

4.1 Examining Passenger Flow Choke Points at Airports Using Discrete Event Simulation

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Abstract. The movement of passengers through an airport quickly, safely, and efficiently is the main function of the various checkpoints (check-in, security, etc) found in airports. Human error combined with other breakdowns in the complex system of the airport can disrupt passenger flow through the airport leading to lengthy waiting times, missing luggage and missed flights. In this paper we present a model of passenger flow through an airport using discrete event simulation that will provide a closer look into the possible reasons for breakdowns and their implications for passenger flow. The simulation is based on data collected at Norfolk International Airport (ORF). The primary goal of this simulation is to present ways to optimize the work force to keep passenger flow smooth even during peak travel times and for emergency preparedness at ORF in case of adverse events. In this simulation we ran three different scenarios: real world, increased check-in stations, and multiple waiting lines. Increased check-in stations increased waiting time and instantaneous utilization, while the multiple waiting lines decreased both the waiting time and instantaneous utilization. This simulation was able to show how different changes affected the passenger flow through the airport.

1.0 INTRODUCTION

At the turn of the millennium, erroneous information typed into a central database at Hong Kong's \$20 billion Chek Lap Kok airport triggered a domino effect that sent the new facility into almost comic confusion: flights taking off without luggage, airport officials tracking flights with plastic pieces on a magnetic board, and airlines calling confused ground staff on cellular phones to say where even more confused passengers could find their planes. Similar scenes were played out at Malaysia's \$2.2 billion Kuala Lumpur International Airport, where stranded cargo translated quickly in the tropical heat into rotting refuse. Such examples drive home one of the oldest rules of computer programming, the simple postulate that a machine is only as good as the humans using it.

Clearly airports are very complex environments in which passengers are the consumers and efficiency is the key to organizing the complexity. Airports can be thought of as systems with many parts that need to work together in order to accomplish a task. This task is to get passengers through the airport and onto waiting airplanes. This system can break down when problems occur. Therefore, modeling of processes to optimize traffic flow is where emergency planning can come into play. Some of the integral components of an airport are infrastructure features such as buildings, passenger ground transport systems, runways, taxiways, and vehicles (needed for getting baggage, fuel, and food onto the planes).

Additional features of the system are the computer systems such as baggage check computers and x-ray baggage machines. The final link in the airport system is the human component, i.e., workers that operate the machinery and computers.

1.1 Role of the runway

The runway plays an important part in regulating traffic flow by allowing aircraft to land and take off safely. Taxiways serve the same purpose, although they are primarily used to get the planes from the runway to the terminal. The bigger the aircraft, the longer and tougher the runway and taxiways must be to handle the weight.

1.2 Role of computer systems

The computer systems in an airport are important to the flow of traffic in that they help keep track of all the flights coming and going, as well as the flow of passengers and their baggage. In addition, computer systems play an important role in airport security by screening luggage, and profiling passengers using video cameras.

1.3 The human component

The presence of humans is integral to the running of all the above components. The workers that operate the systems are an important factor to take into account when looking at the airport as a system of systems. It is the humans that make the decisions, and keep the other systems working. A significant proportion of errors in these systems, therefore, are due to incidences of human error. This raises the importance of modeling human behavior to better understand the behavioral

implications on traffic flow in a large system of systems such as an airport.

A few attempts have been made so far to quantify and model passenger flow in various contexts ranging from train station platforms to elevators of tall buildings [1,2]. Nahke created a simulation of Hartsfield Atlanta International Airport's passenger movement system which consisted of nine trains moving passengers from terminal to terminal [3]. Through the use of this simulation, Nahke were able to see what effects increasing the number of trains had to try and increase passenger capacity. They were able to show that through small changes the train system that was designed for a maximum of nine trains could easily handle ten trains, increasing passenger capacity [3]. Ke, Zizheng, and Liling used simulation to optimize bus schedules during peak times [4]. Wusheng and Qian created a simulation using queuing theory to examine passenger flow at the curbside of an airport [5]. Another study examined the flow of traffic in an airport through simulation and modeling in a similar way to what is being proposed [6]. Although this study effectively examined the problem of passenger flow from the standpoint of scheduling, the model ignored the degree of heterogeneity among the passengers themselves that are largely accountable for several system bottlenecks. Specifically, the model did not take into account passenger behaviors that would be related to their degree of flight experience, physical abilities, presence of children, etc, which would certainly impact the overall rate of passenger flow through an airport. Furthermore, the earlier model is dated and does not include data on baggage screening procedures, which are an integral component of airport security in the present day.

Simulation can also be used in the design process. It can be used to look at how people will move through a building, or to see how a change affects the rest of the system being designed. Brown and Garcia [7] used Simulink, in Matlab, to help design a control system for unmanned aerial vehicle helicopters. This allowed them to try different control systems without incurring the cost of building them and testing them in the real world. The goal of our current research therefore is to develop a working model of an airport using discrete event simulation with particular emphasis

on homeland security. The simulation can be used for homeland security purposes to understand better where workers are needed to provide optimal security for waiting passengers.

Through this model, we represent traffic flow through an airport as a chronological set of events that is tied in to passenger behavior. Each event (e.g., arriving at check-in, carry-on baggage check, and final ticket check) occurs as an instant in time and marks a change of state in the system. The simulation was designed using ARENA Discrete Event Simulation software as described in the next section. Discrete Event Simulation (DES) software was created to simulate real world events that have random components to them and that are not time driven. How the simulation moves forward is based on arrival and service times drawn from a random number generator, which can be given functions from which to draw these numbers. These random times tell when an entity will arrive, and how long it takes to process the entity. The reason to use DES for the airport simulation is due to its simplicity in creating, the ability to recreate the random arrival and service times, and that the arrival of passengers and the time it takes to process them is not moved forward by the time moving forward.

2.0 THE SIMULATION

2.1 Materials

Laptop computer with Windows XP running ARENA DES Software Version 10.0 build 30.

2.2 Simulation Components

The simulation can be broken into multiple components each of which is combined in different places of the simulation to create the integrated airport simulation.

2.2.1 Creation module

This module is used to populate the simulation with entities, which in this simulation are passengers. The creation module determines how many passengers are going to arrive at the airport, and how often they arrive. With having a creation module, at the end of the simulation a delete module must be used to remove the passengers and have them leave the simulation.

2.2 Assign module

This module allows specific attributes to be assigned to the passengers, such as a function to predict how long it should take the passenger to get through the baggage check-in.

2.2.3 Decision module

The decision module is used to route passengers through a choice. For example one decision module routes the passenger to either the automated self check-in, or the manned check-in counter based on random chance, based on a percentage of passengers or even a formula.

2.2.4 Process module:

This module is used to carry out a specific process, such as the check-in process or the luggage screening process. Each process has specific resources that are assigned to it, such as the security screeners, baggage handlers and check-in agents.

2.3 Data Collection

Data for the simulation was collected from the Norfolk International Airport with consent from the different airlines and also the Transportation Security Administration for the airport. Data was collected between 7:00 am and 3:00 pm Monday through Thursday for two weeks. Arrival times were collected by using a stop watch and measuring the time between each passenger crossing a particular point when arriving into the airport building. These times were then recorded for later use in the simulation.

The processing times for the check-in were measured by observing passengers checking in. When the passenger started talking with the ticket counter agent or when they first touched the computer screen the stop watch was started. When the passenger gathered their luggage and moved away was when the time would stop. This data was recorded for later use in the simulation.

Processing times for the carry-on luggage screening were collected by observing passengers going through the security checkpoint. The stop watch was started once passengers put their luggage on the conveyor belt and stepped away to go through the metal detector. The time was stopped once they picked up their luggage.

These different times were put into the input analyzer of Arena DES so that an equation could be fit to the data and then put into the simulation. See table 1 for the airport data.

2.4 The Airport Simulation

Since this simulation deals primarily with passenger flow through an airport, the only parts of the airport that were simulated were those that directly affect the passengers themselves as they enter and travel through the airport, and finally board their plane.

Three main areas that were used in the simulation:

- (i) the initial check-in,
- (ii) the carry-on luggage screening

Input Equations

Arrival times	$-0.001 + \text{GAMM}(0, 0)$
Manned check-in Times	$54 + \text{EXPO}(0)$
Self-check-in times	$60 + \text{WEIB}(0, 0)$
Security check point	$10 + \text{WEIB}(0, 0)$

See Figure 1 for a diagram of the ARENA simulation. These two points were chosen because they are the points where passenger flow is controlled by airport authorities, yet have the most impact on passenger behavior. The time when the passenger arrives at the airport cannot be controlled, and is therefore a random variable within the simulation, and is treated as such.

The arrival times of passengers are randomized based on data collected at the Norfolk International Airport. The passengers were categorized based on the main air carriers operating at the Norfolk Airport:

- American/Continental Airlines
- Southwest Airlines
- USAirways

American and Continental Airlines were grouped together due to the extremely low passenger rate observed at the airport. Each passenger category was assigned a different process time based on times collected from each processing area. The check-in area (see Figure 1) is divided into self check-in and manned check-in, for each airline. For the self check-in, the primary resource is the automated check-in machine. For the manned

station the primary resource is personnel manually checking the passengers and their luggage.

The next area the passengers went through was the luggage screening security checkpoint (see Figure 1). Each passenger goes through this section, just as they do in the real world. Random stops were able to be initiated in the simulation at this point. For example, the number of passengers stopped could be set as a predetermined percentage, and that many passengers will be stopped. Alternatively, certain passengers can be assigned a particular attribute tag such as race, gender or physical ability; then those passengers would be stopped more often in the simulation than other types of passengers. The simulation was run for 80 iterations, one iteration being a 24 hour a day.

3.0 SIMULATION RESULTS

After running the simulation, the average number of entities that entered the simulation was 179.14 for American/Continental, 1068.43 for Southwest, and 957.09 for USAirways. See table 2 for the range and average wait times.

The wait time for USAirways in the simulation indicated a significant difference between the manned check-in and self-check-in ($t(78) = 4.33, p < .001$), with the manned check in having a lower wait time ($M = 2.64, SD = 1.23$) than the self-check-in ($M = 12.07, SD = 3.98$). The manned check-in and automated check-in for American/Continental and Southwest airlines were not statistically different ($t(78) = 0.16, p = ns; t(78) = 0.07, p = ns$). In the simulation, Southwest's manned and self-check-in ($t(78) = 2.11, p < .05; t(78) = 2.72, p < .01$) and USAirways's self-check-in ($t(78) = 5.10, p < .001$) had significantly longer wait times than did the security checkpoints.

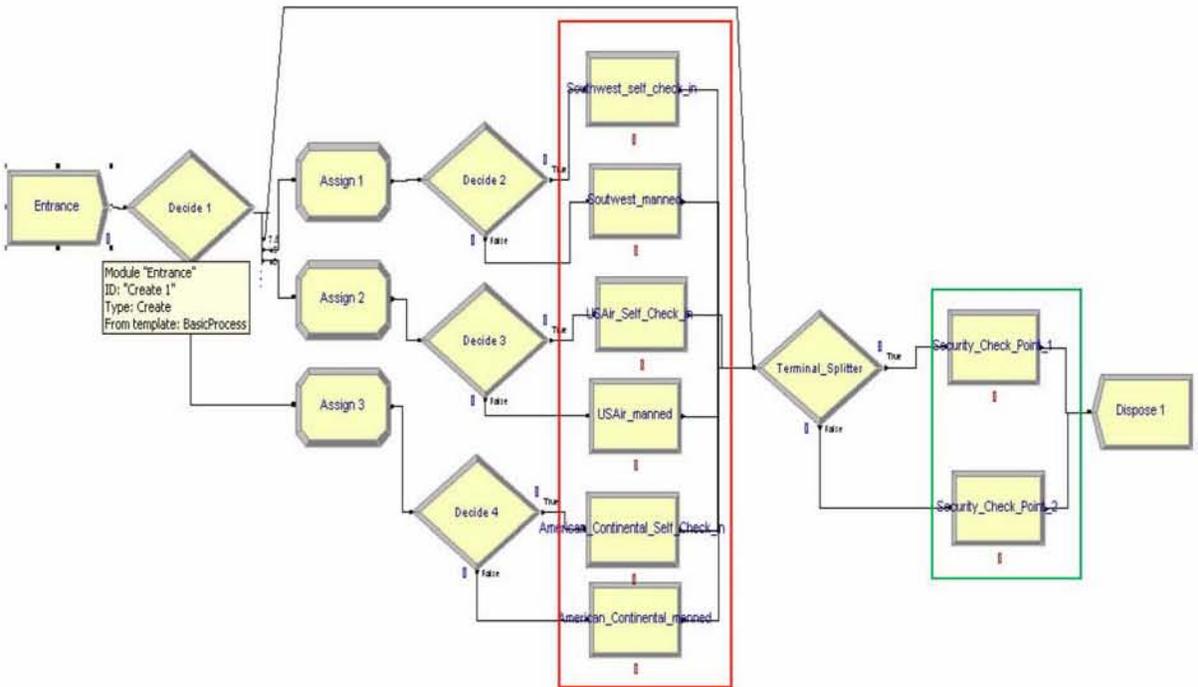


Fig. 1. ARENA diagram of Airport Simulation. The red area represents the check-in area. The green area represents the carry-on luggage check points.

Table 2

Airline/Checkpoint	Average	Minimum	Max
American_Continental			
manned	2.51	0.00	33.28
self check-in	2.71	0.00	56.57
Southwest			
manned	6.74*	0.00	67.72
self check-in	6.60*	0.00	75.26
USAir			
manned	2.64	0.00	33.92
self check-in	12.07***	0.00	105.48
Security Check point 1	1.46	0.00	17.71
Security Check point 2	1.45	0.00	18.78

Note: time in minutes;

* $p < .05$, *** $p < .001$

Instantaneous utilization is another way to look at how resources are being used within the simulation. See table 3. Instantaneous utilization shows the percentage of time that the resource was used. The higher the percentage, the more the resource was used.

Table 3.

Type of Service	Average
Norfolk Airport	
Manned Check-in	78.40%
Self Check-in	83.38%
Security Checkpoint	82.43%

4.0 OPTIMIZING PASSENGER FLOW

As the results indicate, Southwest and USAir have the longest waiting times for both manned check in as well as self check-in. To decrease the wait times, one would assume that increasing the number of stations would decrease this wait time. As table 4 shows, the wait times actually increase significantly with increased stations, in this case 2 additional workers and 10 additional self check-in stations.

Another way to optimize the Southwest and USAir wait times is to divide the check-in

stations into multiple lines, for this case two.

This allows people to choose a line that is shorter decreasing their wait time. As Table 5 shows, dividing the check-in lines to two lines for Southwest and USAir, wait times were cut by over half.

These wait times, however, do not tell the whole story. To get the full story, we also need to examine the resource utilization for these two changes. See table 6. By increasing the number of check-in stations, utilization was increased by five to six percent, though the security checkpoint utilization was decreased. So even though the wait times were increased, the resource usage was also increased. By dividing the waiting lines, table 6 shows that resource usage was cut by 37-39 percent for the check-in stations. This means that the workers were only working for 9-10 hours of the 24 when the waiting lines were split in two.

Table 4

Airline/Checkpoint	Average	Min	Max
American_Continental			
manned	2.51	0.00	33.28
self check-in	2.71	0.00	56.57
manned 2 additional	1.38	0.00	33.28
self check-in 10			
additional	0.83	0.00	33.28
Southwest			
manned	6.74	0.00	67.72
self check-in	6.60	0.00	75.26
manned 2 additional	25.13***	0.00	33.28
self check-in 10			
additional	34.05***	0.00	33.28
USAir			
manned	2.64	0.00	33.92
self check-in	12.07	0.00	105.48
manned 2 additional	24.63***	0.00	33.28
self check-in 10			
additional	34.45***	0.00	33.28

*** $p < .001$

Note: time in minutes

Table 5

<i>Wait Time</i>		
<i>Airline/Checkpoint</i>	<i>Average</i>	
American_Continental		
manned	2.51	
self check-in	2.71	
Southwest		
manned	6.74	
self check-in	6.60	
manned 2 lines	0.19***	
self check-in 2 lines	0.088***	
USAir		
manned	2.64	
self check-in	12.07	
manned 2 lines	0.06**	
self check-in 2 lines	0.14***	

Note: time in minutes

** $p < .01$, *** $p < .001$

Table 6

<i>Instantaneous Utilization</i>		
<i>Type of Service</i>	<i>Average</i>	
Two Lines		
Manned Check-in	40.70%	
Self Check-in	43.89%	
Security Checkpoint	82.32%	
plus 10 Self Check-in		
Manned Check-in	85.39%	
Self Check-in	89.11%	
Security Checkpoint	79.69%	

5.0 DISCUSSION AND IMPLICATIONS FOR OPTIMIZING PASSENGER FLOW

Airplanes move a large percentage of the population - about 580 million passengers just in the year 2008 in the US [8]. When there is a procedural failure in any one section of an airport it can have a drastic effect on the entire air transportation system. Therefore, the primary application of this simulation is to assist in optimizing traffic flow within airports. The results from the simulation runs indicate that the chokepoint at Norfolk International Airport resides with the initial ticketing and baggage checkpoints.

Southwest and USAirways are the primary carriers that can take a number of actions to try and reduce the waiting time associated with check-in. One possible method of redressal is to increase the number of self-check-in stations so that more people can use them at once. Another option is to do a usability analysis on the self-check-in station to make sure the process is smooth, efficient, and easy for inexperienced travelers to use. Finally, more workers could be brought in to help the passengers check-in.

The maximum utility of the airport model is that the effects of these changes can be tested in the simulation before changes in the system can be made. The number of self-check-in stations and manned stations can be repeatedly adjusted and the wait times can be analyzed to see what the optimum number is. The effects of failures and emergencies can also be examined within the model.

For emergency planning and error redressal, the ultimate goal is to try and plan for future events by using past experience [9,10]. As described above, our model allows for the quantification of each contingency situation into a discrete variable. These discrete variables include passenger behaviors that can be quantified to create individual 'agents' that exhibit different behaviors at different points in time. Each variable is then built into the simulation as described to ultimately predict the parameters required for optimal rate of passenger flow inside an airport. All of these ideas will be done in future testing of the simulation model.

6.0 CONCLUSIONS

The simulation model has indicated that there are choke points within the Norfolk International Airport. Those choke points are the check-in stations where passengers check their luggage. We recommend that the airlines in charge of the specific stations should decrease the wait time by increasing the number of staff and/or increasing the number of self-check-in stations. Besides to the obvious economic advantages of regulating passenger flow, minimizing choke

points will also ensure fewer instances of confusion and crowding at airports thereby strengthening the degree of passenger security to a large extent.

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7.0 REFERENCES

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