Skyrocketing Wait Times

Modeling Passenger Flow through Airport Security Check Points

Caroline Buck[1], Theresa Maloney[1], Delsey Sabu[1]

[1]Seattle Pacific University

MCM 2017

Contents

Survey of Airline Security 3
- Current Issues 3
- TSA Action 3

Modeling Current Passenger Flow 3
- Assumptions 4
- Modeling Passenger Flow 6
- Data Calculations 7
- Identifying Bottlenecks 8

Suggested Modifications 9
- Determining an Optimal Ratio of Screening Stations 9
- Algorithmic Optimization Model (AOM) 10
- Suggested Check Point Configurations 10
- Creative Solutions 12

Addressing Passenger and Cultural Diversity 12
- Perceptions of Time 12
- Queuing Psychology 13

Policy & Procedure Suggestions 13
- Investing in the Latest Scanning Devices 13
- Automated Threat Detection Technologies 14

Considerations 14
- Validating Our Model 14
- Strengths 15
- Weaknesses 15
- Further Research 16

Appendix 17
- Check Point Element Costs 17

References 18

Survey of Airline Security

Since the terror attacks on September 11, 2001, the emphasis on effective airport security measures has skyrocketed. With the subsequent creation of the Transportation Security Administration (TSA) by the United States government, the question remains: how best to maximize threat detection accuracy while moving passengers through as quickly and painlessly as possible.

Current Issues

In early 2016, security lines at airports across the United States exploded with uncharacteristically long wait times, causing over 6,700 Americans to miss flights during one week alone [13]. Airports in Atlanta, Chicago, Los Angeles, and Dallas were some of the hardest hit, resulting in major delays in what are some of the world's busiest airports [17]. Reports are unclear on what specifically caused the unusual spike in wait times at security check points.

TSA Pre-Check is a service created to expedite screening time for trusted travelers. Passengers who pay $85 and pass the background check are directed to specific Pre-Check security lanes and able to skip steps in the screening process, such as removing their shoes and jackets and placing their laptops in separate bins. This lessens the baggage loading time per passenger and increases passenger throughput at baggage loading stations, an important feature since lanes rarely have enough space for more than 4 individuals to load baggage at one time [11]. Currently, 45% of passengers are enrolled in Pre-Check, but only about 25% of lanes are designated for Pre-Check passengers.

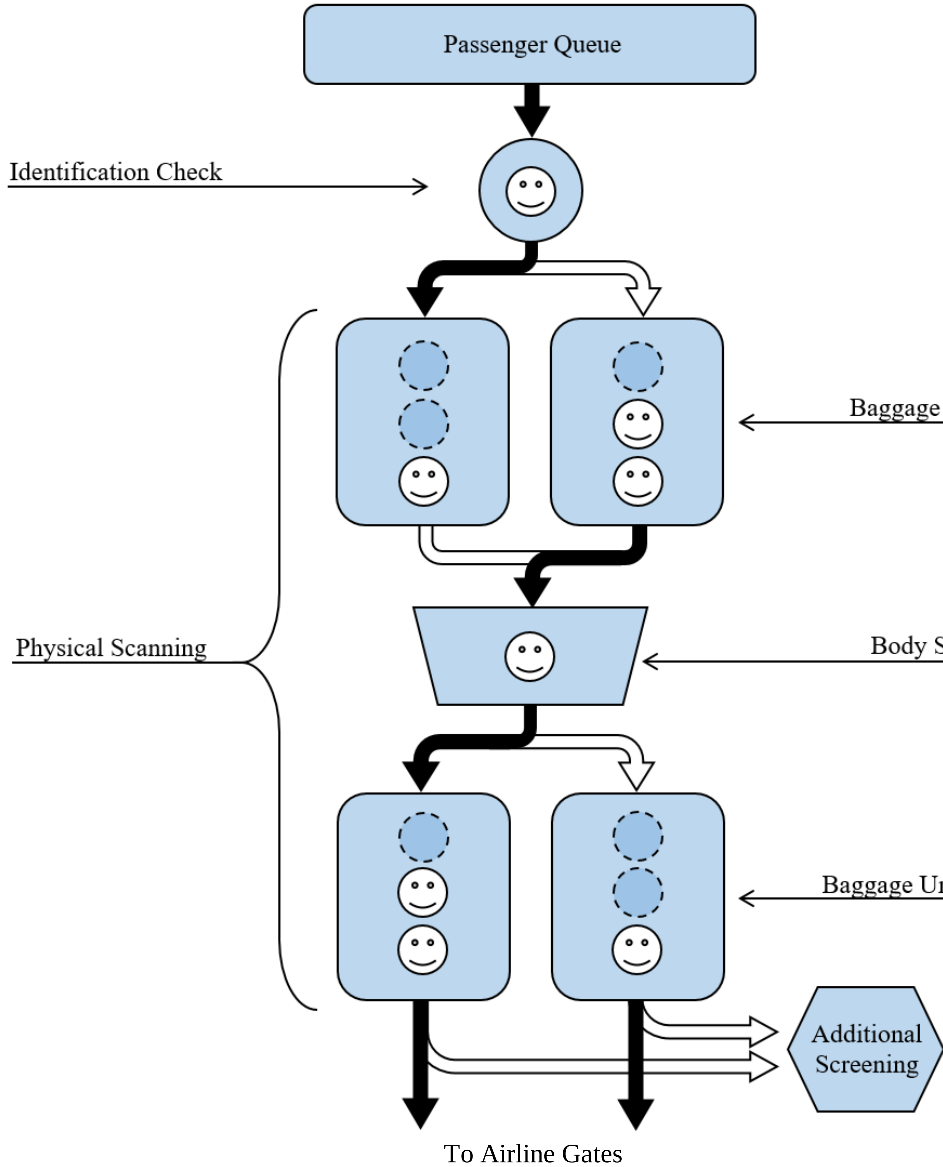
TSA Action

In order to combat the surge of passengers, the TSA temporarily increased its number of on-duty security officers, increasing the number of employees working overtime and moving many employees from part-time to full-time. However, this was only possible due to a small stipend from Congress; the overstaffing at security check points is not cost effective and does not directly increase passenger throughput [15].

Modeling the Current System

Our data simulation model focuses on the individual passenger TSA security screening processes, including Identification Check, where TSA officers inspect passengers' boarding passes and credentials, and Physical Scanning, which is broken up into 3 sub-processes: Baggage Loading on the conveyor belt to be scanned, an individual Body Scan using a millimeter wave scanner or metal detector, and Baggage Unloading from the conveyor belt after it has passed through an x-ray (see Figure 1). Passengers who are flagged for additional screening are taken to a separate space in the check point area.

Figure 1. Diagram of sample security check point lane



Assumptions

We made a number of assumptions about the general function of security check points and the roles passengers and security officers play in them for the simplification of our model.

- Time is discrete. We treat it as a step function.
- Each passenger will only go through a security check point once, in the order they arrive. (There are no exceptions for earlier flights.)
- There is no lag time waiting for an initial queue to form at the security check point; we model the worst-case scenario where there are always people waiting to go through the security check point.

- Sufficient competency and compliance of all Transportation Security Administration (TSA) officers and all passengers. Any errors or confusion have a negligible effect on process time.
- Pre-Check lanes are ignored. We assume that our modifications to improve passenger throughput in regular screening lanes will also improve flow in Pre-Check lanes.
- Clear 'fast lanes' for bypassing traditional identification checks are not included in this model, as Clear is a new business and its negligible (if at all) impact on overall wait time can be ignored.
- Language barriers do not pose a problem; we assume that sufficient signage exists and any disruptions are negligible and do not add to the overall wait time.
- The average Body Scan time using a millimeter wave scanner is 7 seconds, including 3 seconds for operation of the machine and 4 seconds of analyzation of the scan results. We assume this based on a total scan time of 15 seconds for backscatter technology, which includes entering and exiting the machine [1]. We assume no difference in effective scan time between the Millimeter Wave scanners and metal detectors.
- Passengers are scanned in the Millimeter Wave AIT scanners as the gender they present themselves as and any issues with incorrect scanning procedure due to this are negligible.
- Baggage Scanning for each passenger uses x-ray screening machines and is completed by the time the passenger completes a Body Scan.
- There is at least one Baggage Scanner for every Body Scanner.
- Each lane contains exactly one baggage scanner.
- Baggage Loading time and Baggage Unloading time are equal.
- Travel time between process stations is negligible.
- No waiting time occurs due to an absence of conveyor belt bins.
- Any extra inspections required for flagged baggage or persons take place in a separate screening zone and do not disrupt the overall flow of passengers through the security check point. We model the overall flow of passengers, and assume if one is pulled aside, it does not affect others.
- Baggage waiting to be scanned does not take up space at the Baggage Loading station

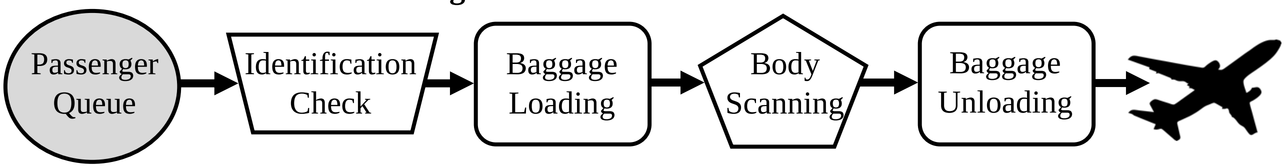
We also made several assumptions about the data we were provided with, and data we generated and extrapolated from the given data.

- Assume the data provided by the TSA is accurate and reflective of a full spectrum of passenger speeds, and that any data extrapolated and generated is generally representative of reality and can be used for modeling passenger flow through a security check point.
- The data provided by the TSA regarding time from arriving at conveyor belt to retrieving baggage does not include repacking or redressing.
- Assume any difference in speeds caused by rounding from milliseconds to seconds is negligible and can be ignored.

Modeling Passenger Flow

To model passenger flow through a security check point, we created a simple processor-based system based on the time it takes a group of passengers to move through each screening process (see Figure 2). We then created equations to determine the amount of time it takes at each station relative to the number of open identification check stations and available body scanners.

Figure 2. Processor-based model



The Identification Check process consists of the time to present appropriate travel documents to the Identification Check Security Officer, verification of those travel documents by said officer, and any other actions that occur before the passenger can move to a Baggage Loading station. We account for occasional fumbles in the Identification Check process, assuming 10% of passengers are detained an average of 10 seconds in finding their documents or in officer scanning errors.

The Baggage Loading process includes the time for a passenger to remove all required items (including shoes, belts, electronic devices, liquids, and baggage) and place them in bins on the conveyor belt.

The Body Scan process involves the amount of time it takes for a passenger to be scanned in a millimeter wave scanner and for the security officer operating the scanner to verify that passenger's scan image.

The Baggage Unloading process incorporates time required for a passenger to retrieve baggage from the conveyor belt after it has been scanned and replace any personal items that were scanned.

We used three variables to quantify security check point configuration (see Table 1). We use p to limit the size of each group that moves through the processors. That way, an entire group completes the Baggage Loading process at the same time step and no overlap or queueing time occurs between groups.

Table 1. Variable names and definitions

Variable	*Definition*
p	Total number of baggage loading stations at the security check point; Equal to the number of passengers in each group
i	Total number of operating identification check stations
s	Total number of operating body scanners
t_x	Time it takes for a group of p passengers to complete screening process x

Data Calculations

In our data simulation model, we used the data provided on how passengers proceed through the security check point process to generate sample individual process times. In reviewing the simulated data, we found mean times for Identification Check and Physical Scanning (see Table 2).

Table 2. Mean security process times per passenger

Sample (1000 passengers)	*Mean Identification Check Time (sec)*	*Mean Physical Scanning Time (sec)*
1	12.5	52.0
2	12.0	52.7
3	12.1	50.3

We break apart Physical Scanning time into Baggage Loading time, Body Scan time, and Baggage Unloading time using the equation below:

$$t_{physical\ scanning} = t_{loading} + t_{body\ scan} + t_{unloading}$$

Using our assumptions of

$$t_{body\ scan} = 7 \text{ and } t_{loading} = t_{unloading},$$

we simplify the previous equation to:

$$t_{physical\ scanning} = 2 \cdot t_{loading} + 7$$

This allows us to separate the mean times for Physical Scanning obtained from our data simulation model (see Table 3).

Table 3. Mean screening process times per passenger

Sample (1000 passengers)	*Identification Check time (sec)*	*Physical Scanning time (sec)*	*Baggage Loading time (sec)*	*Body Scanning time (sec)*	*Baggage Unloading time (sec)*
1	12.5	52.0	22.5	7	22.5
2	12.0	52.7	22.9	7	22.9
3	12.1	50.3	21.7	7	21.7

In order to simplify our calculations, we used the rounded means of the Identification Check time (12 seconds) and Baggage Loading time (22 seconds) per person to calculate the amount of time it takes for a group of p passengers to move through each screening process as follows:

$$t_{ID\ check} = 12 \cdot \frac{p}{i}$$

$$t_{loading} = t_{unloading} = 22$$

$$t_{body\ scan} = 7 \cdot \frac{p}{s}$$

Identifying Bottlenecks

To minimize bottlenecks, a group should move to the next station at the same time or just before the next group finishes at the previous station. Since only one group of p passengers can load baggage at one time, the second group, for example, cannot advance to the Baggage Loading station until the first group has finished and advanced to the Body Scan station. Using the equations above, we can estimate the total screening process times for groups of p passengers (see Table 4).

Table 4. Estimated screening process times for 6-passenger group in a sample configuration ($i = 1, p = 6, s = 1$)

Identification Check time (sec)	*Baggage Loading time (sec)*	*Body Scanning time (sec)*	*Baggage Unloading time (sec)*
72	22	42	22

Based on the time estimates for a sample configuration of 1 Identification Check station, 6 Baggage Loading stations, and 1 Body Scanning station, we can see that it takes almost twice as long to complete the Body Scanning process than the Baggage Loading process. This illustrates the main bottleneck of the current system: only one person can proceed through each millimeter wave scanner at one time. It is impractical for security checkpoints to have fleets of wave scanners, as the cost of a single scanner is around $175,000 [4].

However, the Identification Check time is more than the sum of the Baggage Loading and Body Scanning times. This ensures that the last person of the first group completes the Body Scanning process before the next group arrives at the Baggage Loading station. In order to maximize efficiency of security check points, the first group should just be completing Body Scanning as the second group arrives at the Baggage Loading station, since people with no luggage will most likely complete the Baggage Loading in less than the average of 22 seconds.

We can ignore Baggage Unloading time since the time is relatively fixed and the simple addition of more table space allows for overflow passengers to complete the station at the same time.

Suggested Modifications

Determining an Optimal Ratio of Screening Stations

To alleviate the bottlenecking observed at Body Scanning stations, we propose that an optimal ratio of number of Identification Check to Body Scanning stations can be reached if, for a fixed capacity of Baggage Loading stations, the Baggage Loading time and Body Scanning time is equal to the Identification Check time for same number of passengers to pass through the Identification Check station. Suppose we calculate the total time it takes for a group of p passengers to pass through the entire security check point process as:

$$t_{total} = t_{ID\ check} + t_{physical\ scanning},$$

where $t_{ID\ check}$ represents the time for the group to complete the Identification Check process and $t_{physical\ scanning}$ represents the time for the group to complete all aspects of the Physical Scanning processes.

From our data analysis and assumptions, suppose:

$$t_{ID\ check} = 12 \cdot \frac{p}{i} \text{ and } t_{physical\ scanning} = 7 \cdot \frac{p}{s} + 44$$

Combining these, we get:

$$t_{total} = 12 \cdot \frac{p}{i} + 7 \cdot \frac{p}{s} + 44 = \frac{12ps + 7pi + 44is}{is}$$

If we treat p as a constant parameter and not a variable, we take the partial derivatives of t_{total} with respect to s and i:

$$\frac{\partial}{\partial s} t_{total} = \frac{-7p}{s^2} \text{ and } \frac{\partial}{\partial i} t_{total} = \frac{-12p}{i^2}$$

Setting these equal,

$$7pi^2 = 12ps^2$$

$$p = 0 \text{ and } i = \sqrt{\frac{12}{7}} s \cong 1.309s$$

Ignoring the solution where $p = 0$ (number of passengers must be greater than 0), we find that the optimal ratio for minimum ID check and physical scanner stations is $i \cong 1.309s$, or $3i \cong 4s$.

So, we have shown that to alleviate the bottlenecks between identification check and physical scanner stations, we need to find the optimal ratio of i to s so that $t_{ID\ check} = t_{load} + t_{body\ scan}$. This optimal ratio is approximately four identification check stations for every three physical scanning stations. We model this modification to the current physical structure of a security check point in the next section.

Algorithmic Optimization Model (AOM)

In our assessment of the current security check point layout used by the TSA, we chose four fundamental elements to quantify (see Table 5). Note that $b \cdot b_l$ is the total number of Baggage Loading stations at the security check point.

Table 5. Check point elements used in optimization algorithm

Variable	*Definition*
i	Total number of identification check stations
s	Total number of body scanning stations
b	Total number of baggage scanners
b_l	Number of loading stations per baggage scanner

We assert that increasing the quantity of each element will help to decrease passenger queue time, which in turn increases passenger throughput. However, since the TSA has limited financial resources, we also factor in the individual marginal expense associated with each element in our algorithm. In reality, the quantities of each element differs greatly with the size of the airport and average number of passengers that go through the security check point annually. Our Algorithmic Optimization Model (AOM) can be scaled to fit most airports' security needs, however for simplification of our calculations and to reflect a reasonably realistic check point environment, we restricted the maximum number of each element to ten.

Given the task of modeling the most efficient combination of check point elements, it is important to look at all the possible combinations. The AOM computes every possible way the four characteristics can come into play within the given range of 1 to 10 for each element. The number of variations of the four elements is 10^4, or 10,000.

Thus, there are 10,000 different possible security check point configurations of our four elements. Each of these configurations are then put through an efficiency-cost function that evaluates it and assigns it an efficiency score. The efficiency-cost function accounts for the financial expense of each element and the passenger time-cost saved by incrementing elements (see Appendix for marginal cost of each element).

Suggested Check Point Configurations

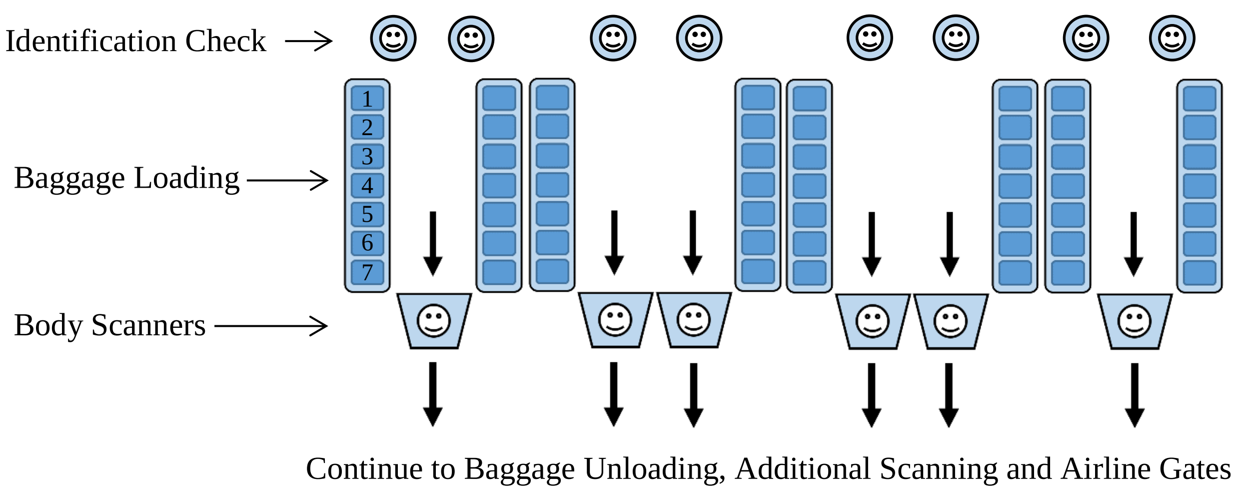
The AOM eliminates configurations that do not comply with the rule of 4 Identification Check stations to 3 Body Scanners that we outlined in the previous section. We identified this as an important characteristic in order to minimize bottlenecks. The AOM ends after finding a given number of configurations and sorts them by efficiency score. The top three configurations are represented in Table 6.

Table 6. Results from Algorithmic Optimization Model (AOM)

Identification Check stations	*Baggage Scanners*	*Baggage Loading stations per Baggage Scanner*	*Body Scanners*	*Efficiency Score*
8	8	7	6	351,876
8	9	6	6	387,933
8	10	6	6	428,648

Although the third configuration has the best efficiency score, we suggest implementing the 8-8-7-6 configuration in the interest of minimizing financial cost. For airports with exceptionally large security check points, we recommend multiples of our suggested 8-8-7-6 ratio to maximize passenger throughput while still conserving financial resources. The AOM does not prescribe specific spacing of the elements, so several different layouts of the suggested configuration could be adopted. We recommend one that relatively minimizes the space between the check point elements so that passengers could be easily re-routed if a machine malfunctions or other abnormal occurrence disrupts passenger flow (see Figure 3.) The increased number of baggage loading stations suggested by our AOM identifies the insufficient Baggage Loading stations as an additional bottleneck not presented by our data simulation model.

Figure 3. Example layout of optimal check point configuration



Since these modifications are based on the worst case scenario (an infinite queue of passengers), it can handle an unending flow of passengers and all sizes of decreased flow. Our model is scalable and can be applied to any maximum passenger flow through a security check point. Thus, our model attempts to reduce the overall variance and unpredictability of wait times at security check points.

Creative Solutions

In addition to physical modifications to our model, we also propose several creative solutions for the TSA to consider with regards to airport security.

- The use of shopping-style carts in place of plastic bins on a conveyor belt. Carts could eliminate the need for conveyor belts entirely, and would allow travelers to prepare in advance for physical scanning while waiting in the queue, rather than having to quickly unload items and remove clothing at the front of the queue.
- Implementing an “express lane” for physical scanning for travelers with 0 or 1 bag (and are thus more likely to require less time to unload items and prepare for scanning).
- Decreasing the body scanning time per passenger. This could include the possibility of 1 or 2 people passing through the Millimeter Wave Scanner AIT at once. If technology could sufficiently support faster scan times, passenger throughput would be increased and the bottleneck would be sufficiently reduced.

Addressing Passenger and Cultural Diversity

Perceptions of Time

To address several cultural and social impacts on the airport security process, we consider individualist versus collectivist and monochronic versus polychronic worldviews. Individualist cultures tend to place higher importance on the individual over the group, while collectivist cultures tend to focus on the well-being of the whole group. Additionally, monochronic societies view time as a limited resource, something that can be “lost” or “saved,” whereas polychronic societies view time as a somewhat “unlimited resource” where there is always more time. The US and UK fall at the extreme end of both spectrums as very individualistic and monochronic. On the other hand, China, Mexico, Africa and the Middle East fall at the other end of the spectrums as cultures that are more collectivist and polychronic [3]. These differences may play a role in security check points as some passengers may be more cooperative, impatient or move slower than others. We encourage TSA officers to address all passengers in a polite and efficient manner while recognizing that there may be differences in how time and individual importance are perceived. For improving efficiency and overall travel experience, we suggest that all passengers, regardless of their personal background, be aware that cultural differences exist and to be patient and gracious with those who may need additional time or support. These recommendations for grace and patience extend to handicapped and elderly travelers who also may require additional support. While human empathy plays an important role, our model optimizes the physical structure of a security check point to improve efficiency and passenger throughput for all passengers, regardless of specific passenger needs.

Queuing Psychology

In addition to social and cultural considerations, we evaluate the psychological impact of waiting. Waiting in queues makes up a large part of people's daily lives, and the resulting satisfaction at the end of the queue can be described as:

$$satisfaction = perception - expectation.$$

This field of study focuses on several aspects of waiting, with the end goal to make queueing more 'enjoyable' by reducing boredom, anxiety and uncertainty. Being in a queue is more tolerable if the time is occupied, finite, fair, explained and experienced with others [8]. While not all would consider TSA screening to be an 'enjoyable' end to the queue, many people recognize and appreciate the concerns for safety and security and are willing to wait a bit longer to ensure security [10]. However, the TSA could also do its part to make security a more pleasant experience with wall art and decorations, signs estimating wait time and reducing perceived inequities of travelers getting to 'cut' the line due to an early flight or various other reasons.

Policy & Procedure Suggestions

Our analysis of the current U.S. airport security system revealed bottlenecks at, and between, the identification check kiosks and body scan stations. Calculations and data simulations yielded an optimum ratio between the number of identification check stations and body scan stations. While in reality the physical structure of a security check point varies depending on airport, time and number of passengers, we recommend having approximately a three to four ratio of identification check kiosks to body scan stations to increase passenger throughput while ensuring thorough security.

Investing in the Latest Scanning Devices

After thorough investigation of current issues in TSA security check points and research of developing technology, we propose several policy and procedural recommendations. At the simplest level, we recommend TSA implements conveyor belts for loading baggage where travelers walk up to an empty slot, load up their belongings, and then push the bin back onto the conveyor belt. Bins automatically return to the front via a conveyor belt under the main one, eliminating the task of a TSA officer to simply relocate bins. In this model, travelers can move forward when space is available and slower travelers do not bog down the whole system. To additionally improve efficiency, suspicious bags that require additional screening should be diverted off of the main conveyor belt automatically to avoid interrupting the flow of other baggage. Current research in airport security is working to test new CT baggage scanners that generate 3-D images of bag contents and are much more accurate at detecting bombs and other threats. Previously, CT scanners have just been used for checked luggage due to their noise and size. But with the latest medical technology advances, these scanning machines will likely soon be able to be used for carry-on luggage as well and will be very beneficial for efficiency's sake- passengers would be able to leave laptops and liquids in their bags [7]. We encourage airline executives and TSA officers and employees to implement simple procedure changes and to continue investing funds in the research, development and testing of sophisticated scanning devices. These devices will achieve dual goals: increased efficiency and passenger throughput, and thorough security checks.

Automated Threat Detection Technologies

Research is also moving in the direction of automation and artificial intelligence to complete tasks previously done by humans. Numerous studies exist that show humans are bad at staying alert and focused, which poses a significant problem for airport security check points. To address this issue, we emphasize the need to develop artificial learning algorithms for automatic threat detection, with human TSA officers tasked with responding to alerts raised. This is a natural balance; machines nowadays can reliably identify and predict threats, while humans are more suited to addressing threats due to our ability to be flexible, recognize patterns, reason abstractly and spatially visualize [5]. We also encourage the increased installation and use of video cameras in security check point areas to monitor passenger behavior and identify irregularities. Israel’s Ben Gurion International Airport is arguably the most secure in the world, and while some of its security tactics may be questionably extreme, we recommend implementing a similar use of surveillance cameras in US airports [14]. We propose a live-monitoring situation where threats, issues and check point needs can be identified and dealt with in real time. For instance, during a peak travel period, waiting times may be excessive and TSA officers could be added to open additional lanes to help alleviate the long queue of travelers. Or if there is a security breach (an unauthorized person enters a restricted area), TSA officers would be able to more quickly locate the perpetrator and avoid extensive delays and airport terminal closure. Some progress with regards to video surveillance may have been limited due to privacy concerns, but research has shown that a person’s identity is not associated with their image, and video recordings can only be stored for a limited amount of time. The use of live video surveillance would help maintain a high level of security while also maximizing efficiency [12].

Considerations

Validating Our Model

Our model suggests an increased number of Baggage Loading stations per lane, almost double the current (and rare) maximum of 4 stations per lane. In the past year, Delta Airlines has invested in creating their own security lanes for their passengers which include five baggage loading stations per lane, and their initial trials at Atlanta Hartsfield Jackson International airport have proven to be much more efficient and cost-effective than the TSA’s security check points [11]. This is consistent with our model’s recommendations and illustrates the potential benefits of implementing our optimal check point configuration.

One of the reasons TSA Pre-Check is able to increase passenger throughput is the reduced baggage loading time. This means that the identification check time for a group of passengers is closer to reaching an equilibrium with their baggage loading and body scanning times. We used that equilibrium in modeling an optimal scenario to identify and reduce bottlenecks.

Based on observed norms, queues also form within the security check point, with the longest being between the identification check and physical stations. We postulate that this occurs due to a lack of baggage loading stations, which our AOM model both identified as a bottleneck and remedied in the optimal check point configuration suggested, and a lengthy body scanning process, which was highlighted by our data simulation model and remedied by our optimized ratio of 4 to 3 identification check to body scanning stations.

Strengths

- We consider physical structure modifications and additional innovative solutions to reducing wait time at security checkpoints while maintaining level of safety and security.
- Algorithmic Optimization Model is a simplified form of a genetic algorithm and can be used to find a heuristic; a likely best solution for the physical structure of a security checkpoint.
- Our data simulation model does not model passenger flow through the Baggage loading station and therefore does not identify it as a bottleneck. Our AOM takes into account different ratios of Baggage Loading stations, however, and suggests an increased number of Baggage Loading stations per Baggage Scanner (relative to the standard maximum of 4).
- Our model can be scaled and personalized to individual airport needs based on available data on funding, passenger speeds, and throughput.
- We consider not only the mathematical model and process of waiting, but also the perceived, psychological effect of waiting.
- We offer some creative solutions and modifications, and propose where the TSA should invest money based on thorough research of new and developing scanning technology and procedures.

Weaknesses

- Our model does not represent the added flow of Pre-Check passengers, in their own lane or otherwise. It also does not take into account the new Clear fast lanes due to a lack of data and real-world implementation.
- If a person takes longer to do one thing, they may be more likely to be slower going through another process as well. Our data simulation models overall passenger flow, so it is not reflective of individual passenger speeds. However, these variations in speed average out in the end (faster passengers balance out slower passengers).
- There is limited data available on passenger speeds through specific, individual parts of a security check point. To make up for this lack of data, we generated more through physical simulation and extrapolation of the given data set. While this artificial data fits with the data provided, it is not real-world data.

- We do not account for relationships between baggage quantity and general speed of passengers. We could generate reflective data with more specific statistics to include in an individual passenger-flow model.

Future Work: Genetic Algorithm

A genetic algorithm is an optimization algorithm that is modeled after the processes of natural selection and evolution. A simple genetic algorithm will start with a given number of organisms n who each have unique but random gene combinations. The n organisms are the first generation and each organism is evaluated through some criteria and given a fitness score. Some organisms with higher fitness scores are chosen from the population based to reproduce. Thus, the fittest organisms are not guaranteed to be selected, but there is a higher chance that higher scoring organisms will be chosen for reproduction and creation of a new generation. Another significant factor in evolution is mutation. When a new organism is made, there is a chance that some of the genes are rearranged, creating an organism that could have a higher or lower fitness score. This cycle of evaluation, reproduction, and mutation repeats until a perfect organism is found that matches up with criteria, or until the algorithm is stopped at a set number of generations [6].

For the purpose of finding the best security check point configuration, we can treat the different configurations as organisms, and each element of the configurations as genes. The criteria for evaluation of each configuration is its efficiency, financial expense, and effect in reducing passenger queue time. Thus, the perfect organism is the configuration whose combination of elements that fits the criteria. While a high scoring configuration has a higher chance of passing its combination of elements down to next generation, the mutation is a reality benchmark. The reality is that some configurations do not make it through various decision channels for various reasons. Therefore, the "survival of the fittest" concept sets the genetic algorithm apart from other heuristic solution techniques when finding the optimal security check point configuration.

While our Algorithmic Optimization Model (AOM) exhibits behavior similar to a genetic algorithm in looking at various combinations of elements, it lacks the luster of a genetic algorithm. Our AOM does not create the perfect configuration by passing on the best elements of previous generations, nor does it account for reality through mutation. Given more time and sufficient data, we could implement a genetic algorithm to produce an optimal security check point configuration.

Appendix

Check Point Element Costs

- Each baggage scanner costs $ 15,000.00 [16]
- Each baggage loading station costs $ 200.00 [2]
- The cost of one identification check station is approximately the average pay of a TSA security officer, which is $ 40,000.00 [9]
- Each millimeter wave body scanner costs $ 175,000.00 [4]

References

[1] Accardo, Julie, and M. Ahmad Chaudhry. "Radiation Exposure and Privacy Concerns Surrounding Full-body Scanners in Airports." *ScienceDirect*. Journal of Radiation Research and Applied Sciences, 11 Mar. 2014. Web. 22 Jan. 2017.

[2] Bastian II, Bill. "Project Planning: How Much Does Conveyor Cost?" *The Material Handling Blog*. Bastian Solutions, 09 Sept. 2013. Web. 22 Jan. 2017.

[3] Corbett, Steve, and Brian Fikkert. When Helping Hurts: How to Alleviate Poverty without Hurting the Poor-- and Yourself. Chicago, IL: Moody Publishers, 2009. Print.

[4] Groeger, Lena. "Scanning the Scanners: A Side-by-Side Comparison." *ProPublica*. ProPublica, 28 Dec. 2011. Web. 22 Jan. 2017.

[5] Harris, Douglas H. "How to Really Improve Airport Security." *Economics in Design* (2002): n. pag. Web. 22 Jan. 2017.

[6] LeFlohic, John. "Genetic Algorithms Tutorial." *Genetic Algorithms Tutorial*. Stanford University, Feb. 1999. Web. 22 Jan. 2017.

[7] Levin, Alan. "New Scanners and Conveyors Could Make Airline Security Faster and Safer." *Bloomberg.com*. Bloomberg, 27 Oct. 2016. Web. 22 Jan. 2017.

[8] Maister, David. "The Psychology of Waiting Lines." *Davidmaister.com*. D.C. Heath and Company, Lexington Books, 1985. Web. 22 Jan. 2017.

[9] "May 2015 National Occupational Employment and Wage Estimates." *U.S. Bureau of Labor Statistics*. U.S. Bureau of Labor Statistics, 30 Mar. 2016. Web. 22 Jan. 2017.

[10] "Most Back Shooting Down Passenger Planes." *Los Angeles Times*. Los Angeles Times, 13 Oct. 2001. Web. 22 Jan. 2017.

[11] Nicks, Denver. "Why Delta's New Security Checkpoints Are So Much More Efficient Than TSA's." Time. Time, 31 May 2016. Web. 21 Jan. 2017.

[12] Nixon, Ron. "Airport Security Advances Clash With Privacy Issues." *Nytimes.com*. The New York Times, 8 May 2015. Web. 22 Jan. 2017.

[13] Schuppe, Jon. "Long Lines and Missed Flights Fuel Criticism of TSA Screening." CNBC. CNBC, 14 Apr. 2016. Web. 19 Jan. 2017.

[14] Wagner, Daniel, and James Bell. "What Israeli Airport Security Teaches the World." *International Policy Digest*. International Policy Digest, 19 June 2012. Web. 22 Jan. 2017.

[15] Wisniewski, Mary. "At Chicago Airports, Wait times in TSA Lines Are 10 Minutes or Less." *Chicagotribune.com*. Chicago Tribune, 23 Aug. 2016. Web. 22 Jan. 2017.

[16] "X-ray Baggage Scanner." *X-ray Baggage Scanner, X-ray Baggage Scanner Suppliers and Manufacturers at Alibaba.com*. Alibaba.com, n.d. Web. 22 Jan. 2017.

[17] Zhang, Benjamin. "RANKED: The 16 Busiest Airports in the World." *Business Insider*. Business Insider, 04 Apr. 2016. Web. 22 Jan. 2017.