magnetics 2002].

- **Millimeter wave imaging** is a noninvasive technique that detects short wavelength electromagnetic radiation from scanned objects. While this appears to work well for locating weapons concealed about a person, it does not seem able to distinguish explosive materials from inert ones and is thus not useful for baggage scanning [Homeland Security Research 2002]. Microwave imaging is similar to millimeter wave imaging.

Conclusion

> Frankly, we've tried everything else . . . . We've put up more metal detectors, searched carry-on luggage, and prohibited passengers from traveling with sharp objects. Yet passengers still somehow continue to find ways to breach security. Clearly, the passengers have to go.
>
> —*The Onion* (16 October 2002)

Since excluding passengers is unrealistic, we study the more practical technique of scanning baggage. Our results are:

- We develop a model that predicts the behavior of a queueing system for baggage in an airport security screening system and allows prediction of delays caused by the system. This model is then expanded to include multiple types of screening machines and false-positive results.
- We evaluate our model against real-world data for Denver International Airport and for the data given for airports A and B.
- Using our model, we predict the optimal number of Explosive Detection System (EDS) or Explosive Trace Detection (ETD) machines to use at several different airports and provide other recommendations for the implementation of a security screening system. For Denver, we recommend 48 EDS machines; at airports A and B we recommend 10 and 11 machines, respectively. We also compare these figures to actual figures for EDS use at the Dallas/Fort Worth Airport.
- We study how the distribution of flights during the peak hour of the day affects the efficiency of the system. We propose a greedy algorithm for optimally scheduling flights.
- We review promising technologies for future security screening machines.

Our evaluation of the requirements for 100% baggage screening suggests that such high security goals are cost-ineffective, so research into alternative technologies and screening systems is needed.

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Advancing Airport Security through Optimization and Simulation

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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.

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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 non-linear 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:

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

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.

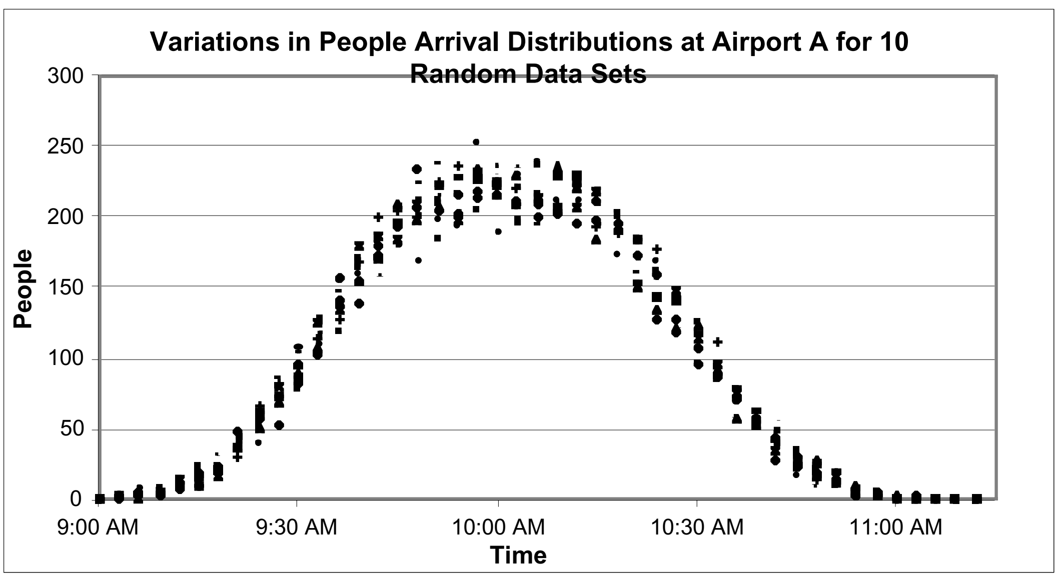

Figure 1. Variations in people arrival distributions at airport A for 10 random data sets.

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.

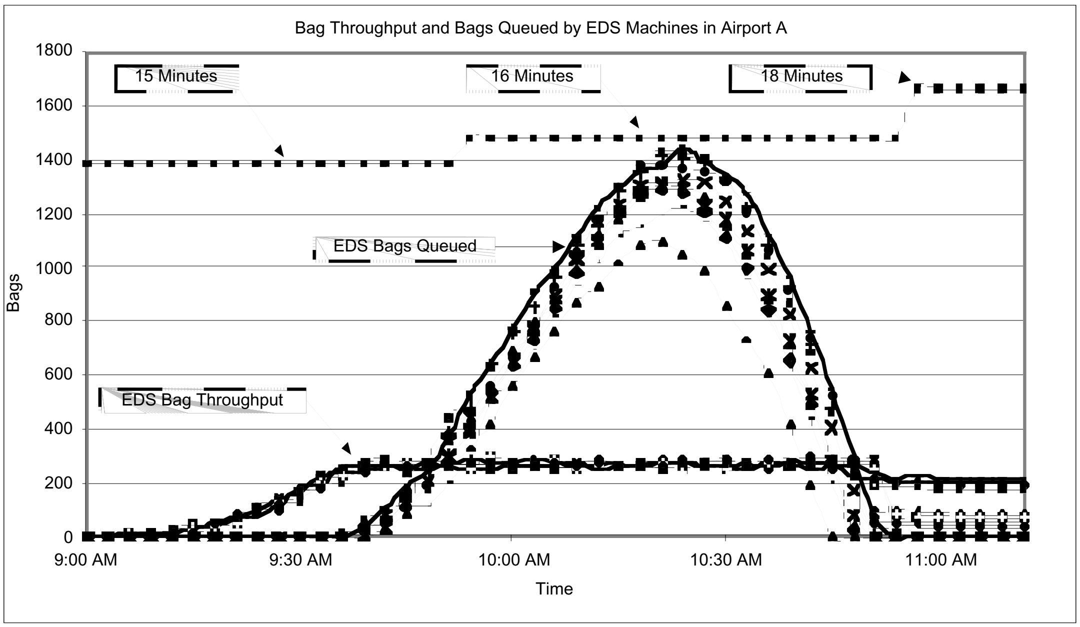

Figure 2. Variability of model response to ten data sets with respect to bag throughput and bags queued by EDS machines in airport A.

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**.

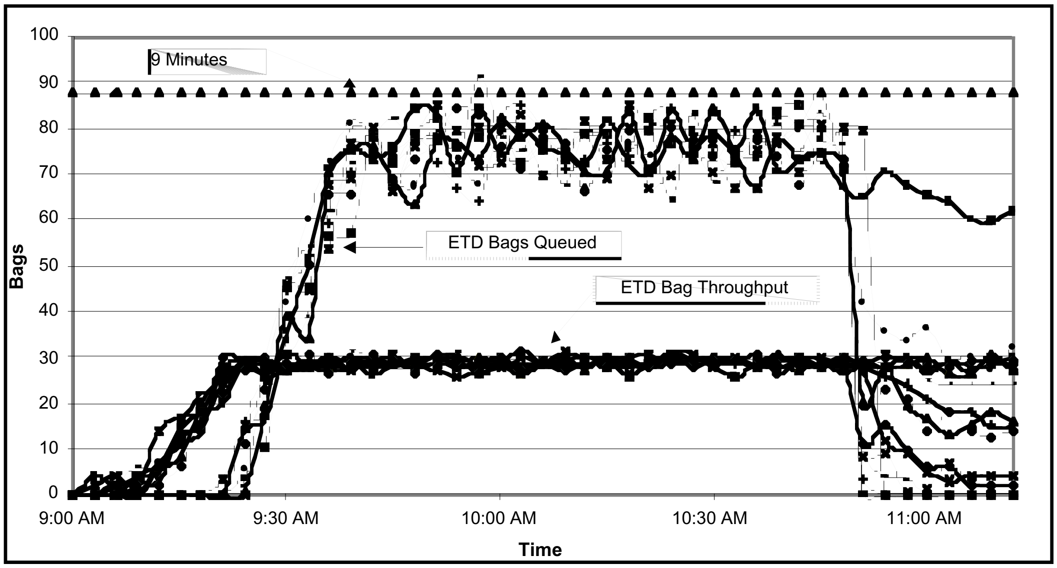

Figure 3. Bag throughput and bags queued by ETD machines in airport A.

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

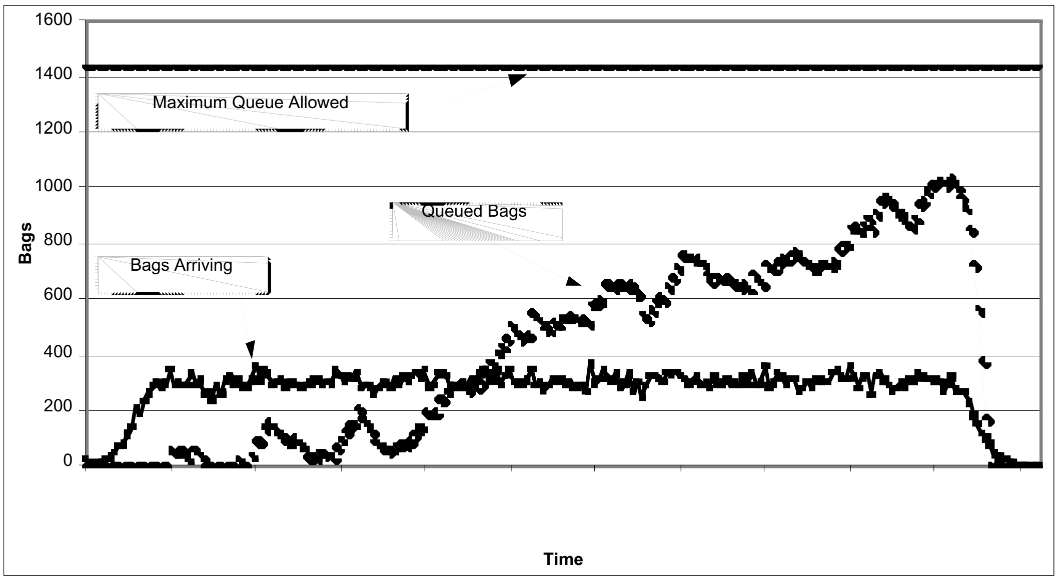

Figure 4. Bag arrival and queued bag distributions over 10 peak hour period in airport A.

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.

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The Price of Security: A Cost–Benefit Analysis of Screening of Checked Baggage

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Summary

This report examines a model constructed to optimize the number of EDS machines necessary to provide desired security at airports. Based on this model, we recommend 16 EDS systems for airport A and 18 for airport B. Furthermore, we provide a set of security objectives for the airline as well as an ideal flight-scheduling solution. We find that a three-level EDS and human inspection system is best.

However, EDS is not a permanent solution to the security screening problem; it is too inefficient for the expense incurred. In addition, we currently see little reason to incorporate ETD systems into our security proposal. The best hope for the baggage screening problems that we face today lies in future technology; neutron-based detection and quadruple resonance offer the most promising solutions.

Problem Approach

The model of the baggage screening system can be broken down into three phases:

- Check-In Phase, which consists of:
  - Arrival rate of passengers to the airport

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Table 1.
Symbols used.

μ	mean arrival time of passengers before departure (min)
σ	standard deviation of normal distribution of passenger arrival to airport (min)
P_A	number of passengers that arrive in a 10 min interval at the airport (passengers/10 min)
$r(t)$	arrival rate per minute. A function of time and the normal distribution shown in Appendix B
P_T	total number of passengers to arrive in airport during peak hours
L_F	load factor (percent of plane seats that are filled)
C_p	percentage of passengers traveling on connecting flights
l	queue length at every 10-min interval
T	number of ticket agents
T_r	service rate of ticket agents (passengers/min)
ΔT	number of ticket agents to be added based on queue length
l_o	optimal passenger line length (passengers)
P_p	number of passengers processed through ticket counter
l_i	line length at beginning of 10-min interval (passengers)
B_N	number of bags added in system to be inspected every 10 min
$\max I_R$	maximum inspection rate of EDS (bags/min)
EDS	Number of EDSs in the system
EDS_r	EDS inspection rate (bags/min)
l_B	bag line length for EDS (bags)
ΔEDS	number of EDS to add to system
l_{BO}	optimal baggage line length for EDS (bags)
EDS_O	number of operational EDSs
$\max I_{R\,H}$	maximum inspection rate of human operated EDS (bags/min)
EDS_H	number of human operated EDS (machines)
$l_{B\,H}$	bag line length for human operated EDS (bags)
$\text{EDS}_{r\,H}$	human operated EDS inspection rate (bags/min)
ΔEDS_H	number of human operated EDS to add to system
$l_{BO\,H}$	optimal baggage line length for human operated EDS (bags)
$\max I_{R\text{Hand}}$	maximum inspection rate of hand inspectors (bags/min)
Hand	number of hand inspectors available
$l_{B\text{Hand}}$	bag line length for human inspectors (bags)
Hand_r	human inspection rate (bags/min)
$l_{BO\text{Hand}}$	optimal baggage line length for human inspectors (bags)
ΔHand	number of human inspectors to add to system

  - Passenger check in rates to ticket counters

- Baggage Inspection Phase
- Movement Phase—Movement of inspected baggage to appropriate planes

Our initial approach was to implement the model in the simulation software system Arena [Rockwell Software 2000]. However, the version of the software did not have the capacity, allowing only 100 entities in the system, instead of the 5,000 that we needed for proper testing. As a result, our second implementation model uses Microsoft Excel.

Assumptions

- The average amount of time that a passenger spends at a ticket counter is 105 to 150 ; we assume 120 s.
- The passenger arrival distribution at Las Vegas Airport is representative of airports throughout the country and in the Midwest.
- Passenger arrival is normally distributed, an assumption supported by analysis in later sections.
- Ticket counters are uniformly distributed throughout the airport, and all ticket counters work for all airlines.
- All airlines follow the same basic system: Passengers check in at a ticket counter, an agent checks bags, and the airline delivers them to the plane.
- There is no curbside check-in, which in fact is only a small part of the overall baggage checking. Also, with the advent of new security measures, curbside check-ins will have to be much more secure [Federal Aviation Administration 2001, 104], and we assume that most airlines will be unwilling to incur this additional cost.
- Passengers departing during the peak hours of flight operations are the only passengers we need to be concerned about. This is because at peak hours the maximum number of bags are checked,l hence this is the most important time to consider.
- Airports A and B are single-terminal airports. The reason for this assumption is that EDS machines must be centrally located to ensure reliability and a rapid flow rate. If the EDSs were spread out, then our model would not be valid, since there would be transportation time between the ticket counters and the EDS machines. In multiple-terminal airports, the EDS machines should be positioned centrally in each individual terminal.
- When adding a new ticket agent, EDS, or inspector to the system, the change is instantaneous; there is no warm-up period and no transit time. Although this assumption is a little unrealistic, it allows for an easier representation of the data and a smoother analysis.
- Since we are modeling two of the largest airports in the Midwest, we base any additional information needed on the Chicago O'Hare Airport, the largest airport in the region and the second largest in the world [Aviation Statistics 2002]. For example, the percentage of passengers on connecting flights (55%) is from Chicago O'Hare [Merringer 1996].
- The data given in the problem statement about the distribution of the number of bags that passengers check is accurate. We want to process every entity through the system with 30 min remaining to allow for the movement stage.

However, we recognize that this isn't possible because of extraneous factors that we don't control, such as late arrivals. Therefore, our model requires that 95% of the passengers and bags are processed before that 30-min window before departure.

- The EDS reliability rate (92%) and speed (160 to 210 bags/ min) in the problem statement are accurate.

Model Design

Check-In Phase

The key to the check-in phase is determining the distribution of passengers arriving; in other words, we need to find the rate at which passengers arrive at the airport. The second part is determining the length of the queue so that we can estimate the number of ticket agents and the time required for passengers to get through ticket lines to check their bags.

Arrival Rate of Passengers

Data from Las Vegas Airport are given in **Figures 1** and **2**.

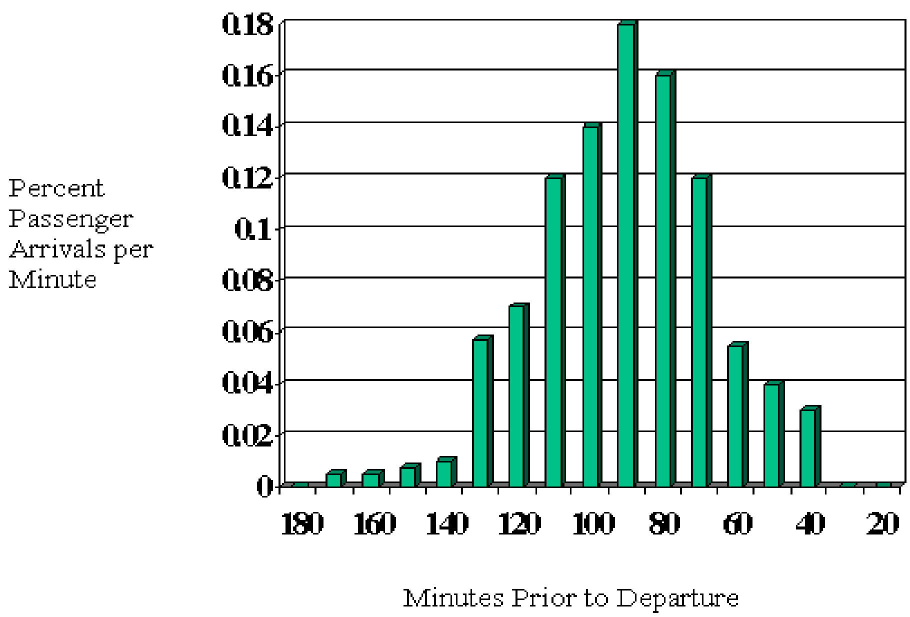

Figure 1. Las Vegas Airport passenger arrival distribution [Leaving . . . 2003].

We assume that Las Vegas Airport provides us with arrival information that is consistent with airports in the rest of the country. This passes the common-sense test, since people behave similarly throughout the country.

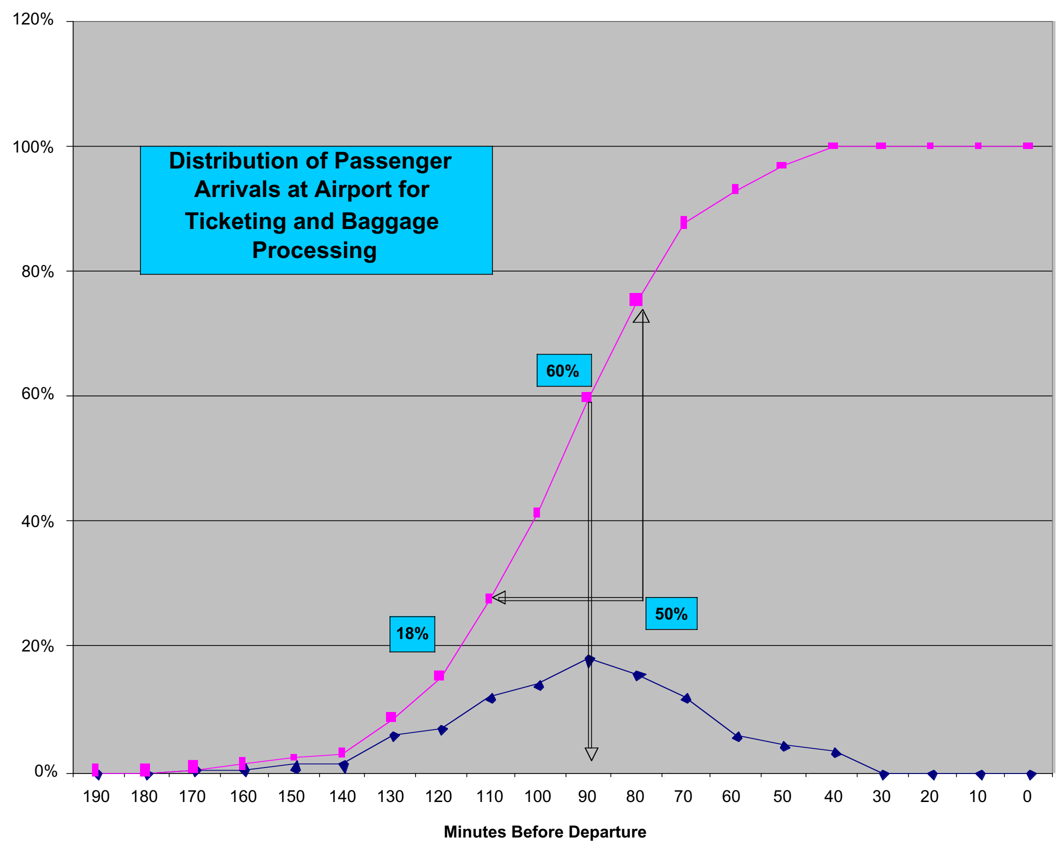

Figure 2. Las Vegas Airport passenger arrival distribution: lower curve, probability density function; upper curve, cumulative distribution function [Leaving . . . 2003].

The arrivals seem to follow a normal distribution. However, the graphs were created with discrete values, and not a function; we have the percentage of passengers that arrive every 10 min from 190 min to 0 min prior to departure. For these data, the sample mean is 91.15 min, and 50% of passengers arrive between 70 min and 100 min prior to departure. To get a continuous function, we adjust the mean and standard deviation of a normal distribution to fit the data; the simulated distribution has $\mu = 99.8$ min and $\sigma = 21.2$ min (see **Figure 3**).

Flow Rate

The second part of the check-in phase is the flow rate through the ticket counters. Using the information from the problem statement, we calculate the number of passengers arriving during peak hours by multiplying the number of seats in a flight times the number of flights with that many seats. The total over all flight types gives the total number of passengers: 5,396 passengers for airport A and 5,781 for airport B.

To determine the number of passengers who arrive in a particular 10-min interval before departure, we multiply the proportion of arrivals per minute

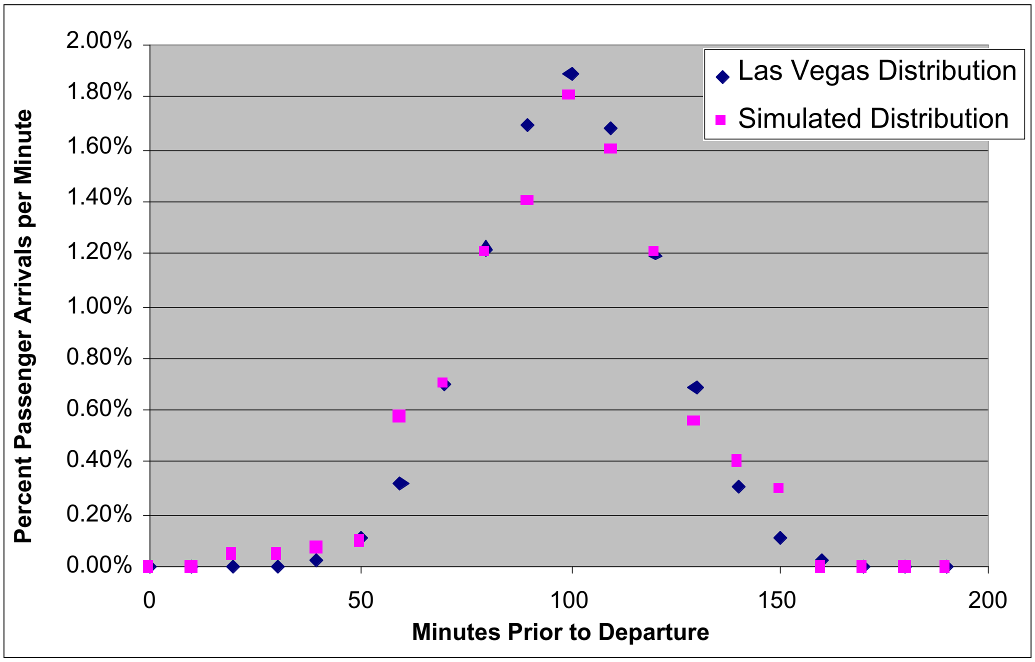

Figure 3. Hypothesized normal distribution of arrivals compared with data. Note: Labels for the distributions are reversed: The diamonds in fact are for the simulated distribution and the squares for the Las Vegas distribution. The correction could not be made by press time.

$r(t)$ (calculated from the normal distribution) by 10 min and then by the total number of passengers (P_t) who arrive at the airport. Also, we have to consider the load factor (L_F: percentage of the flight that is actually filled) and the percentage of passengers on connecting flights (C_p) who arrive but don't have to check in. The overall equation is

$$P_A = r(t) \times 10 \times P_T \times L_F \times (1 - C_P).$$

Since 55% of passengers are taking connecting flights, we have $C_P = .55$

To find the overall load factor, we divide the total number of passengers by the total number of seats available: 80.4% for airport A and 80.7% for airport B.

For airport A, the final equation for the number of passengers arriving to check in is

$$P_A = r(t) \times 5396 \times 10 \times .804 \times .45.$$

We use Excel to simulate the dynamic arrival rate, using the normal distribution calculated earlier. To determine the queue length (l) at every 10-min interval, we simply consider the number of ticket agents (T) available, multiply by the server rate (T_r) and by 10 min, and then subtract the result from the number of passengers who have checked in:

$$l = P_A - 10 \times T \times T_r.$$

We assume that the server rate is 0.5 passengers/min, or 2 min per passenger [EDS Bag Screening Analysis n.d.].

At the start of every 10-min interval, there is an initial line length, which consists of both the additional passengers that arrive and the final line length from the iteration before. In other words, in each interval, new passengers are added at the end of the line—i.e., we have first-in, first-out queueing.

A unique element in the model is that we allow for an increase in ticket agents if the queue increases. Based on the optimal line length (l_O) or on the acceptable length of the line as set by the airport, the model adds ticket agents (ΔT). The maximal acceptable length of the queue is twice the service rate in a 10-min interval, in other words, the number of passengers who can be served in 20 min. If the actual line length (l) is longer than the acceptable line length, then, based on how much longer, the model adds additional ticket agents, using the equation

$$\Delta T = (l - l_o) \times 10T_r.$$

The model also removes ticket agents when the line is under the optimal line length, since a negative ΔT is possible when $\ell < l_o$.

With these equations, the model tracks the time that it takes for all the passengers to get through the ticket counters. We find the number of passengers processed by taking the difference in the line length at the end of the interval (l_f) and the line length at the beginning of the interval (l_i). This difference is the passengers processed (P_P):

$$P_P = l_f - l_i.$$

Inspection Phase

Overall Picture

In the inspection phase, baggage is sent through the EDS machines and checked for explosive components, following the simple flowchart in **Figure 4**.

Initial EDS Inspection

The number of passengers P_p who get through the check-in and deposit their bags each 10-min interval is based on the Check-In Phase calculations. This number of passengers is then the number of passengers who have bags to check and be screened.

According to the problem statement, 20% of passengers check 0 bags, 20% check 1, and 60% check 2, for a weighted average of 1.4. The total number of bags B_N checked in a 10-min interval is

$$B_N = 1.4P_P.$$

According to the the problem statement, EDSs are operational only 92% of the time. Therefore, the number of operational EDSs (EDS_O) is

$$\text{EDS}_O = .92\text{EDS}.$$

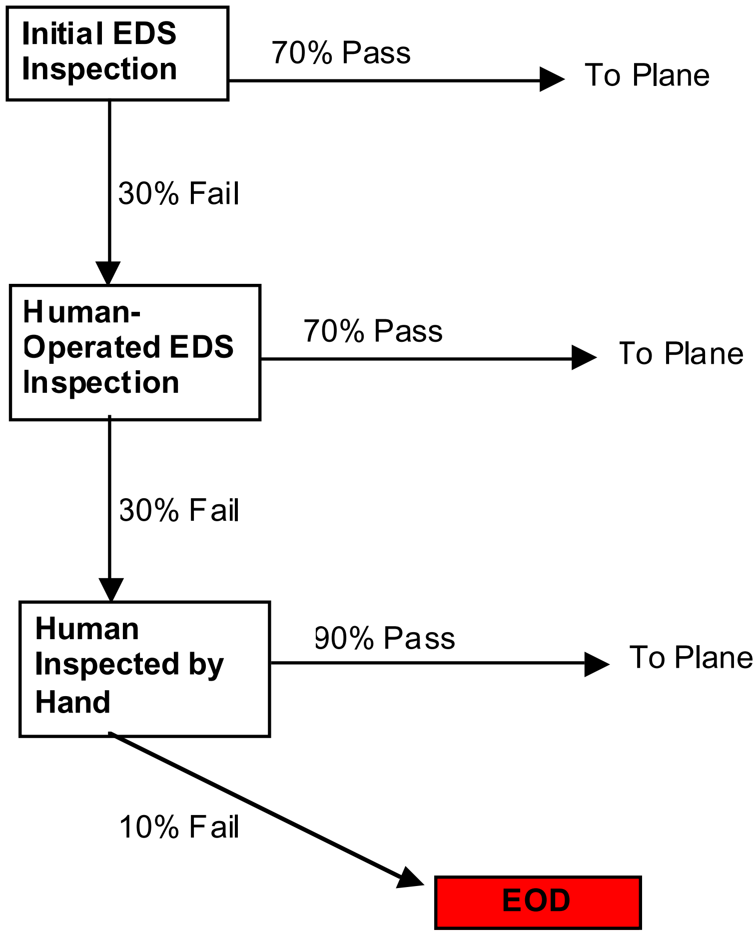

Figure 4. Flowchart of inspection stage.

The maximum number of bags that can be inspected in a 10-min interval depends on the number of EDSs in the system (EDS) and their inspection rate, which we take to be 180 bags/hour, or 3 bags/min. The maximum inspection rate is

$$\max I_R = (3 \text{ bags/min}) \times \text{EDS}_O \times (10 \text{ min}).$$

This model is similar to that of the ticket agent and the passenger. Using the same techniques and only mildly changing the equations, we find the number of bags that are checked in each interval ($\text{EDS} \times \text{EDS}_r \times 10$) and then determine the line length of the bags (l_B):

$$l_B = B_N - \text{EDS}_O \times \text{EDS}_r \times 10.$$

As with the passenger queue, we bring additional EDS machines into service based on need. When the queue gets to be longer than the optimal line length (l_{BO}), we add the appropriate number of EDSs to the system (ΔEDS):

$$\Delta\text{EDS} = (l_B - l_{BO}) \times 10 \times \text{EDS}_r.$$

Conversely, we subtract machines when the line length falls below the optimal length.

Human-Operated EDS

Because of the 30% false-positive rate for the EDSs, we run positives through a human-controlled EDS, which is a more thorough and accurate inspection [Butler and Poole 2002, 4]. This system follows the same process and equations as the initial baggage screening on the EDSs. However, the difference is that the flow rate is reduced to 1.2 bags/min, since it takes 50 sec for a human-operated EDS to inspect a bag [Recommended Security Guidelines . . . , 102]. So EDS_{RH}=1.2 and we have

$$\max I_{RH} = (1.2 \text{ bags/min} \times \text{EDS}_H \times (10 \text{ min}).$$

Since only 30% of bags screen as positive, the number of bags to inspect is now 30% of the original number:

$$I_{BH} = 0.3B_N - (\text{EDS}_H \times \text{EDS} \times 10).$$

Human-operated machines are added and taken away based on need and queue length:

$$\Delta\text{EDS}_H = (l_B - l_{BOH}) \times 10 \times \text{EDS}_{rH}.$$

Bags that pass inspection are routed to their planes; bags that fail are routed to the hand inspection.

Hand Inspection

In addition to the bags that register positive with the human-operated EDS inspection, we pull off 30% to hand inspect, as an additional safety measure to double check the machines and human operators for accuracy. A number (Hand) of trained inspectors inspect at a rate (Hand_r) that is much slower: 0.286 bags/minute, or 3.5 min/bag, the average between 2 and 5 bag/min [Butler and Poole 2002, 2].

$$\max I_{R\text{Hand}} = (0.286 \text{ bags/min}) \times \text{Hand} \times (10 \text{ min}).$$

The length of the line of bags awaiting hand inspection is

$$l_{B\text{hand}} = 0.09B_{N\text{Hand}} - \text{Hand} \times \text{Hand}_r \times 10.$$

Again, inspectors are added or subtracted as needed, and the number of bags left in the system is tracked throughout the 190 min of peak time.

$$\Delta\text{Hand} = (l_{B\text{Hand}} - l_{BO\text{Hand}}) \times 10 \times \text{Hand}_r.$$

From here, bags that are negative go to planes, while bags with explosive devices or compounds go to Explosive Ordnance Disposal teams.

Movement Phase

After a bag has been inspected and cleared, it is routed to its flight. The time that it takes a bag to get to its flight after inspection is the time to get to the plane (5 min, say) plus the time to be loaded into the plane (10 min, say). Hence we need to ensure that all bags are through inspection some 15 min before departure. However, we are not sure of this exact number and do not have any supporting data; so, to play it safe, we ensure that 95% of bags are finished being processed 30 min before departure, so that there will be no flight delays because of screening.

Results and Discussions

Using Microsoft Excel, we put into simulation the model formed from the equations and theory described above for both airports A and B. The results are given below.

Airport A

Using the initial conditions for airport A given in the problem statement, we calculate the optimal numbers of counter workers, automated EDS machines, human-operated EDS machines, and human inspectors required to meet the goal of 95% of passengers and baggage processed by 30 min prior to departure. The last set of initial conditions necessary are the maximal acceptable line lengths shown in **Table 2**.

Table 2.
Optimal line lengths for airport A.

Counter line	10	people
Bag line	20	bags
Human bag scan line	12	bags
Hand search line	2.86	bags

For airport A, 16 EDSs are required to handle peak-hour traffic. In addition, 35 ticket agents, 7 EDS operators, and 8 human inspectors are needed.

Looking deeper at the average line lengths throughout the whole peak hour process, we get **Table 3**, which confirms that the line lengths stay below the maximum acceptable lengths.

Costs

The cost of installation of EDS machines at airport A is $17.6 million, and worker cost is $1,639 per 190 min period. The worker cost for the 190 min period will not exceed $4 million/year.

Table 3.
Line lengths for airport A.

	Ave.	Max.	
Counter line	6.0	20	people
Bag line	17.5	21	bags
Human bag scan line	6.9	11	bags
Hand search line	1.6	2.86	bags

Airport B

Similar analysis shows that airport B requires 18 EDSs, 38 ticket agents, 8 EDS operators, and 9 human inspectors to achieve the same maximum acceptable line lengths. The corresponding average line lengths are 5.9, 19.1, 9.0, and 1.4, and the costs are $19.8 million for equipment and $1,807 worker costs per 190-min period.

Flight Departure Scheduling Model

There are two major considerations for a departure schedule:

- We must distribute the flight operations throughout the peak hour so that the runways are never more crowded than other times.
- We must distribute the various flights and their sizes so that the number of people departing at any given time during peak hour can be represented by a uniform distribution.

The time before departure that passengers arrive is independent of the number of seats on the flight.

First, we build a matrix for possible flight departure times. We split the hour window into six 10-minute windows, each with four 2.5-min smaller windows. Next, we record every flight's passenger load.

On a spreadsheet, we fill in a matrix, inserting flights into the flight schedule so that flights are evenly distributed by number and size of passenger load. We accomplish this by inserting the largest flights first. After the largest flights are entered, we use the small flights to fill in passenger-load disparities. Finally, to balance flight loads and passenger loads, we can always swap flights once we've placed them. For both airports, we achieve the goal that every 10-min and 2.5 min interval has an equal flight operation rate, and the number of passengers departing in each 10-min interval is nearly constant.

Recommendations

We recommend against a combined EDS/ETD system.

Such a system provides meager security improvements over an all-EDS system, increases fixed costs, and increases the possibility of baggage delays. We give details of our reasoning.

Re-screen positives Because of the high false-positive rate (30%) for EDS machines, bags that fail a first EDS test should be give a second one before any further screening.

Use ETDs on a 10% sample Airports A and B can incorporate the use of ETD machines into the proposed EDS model if they replace each human inspection point with an ETD machine. The ETD machines should inspect all bags that fail the first two EDS machine tests. Since ETDs use mass spectrometry technology, as opposed to the computed tomography technology that EDS machines use, the airports' security systems should send 10% of all bags that pass the initial EDS machines into ETDs, to try to find explosives that EDSs normally will not find, such as minute traces of explosive residue on the lining of a bag.

Open bags for ETD inspection ETDs most accurately detect explosives when security agents use the "open bag" form of trace detection. It takes additional time to open bags and prepare them to enter the ETD machine, but doing so reduces the machine's false negative rate (rate at which the machine fails to recognize explosive material) by nearly 50%. Open-bag ETD inspections take 2–2.5 min per bag, which is less than or equal to the time it takes for a physical human inspection (2–5 min) [Butler and Poole 2002]. This means that it will not take more to send the bags that fail the two EDS tests through an ETD machine than for a human to inspect each of these bags. It will, however, take more time to test 10% of the bags that pass the initial EDS machine.

How many ETDs? In addition to the 16 EDS machines, airport A will require 5 ETD machines; airport B, in addition to its 18 EDS machines, will require 4 ETD machines.

Greater possibility of delays Both airports can still meet departure schedules even if they conduct the additional ETD inspections on 10% of bags that pass the EDS machines. However, the length of the lines at an ETD machine suggest greater possibility of delay.

Actual costs According to Butler and Poole [2002, 7], installing 50,480 ETD machines would cost $3.0 billion, or $59,500 per machine. However, the same report indicates that the installation cost of 6,000 EDS machines is $6.0 billion, or $1 million per EDS machine. These costs include both the cost of the machines and the associated cost of placing them in the airport, and they substantially agree with those in the problem statement.

Cost comparison One can argue that ETD machines cost nearly ten times as much to operate as EDS machines because they inspect bags at one-tenth the rate of EDS machines. However, the ETD system that we suggest does not require any human inspectors. The costs (fixed and variable) of EDS and of EDS/ETD differ unsubstantially, for either airport A or airport B.

Security is not enhanced The security benefits of incorporating ETD machines into an all-EDS system do not appear significant. ETD machines are less accurate in detecting explosive materials than an EDS machine [Kavuar et al. 2002] and fail to identify explosive materials in 15% of bags that actually contain explosive materials [Butler and Poole 2002].

We recommend investment in development of new technologies.

We specifically suggest quadrupole resonance and neutron-based detection systems, which have the potential to lower costs while increasing security system effectiveness. We describe various research opportunities.

Quadrupole resonance: Quantum Magnetics is conducting research on quadrupole resonance (QR) to detect explosives, contraband, and weapons. QR-based technology may be cheaper, faster, and more accurate than EDS and ETD machines. QR detection systems are very simple to operate: a red light appears if a bag contains hidden explosives or biochemical agents, a green light appears if the bag contains no explosives or biochemical agents. The simplicity of use reduces the possibility of human error, which can occur with EDS technology if the operator poorly judges the machine's X-ray images. QR technology may also reduce airports' variable costs if they do not have to compensate security personnel for the technical education EDS operators receive [InVision Technologies 2002].

Neutron-based detection: Neutron-based devices can quickly detect hidden substances, such as liquid explosives hidden in a sealed container or plastic explosives stuffed inside a baseball. The HiEnergy Technologies Corporation has conducted tests in which neutron-based devices detected concealed explosives in less than 10-sec, nearly half the time it takes for an EDS machine to inspect a bag. Like QR technology, neutron-based systems determine the chemical formula of hidden substances, which reduces the likelihood of false positives that occur in EDS machines when the machine cannot accurately distinguish explosives from other objects with similar sizes and densities. Neutron-based technology also eliminates the need for drawn-out human interpretations [Fast neutron technologies . . . 2002].

Elastic (coherent) X-ray scatter: This technology is currently in use in Germany at Cologne, Düsseldorf, and Munich airports. X-ray scatter detection systems can only inspect 60–240 bags/h [Butler and Poole 2002, 3], but they have a false positive rate well below 1% [Automatic detection . . . 1998], much more efficient than EDS machines with their 30% false positive rate.

Millimeter and microwave imaging: This technology can improve overall airport security but is more applicable to inspecting passengers than baggage. Millimeter and microwave systems use temperature and emissivity to create images: the greater the contrast, the sharper the image. This is an excellent way to detect a passenger carrying a gun, since human bodies have high emissivity while metal objects have low emissivity [Murray 2001].

Recommendation for further research: Our model shows that if manufacturers can make enough EDS systems, and if airports can fit them and train enough operators, then they should be able to screen all bags checked in at least 30 min before departure. However, screening all checked baggage does not guarantee detecting all explosives; EDS and ETD machines cannot be a permanent solution. Investing in research and development opportunities is the only way to ensure that airlines are safe while minimizing space and labor costs. Ultimately, "The common goal should be a fully functioning air transportation system that provides passengers with safe, efficient, and convenient means of carrying out the nation's business" [Kavuar et al. 2002, 7].

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Feds with EDS: Searching for the Optimal Explosive Scanning System

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Summary

A May 2002 Transportation Security Administration (TSA) press release describes pilot testing of different baggage screening programs at three airports [Melendez 2002]. One airport used all Explosive Trace Detection (ETD) machines, one used all Explosive Detection System (EDS) machines, and a third airport used half and half. We show that these pilot tests were unnecessary.

We focus on maximization of productivity of the machines and of the amount of time they have to process the highest peak in checked bags. We show the importance of proper flight schedule planning and the ideal method for scheduling.

The implementation of the model's conclusions will save money in purchasing and installing machinery. Security will be paramount. Minimizing passenger inconvenience will be the secondary concern; but under our model, we eliminate, or at least minimize, expected delays.

By extending our model, we can also potentially find the optimal amount of time before takeoff when passengers should be required to arrive at the airport. To minimize cost, this time may need to be increased or decreased, depending on experimental data.

General Assumptions

- We assume all data as given on the problem statement.

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- Flight delays due to baggage inspection are unsatisfactory. However, a 15-minute delay is considered on time, according to FAA policy [Mead 2002].
- The percentage of planes that are cancelled before baggage is checked is negligible.
- There are no extreme unforeseen circumstances, e.g., striking workers that might affect baggage screening and flight departures.
- The number of passengers who check more than two bags is negligible.
- All airports have EDS or other scanning machines functional, so we do not need to rescan bags from connecting flights originating elsewhere.
- A system of bag queuing and prioritizing process is in place.
- Prioritizing negates the benefits of passengers arriving earlier than mandatory time.
- There is no significant delay in having to re-scan or hand-examine bags due to false positives.
- The throughput rate of bags per hour per EDS machine can be increased to 210 bags/h/machine by training the operators.
- We ignore the cost of repurchasing EDS or ETD machines due to defects and breakdowns. We also assume that performing scheduled maintenance on these machines reduces the chance of machine failure.
- We ignore potential lines at the airline check-in desk.

The Model

$$Q_{\text{EDS}} = \left\lceil \frac{\phi \displaystyle\sum_{i=1}^{8} \left(t_i n_i P_{\text{seats filled}_i}\right)}{\Omega \ell (1 + \tau - \mu)} \right\rceil \tag{1}$$

where

Q_{EDS} = number of EDSs needed;

ℓ = throughput rate of each machine (bags/h/machine);

τ = minimum early passenger arrival time (h), i.e., how long before departure the airline closes bag check-in;

μ = travel time of one bag between EDS and the plane (h);

t_i = number of seats on flight of type i;

n_i = number of flights of type i during the peak hour;

$P_{\text{seats filled}_i}$ = estimated percentage of seats filled in flights of type i;

ϕ = summation shift constant, defined below;

Ω = percentage of time that the EDS is operational (given as 92%).

Derivation

We are dealing with a model of rates, such that B_{peak}, the number of bags in the peak hour, equals the rate of bags processed multiplied by the amount of time T. The rate of bags per hour depends on ℓ, the number of bags that one machine can process in one hour, times Q_{EDS}, the number of EDSs. We combine these equations and solve, getting

$$Q_{\text{EDS}} = \frac{B_{\text{peak}}}{\ell T}.$$

Since each EDS is operational only portion Ω of the time, we must discount the time by this constant, Ω, yielding

$$Q_{\text{EDS}} = \left\lceil \frac{B_{\text{peak}}}{\Omega \ell T} \right\rceil.$$

We add the ceiling brackets because the number of EDS must be whole. We now derive formulas for B_{peak} and T.

$B_{\textbf{peak}}$

The aggregate number B_{peak} of bags on one flight is the number of passengers times the average number of bags that each carries. The average number of bags per passenger, $\bar{b}$, is $b_1 + 2b_2$, where b_1 and b_2 are the proportions of passengers who check one bag and two bags, respectively.

The problem statement lists seating capacities of eight flight types, but the number of passengers per flight depends on the probability that those seats are filled, $P_{\text{seats filled}_i}$. By multiplying the number of bags on one flight, $\bar{b}t_i P_{\text{seats filled}_i}$, by the number of flights of the same type departing in the peak hour, n_i, we get the total number of bags on all flights of type i. By summing up all eight flight types, we arrive at

$$B_{\text{peak}} = \sum_{i=1}^{8} t_i P_{\text{seats filled}_i} \bar{b} n_i.$$

However, a couple of other factors need consideration.

Flight cancellations. The problem statement says that 2% of flights are cancelled daily. However, in our flying experiences, a flight is generally not cancelled until after the bags have been checked and the passengers are waiting at the gate or perhaps already on the flight. When forced to, airlines tend to delay flights as long as possible, canceling only after all other options have been exhausted. Thus, we assume that the cancellation of flights does not affect the number of checked bags to be scanned.

Connecting passengers. Since airports must scan all bags, and since typically the EDS machines are in the passenger check-in area, we assume that bags of connecting passengers do not need to be rescanned, in agreement with current FAA policy. We define the percentage of non-connecting passengers, i.e., those originating in our airport, as P_{orig}.

Including these factors, we get

$$B_{\text{peak}} = \sum_{i=1}^{8} t_i P_{\text{orig}} P_{\text{seats filled}_i} \bar{b} n_i .$$

Defining the summation shift constant $\phi = \bar{b} P_{\text{orig}}$, we have

$$B_{\text{peak}} = \phi \sum_{i=1}^{8} t_i P_{\text{seats filled}_i} n_i .$$

Substituting this into the formula for Q_{EDS}, we get

$$Q_{\text{EDS}} = \left\lceil \frac{\phi \sum_{i=1}^{8} (t_i n_i P_{\text{seats filled}_i})}{\Omega \ell T} \right\rceil ,$$

with T yet to be shown to be $(1 + \tau - \mu)$.

The Cost Function Caveat

The ultimate goal is to minimize cost. This model's cost function (in thousands of dollars) for airport A is $Q_{\text{EDS}}(1100 + \omega)$, and for airport B, $Q_{\text{EDS}}(1080 + \omega)$, where ω is the operating cost per machine, and 1100 and 1080 are the costs to purchase and install the machines at each airport, according to data in the problem statement. To minimize cost, we minimize Q_{EDS}, either by reducing B_{peak}, increasing ℓ, or increasing T.

Minimizing B_{peak} would involve having passengers check fewer bags or else reducing the number of passengers flying during peak hour, via either flight cancellation or rescheduling to non-peak times. Flight cancellation would involve lower airline revenue and fewer choices of flights for consumers and is clearly undesirable. Rescheduling to non-peak times seemingly would be desirable; but surely the airlines and airports have already tackled this issue in the past, so further progress in rescheduling cannot be expected. Finally, requiring passengers to check fewer bags (which the threat of longer wait times might indirectly accomplish) would be unpopular; furthermore, merely suggesting passengers bring less checked luggage cannot be relied upon.

Maximizing ℓ, the number of bags per hour that each machine can process. We assume that the range between 160 and 210 depends on the competence of the operator. Thus, by instituting a more comprehensive and extensive training regimen, we can hope to increase ℓ. We also assume that the savings due to needing fewer machines outweigh the costs of increased training. Acknowledging that other factors could limit the machine's output, we estimate ℓ to be a modest 190 bags/hour/machine.

Maximizing T. All airlines have a time τ before departure after which a passenger may not check in and board. Taking into account data supplied in the problem statement, we have $\tau = 45$ min. By then, all bags will be present, so EDS operators can be guaranteed $\tau - \mu$ min to process bags for a flight, where μ is the time to load the bags onto the plane. As we have no data, we arbitrarily set $\mu = 6$ min, so EDS operators have at least 39 min (0.65 h) to process the bags. Our task is to maximize this amount of time.

If the peak hour were the only hour in which flights departed, EDS processing for peak hour can begin 45 min before the first flight, and the last bag of the last flight must finish being processed 6 min before the end of the hour. Thus, we have at most 1 h 39 min to process all of the bags. Therefore, the total time is $T = 1 + \tau - \mu$.

To use this maximum time interval best, we need a steady supply of bags coming in, to allow the machines to operate at maximum output for the entire time interval. As we will show, we can come close to a constant flow.

We now revoke the assumption that the peak hour is the only hour of flights. The bags in the hours immediately before and after peak, by definition fewer than B_{peak}, can be processed in less time than needed to process B_{peak}. When the peak hour's first bags arrive 45 min before the peak hour begins, we cannot yet assume that the EDSs will be available to process them, because flights departing during the hour before peak will have bags that still need to be processed. Similarly, we cannot assume that the EDSs can process our peak hour's bags all the way up to the last moment, since the bags of the next hour's first flight will likely require more than a few minutes to process. So, we should expect encroachments on the 1.65-hour maximum time interval. However, both the highest morning and evening peak hours are sufficiently greater in volume than the neighboring hours [Bureau of Transportation

Statistics n.d.], so we can operate at maximum time, 1.65 hours, without fear of other periods' effects. So, we define $T = (1 + \tau - \mu)$ and arrive at **(1)**.

Solving for the Optimal Q_{EDS}

Calculating B_{peak}

We examine each component of the equation

$$B_{\text{peak}} = \sum_{i=1}^{8} t_i n_i P_{\text{seats filled}_i} \bar{b} P_{\text{orig}}.$$

The problem statement tells us that 20% of passengers check no bags, 20% check just one bag, and 60% check two bags. So, the average number of bags per passenger is $\bar{b} = 1.4$.

Using the given proportions of seats filled for the various types of flights plus data from the T-100 Domestic Segment table in the Large Air Carriers database from the Intermodal Transportation Database [Bureau of Transportation Statistics n.d.], we calculate the averages for each flight type i:

$$P_{\text{seats filled}_i} = \begin{cases} .8679, & 1 \le i \le 3; \\ .8194, & 4 \le i \le 7; \\ .7705, & i = 8. \end{cases}$$

On average, 15% of passengers are from connecting flights, so $P_{\text{orig}} = .85$.

Our equation has now become

$$B_{\text{peak}} = (.85)(1.4) \sum_{i=1}^{8} t_i n_i P_{\text{seats filled}_i} = 1.19 \sum_{i=1}^{8} t_i n_i P_{\text{seats filled}_i}.$$

Substituting in the values for airports A and B for t_i and n_i (from the Technical Information Sheet) and our values for $P_{\text{seats filled}_i}$, we get

$$B_{\text{peak at A}} = 5286 \text{ bags}, \qquad B_{\text{peak at B}} = 5683 \text{ bags}.$$

Calculating Q_{EDS}

An EDS is operational $\Omega = 92\%$ of the time. We use $\ell = 190$ as an average value for the rate of bags per machine per hour. We have $\tau = 0.75$ h and $\mu = 0.1$ h. Using these values and the respective values of B_{peak} for each airport, we arrive at

$$Q_{\text{EDS for A}} = 19, \qquad Q_{\text{EDS for B}} = 20.$$

Exploring ϕ

During holidays, passengers are more likely to carry more bags. We examine the extreme of each passenger carrying two bags, which alters ϕ to 1.7. **Table 1** shows the effect on delays for airport A; results for airport B are similar.

Table 1.

Delays (in min) for airport A, for various machine speeds ℓ, values of ϕ, and proportions of seats filled. The value $\phi = 1.7$ corresponds to each passenger checking two bags.

ℓ	$\phi = 1.19$			$\phi = 1.7$		
	max	est.	min	max	est.	min
160	39	14	0	98	63	21
190	17	0	0	67	37	2
210	6	0	0	51	24	0

As expected, delays are greater when each passenger checks two bags. In addition, there will probably be more seats filled during this time period. However, since these busiest times of the year occur so rarely, we believe it is not worth buying extra machines to handle this overload. A possible solution to increased baggage is to turn to more temporary solutions, such as renting other portable screening devices or hiring extra workers or K-9 dogs.

In the worst-case scenario, on the busiest day of the year in airport A or B, when every flight in the peak hour is full, and the EDS is operating at its highest rate ($\ell = 210$), there will be only about 50 min of delay. We believe this is acceptable.

Scheduling Algorithm

We developed the following algorithm to schedule the departure of different flight types within the peak hour so that the number of passengers, and, consequently, the number of bags, is evenly distributed.

1. Obtain data on the number of flights and seats on each flight.
2. Modify the seat data to represent the average number of people on each flight. To do this, multiply by the estimated percentage of seats filled for the type of the given flight.
3. Calculate total number of people on all flights during the peak hour.
4. Determine the desired number of time intervals during the peak hour. We chose 6 as an appropriate number.
5. Determine the average number of people to fly during each time interval. Allocate that number of spaces for each interval, i.e. total number of people divided by 6.

6. Do the following n times (where n = total number of flights):
   (a) Find the flight with the most people on it.
   (b) Starting at the first interval, and searching sequentially through to the last, find the time interval with the most number of spaces still available.
   (c) Assign said flight to this time interval.
   (d) Subtract the number of available spaces by the number of people on said flight.
7. Make sure there is a flight at :00 and one at :59 to ensure the efficiency of our model, so as to maximize the time interval available for processing and allow the use of machines at full capacity. To do this:
   (a) For the first 30 minutes, start at the beginning of the time interval and evenly distribute the interval's assigned flights in order of decreasing flight capacity and increasing time.
   (b) For the second half hour, start at the end of the time interval (:39, for instance) and evenly distribute the interval's assigned flights in order of decreasing flight capacity and decreasing time.

Essentially, we are evenly distributing the flights scheduled in this peak hour among six 10-minute intervals. The flights were modified to represent the average number of passengers per flight, rather than the number of seats per flight, since the former has more impact on the number of bags scanned than the latter. The manner in which the flights are distributed among those intervals is analogous to filling a jar with different-sized rocks. Begin by adding the largest rocks, then smaller rocks, then pebbles, then sand, and finally water. With each additional step, you are filling in gaps. If you start with water and fill up the jar, then there is no room left for anything else. Thus, we start with the larger capacity flights and move our way down.

We wrote a computer program in C++ to implements the algorithm. [Editor's Note: We omit the program code.]

Figure 1 shows the number of bags still left for the EDS to process at airport A after each minute in airport A, as a function of time, according to our algorithm. For airport B, the results are similar.

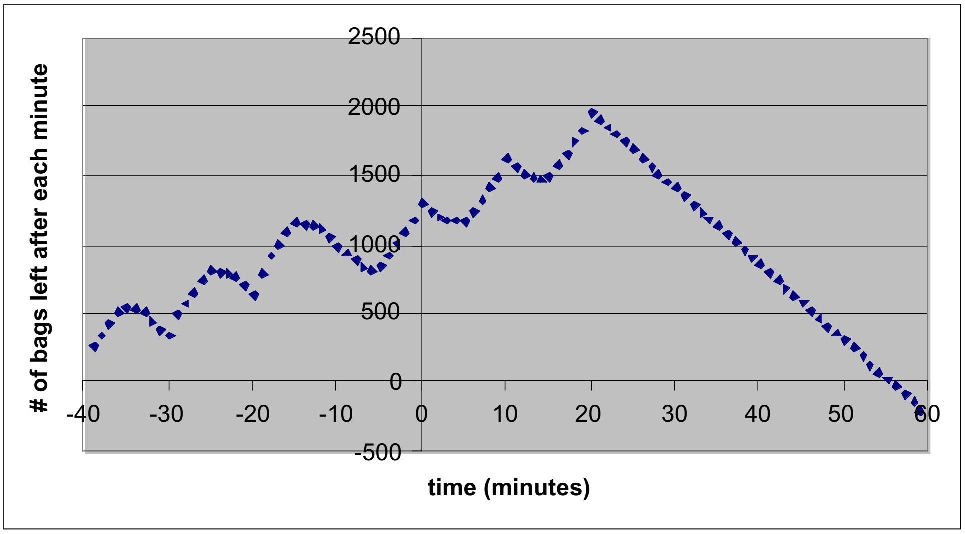

Figure 1. Bags left to process at airport A, as a function of time, according to the flight-distribution algorithm.

Cost Analysis of EDS and ETD

$$C(\alpha, \omega, Z) = B_{\text{peak}} \left(\frac{\alpha(1000 + c_i + \omega Z)}{\Omega_{\text{EDS}} \ell_{\text{EDS}} (1 + \tau - \mu)} + \frac{(1.2 - \alpha)(45 + 10\omega Z)}{\Omega_{\text{ETD}} \ell_{\text{ETD}} (1 + \tau - \mu)} \right)$$

where

C = total cost of recommended system;

$B_{\textbf{peak}}$ = total number of bags during the peak hour;

α = percentage of B_{peak} that the EDS will screen;

ω = hourly operational cost of EDS; cost of ETD machine is 10 times this amount;

Z = years

c_i = installation cost of EDS, dependent on airport (thousands of dollars);

ℓ = throughput rate of each machine (bags/h/machine);

Ω = percent of time that the machines are operational;

τ = minimum early passenger arrival time (h);

μ = travel time of one bag between EDS and the plane (h);

1000, 45 = cost of EDS and ETD machines, respectively (thousands of dollars).

We also assume that the installation cost of the ETDs is negligible.

Deriving the Model

By requiring that 20% of all bags be screened through both an EDS and an ETD machine, the effective number of bags to screen increases by 20%. The number of bags that go through the EDS, B_{EDS}, plus the number of bags that go through the ETD machine screening, B_{ETD} , must equal this effective number of bags. Therefore,

$$B_{\text{eff}} = 1.2B_{\text{peak}} = B_{\text{EDS}} + B_{\text{ETD}}.$$

The time to screen all these bags remains the same as in our previous model, and therefore τ and μ have the same values as given earlier. Likewise, the equation to determine the number of EDSs remains the same, and the number of ETD machines can be determined using the same equation with parameters for ETDs substituted.

Cost

The initial cost per machine equals the machine cost plus installation cost. EDSs are given as costing \$1 million, while ETD machines are only \$45K. Luckily, ETD machines are usually fairly small and portable, so their installation costs are assumed to be negligible. However, the installation cost of EDSs, c_i, is substantial: \$100K for airport A and \$80K for airport B. The annual variable cost of operating the machinery is ω for an EDS, 10ω for an ETD. We adopt a horizon of Z years.

The total cost C is the fixed cost plus the variable cost of each machine over the time horizon. All costs in the following equations are in thousands of dollars.

$$C(\omega, Z) = Q_{\text{EDS}}(1000 + c_i + \omega Z) + Q_{\text{ETD}}(45 + 10\omega Z).$$

Substituting, we get:

$$C(\omega, Z) = \frac{B_{\text{EDS}}(1000 + c_i + \omega Z)}{\Omega_{\text{EDS}}\ell_{\text{EDS}}(1 + \tau - \mu)} + \frac{B_{\text{ETD}}(45 + c_i + 10\omega Z)}{\Omega_{\text{ETD}}\ell_{\text{ETD}}(1 + \tau - \mu)}.$$

However, the number of bags going through each EDS is related to the number of bags going through each ETD machine. In addition, the number of bags going through each EDS is between 20% and 100% of the total number of peak-hour bags. We represent this relationship by the coefficient α, with $0.2 \leq \alpha \leq 1$.

$$B_{\text{EDS}} = \alpha B_{\text{peak}}.$$

Substituting into the cost equation, we are left with

$$C(\alpha, \omega, Z) = B_{\text{peak}} \left(\frac{\alpha(1000 + c_i + \omega Z)}{\Omega_{\text{EDS}}\ell_{\text{EDS}}(1 + \tau - \mu)} + \frac{(1.2 - \alpha)(45 + 10\omega Z)}{\Omega_{\text{ETD}}\ell_{\text{ETD}}(1 + \tau - \mu)} \right).$$

Using Maple, we plot C as a function of α and keep ω constant at an arbitrary \$50K. We can see in **Figure 2** that after various number of years, the cost of the machine can significantly depend on the number of bags that go through each machine, which depends on α.

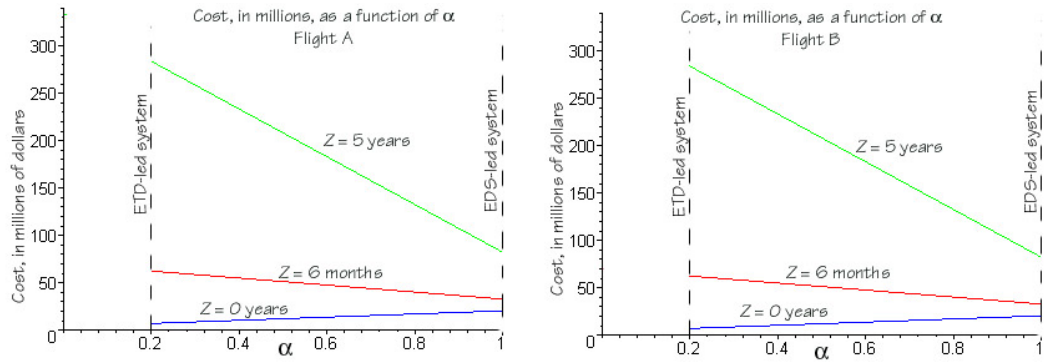

Figure 2. Costs over various time horizons for airports A and B.

For any α, the function C is linear in Z. Except for the particular Z value that makes the slope 0, only 0.2 and 1—the extreme values for α—can yield minimum values for C. This means that there are two significant cases to study:

- the EDS-led system, in which EDSs are the first tier of baggage scanning, processing 100% of the bags, and ETD machines are the fail-safe, scanning 20% of the bags; or else, vice versa,
- the ETD-led system, in which ETD machines process 100% and the EDSs scan 20%.

We show later that the case of α between these two extremes is undesirable.

Installing an ETD-led system (i.e., $\alpha = 0.2$) would be cost-effective only for a very short time horizon of a few months. This makes sense since the installation cost of an all-EDS system is very expensive, while the total of the high variable cost of operating the ETD machines is low over a short duration. However, after a few months, it is optimal to have $\alpha = 1$, or an EDS-led system, since this has minimum cost in the long run. The graphs assume that the cost of operation of the EDS is $\omega = \$50\text{K}$ per year, which may or may not be realistic. A different value of ω will affect the slopes of the hs, thereby affecting when $\alpha = 1$ becomes optimal. Therefore, by finding where the derivative of the cost function is zero, we can find the critical turning point for our model at any ω, such that after this time, an EDS-led system would be more desirable. We have

$$\frac{\partial}{\partial \alpha} C(\alpha, \omega, Z) = B_{\text{peak}} \left(\frac{1000 + c_i + \omega Z}{\Omega_{\text{EDS}} \ell_{\text{EDS}} (1 + \tau - \mu)} - \frac{45 + 10\omega Z}{\Omega_{\text{ETD}} \ell_{\text{ETD}} (1 + \tau - \mu)} \right).$$

Setting this expression equal to 0 and solving for Z, we find

$$Z(\omega) = \frac{1}{\omega} \left(\frac{45 \Omega_{\text{EDS}} \ell_{\text{EDS}} - (1000 + c_i) \Omega_{\text{ETD}} \ell_{\text{ETD}}}{\Omega_{\text{ETD}} \ell_{\text{ETD}} - 10 \Omega_{\text{EDS}} \ell_{\text{EDS}}} \right).$$

Notice that Z is inversely related to ω. Also, B_{peak} and $(1 + \tau - \mu)$ cancel out, thereby not influencing the critical cutoff time. Therefore, the only difference between airports A and B is the installation cost, which is unnoticeable when plotted. Therefore, just for airport A, we plot Z as a function of ω in **Figure 3**.

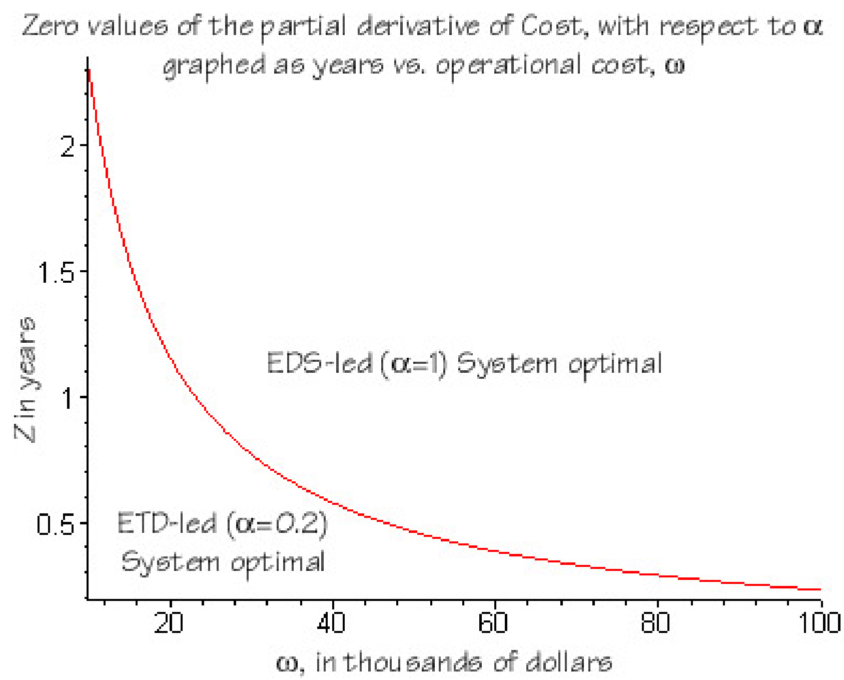

Figure 3. Time to equal cumulative cost as a function of annual operation cost of an EDS.

For (ω, Z) combinations below the curve, an ETD-led system is more cost-efficient; however, the operational cost of each machine will be high enough to make an EDS-led system cheaper in less than one year. Given not only a life expectancy of EDSs around 10 years but also bureaucratic inertia, we cannot expect the EDS-ETD system baggage inspection system to be replaced soon enough so that an ETD-led system will minimize costs. An EDS-led system is more desirable

Even though ETD machines become quite expensive after a short amount of time because of high operational cost, the low fixed cost might come in handy during the peak hours of peak times of the year. It would not be cost-efficient to buy extra EDSs just to handle these periods, but airports could buy extra ETD machines and store them until needed.

Determining Q_{EDS} and Q_{ETD}

We have determined that 100% of the bags should go through an EDS. We can calculate the total number of machines to buy by plugging the numbers into our initial equations:

$$Q_{\text{EDS}} = \frac{\alpha B_{\text{peak}}}{\Omega_{\text{EDS}} \ell_{\text{EDS}} (1 + \tau - \mu)}, \qquad Q_{\text{ETD}} = \frac{(1.2 - \alpha) B_{\text{peak}}}{\Omega_{\text{ETD}} \ell_{\text{ETD}} (1 + \tau - \mu)}.$$

We estimate $\ell_{\text{ETD}} = 47$ bags/hour/machine, the average throughput rate of the ETD machines at the Winter Olympics in 2002 [Butler and Poole 2002]. The other constants have the same values as we used in our earlier model:

$$\begin{aligned} B_{\text{peak at A}} &= 5286, & B_{\text{peak at B}} &= 5683 \\ \ell_{\text{EDS}} &= 190, & \ell_{\text{ETD}} &= 47 \\ \Omega_{\text{EDS}} &= .92, & \Omega_{\text{ETD}} &= .98 \\ \tau &= .75, & \mu &= 0.1 \end{aligned}$$

Using these values, we find

$$\begin{aligned} Q_{\text{EDS}\,A} &= \lceil 18.33 \rceil = 19, & Q_{\text{EDS}\,B} &= \lceil 19.70 \rceil = 20; \\ Q_{\text{ETD}\,A} &= \lceil 13.91 \rceil = 14, & Q_{\text{ETD}\,B} &= \lceil 14.96 \rceil = 15. \end{aligned}$$

As expected, the EDS values for both airports are unchanged from our previous results, when we had not yet considered the ETD machines.

Recommendations for the Future

Although an EDS-led system, with merely enough ETD machines to cover 20% of the bags, is optimal based on our calculations, it might not be the absolute best solution. An important consideration is whether or not new technology might replace the machines before the critical cutoff time. For example, if current technology trends show that a better baggage screening system will be ready in less than a year, it might be worth taking the risk and buying an ETD-led system. Then, within the year, buy the better machines, with lower operational costs, that can replace the ETD machines. However, not only would this save very little, but this is quite a risk to take since your operational cost for the ETD machines will hurt the airport terribly if better technology does not come out in time. Therefore, our model shows that unless current trends show an immediate market introduction of new and advanced technology,

the best solution is to have all bags screened by EDSs and only 20% screened by ETDs

Down the road, however, we may need to re-evaluate the system.

Other variables that we should weigh heavily are the false positive rate, the false negative rate, and the human reliability factor. The false positive rate and the false negative rate should both be kept as low as possible, but it is more important that the false negative rate be extremely close to 0, as this affects the accuracy of the machine, while the false positive rate merely affects the efficiency of the machine. Increased precision would not only increase the safety of our air traffic system but also reduce the number of secondary, fail-safe screening devices, thus saving money. Currently, EDSs are widely reported to have between 22% and 30% false positive rates, which is ridiculously high.

New technology seems to be decreasing significantly this inefficiency, which will result in less required re-screenings and human intervention. A machine with high false negatives used as a first-tier scanner (as in the EDS in the EDS-led system) is very dangerous, and to counter the threat of explosives slipping through, costly random screening of negatives with a second device will be needed, though still not eliminating the said threat.

Conclusion: Strengths and Weaknesses

The main strength of our model is that the number of EDS machines it projects will work well even if some assumed constants and probabilities shift. More accurate statistical data, as should be available to airport administrators, would yield a more accurate optimal number of machines needed. The delays caused by fluctuations in assumptions are, under most every case, within acceptable ranges for delay, i.e., delays for other reasons happening at the same time. If this model is implemented, it should be stressed that the system is designed so that no extra delays should be expected. If this argument is sold to the people convincingly enough, instances of delay should not make passengers more likely to blame the EDS system over other causes for delay, such as waiting for connecting passengers, bad weather, or mechanical difficulties. Extreme circumstances, such as holiday travel days, normally force delays; any delay in the EDS system on such a day, if not compensated with temporary ETD machines, would run parallel to—not in addition to—delays already occurring. Besides, air travelers will be willing to wait a few extra minutes occasionally if it gives them a sense of security that many lacked following September 11.

One weakness of our model is that we did not go into different methods for implementing the prioritization and queuing regime for bags entering the explosives scanners. We considered several options. The tags placed on the bags at the check-in desk could list departure time, thus allowing easy sorting. This, however, does not allow for changes in departure time due to delays. A departure-listing screen, like those posted throughout the airports for passengers, could be displayed by the EDS machines. This list will be very long at a large airport, though, and would require EDS operators to recheck the display frequently.

Another weakness is that we ignored the placement of the EDS machines. Most EDSs are placed in the airport lobby near the check-in area. In a large airport, this could mean that the machines are spread out over a large area. So, the EDS machines could not work together like one unit, as our model implicitly assumes. This would mean a loss of efficiency: machines at one end of the airport could run out of bags while those at the other end could have too many. This problem could be remedied in the flight scheduling process, factoring in airline check-in desk placement in the even distribution of bags over the hour. The scope of that undertaking is far outside what we can accomplish here, though it ultimately deserves consideration.

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Judge's Commentary: The Outstanding Airport Screening Papers

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Introduction

The final judging for the 2003 Interdisciplinary Contest in Modeling took place at the United States Military Academy on March 8, 2003. The judges spent a long, but enjoyable, day reading an excellent set of papers submitted by the student teams. Because of the complexity of the problem and the wide variety of available and reasonable solution approaches, the judges' evaluation process focused on the following general areas.

Modeling

The judges evaluated the student teams' creative application of existing and novel mathematical modeling techniques to the defined problems. Particular attention was placed upon the identification and appropriateness of the underlying modeling assumptions and model validation efforts.

Analysis

The judges evaluated the breadth and depth of the numerical analysis each team performed using their models. Particular attention was placed upon the reasonableness of conclusions and sensitivity analysis.

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Communication

To convey the quality of their modeling and analysis activities, student teams had to communicate effectively in their report. Key factors in this communication included organization, clarity and brevity of information. Particular emphasis was placed upon each team's one-page summary.

The Outstanding papers were the ones that provided excellent communication of valid modeling activities, meaningful numerical analysis and thoughtful conclusions. Papers that fell short typically fell into one of two categories:

- well-written papers with questionable models or limited analysis, or
- papers that hid excellent modeling and analysis work with marginal communication.

The Problem

This year's problem dealt with baggage screening and flight scheduling at a commercial airport. Clearly, these areas have received increased attention (especially baggage screening) since the tragic events of September 11, 2001. The student teams were required to analyze the required capacity for two types of baggage screening machines and to develop a recommended flight schedule for the airport's peak hour. Limited data was provided on the characteristics of peak hour flights and the passengers that utilize them. In addition to the modeling and analysis, the teams were asked to investigate emerging technologies in the area of baggage screening. In addition to the documentation of their modeling and analysis efforts, student teams drafted a position paper and two memos that communicated their findings, conclusions and recommendations.

This problem was an excellent choice for ICM. The multidisciplinary nature of airport security is clear, and the specific problems defined by the authors captured the essence of many fundamental areas of mathematical modeling. Most importantly, the problems included sufficient complexity to require the students to go beyond "textbook operations research" and utilize their creative problem-solving skills.

The problem was written by Dr. Sheldon Jacobson and Dr. John Kobza. Dr. Jacobson is Associate Professor of Mechanical and Industrial Engineering and Director of the Simulation and Optimization Laboratory at the University of Illinois Urbana-Champaign. Dr. Kobza is Associate Professor of Industrial Engineering at Texas Tech University. They have significant research experience in the area of transportation security, and they recently received the Aviation Security Research Award for their work in access control and checked baggage screening. In addition to authoring the problems, Drs. Jacobson and Kobza made valuable contributions as insightful members of the final judging panel.

Modeling Approaches

The majority of the mathematical modeling and analysis utilized by the student teams was applied to Tasks 1, 3, and 6. The approaches to Tasks 1 and 6 were very similar. Many teams attempted to apply the results of queueing analysis for M/M/s systems. While the baggage screening system is a queueing system, there were several common shortcomings in analyses of this type. First, many teams failed to identify and discuss the underlying assumptions of an M/M/s queue. Certainly, the assumption of constant average arrival rate is questionable at best. Second, many teams applied the steady-state (long-run) results from queueing theory to a period of time ranging from one to three hours.

Other teams applied "back-of-the-envelope" or simulation-based capacity analysis. This approach avoided the restrictive assumptions of queueing theory but led to two other common shortfalls:

- Many teams assumed that the baggage screening system is "empty and idle" at the beginning of the peak hour. In reality, it is more likely that the hours preceding and following the peak hour are "near peak."
- Many teams identified the number of machines that could handle the required load without any required queueing. A more cost-effective approach would be to design a system that experiences some queueing during peak demand but has the ability to "recover" in time.

A common shortcoming in both the queueing analysis and capacity analysis approaches was that teams did not recognize that a large proportion of passengers would be connecting through the airport. The baggage for these passengers would not have to be screened.

The majority of student teams recognized Task 3 as a scheduling problem, but they also realized that this problem is much more complex than traditional scheduling problems found in the literature. As a result, most teams developed heuristic procedures that "smooth" the flow of passengers through the airport during and around the peak hour. Many of these procedures suffered from several of the assumptions mentioned above regarding Tasks 1 and 6. Some teams did manage to formulate reasonable mathematical optimization models of the scheduling problem. Solution approaches for these optimization models ranged from traditional discrete optimization algorithms (embedded in software) to search-based heuristics such as genetic algorithms.

It was somewhat surprising that few teams modeled the problem in such a way that captured the interactions between the baggage screening and fight scheduling sub-problems. A few of the teams did combine the two problems into a large-scale simulation effort with simulation-based optimization heuristics applied to derive the solution. However, these comprehensive approaches were the exception not the rule.

The papers that moved forward in the competition tended to have a foundation in well-known modeling approaches with problem-specific customization based on the creativity and skill of the team. Many of these papers included self-evaluation of the modeling assumptions and some degree of validation based on preliminary analysis. Some teams used data from real airports and airlines to contribute to or validate their results. As always, sensitivity analysis was appreciated and rewarded by the judges.

Conclusions

My recommendations for future student teams are:

Assumptions Identify and critique (in writing) the assumptions of your models. Sometimes restrictive assumptions have to be made. Be sure that the judges realize you are aware of and concerned about these assumptions.

Analysis Spend as much time as you can on numerical analysis of the model. Use this analysis to perform "sanity checks" on the model. Do not just report the output. Comment on the reasonableness of the results. Perform extensive numerical experiments to eliminate bias resulting from assumptions, estimations or initial conditions. Summarize your analysis clearly in tabular or graphical form.

Communication Do not neglect the writing. Clear communication makes it easier to identify outstanding work. To be perfectly honest, good communication improves the judges' frame of mind.

References Clearly cite information that you utilize from published sources (books, papers, Websites, etc.). This will make it clear to the judges that you have properly and completely researched the problem. However, do not rely exclusively on existing work and do not copy text from existing sources without properly documenting the sources. Note that we did experience a few isolated instances of plagiarism and excessive copying in the competition.

About the Author

Richard Cassady is an assistant professor in the Dept. of Industrial Engineering at the University of Arkansas. His primary research interests include application of operations research in the area of repairable systems modeling. He teaches undergraduate and graduate courses in the areas of probability and statistics, stochastic processes, and reliability.

Authors' Commentary: Aviation Security Baggage Screening Strategies: To Screen or Not to Screen, That Is the Question!

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Introduction and Background

The events of September 11, 2001 make it the worst day in the history of commercial aviation. These events have lead to massive changes in the manner in which aviation security is organized and implemented at the 429 commercial airports throughout the United States. These changes include, for example,

- the creation of the Transportation Security Administration (TSA),
- the federalization of aviation security personnel,
- a more extensive use of air marshals on domestic flights,
- extensive positive passenger baggage matching protocols, and
- enhanced passenger and baggage security screening at airport terminal checkpoints and gates.

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The problems posed in this year's modeling competition, based on research supported by the National Science Foundation through the Division of Design, Manufacturing and Industrial Innovation, Program in Service Enterprise Engineering, are motivated by several of the challenges faced by the TSA in addressing the December 31, 2002 Congressionally-mandated deadline for 100% screening of all checked baggage on all domestic commercial flights in the United States. This mandate has resulted in the rapid manufacturing and deployment of several thousand explosive detection systems (EDSs) and explosive trace devices (ETDs). Key questions faced by the TSA have included

- where to deploy such baggage screening devices,
- what combination of EDSs and ETDs should be used at individual airports, and
- how such devices should be used once deployed.

The problems in this year's competition embody several of these questions.

Aviation and Transportation Security Act

On November 19, 2001, the United States Congress passed the Aviation and Transportation Security Act (ATSA), resulting in widespread and sweeping changes in how security is addressed for all forms of transportation (with a particular emphasis on air travel). An aggressive schedule was included for the federalization of airport security personnel (with a deadline of November 19, 2002) and the screening of all checked baggage on commercial flights using federally approved security screening devices and systems (with a deadline of December 31, 2002). Skeptics in both industry and government questioned whether these deadlines could be met, given the magnitude and scope of this undertaking. Moreover, the costs associated with such an endeavor were estimated to be in the billions of dollars (US). As the deadlines approached, the director of the TSA, Admiral James M. Loy, remained committed to meeting all specified deadlines. By December 31, 2002, over 90% of all airports had met this deadline, with the remaining airports aggressively moving towards compliance.

Formulation of the Contest Question

The authors of this year's contest question have been working in the area of operations research modeling of aviation security system since the mid 1990s. Their research has been disseminated in a wide variety of journals. The problems that they have addressed include

- a probabilistic analysis of access control security systems [Kobza and Jacobson 1996; 1997],

- a sampling procedure to estimate risk probabilities in access control security systems [Jacobson, Kobza, and Nakayama 2000],
- the analysis of baggage value performance measures for checked baggage security systems [Jacobson, Bowman, and Kobza 2001],
- a knapsack-problem model formulation for addressing aviation security system design problems [Jacobson, Kobza, and Easterling 2001],
- models for analyzing the impact of connecting passengers on selectee rates [Virta et al. 2002],
- a case study for checked baggage screening security system design [Jacobson et al. 2003a], and
- a cost/risk analysis of various checked baggage screening strategies [Jacobson, Virta, and Kobza 2003b].

All these research contributions focus on identifying strategies or procedures for enhancing the operation and design of aviation security systems.

This year's contest question relates to purchasing and deploying EDSs and ETDs for checked baggage screening at the 429 commercial airports around the United States. Many of the specific issues raised in the tasks described in the problem description grew out of ongoing discussions with TSA personnel, as well as from information extracted from Congressional testimonies by, for example, Kenneth Mead, the Inspector General of the United States Department of Transportation [Mead 2002a; 2002b], and a variety of newspaper and newswire sources. Factors that affect security equipment purchase and deployment decisions include

- the size of airports,
- the number of concourses within airports, and
- the schedule of flights departing from each airport (as well as their distribution throughout the day).

On a broader scale, the potential for growth at an airport must also be considered. All these factors play an important role in the decision-making process.

The initial goal of the TSA was to meet the requirement as defined in the ATSA. Therefore, feasibility was of paramount concern. However, once feasibility was attained, cost-effectiveness and operational efficiency became important. This year's modeling problem weaves together the feasibility issues that arose during the frenetic ramp-up period following the passage of the ATSA and the current cost-effectiveness issues to provide timely problems for the competition participants and an interesting and challenging evaluation process for the judges.

Conclusions

The transition process for aviation security operations since September 11, 2001 has not been smooth, but much progress has been made. However, aviation security is still a "work in process." New technologies being developed will significantly affect many of the operations in place today and require substantial changes. With the changing nature of system threats, aviation security will continue to evolve. This year's modeling competition clearly points out that there are many young people around the world who have the talent and the outstanding ideas needed to guide this evolution and affect the security of our world.

Acknowledgments

The authors wish to thank Dr. Chris Arney and Colonel Gary Krahn for organizing this year's competition and for providing invaluable feedback and suggestions on the design and revisions of the problem statement. Without their assistance, this year's competition would not have been the enormous success that it has turned out to be. The authors wish to thank the triage graders at the United States Military Academy who devoted countless hours to the initial grading of the submissions. Special thanks go to the final round of graders who not only provided expert advice and evaluation but also made the weekend of grading an enjoyable experience. The authors also wish to acknowledge the many individuals within the Transportation Security Administration without whom this problem could never have been developed. Lastly, the motivation for the problems in this year's competition is based on research supported in part by the National Science Foundation (DMI–0114046, DMI–0114499).

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Guide for Authors

Focus

The UMAP Journal focuses on **mathematical modeling and applications of mathematics at the undergraduate level**. The editor also welcomes expository articles for the On Jargon column, reviews of books and other materials, and guest editorials on new ideas in mathematics education or on interaction between mathematics and application fields. Prospective authors are invited to consult the editor or an associate editor.

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