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Analysis of Airport Security Screening Checkpoints using Queuing Networks and Discrete Event Simulation: A Theoretical and Empirical Approach

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by

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This thesis was prepared under the direction of the candidate's thesis committee chair, Dahai Liu, Ph.D., Department of Human Factors and Systems, and has been approved by the members of the thesis committee. It was submitted to the Department of Human Factors and Systems and has been accepted in partial fulfillment of the requirements for the degree of Master of Science in Human Factors and Systems.

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Abstract

Author: Stephen Louis Dorton

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This study utilized discrete event simulation (DES) and queuing networks to investigate the effects of baggage volume and alarm rate at the Security Screening Checkpoint (SSCP) of a small origin and destination airport. A Jackson queuing network was considered for a theoretical assessment to SSCP performance. A DES model using Arena version 12 was utilized for an empirical approach. Data was collected from both literature and by manual collection methods. Manual data was collected during the peak operating time of 6am - 7am local time at the airport being modeled. The simulation model was verified and validated qualitatively and quantitatively by statistical testing before experimentation. After validation, a sensitivity analysis was performed on baggage volume of passengers (PAX) and the alarm rate of baggage screening devices, where SSCP throughput and PAX cycle time were the dependent measures. The theoretical queuing network approach proved an accurate method of predicting cycle time, but only under limited steady-state conditions. The empirical model and sensitivity analysis showed that SSCP performance is highly sensitive to alarm rate in both throughput and cycle time. Furthermore, empirical modeling and sensitivity analysis showed that SSCP performance was moderately sensitive to alarm rate, and completely resilient to the effects of baggage volume. Practical implications and future directions were also discussed at the conclusion of the study.

Introduction

Airport Security

Airport security is an integral part of national transportation infrastructure and a critical aspect of airport operations globally. With over 600 million passengers (PAX) and 700 million pieces of baggage being checked annually in the United States, airports and aircraft have become a high-level target for terrorism (Yildiz, Abraham, Panetta, & Agaian, 2008). Meanwhile, with a growing number of PAX, efficient and accurate security screening measures and practices are at a premium to ensure that air transportation operations remain effective and do not incur significant delays.

A brief history of airport security.

Transportation security measures have constantly evolved with time and trends in activities. The most significant event that has spurned constant change in aviation security is the terrorist attacks of September 11, 2001. The attacks of 9-11 have caused security measures in America as well as other countries to improve security processes, policies, technology, and programming (Frederick-Recascino, Greene, Burns, & Flynn, 2003). For a complete list of aviation and security acronyms see Appendix A.

Before 9-11 there were already policies and advanced screening technology in place for commercial aviation. Explosive Detection Systems (EDS) were being used on selected baggage, but not all baggage checked for a flight. Baggage was selected for screening based on a computerized profiling system. The Computer-Assisted Passenger Pre-screening System (CAPPS) selected passengers and their baggage for more in-depth screening based on a number of factors that qualified them as a high risk passenger. After 9-11 congress enacted the Aviation

Transportation Security Act (ATSA) in November of 2001, which mandated that 100% of all checked baggage be screened by EDS (Hafizogullari, Bender, & Tunasar, 2003).

After the enactment of the ATSA in November of 2001, an entire series of laws and regulations on transportation security followed that governed airport security into the process into its current state. By January of 2002 implementations were made to screen 100% of all checked baggage and a list of approved screening methods and equipment was introduced. By February of 2002 the Transportation Security Administration (TSA) was made responsible for all aviation security functions, and by May of 2002 an implementation plan for deploying EDS at all airports was submitted to congress for approval. November of 2002 was the deadline for the deployment of Federal Screening Personnel (FSP) and the checking of all airports for installation of approved baggage screening methods. December 31, 2002 was the final deadline for deployment of EDS at all airports in the United States (Leone, 2002). The TSA currently scans 100% of checked baggage and carry-on baggage, as well as utilizes technologies described in further sections.

Post 9/11 attitudes of security.

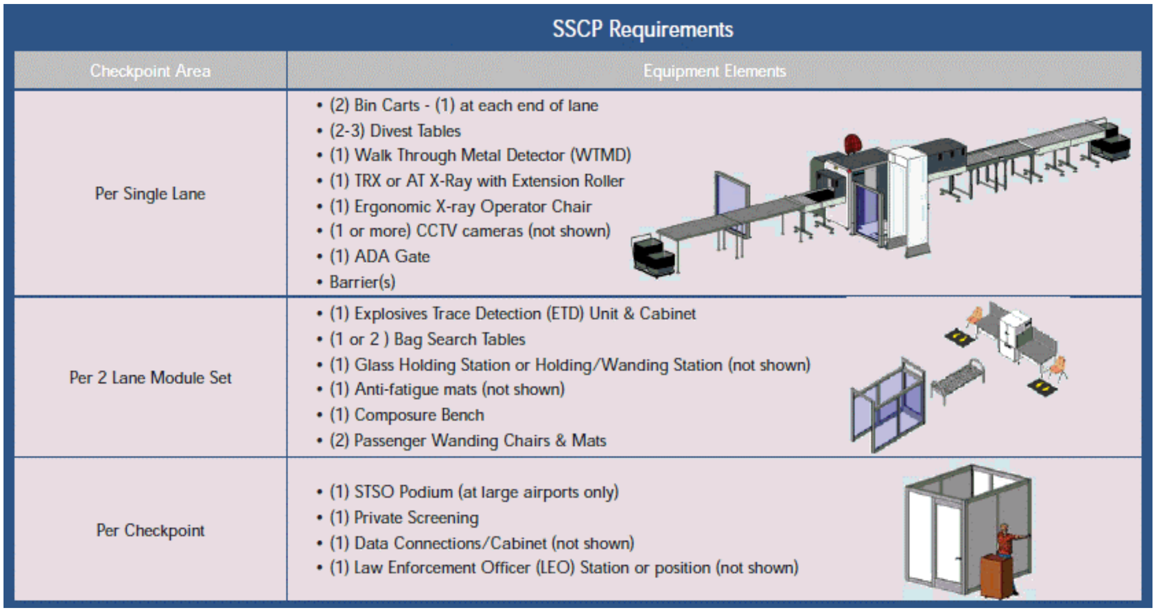
While the purpose of airport security and passenger screening is to ultimately ensure the safety and well being of PAX, there have been some negative effects on perception of security. Security measures have become all too familiar, where the trade-off for increased security measures comes at the price of inconvenience and timely delays (Pendergraft, Robertson, & Shrader, 2004).

A study by Frederick-Recascino et al. (2003) assessed the attitudes and behaviors of American and British PAX regarding safety and security issues in post 9-11 air transportation. American and worldwide security efforts have increased greatly to provide commendable security; however, some view these policies as tedious, unnecessary, or as a violation of civil liberties. Of their top five concerns, the third and fourth highest concerns by American participants were the competence of security screeners at security screening checkpoints SSCPs and the ability of airlines to screen for explosive devices, respectively. The British participants were more accepting of security procedures that may seem personally invasive than American participants. Finally, the study showed that in the American sample, participants were willing to wait an extra 28 minutes for enhanced security measures.

Security Screening Checkpoints (SSCPs).

Operations and processes involved with baggage screening at SSCPs are an integral component of airport security. The purpose of SSCPs is to screen PAX and their baggage to intercept prohibited items that may be a hazard to the safety of persons involved in aviation transportation. On a larger scale, the SSCP is one of 20 layers of security employed by the TSA to deter criminal activity. While each airport is different in size, throughput, and layout, all SSCPs must follow TSA established requirements unless written approval for deviation has been granted (Transportation Security Administration, 2009).

While no two airports are the same, the requirements for SSCP equipage are standardized and available in the Checkpoint Design Guide (CDG). Each airport must have a specific amount of each component of an SSCP based on the number of lanes and module sets including large equipment such as Walk Through Metal Detectors (WTMD) and Explosive Trace Detection (ETD) cabinets down to smaller items such as benches and anti-fatigue mats. Figure 1 shows a complete breakdown of SSCP equipage requirements with accompanying visual depictions.



SSCP Requirements	
Checkpoint Area	Equipment Elements
Per Single Lane	• (2) Bin Carts - (1) at each end of lane • (2-3) Divest Tables • (1) Walk Through Metal Detector (WTMD) • (1) TRX or AT X-Ray with Extension Roller • (1) Ergonomic X-ray Operator Chair • (1 or more) CCTV cameras (not shown) • (1) ADA Gate • Barrier(s)
Per 2 Lane Module Set	• (1) Explosives Trace Detection (ETD) Unit & Cabinet • (1 or 2) Bag Search Tables • (1) Glass Holding Station or Holding/Wanding Station (not shown) • (1) Anti-fatigue mats (not shown) • (1) Composure Bench • (2) Passenger Wanding Chairs & Mats
Per Checkpoint	• (1) STSO Podium (at large airports only) • (1) Private Screening • (1) Data Connections/Cabinet (not shown) • (1) Law Enforcement Officer (LEO) Station or position (not shown)

Figure 1. SSCP equipage requirements. Adapted from “Checkpoint Design Guide” by Transportation Security Administration, 2009.

Airport Security Screening Process.

The SSCP considered in this study is comprised of two lanes and multiple components, each serving a different purpose. The first component of the SSCP is the Travel Document Checker (TDC). The TDC is a designated Transportation Security Officer (TSO) that verifies identification and boarding documentation of PAX before allowing them through the SSCP (Transportation Security Administration, 2009). The next process for PAX is to divest their personal belongings into bins at the leading edge of the divesting table. Once PAX have taken off all appropriate personal belongings they place their bin(s) and carry-on baggage onto the feed belt of the Threat Image Protection Ready X-ray (TRX). The baggage and bins pass through the TRX while a TSO observes a monitor and looks for contraband and prohibited items in the baggage (Transportation Security Administration, 2009). If there is an alarm in the TRX, the suspected baggage is be removed from that process by a TSO and brought to an ETD table for more rigorous searching while the person proceeds through the WTMD.

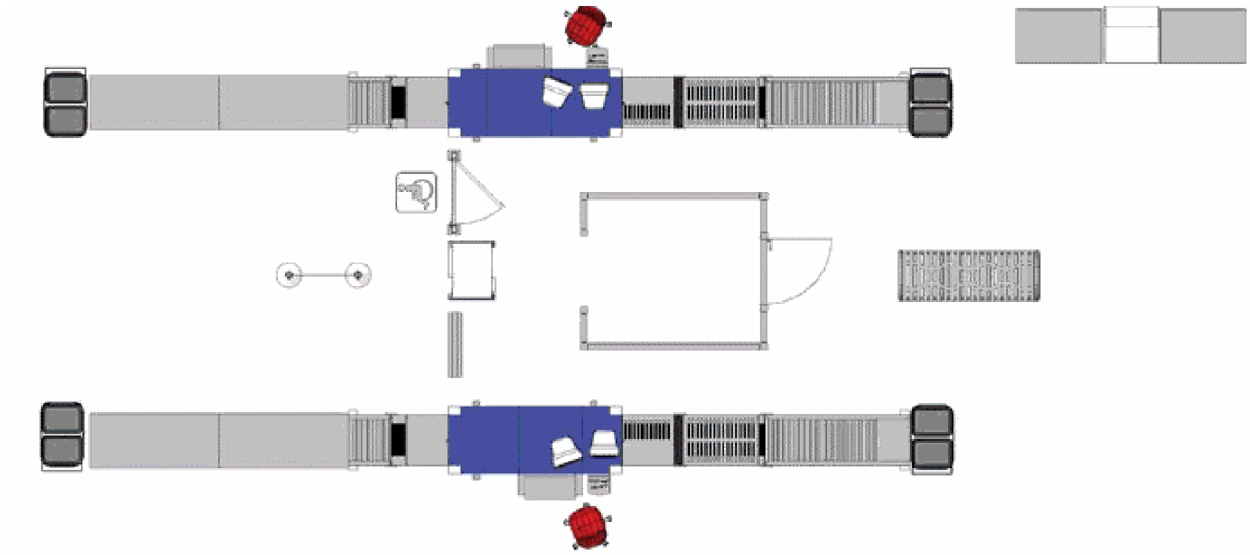


Figure 2. Approximate SSCP layout at modeled airport with divesting tables, TRXs in blue, vesting tables, WTMD center left, manual screening area center, and ETD top right. Adapted from "Checkpoint Design Guide," by Transportation Security Administration, 2009.

PAX then funnel into a single WTMD, which is used to detect metallic weapons and/or metallic contraband. After passing through the WTMD PAX proceed to their respective vesting table and wait for their baggage to be searched before exiting the SSCP. If there is an alarm with the WTMD, the person is searched with a hand operated metal detector to attempt to localize what object is setting the alarm off. After the wand search the person removes the suspect item and walk back then re-enter the WTMD while subsequent PAX queue at the WTMD. If the alarm is resolved they proceed to their vesting table and exit the SSCP. Only PAX who have pacemakers, wheelchairs, or physical limitations would bypass the WTMD and undergo a manual screening before vesting and exiting the SSCP (Transportation Security Administration, 2009).

The SSCP being modeled is represented by the depiction in Figure 2, only the ETD and manual screening areas are located in different positions with regards to the two TRX lanes. While Figure 2 represents the entirety of the system being investigated, the scope of this study focuses on the baggage screening operations specifically because they have been identified throughout the literature as being the most crucial aspect of SSCP performance.

Queuing Theory and Queuing Networks

One method of approximating cycle time or average waiting time in systems is by the utilization of queuing theory and queuing networks. Queuing network theory has been a staple of operations research since Jackson (1963) identified the need for stochastic modeling of queuing in multipurpose production systems and proceeded to establish joint probability distribution and create the M/M/1 queue. Blanchard and Fabrycky (2006) define queuing systems as a Monte Carlo analysis to understand entity arrivals and service of entities based on probability rather than an absolute rate. There are multiple applications of queuing theory from manufacturing, maintenance, toll gates, doctor offices, restaurants, and movie theatres. Queuing theory allows for an analysis of a system based on a probabilistic model, rather than constant arrival and service times. Queuing networks are compilations of different service processes that are stochastic, or dependent on other processes and times in the work flow (Shanthikumar, Ding, & Zhang, 2007).

Basic Queuing Notation.

In any generic queuing system such as an M/M/1, the arrival rate is typically denoted as λ, while service rate for a process is denoted as μ. The arrival mechanism (λ) depends on the nature of the population of entities that create the need for services by the system. Arrival rates can also be constant, probabilistic, or based on a schedule depending on the nature of the system. The service mechanism of the system (μ) is a discrete entity because items are processed on a unit to unit basis. Cycle time is the amount of time an entity spends in the queuing network, and is denoted as CT. The amount of time spent waiting at a specific service mechanism for service is commonly denoted as t_q, and *s* is the actual service time. CT is a sum of all t_q and *s* in a queuing network (Blanchard & Fabrycky, 2006; Shanthikumar et al., 2007). A generic queuing model is shown in Figure 3, with λ and μ illustrated.

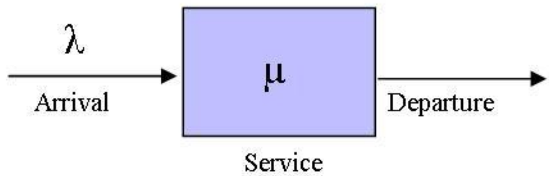


Figure 3. A generic single server queuing network.

Common Queuing Models.

Shanthikumar et al. (2007) described using queuing networks in place of simulation for a relatively simple scenario of a manufacturing process. If certain assumptions of a model are made then an application of queuing theory can be a simple alternative to a more labor intensive simulation study. The most basic queuing model is the M/M/1 model, developed by Jackson (1963). The M is indicative of a Markov Poisson arrival and Markov Exponential service time, where the "one" indicates a single server system which relies on the assumption that arrival and service processes are independent of each other. The cycle time (CT) an entity spends in an M/M/1 system can be calculated using Equation 1 and Equation 2 where *s* is the average service time ($s = 1/\mu$), λ is the arrival rate, t_q is the average waiting time for service, and ρ denotes server utilization.

$$CT = s + t_q = s + \frac{\rho}{1-\rho}s \tag{1}$$

$$\rho = \lambda s = \frac{\lambda}{\mu} \tag{2}$$

A basic extension of the M/M/1 model is the M/M/*c* model. The M/M/*c* is a server model that represents multiple M/M/1 servers in parallel with each other, where *c* is the number of service channels where each can service one entity at a time. An arriving entity will go to the first available service channel. If there are no available service channels a single queue will be formed whereupon the first entity in queue will be released to the first service channel available (Blanchard & Fabrycky, 2006). Hopp and Spearman (2001) utilized the M/M/1 equation along with principles of universal relations to produce the M/M/*c* model shown in Equation 3, where *c* is the number of parallel servers with identical mean effective service times.

$$CT = \frac{\rho^{\sqrt{2(c+1)}-1}}{c(1-\rho)}\mu \tag{3}$$

If Markov assumptions are violated, a closer approximation can be made by queuing models with general distributions. Shanthikumar et al. (2007) also utilized the M/G/1 model, where the G signifies a service time with a general distribution. The M/G/1 cycle time is shown in Equation 4, where the c_s^2 is the squared coefficient of variation of the service times. Also an approximation has been proposed for a more generalized model referred to as the G/G/1 queue, where c_a^2 squared coefficient of variation for arrival times, as shown in Equation 5.

$$CT = \frac{\rho(1+c_s^2)}{2(1-\rho)}s \tag{4}$$

$$CT = \frac{\rho(c_a^2+c_s^2)}{2(1-\rho)}s \tag{5}$$

These models are good for looking at the relationships of different aspects of a queuing system, yet are not accurate enough to model even a moderately intricate manufacturing system because of the amount of assumptions made in the mathematical model. Based on the G/G/1 approximation model, a G/G/m model has been proposed in Shanthikumar et al. (2007) that allows for the estimation of cycle time for m number of identical machines in a queuing network. Equation 6 shows the G/G/m model for CT, which most notably shows that the higher the variance of waiting time or service time the higher the average cycle time. Also, it should be noted that for G/G/m systems ρ equals $\lambda/c\mu$.

$$CT = \left(\frac{c_a^2 + c_s^2}{2}\right)\left(\frac{\rho^{\left(\sqrt{2(m+1)}-1\right)}}{1-\rho}\right)s \tag{6}$$

Mathematical models using queuing networks are useful for examining system performance without investing time and money into a simulation study (Kelton et al, 2007). Queuing theory has been established for hundreds of years and queuing networks have been successfully used across a wide variety of industrial applications since the 1960s (Blanchard & Fabrycky, 2006; Jackson, 1963). Even if a mathematical model cannot empirically solve CT or throughput of a system, it can be used to examine relationships between multiple facets of a system. When a system lacks significant data to power an empirical simulation with confidence a mathematical model can offer valuable insight to system performance and supplement a DES approach (Leone & Liu, 2010; Shanthikumar et al., 2007).

The major limiting factor to the use of queuing networks is that queuing models rely on assumptions that are not typically justified in more complex systems. Shanthikumar et al. (2007) were dissuaded from using queuing networks for semiconductor manufacturing because of the balking and reworking of chips, despite assessing system that has fairly consistent arrival and service times. Leone and Liu (2010) built a queuing network for a SSCP system with one TRX and one WTMD, assuming each process as an M/M/1. DES was instead used because these processes violate the assumption of being independent of each other and the assumption of Markov distributions for all λ and μ. As stated by Blanchard & Fabrycky (2006), the arrival mechanism of a system is determined by the nature of the system itself. In the case of an airport the scheduled departures would make a Poisson arrival schedule very unlikely.

Discrete Event Simulation

Simulation is a general collection of theories, methods, and applications to replicate behavior of real systems for assessment or experimentation. Simulation can be done by hand, by spreadsheet, or even by advanced computing programs. While simulation has existed in many forms for quite some time, advancement in technology is making it more powerful and popular than ever. Simulation involves modeling a system, oftentimes to measure performance, improve operation, or design the system if it does not yet exist (Kelton, Sadowski, & Sturrock, 2007). Blanchard and Fabrycky (2006) characterize simulation as a form of indirect experimentation, where systems analysis is performed without changing the operational system itself. Simulation in general is an effective tool that allows for control of extraneous variables while allowing the researcher to generalize their results (Bordens & Abbott, 2008).

There are multiple types of simulations, which can be identified by three key characteristics. First, simulations can be static or dynamic in nature. Static models are not time sensitive, where events have the same validity if they are done a second apart or a year apart. Dynamic simulations are more common where events are time sensitive such as a manufacturing process or a SSCP. Secondly, models can be defined as continuous or discrete. Continuous simulations represent systems with a continuous change such as pressure levels or fluid levels, whereas discrete event simulations model systems where events occur at specific points in time. Discrete simulations are effective in modeling parts or people arriving at specific times and undergoing processes at specific times. The operations at a SSCP are discrete and would be modeled accurately by DES. Finally, simulations can be deterministic or stochastic. Deterministic simulations have no random input, meaning that events always happen at exactly the same time such as fixed appointments. Stochastic simulations are simulations where at least some of the events occur at random times, such as PAX arrival and baggage screening times in the case of a SSCP simulation (Kelton et al., 2007).

Based on the definitions of simulation provided by Kelton et al. (2007), the operations of an airport SSCP are best analyzed with DES. The system is dynamic in nature, where events happen on a timeline and one event can and often will affect another. In a SSCP events occur at discrete times from entering the system until exiting the system, calling for the use of DES. Finally, the events in a SSCP are heavily affected by the human element, causing them to be stochastic or random in nature. Because of these system descriptions, a DES approach is the most fitting way to simulate the SSCP system. Crook (1998) advocates the use of DES in airport operations research because of its ability to analyze complex logistical problems in various parts of the system lifecycle, from feasibility studies to in-service studies and evaluation.

Advantages and limitations of DES.

There are several advantages of DES in simulating systems. While DES originated as a method to assess manufacturing systems, it now has nearly limitless applications in non-manufacturing systems such as healthcare and airport operations (Tavakoli, Mousavi, & Komashie, 2008). Additionally, once a system is modeled and validated DES allows researchers and decision makers to examine nearly any aspect of the system from staffing to process management and resource availability (Werker, Saure, French, & Schechter, 2009). An advantage of DES over a pure mathematical queuing model is that DES accounts for the randomness that the human element adds to a system. The human element can and usually does significantly alter process times and advertized throughput rates of machinery (Kelton et al., 2007; Leone, 2002). Finally, DES allows for any empirical or theoretical probability distribution to be applied to service times or arrivals, as well as allow for scheduling and batch arrivals in the system rather than rely solely on empirical distributions.DES serves as an invaluable tool when it is too costly to change a process or system design. The ability to closely mimic a systems performance and change different characteristics provides a non-invasive and cost efficient method to perform system analysis (Kelton et al., 2007; Law, 2006). These advantages make DES a desirable method to assess a complex operational system such as a SSCP.

With any method, technique, or tool there are disadvantages or limitations. This also applies to DES. Tavakoli et al. (2008) identified two limitations of applying a DES approach to systems analysis. One limitation of DES is that it is typically a timely process. From creation of a problem statement and designing a model through model validation and eventual analysis can take a large amount of time. If there is a deadline for requirement or equipage implementation and the system is relatively simple, a mathematical model may be a better solution. Also, DES models are inaccurate for predictions. DES can be used to assess future "what-if" scenarios, but only based on data collected in the past. If a system has seasonal performance or if entity arrivals double the next year, new data would have to be acquired to make the simulation valid. The most significant limitation to DES is that a simulation or model is not useful unless the model has been verified and validated by a number of qualitative and quantitative methods (Law, 2006). The less adequate the validation of a model the less generality a simulation has.

DES in airport operations.

Acknowledging the advantages of a DES approach to analyzing airport operations, multiple researchers have used DES in the realm of aviation transportation and security. Most studies where DES was used on airport operations either specifically investigate the check in process, the checked baggage screening process, or the entire airport departure experience, only a handful of studies have been performed on SSCPs. Arena simulation software which was used in this study was commonly used throughout the literature for a DES approach.

Brown and Madhavan (2010) performed a study on identifying choke points in airport departure operations. Arena simulation software was used to simulate passenger arrival, check in modality (self or clerk) at each airline, and security times in order to identify bottlenecks that cause the need for early arrival times. This model looked at SSCP as one process, where only the overall throughput was used as aggregate. The check in process was identified as the largest delay, and recommendations were made that the number of self check in kiosks should be increased.

Guizzi, Murino, and Romano (2009) performed a study using DES to predict delays and make management decisions to increase PAX flow at a large international Italian airport. A discrete stochastic model was used with Arena simulation software to model the process from PAX arrival at the airport, check in, SSCP, to the eventual boarding of the aircraft. The number of SSCPs available was adjusted and simulated to find the optimum level of performance and cost via OptQuest software. While the simulation offered valuable insight, it is typically not feasible to construct extra SSCPs at an airport.

A study by Appelt, Batta, Lin, and Drury (2007) used DES and Arena simulation software to simulate and analyze PAX cycle time of the airport check in process. The check in times of PAX was analyzed by method of check-in (online or in person) and the number of bags the PAX checked in. The use of DES rather than a mathematical model allowed for the travelers experience levels with check-in kiosks to be adequately integrated into the model. It was found that because business travelers (with carry-on bags only) used the kiosks, so other PAX with large luggage were bottlenecked into the few staffed check in counters. A recommendation was made to increase the staffing of check in counters to reduce check in cycle time.

A proceeding by Wilson, Roe, and So (2006) showcased a new DES software package called Security Checkpoint Optimizer (SCO). The SCO program utilized the mathematical and logical concepts of DES, while adding a graphical user interface to allow TSA researchers to drag and drop equipment into a model. The integration of drag and drop and drawing tools into a DES engine allows for analysis of SSCP performance as well as assessing the feasibility of adding equipment to a finite area.

A study by Hafizogullari et al. (2003) utilized DES to evaluate different SSCP configurations to satisfy the 95-10 requirement, or the performance metric that 95% of all passengers during peak operations must wait no longer than 10 minutes for baggage screening. Scenarios were run with the use of ETDs or Explosive Detection Systems (EDS) and different levels of staffing. While throughput for the EDS was advertized as being greater, the high False Alarm Rate (FAR) caused the ETD machine to be a superior choice during peak operation. Policies on baggage cart utilization were analyzed and it was determined that waiting for the baggage carts to fill before taking them to the airplane caused unacceptably long process times.

A study by Pendergraft et al. (2004) used DES to understand operational dynamics of both checked baggage screening and the SSCP at a major U.S. airport during peak operating hours. PAX arrivals were generated randomly based on historical data, and random probability functions were used to trigger alarms in the WTMD. Alarm resolution was not explicitly modeled in the simulation, yet very accurate results were still attainable. This study was received so well that it resulted in the promulgation of the 85-10 methodology where 85% of passengers wait 10 minutes or less for screening. Likewise, requirements for staffing, equipage, and compliance levels were promulgated from this study.

A study by Wetter, Lipphardt, and Hofer (2010) used DES to assess throughput of SSCPs by examining internal and external factors. Internal factors were factors that were influenced by security personnel such as training and teamwork, while external factors were factors that could not be influenced by security personnel such as passenger arrival and baggage variability. Aside from quantitative data such as throughput and cycle time, subjective data from TSOs was collected to evaluate all aspects of the SSCP process. It was demonstrated that there was a significant effect on throughput by altering the number of manual baggage screenings performed. Higher WTMD alarms did not decrease throughput, but did increase the TSOs subjective workload ratings. Wetter et al. (2010) speculated that if screening technology increased to where passengers could divest less, then throughput may be seriously increased because of the shortened divesting and vesting times.

Other applications of DES.

DES has been used to assess and analyze several aspects of airport operations throughout the literature; however, it has many other applications where it has also proven useful. For example, a study by Giachetti, E. A. Centeno, M. A. Centeno, and Sundaram (2005) used DES to assess the patient scheduling at an outpatient dermatology clinic. After analysis and experimentation scheduling policies were identified that decreased the patient cycle time by 50%

and significantly reduce the number of no-show patients. Furthermore, the variability of physician utilization was considerably stabilized.

Tavakoli et al. (2008) performed a study where DES was used in conjunction with real time software to monitor and analyze a large manufacturing system and a health care operation. By coupling the power of DES with Labview inter-communication module a constant adjustment of data was achieved to provide accurate simulation of the system. Further applications of this study involve using real time data to track trends in the system being modeled. This technology allowed for accurate analysis of system performance to reduce costs and idle time.

Werker et al. (2009) used DES to make adjustments to a pre-existing system that was already considered efficient. Arena simulation software and historical data were used to assess the radiotherapy planning process primarily with regards to staffing availability and skill level of oncologists. A sensitivity analysis showed that by standardizing oncologist delays the radiotherapy planning process was reduced from an average of seven days to two. There is extensive literature on applications of DES in a wide variety of domains.

Conducting a Successful Simulation Study

There are many considerations when performing a successful simulation study. Kelton et al. (2007) defines a successful simulation study as one that not only has a good simulation model, but one that answers the questions of the researcher or decision makers, and does so using understandable metrics. While building an impressive simulation model can be seen at face value to be indicative of a successful study, a model should only be as detailed as the information provided (Kelton et al., 2007; Law, 2006). In fact, a successful or accurate model is just one step of creating a successful simulation study.

Creating a successful simulation study is an iterative process that involves revisiting multiple aspects of the study to ensure verification and validation of the study. Law (2006) proposes a seven step approach to creating a successful simulation, which is also used by Kelton et al. (2007). The model used by Law (2006) is shown in Figure 4, which has been adapted for

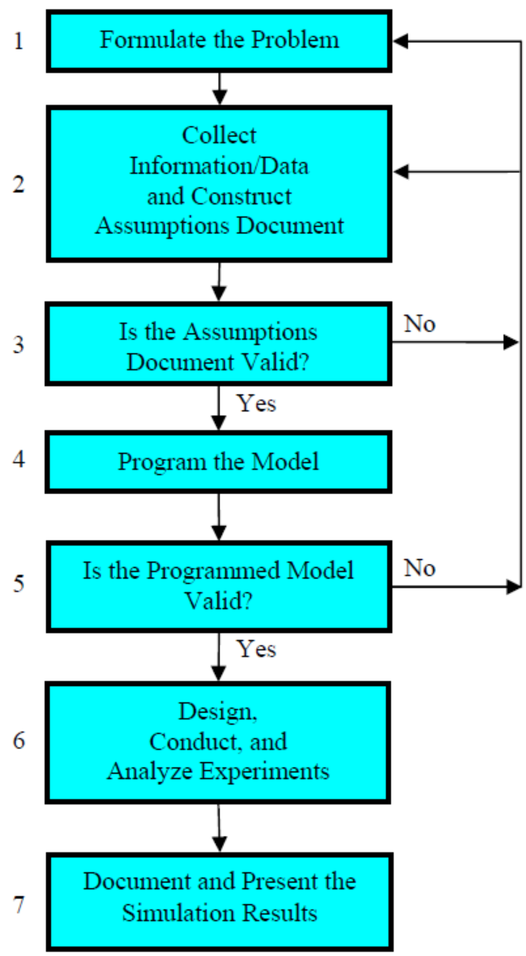


Figure 4. Seven-Step approach for conducting a successful simulation study. Adapted from "How to build valid and credible simulation models," by Law, 2006.

use as the method for completion of this study. The adaptation for this study is that the model and assumptions are made before initial data collection. The approach starts with formulating the problem that will be investigated by the study. The problem formulation involves the identifying the overall objective of the study as well as establishing the scope of the study, and specific questions the study aims to answer (Kelton et al., 2007; Law 2006).

Once the problem has been adequately formulated, data collection and construction of assumptions are the next step. Data collection consists of collecting information on the system layout and operations performed, as well as process times and probability distributions. During collection of data assumptions that need to be made in the model will be documented and later validated before experimentation begins. The level of detail of the model will depend on a number of factors, including but not limited to: the scope of the model, data availability, time and money constraints, and input from SMEs (Kelton et al., 2007; Law, 2006).

After data collection and construction of the assumptions document, the assumptions document was validated using a technique sometimes referred to as conceptual model validation (Law, 2006). The assumptions were validated by conferring with SMEs and literature on similar simulation studies of airport security operations. If assumptions are not validated then further data collection and consultation of SMEs will be performed before proceeding to the next step of the simulation study approach. Once the assumptions were validated the model was programmed in simulation software, specifically Arena version 12. Upon the completion of the simulation model, it must undergo verification and validation before experimentation begins (Kelton et al., 2007; Law, 2006).

Verification is a step of building simulation models that can be best described as debugging, where the model is checked to make sure it works as intended. Models are verified by running excessively small or large batches of entities (in this case PAX) through a system in an attempt to cause the system to create an error in any of its processes or decision algorithms. After running a model multiple times under different parameters a model is considered verified and is ready for validation (Kelton et al., 2007). Validation of a model is the process where the model is tested to see if it represents the system it is designed to simulate. There are generally two types of validation, face validation and quantitative validation. Face validity occurs when SMEs and simulation analysts agree that the model represents the actual system. Results validation or quantitative validation is achieved when the simulation is run and the performance metrics are comparable to that of data collected from the actual system or similar systems (Kelton et al., 2007; Law, 2006).

The final two steps of the simulation modeling approach are to design, conduct, and analyze experiments and to document and present the results. Experimentation is performed by adjusting variables of interest in the system and monitoring changes in dependent metrics identified earlier in the simulation process by systems analysts and SMEs. After analysis of the results, the necessity for further experimentation is identified and documented (Law, 2006).

Summary

From the review of the literature it can be seen that there have been multiple studies on airport operations as a whole, but very few on SSCPs. A variety of approaches have been used from purely theoretical methods with queuing networks to purely empirical methods using DES, along with few utilizing both approaches. While most studies focus on internal factors of SSCP operations such as staffing and equipage, this study aims to investigate the effects of the external factors of baggage volume and alarm rate on SSCP throughput (TH) and PAX cycle time (CT). A mixed methods approach will be applied, where both theoretical and empirical methods will be utilized to make a more comprehensive approach at understanding SSCP operations through the use of Jackson queuing networks and DES with Arena simulation software. The methods will be discussed in greater detail in the following sections.

Method

Problem Formulation

The first step of a successful simulation study is problem formulation, or establishing the need for the study (Law, 2006). Yildiz et al. (2008) cites airport screening operations as the probable cause for the ceaselessly growing delays in airport operations. It is crucial for operational efficiency as well as the financial health of the airport and industry to investigate the optimization of security screening because increased delays are directly linked to lowered customer satisfaction (Appelt et al., 2007; Guizzi et al., 2009; Pendergraft et al., 2004; Yildiz et al., 2008).

Wetter et al. (2010) breaks down SSCP issues into internal and external factors, where external factors are things that cannot be controlled by security personnel such as weather, number of bags each person carries, and number of suspect bags to be inspected; while internal factors are things that can be controlled such as staffing, task allocation, and training. In the study by Wetter et al. (2010), external factors had a large effect on throughput, which proves extremely volatile to SSCP efficiency because oftentimes external factors are regarded as a given fact and not fully considered. This study aims to investigate the problem of external factors such as baggage volume and the alarm rate of suspect bags that require manual inspection. By investigating the sensitivity effects of external factors on SSCP performance, rather than disregarding them as uncontrollable, will allow for the adjustment of internal factors to cope successfully and ensure favorable system performance as well as understand what scenarios will cause SSCP requirements to not be met.

Assumptions Documentation

Kelton et al. (2007) and Law (2006) state that a model should only be as detailed as it needs to be to assess the variable(s) of interest and accurately reflect the system with the data available. The following assumptions were made to the simulation model to ensure simplicity, while still accurately reflecting the phenomena of interest:

- Staffing factors were not investigated in the model. The scope of this study is on external factors as defined by Wetter et al. (2010) and does not investigate staffing issues. Therefore, a fixed staffing schedule is assumed for the SSCP being modeled. Staffing requirements for equipage are already designated in the CDG (Transportation Security Administration, 2009).
- The Travel Document Checker (TDC) was ignored from the model. No studies to the author's knowledge have explicitly modeled the TDC in DES or queuing networks because the primary performance affecting process is baggage screening.
- WTMD operations were ignored from the model; it is believed they did not impact SSCP performance. From observation of the system and corroboration with SMEs, the superior majority of PAX take less time to pass the WTMD or wand searching than for their baggage to be screened. The only PAX who bypass the WTMD and receive longer screening are persons too large to fit through, persons in wheel chairs, and persons with pacemakers or prosthetics (Transportation Security Administration, 2009) which is a negligible occurrence at the system being modeled according to SMEs.

- Travel time between arrival and baggage screening and between baggage screening and secondary screening was ignored from the model. The diminutive size of the SSCP being modeled has negligible time of travel between services and was therefore not included.
- Personal affects bins were assumed to require the same process time distribution for TRX screening as baggage, which is used by other researchers as well (Leone & Liu, 2010).
- Only the peak operational time of 6am to 7am was simulated. Multiple studies on airport operations only simulated the peak hours because it is assumed that the SSCP can handle less than maximal traffic (Appelt et al., 2007; Guizzi et al., 2009; Leone, 2002).
- A 10 minute warm-up period, determined by visual inspection of the Work in progress (WIP) statistics of the system, was utilized to allow the SSCP to achieve steady state.
- All queues and processes were modeled as first-in first-out (FIFO) rule.
- The TRIA[1,4,20] seconds distribution that was used for baggage screening times is an approximation of 98% of recorded times. Leone and Liu (2010) eliminated the other cases from the data because their frequency was negligible.

Mathematical Modeling

To assess throughput of an SSCP, mathematical modeling was used alongside DES for a more comprehensive understanding of the system. A queuing network was constructed based off a combination of M/G/1 servers (an M/G/2) and an M/M/1 server. The M/M/1 model created by Jackson (1963) was used by Leone and Liu (2010) in tandem with alarm/rejection rates to create a single line SSCP queuing model. The approach of an M/G/2 with an M/M/1 server based on probability function β provides a more accurate simulation of the double line system without using DES, by allowing for process times to follow a general distribution without central tendency. This is crucial because although service times are exponential, a series of multiple service times no longer behave exponentially, but rather that of an Erlang-K distribution which is the sum of k curves. Because there is only one server involved in manual baggage screening, an M/M/1 server is a sufficient fit, rather than utilizing an M/G/1 or other model.

For the mathematical model of the SSCP, the system as a whole will be assumed to be in steady state where $\lambda < \mu$, despite instantaneous fluctuations of arrivals. The manual baggage screening service mechanism will be modeled as an M/M/1 process, and the TRX_1 and TRX_2 service mechanisms will be modeled as an M/G/2. The alarm rate, or probability of a bag being cleared from screening is modeled as β, and the probability of the bag needing manual screening is modeled as $1 - \beta$. For mathematical modeling of the SSCP systems, a Jackson open network is considered. The mathematical model is illustrated in Figure 5.

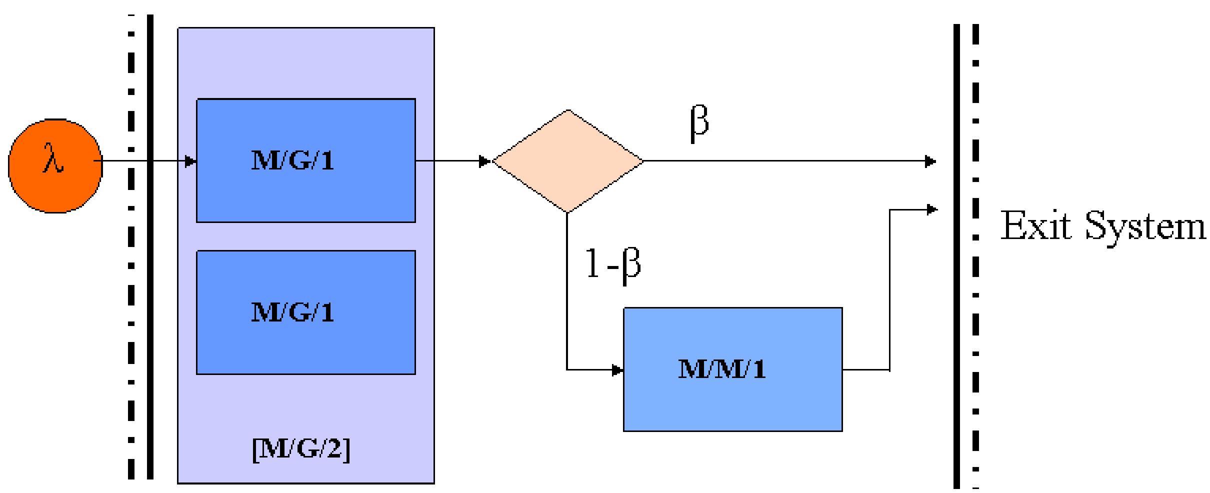


Figure 5. Mathematical Model of SSCP using Jackson open queuing network.

The following notation in the model denotes:

J : the number service node $J = 2$ for the SSCP case;

λ_i: the arrival rate for each service node;

p_{0i} probability of each arrival independently routed to node i; $p_{0i} \geq 0$;

p_{ij}: probability of each passenger route from node i to node j;

p_{j0}: probability of each passenger leaving the system from node j;

It can be shown that the following equation holds

$$p_{i0} = 1 - \sum_{j=1}^{J} p_{ij} \tag{7}$$

In tandem with the following traffic equation

$$\lambda_i = \lambda p_{0i} + \sum_{j=1}^{J} \lambda_j p_{ji}\, , i = 1, 2, \dots, J \tag{8}$$

Let μ_i indicate the exponential service rate for each of the service node, $i = 1, 2, \dots, J$.

Z: the number of bags that each passenger carries, which is a random number that follows a discrete distribution, with $P(Z = k), k = 1, 2, \dots, K,$, K is the upper bound for this number, and $\sum_{k=1}^{K} P(Z = k) = 1$. It is assumed that because bags are proprietary, the same person has to wait until all of their bags are finished, thus the service time for each passenger can be considered as the sum of a series of k independent Exponential distribution. It is known that the sum of k independent Exponential random variables forms an Erlang distribution at the k_{th} order, with the probability distribution function

$$f(x; k, \mu) = \frac{\mu^j x^{k-1} e^{-\mu x}}{(k-1)!} \tag{9}$$

It is easy to derive the mean and variance for Erlang-k distribution as

$$E(x) = \frac{k}{\mu} \tag{10}$$

$$Var(x) = \frac{k}{\mu^2} \tag{11}$$

According to Jackson (1963), the joint distribution of the security screening network is

$$P(Y_1 = n_1, Y_2 = n_2) = \prod_{i=1}^{2} P(Y_i = n_i) \tag{12}$$

Where n denotes the number of PAX in the i_{th} node; (i = 1, 2). The mean number in the SSCP system can be thought as the sum of the two nodes together

$$N = n_1 + n_2 \tag{13}$$

Using standard M/G/2 and M/M/1 queue it can be derived

$$n_1 = \lambda_1 W_1 \tag{14}$$

$$W_1 = W_Q + E[S] \tag{15}$$

$$W_q \approx \frac{{\lambda_1}^2 E[S^2](E[S])}{(2 - \lambda_1 E[S])^2 \left[\sum_{n=0}^{1} \frac{(\lambda_1 E[S])^n}{n!} + \frac{(\lambda_1 E[S])^2}{(2-1)!\,(2 - \lambda_1 E[S])}\right]} \tag{16}$$

$$E[S] = \frac{k}{\mu_1} \tag{17}$$

$$E[S^2] = Var(S) + (E[S])^2 = \frac{k}{{\mu_1}^2} + \frac{k^2}{{\mu_1}^2} \tag{18}$$

Where k is the average baggage number for each passenger (Ross, 1997).

$$n_2 = \frac{\rho_2}{1 - \rho_2} \tag{19}$$

$$\rho_2 = \frac{\lambda_2}{\mu_2} \tag{20}$$

According to Little's law, the mean time for passenger to pass through the SSCP is

$$W = \frac{N}{\lambda} = \frac{n_1 + n_2}{\lambda} \tag{21}$$

The mathematical model is limited in multiple respects such as the inability to account for the non-stationary arrivals to the SSCP and non-exponential service times. Also, any results produced by the production of a queuing network are approximations of cycle time, rather than empirical results derived from DES (Shanthikumar et al., 2007).

Data Collection

Four types of data were collected to power the empirical and theoretical modes: Arrival rates, baggage volume, service rates, and alarm rates. Arrival times and number of bags each person carries on them were recorded for a sample of seven days during the peak time of 6am to 7am at the SSCP being modeled. The sample size of seven days was used to provide a sample of over 1000 PAX during peak operating times. Data was collected by the use of the data collection form in Appendix B, where the number of bags each person carried into the SSCP was marked into a box corresponding with the time they arrived at the system. PAX were considered to have arrived in the SSCP when they physically crossed the threshold into the hallway where the TDC is located. If the queue protruded from the hallway, the passenger was marked as arrived at the moment they came to a complete stop at the end of the queue.

All data collection was performed solely by the researcher after pilot study observations indicated there was a degree of simplicity to the process that would not require multiple persons for data collection. The reliability of arrival data collection process is substantiated by the small difference in observed PAX arrival for the peak hour and reported PAX throughput for the respective samples shown in Table 1. The PAX throughput for the sample dates in Table 1 was reported by a SME with access to privileged information regarding the SSCP.

Table 1

PAX arrivals and throughput by sample.

Sample	1	2	3	4	5	6	7	Average
$PAX_{Observed}$	167	153	159	176	159	163	157	162.00
$PAX_{Reported}$	180	145	194	158	159	153	182	167.29
$Difference_{PAX}$	13	8	35	18	0	10	25	**5.29**

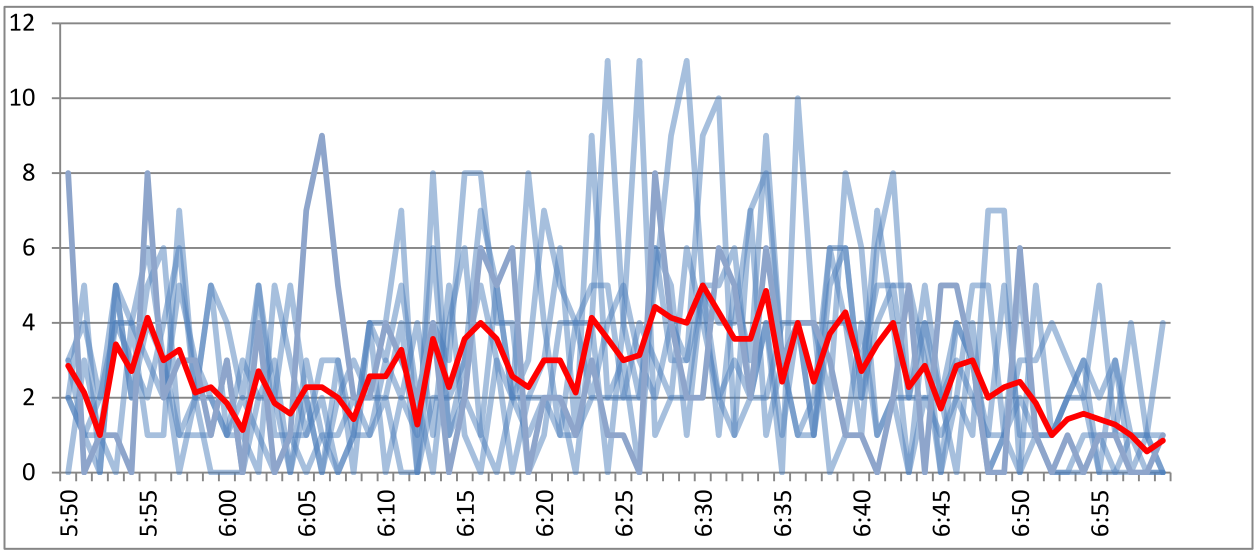


Figure 6. PAX arrival rate with sample arrival rates in blue and mean arrival rate in red.

Since arrivals did not follow a theoretical distribution, but rather a non-stationary schedule, arrivals were split into equal times for a piece-wise distribution, where multiple Poisson curves were fitted based on a schedule (Pendergraft et al., 2004). The instantaneous arrivals rates used in the piece-wise Poisson distribution are shown in Appendix C. The erratic nature of the PAX arrival rate can be seen in Figure 6. Arrivals were scheduled based on three minute intervals of the average arrival rate for each minute, which allowed for a modest smoothing effect of the arrival curve without sacrificing the sensitivity of trends.

The number of bags each person carried was converted to a discrete distribution of baggage to allow for an accurate simulation analysis as shown in Figure 7. The number of bags each person carries was adjusted with a value of 1 added to account for the bin of shoes and personal items that were searched through the TRX and therefore a minimum value of 1 was established for each PAX. A value of 1 was added for any passengers that were wearing or carrying a heavy coat that would require a separate bin and time through the TRX. Therefore all PAX had a value of 1 added to the recorded number of bags they carried, while PAX with heavy coats had a value of 2 added to the recorded number of bags they carried. Purses were counted as one item of baggage because they are typically placed on the belt as a standalone item, as corroborated by a SSCP SME.

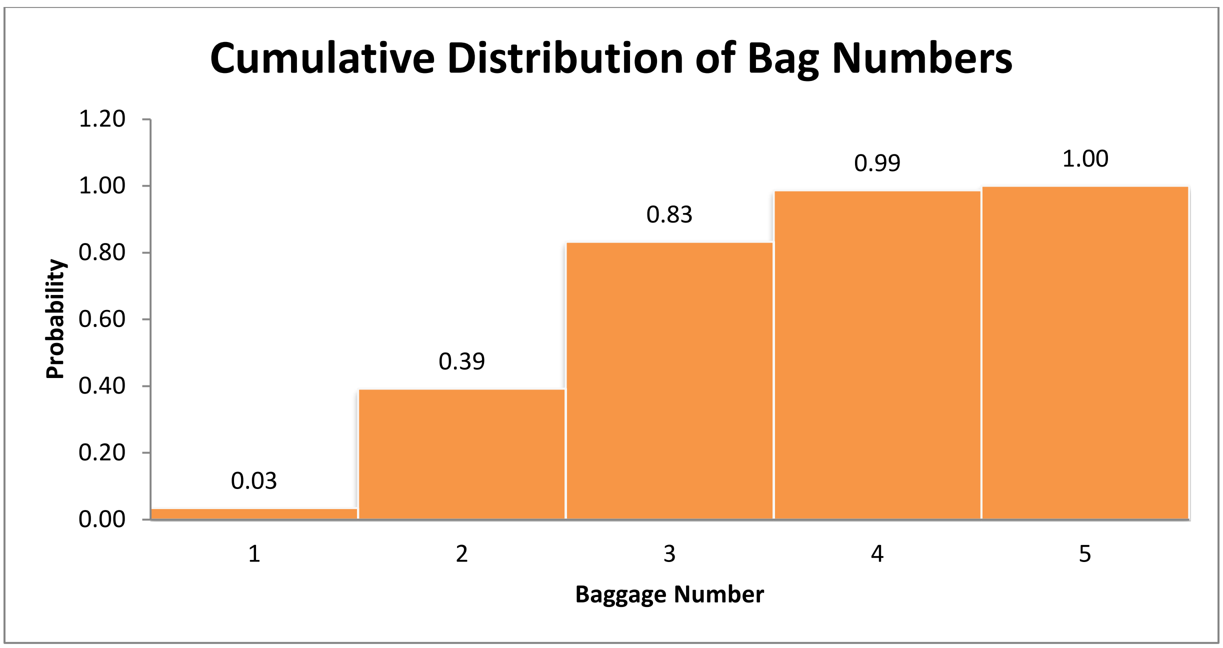


Figure 7. Distribution of sample baggage volume.

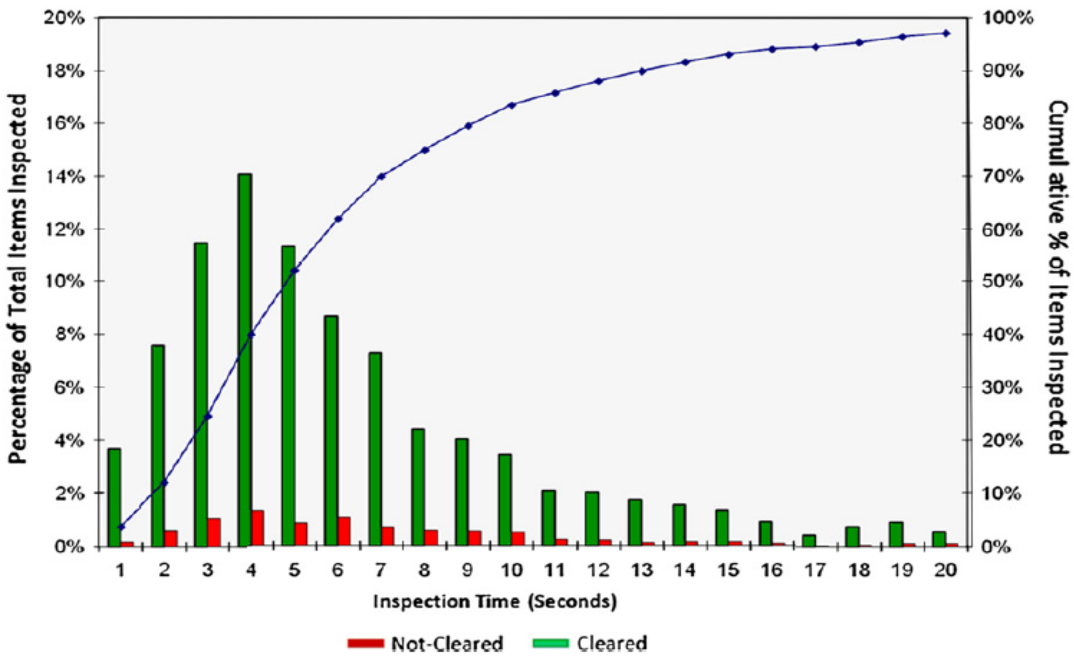


Figure 8. Baggage screening time distribution. Adapted from "Improving airport security screening checkpoint operations in the us via paced system design," by Leone and Liu, 2010.

Table 2

Process times and alarm rates of multiple SSCP operations. Adapted from "Improving airport security screening checkpoint operations in the us via paced system design," by Leone and Liu, 2010.

Sample	N_{PAX}	Mean Time (S)	Percent Passed	N_{Failed}	Percent Failed
1	1149	6.64	91	109	9
2	1223	7.64	89	158	11
3	1247	6.59	88	165	12
4	1264	6.84	94	80	6
5	976	6.92	95	52	5
6	994	6.42	92	92	8
7	1194	7.87	91	111	9
8	1136	6.83	97	41	3
9	1064	6.69	88	149	12
10	1043	6.71	88	136	12
Total	11290	6.93	91	1093	9

Process times and alarm rates for SSCP baggage screening processes were taken from the data reported by Leone and Liu (2010), and are shown in Table 2. The data was collected in 10 samples from five separate locations from multiple days at peak times from different sized airports, and encompasses a sample size of over 11,000 bags. While Table 2 shows the mean times from the samples, Figure 8 shows the distribution of times that more adequately reflect a triangular distribution with values of [1,4,20] than an exponential distribution of five. The process time for manual baggage searches was yielded from a sample of over 500 manual searches provided by the TSA, and is reported to be consistent across all airport types and sizes with a uniform time between 120 and 300 seconds per baggage (Leone & Liu, 2010).

Arena Simulation Software

Because a queuing network relies on many assumptions, the SSCP system was modeled and analyzed with Arena version 12. Arena is developed and distributed by Rockwell Automation and is a Graphical User Interface (GUI) based tool that allows for in-depth experimentation of systems and the ability to examine future options without disturbing the system at hand. Arena allows for the creation, refinement, and simulation of models as well as analysis of simulation results (Rockwell Automation, 2010).

Arena offers a more user friendly interface for the simulation modeling language SIMAN, while still allowing the option to manually code in SIMAN if desired. The drag and drop interface allows for expeditious composure of the conceptual model and ability to simply type in appropriate process and decision parameters. Likewise, the ability to animate the simulation allows for a visual representation of the process being modeled to be more easily corroborated between systems analysts, SMEs, and any involved person not familiar with simulation (Kelton et al., 2007).

SSPC Simulation Model

Arena version 12 was used to create the simulation model of the SSCP, perform all experiments, and collect data on throughput and cycle time in this study. A simple and effective simulation model was run with accurate input, which yielded a validated experimental simulation model to further understand the effects of different external factors on SSCP performance (Rockwell Automation, 2010).

The SSPC simulation model is based off of the conceptual model of SSCP operations shown in Figure 9 with some differences in queuing and stochastic drawing of times for TRX baggage screening.

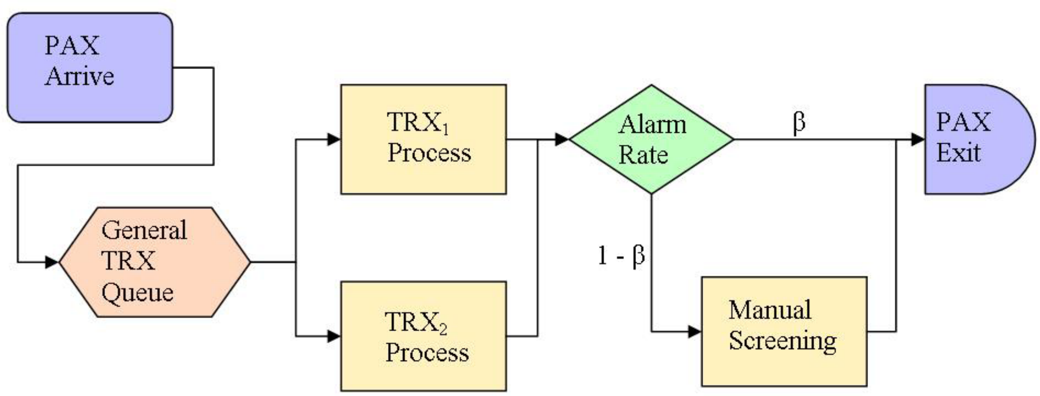


Figure 9. Conceptual DES model of SSCP.

Verification and Validation of the Simulation Model

Before experimentation begins, a simulation model must be verified and validated (Kelton et al., 2007; Law, 2006). The simulation model underwent a verification process and was validated in two methods before the sensitivity analysis was performed.

Verification of the simulation model.

Model verification was performed in the manner prescribed by Kelton et al. (2007). Verification was performed by running the model in a variety of scenarios in an attempt to cause an error in the model, or a process commonly referred to as debugging. Verification consisted of the following tests and expected outcomes as shown in Table 3. The overall purpose of model verification was to ensure that the model represents the conceptual system model accurately with respect to entity paths, queuing, and logic (Kelton et al., 2007).

Table 3

Verification Tests and Expected Outcomes

Test	Outcome
Run with single entity	Verify entity path logic
Run with 20 entity batch	Verify system queuing logic
Run with 100 entity batch	Verify and stress system queuing logic
Run with 1 bag per entity	Verify TRX baggage screening algorithm and separate/batching
Run with 5 bags per entity	Verify TRX baggage screening algorithm and separate/batching

Validation of the simulation model.

The simulation model was validated for both face validity and quantitative validity before experimentation began. Face validation was performed by iterative consulting with SMEs from the airport being modeled, as well as SMEs from simulation and industrial engineering backgrounds. The SMEs cross referenced the simulation model with the assumptions documentation and compared it with their knowledge and expertise of the system and its operations.

After verification and face validation of the simulation model, quantitative validation was performed. For quantitative validation the simulation model was run in a batch of 100 repetitions, so that the throughput of the simulation model could be tested against the throughput of the actual system. Previous studies have used repetitions of 80 or 30 runs for validation and data collection purposes (Brown & Madhavan, 2010; Werker et al., 2009). Because of the short run time and relative simplicity of the system, a replication of 100 runs is more than adequate for all purposes of this study.

Because alarm rate data was not available at the specific SSCP being modeled, the arithmetic mean (91%) of the alarm rates from Table 2 was utilized. The alarm rate of 91% was confirmed by the SSCP SME as an accurate assumption of the actual systems alarm rate. The baseline baggage volume based on data collected from the actual system was used for validation runs.

Sensitivity Analysis

Once the simulation model was validated a sensitivity analysis was performed on the SSCP model, where the independent variables were the baggage volume, and the alarm rate that allows PAX to exit rather than undergo a manual search. Werker et al. (2009) defines a sensitivity analysis as varying an input and measuring the effects on model output. In general, a sensitivity analysis involves running an “as-is” scenario, then running other scenarios with different system parameters in “what-if” scenarios (Leone, 2002; Pendergraft et al., 2004; Werker et al., 2009).

Batches of 100 simulation runs were performed at each level of both variables, where both dependent measures were recorded. Each batch of 100 simulation runs yielded mean values for the dependent measures of cycle time and SSCP throughput. Also, batches of 100 simulation runs were performed for both independent variables, where one variable was left at its baseline validated level while experimentation was performed on the other variable.

Independent Variables.

The independent variables for this study were baggage volume and alarm rate. In this study, baggage volume was defined as the amount of baggage PAX carry with them that requires screening. The baseline baggage distribution is shown in Figure 8. Five levels of baggage volume were used in this study: Baseline baggage volume, Baseline – 1, Baseline – 2, Baseline + 1, and Baseline +2.

The values for baggage volume have a lower bound at a value of one because each passenger must have at least one searchable bin to account for their shoes and personal affects. The different levels of baggage volume are intended to investigate the effects of seasonal changes on baggage volume identified in Wetter et al. (2010) and corroborated by the SSCP SME. Likewise, if a high sensitivity was to be found in lowered baggage volume, airlines could examine incentivizing checking baggage to increase security throughput and enable more flights for higher gains.

The second independent variable for this study was the alarm rate. In this study the alarm rate was defined as the percentage of PAX that are cleared for exit from the SSCP into the sterile area rather than proceeding to a more invasive manual search of baggage, and is denoted as β. There were 22 levels of alarm rate, from 0% through 100% at 5% intervals, in addition to the baseline validated alarm rate (91%). The investigation of the dependent measures based on a function of alarm rate would be invaluable to a SSCP planner, as holidays and other special occasions create trends in alarm rates according to SSCP SMEs. Likewise, if large percentages of PAX can be manually searched and still meet requirements, a decrease in expensive equipage could be a possibility.

Dependent Measures.

There were two dependent measures for this study: SSCP throughput per hour and cycle time. SSCP throughput is defined as the amount of PAX that arrive and exit the SSCP simulation model within the one hour peak time period of 6am - 7am. ARENA automatically records SSCP throughput into batch means throughout replications (Rockwell Automation, 2010). Throughput is a classical measure of system performance in both DES and queuing networks, and reflects the system's ability to process entities under a given set of conditions (Blanchard & Fabrycky, 2006; Jackson, 1963; Shanthikumar et al., 2007). In general, a higher throughput rate is desirable, meaning the system can process more entities in same or less time, usually yielding higher productivity and profits.

Cycle time is the amount of time each passenger spends in the SSCP system, and is recorded by ARENA through a time stamp and recording module for each passenger (Rockwell Automation, 2010). Cycle time is a standard measure of system performance (Blanchard & Fabrycky, 2006; Kelton et al., 2007) and is used in many simulation studies on airport operations and SSCP efficiency (Appelt et al., 2007; Giachetti et al., 2005; Leone & Liu, 2010; Pendergraft et al., 2005). Aside from strictly being a measure of performance, cycle time has a large effect on PAX satisfaction with SSCP and aviation transportation as a whole (Appelt et al., 2007; Guizzi et al., 2009; Yildiz et al., 2008). The current industry standard for cycle time is 10 minutes or less (Hafizogullari et al., 2003; Leone & Liu, 2010; & Pendergraft et al., 2004), while the customer (PAX) requirement for satisfaction and continued use is 30 minutes or less (Frederick-Recascino et al., 2003). The sensitivity analysis allows for a better understanding of the effects of both independent variables on cycle time, as well as illustrates which conditions violate requirements of industry and consumer.

Results

Queuing Network Results

The mathematical model was programmed using MATLAB to allow for efficient calculations of output. The source code is attached in Appendix D. MATLAB is a high level language and program that enables high level computations to be performed much faster than in other programming languages or computation by hand alone (Mathworks, 2011). Because the queuing network model is limited in respects to probability distributions of arrivals and service times, the parameters were taken based on the estimation of the simulation model. These parameters are illustrated in Table 4. Arrival rates and service times were determined by using the arithmetic mean of the distributions by which they followed. The baggage distribution was adjusted by taking the expected value of the distribution, then rounding to the nearest whole integer. The alarm rate was adjusted to 95% to allow for the assumption of steady-state, which will be discussed in greater detail.

Table 4

Differences in DES and mathematical models.

Model parameter	DES value	Queuing network value
Arrival rate (λ)	Non-stationary schedule	2.7 PAX/min
Baggage distribution (κ)	DISC[0.03,1,0.39,2,0.83, 3,0.99,4,1,5]	2, 3
μ_{TRX} (n_1)	1/TRIA[1,4,20] s	8.40 PAX/min
μ_{Manual} (n_2)	1/UNIF[120,300] s	.29 PAX/min
β (Alarm rate)	91%*	95%

* Denotes baseline validated level

The parameters shown in Table 4 were made to the Monte-Carlo simulation (DES) model so that the accuracy of the mathematical model could be assessed. The Monte-Carlo simulation DES model was the DES model modified with the data in Table 4 so that it would mimic a mathematical approach. The Monte-Carlo simulation model was run for a sample of 50 simulation runs, where the mean PAX cycle time was recorded for each run and compared to the cycle time produced by the mathematical model using a *t*-test.

To solve the network for cycle time, given $\lambda = 2.7$, Equation 7 was expanded to provide the following traffic probabilities

$$P_{01} = 1$$

$$P_{02} = 0$$

$$P_{12} = 1 - \beta$$

$$P_{21} = 0$$

$$P_{10} = \beta$$

$$P_{20} = 1$$

Equation 8 for λ_1 and λ_2 became

$$\lambda_1 = \lambda P_{01} + [\lambda_1 P_{11} + \lambda_2 P_{21}], \qquad i = 1 \tag{22}$$

$$\lambda_2 = \lambda P_{02} + [\lambda_1 P_{12} + \lambda_2 P_{22}], \qquad i = 2 \tag{23}$$

Which after applying the traffic probabilities yielded

$$\lambda_1 = \lambda + 0 = \lambda \tag{24}$$

$$\lambda_2 = 0 + \lambda(1 - \beta) + \lambda_2 0 = \lambda(1 - \beta) \tag{25}$$

After applying baggage number of 2 and service time of 7.14 seconds, the mean and variance for the Erlang-K distribution became

$$E(x) = \frac{2}{7.14} = .289 \tag{26}$$

$$Var(x) = \frac{2}{7.14^2} = .0392 \tag{27}$$

Once values were applied, Equation 17 and Equation 18 became

$$E[s] = \frac{2}{7.14} = 0.28 \tag{28}$$

$$E[s^2] = Var(s) + (E[S])^2 = \frac{2}{7.14^2} + \frac{4}{7.14^2} = 0.12 \tag{29}$$

Equation 16 was solved after the values were incorporated into it such that

$$W_q \approx \frac{2.7^2(0.12)(0.28)}{(2-(2.7)(0.28))^2[1+(2.7)(0.28)] + \frac{[(2.7)(0.28)]^2}{2-(2.7)(0.28)}} \approx 0.0701 \text{ (min)} \tag{30}$$

Equation 15 was then used to find the waiting time for n_1

$$w_1 = 0.0701 + 0.28 = 0.3501 \text{ (min)} \tag{31}$$

Equation 14 was then used to find the number of PAX in n_1

$$n_1 = 2.7(0.3501) = 0.9453 \tag{32}$$

To find the number of PAX in n_2, an M/M/1 queue, Equation 20 was used to find ρ_2

$$\rho_2 = \frac{(1-0.95)2.7}{0.2857} = 0.473 \tag{33}$$

So that n_2 could be found with Equation 20

$$n_2 = \frac{0.473}{1-0.473} = 0.898 \tag{34}$$

N was found by adding the sum of $n_1$and n_2 as shown in Equation13. Finally, by using Little's law, the mean PAX cycle time was found using Equation 21 such that

$$W = \frac{1.841}{2.7} = .682\, min = 40.92\, s \tag{35}$$

The same mathematical process was used for two cases with the queuing network, with exception of changing the value of κ, the number of bags each passenger carried. The first test comparison was performed where $\beta = 95\%, \kappa = 2$, which is shown above. The second test comparison was performed where $\beta = 95\%, \kappa = 3$. The cycle time of 40.92 seconds yielded by the mathematical model in the first case was a good fit of the mathematical model. The cycle time of 40.92 seconds yielded by the mathematical model was not significantly different than the mean cycle time of 40.99 (*SD* = 3.91) of the Monte-Carlo simulation model $t(49) = -.018$, $p = .986$. However, when κ was increased to three bags, where $\beta = 95\%$, the result of 60 sec was significantly different than the mean cycle time of 54.07 (*SD* = 2.92) yielded by the Monte Carlo simulation $t(49) = -14.35$, $p = .000$. When k equaled three, the mathematical model is not a good fit of assessing SSCP performance.

Under certain conditions, the mathematical model can serve as a near exact fit for predicting PAX cycle time in an SSCP; however, under other conditions the model fails to be an accurate method of assessment. By investigating the assumption of the system being in steady state the reason behind these results becomes apparent. For queuing networks to work, the system must be in steady state, a condition where $\lambda/\mu < 1$ must be met. If the system fails to converge to steady state, results can be inaccurate or erratic (Blanchard & Fabrycky, 2006; Hopp & Spearmann, 2001; Ross, 1997).

The results of the queuing network identified two points when results would cease to be accurate. If either $\eta 1$ (TRXs) or $\eta 2$ (manual screening) are not within steady state, the queuing network will fail to produce accurate results. Given the equation for steady state

$$\frac{\lambda_1}{\mu_1} < 1 \tag{36}$$

With the modified service time of μ_1, adjusted for κ bags that must exceed λ_1

$$\mu_1 = \frac{7.14}{\kappa} > 2.7 \tag{37}$$

It can be derived that κ must be less than 2.64 bags per passenger. In addition to the limitations at η_1, the process at η_2 must also be in steady state for the queuing network to yield accurate results. In similar fashion to η_1, given the equation for steady state

$$\rho_2 = \frac{\lambda_2}{\mu_2} < 1 \tag{38}$$

Where λ_2 is modified to be a function of alarm rate (β)

$$\rho_2 = \frac{(1-\beta)(2.7)}{.29} < 1 \tag{39}$$

It can be seen that β must be greater than .893, or 89% for the queuing network to remain in steady state. In the first tested scenario where κ was three, the model could not achieve steady state and therefore yielded significantly different results than it should have. However, when a value of two was used for κ, the queuing network yielded impeccably accurate results of PAX cycle time in the SSCP system.

Discrete Event Simulation Results

A DES model was constructed using Arena simulation software. The model accurately reflects the conceptual model of the system, and was verified and validated in multiple ways before experimentation began. After verification and validation of the simulation model, a sensitivity analysis was performed. The sensitivity analysis using the DES/empirical approach yielded results of SSCP performance for 110 different combinations of the two independent variables (baggage volume and alarm rate). Results were collected for the dependent measures of system throughput and cycle time for all 110 scenarios of operation. Both dependent measures were more sensitive to the effects of alarm rate than that of baggage volume. Model description, verification and validation results, and findings for each dependent measure are presented in the following sections.

Modeling results.

The model was built using Arena simulation software, version 12. The simulation model differed from the conceptual simulation model shown in Figure 9 in multiple respects. The simulation model, shown in Figure 10, utilizes multiple assign and record modules to assign multiple entity attributes such as the number of bags each passenger carried (k). Furthermore, the assign and record modules enabled the collection and export of statistics under investigation such as cycle time. Finally, where the conceptual model shows a linear process, the DES model utilizes a pair of separate and batch modules to allow for a stochastic process time of each bag to be assigned.

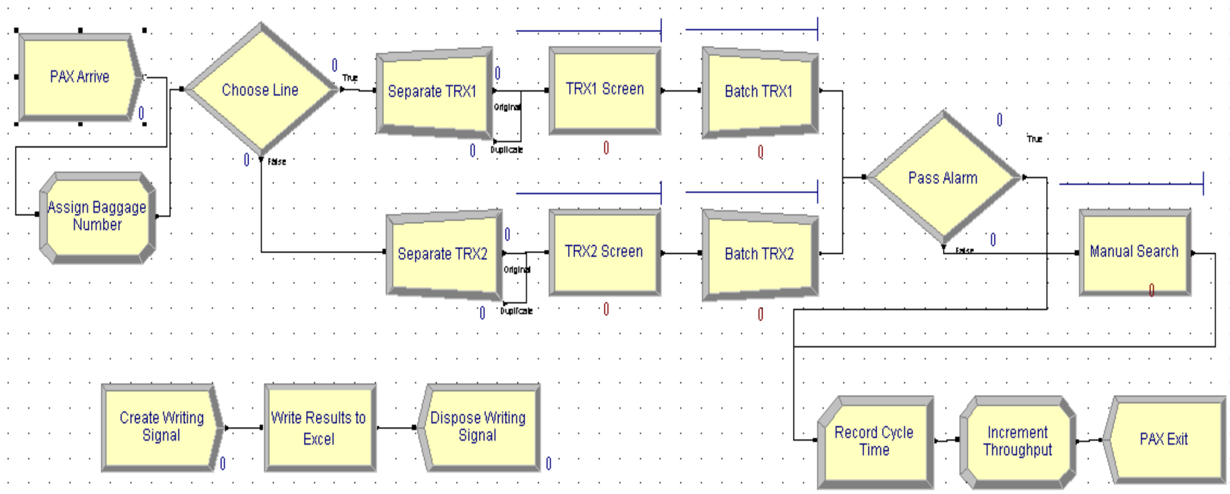


Figure 10. DES model of SSCP.

Verification and validation results.

Verification of the DES model was a simple process. Steps from Table 3 were performed in succession to ensure that the model operated as intended and was free of logical errors. In addition to the verification methods shown in Table 3, multiple SMEs in discrete event simulation used and evaluated the model to further ensure model verification. Once the model was verified, it was validated through qualitative and quantitative methods.

Qualitative validation involved the inspection of the model by SMEs to ensure that it represents the system it intends to simulate. SMEs from multiple disciplines of airport security/SSCPs viewed the DES model and the assumptions documentation and confirmed that it was an accurate representation of the actual SSCP system, therefore qualitatively validating the model. After initial qualitative validation, quantitative validation was performed by statistically testing simulation throughput against throughput reported by SMEs.

Once simulation throughput results were derived, they were checked for the assumption of normality, and then compared to actual throughput results from the dates used for sampling using a *t*-test. The *t*-test is a standard method of testing the difference of means in two samples and comparing them to expected differences in their representative populations (Field, 2009). The simulation runs ($n = 100$) yielded a system throughput of 161.33 PAX ($SD = 12.71$), while the actual sample of system throughput ($n = 7$) yielded a system throughput of 167.29 ($SD = 18.02$). There was no significant difference in the mean system throughput of the simulated and actual results ($t(105) = -1.17$, $p > .05$). Because there is no significant difference in simulation throughout and actual throughput, the model is quantitatively validated. After quantitative validation, the SSCP SMEs were consulted a final time to confirm that the model, assumptions, and preliminary results were all valid before experimentation began.

Sensitivity analysis results.

Results indicated that throughput of the SSCP was not affected by baggage volume. Figure 11 shows the SSCP throughput levels for all combinations used in the sensitivity analysis. It can be seen that throughput levels remain practically the same for all baggage volumes at each level of alarm rate from 0% through 100%. At the baseline alarm rate of 91%, baggage volume only accounts for a change of 164 PAX per hour to 160 PAX per hour, a difference of four.

	Alarm Rate (β)																				
Baggage Vol	0%	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%	55%	60%	65%	70%	75%	80%	85%	90%	91%*	95%	100%
Baseline + 2	18	26	34	42	50	57	65	73	81	89	98	107	115	123	131	139	147	153	159	160	160	161
Baseline + 1	18	26	33	41	49	57	65	73	81	90	98	107	114	122	131	139	147	156	162	162	165	165
Baseline*	17	26	34	42	50	58	67	75	83	91	98	106	115	123	131	140	148	156	162	162	165	164
Baseline - 1	17	25	33	42	49	57	66	74	82	90	98	107	115	123	132	140	148	157	161	162	165	165
Baseline - 2	17	25	33	42	50	59	67	75	83	91	99	107	115	124	132	139	148	155	163	164	164	163

* Denotes Baseline Level

Figure 11. PAX throughput results from sensitivity analysis.

While throughput is unaffected by baggage volume, it is highly sensitive to the effects of alarm rate. In general, as alarm rate decreases and more PAX are sent to manual screening throughput decreases. At the baseline baggage volume, alarm rate accounts for a drop of 164 PAX per hour to 17 PAX per hour, a difference of 147. There is relatively no difference in throughput at the higher alarm rates, where no noticeable change occurs until the alarm rate drops below 85%. Throughput follows a linear trend regardless of baggage volume from 85% to 0%, as shown in Figure 12. Results indicate that SSCP throughput is unaffected by alarm rate until it becomes lower than 85% upon where it declines in a linear fashion until alarm rate reaches 0%.

Unlike throughput, cycle time was found to be slightly sensitive to baggage volume as shown in Figure 14. At the validated alarm rate of 91%, Baggage volume accounted for a change in average passenger screening time from 87 seconds at baseline to 254 seconds at baseline +2 of almost three minutes (167 sec). Furthermore baggage volume accounted for a difference of 190 seconds between baseline +2 and baseline -2 conditions. The effects of baggage volume are less severe at lower alarm rates such as 15% and less, where the cycle times all become nearly equal.

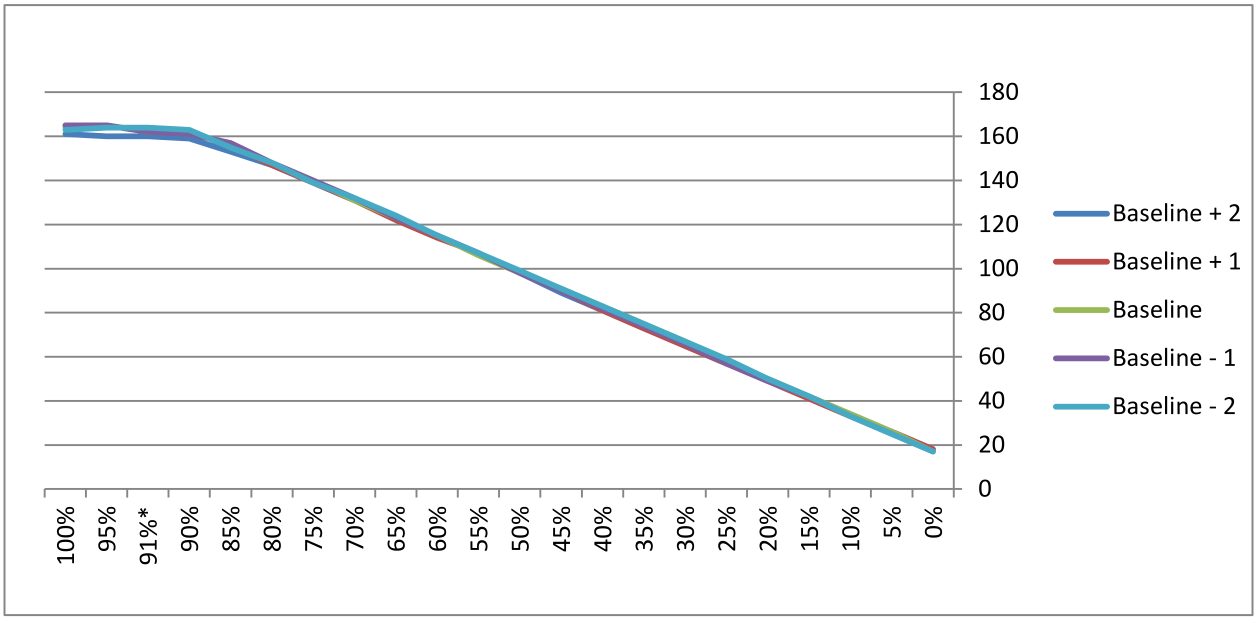


Figure 12. Graphical depiction of PAX throughput from sensitivity analysis.

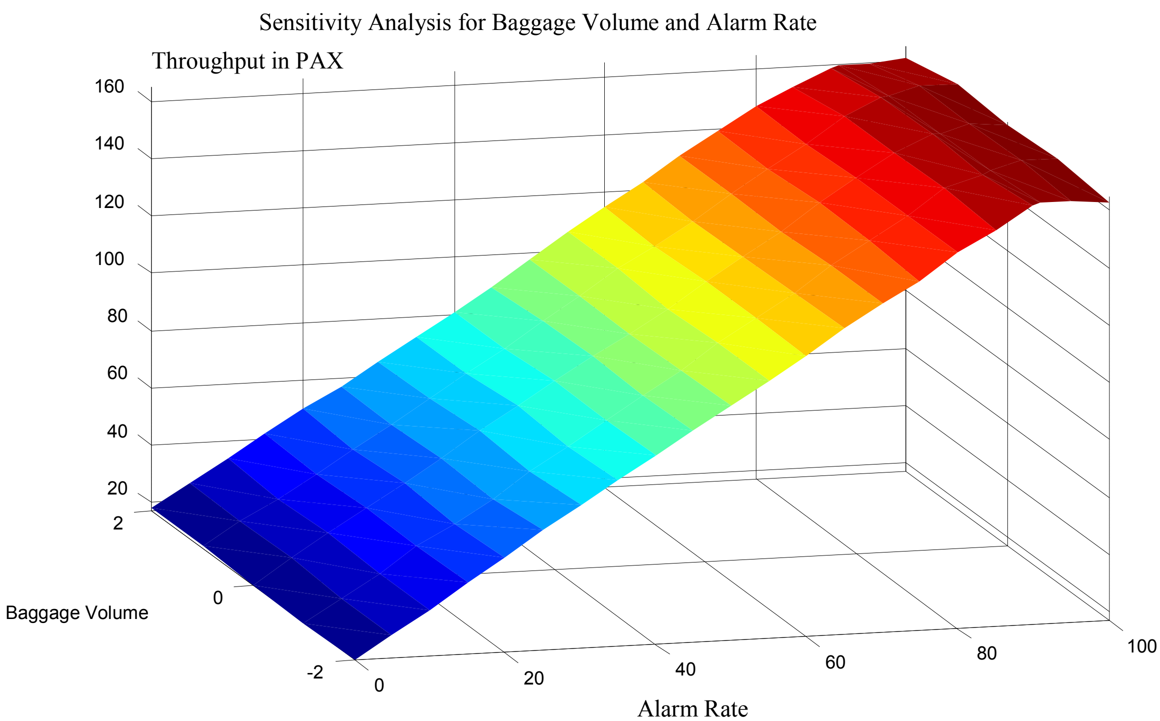


Figure 13. Three dimensional graphical depiction of PAX throughput per hour from sensitivity analysis.

Cycle Time per Condition (S)

Baggage Vol.	Alarm Rate (β) 0	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	91*	95	100
Baseline + 2	2112	1515	1189	986	853	758	683	621	573	531	496	461	431	409	383	354	317	284	254	247	217	217
Baseline + 1	2118	1469	1149	932	790	687	599	535	484	438	402	367	335	301	271	236	205	174	126	116	99	80
Baseline*	2125	1441	1110	888	745	636	556	491	436	395	361	322	287	254	227	193	162	129	87	80	49	33
Baseline - 1	2122	1433	1087	870	732	622	537	472	417	377	342	304	271	241	211	180	145	112	72	65	34	18
Baseline - 2	2146	1462	1119	883	731	615	534	471	419	375	340	302	273	237	206	175	144	108	67	57	28	12

* Denotes Baseline Level | Requirements: | Industry < 600 | PAX < 1800

Figure 14. PAX cycle time results from sensitivity analysis, where green indicates performance within industry requirements, yellow indicates performance within PAX requirements, and red being unacceptable performance.

As with throughput, cycle time was very sensitive to alarm rate. Unlike throughput however, cycle time is affected by alarm rate at nearly every baggage volume level from the baseline level of 91% to 0%. Unlike throughput, the effects of alarm rate on cycle time occur in a nonlinear fashion, as shown in Figure 15 and Figure 16. Cycle time increases in a nonlinear fashion, where the difference in cycle time is of greater magnitude the lower the alarm rate gets.

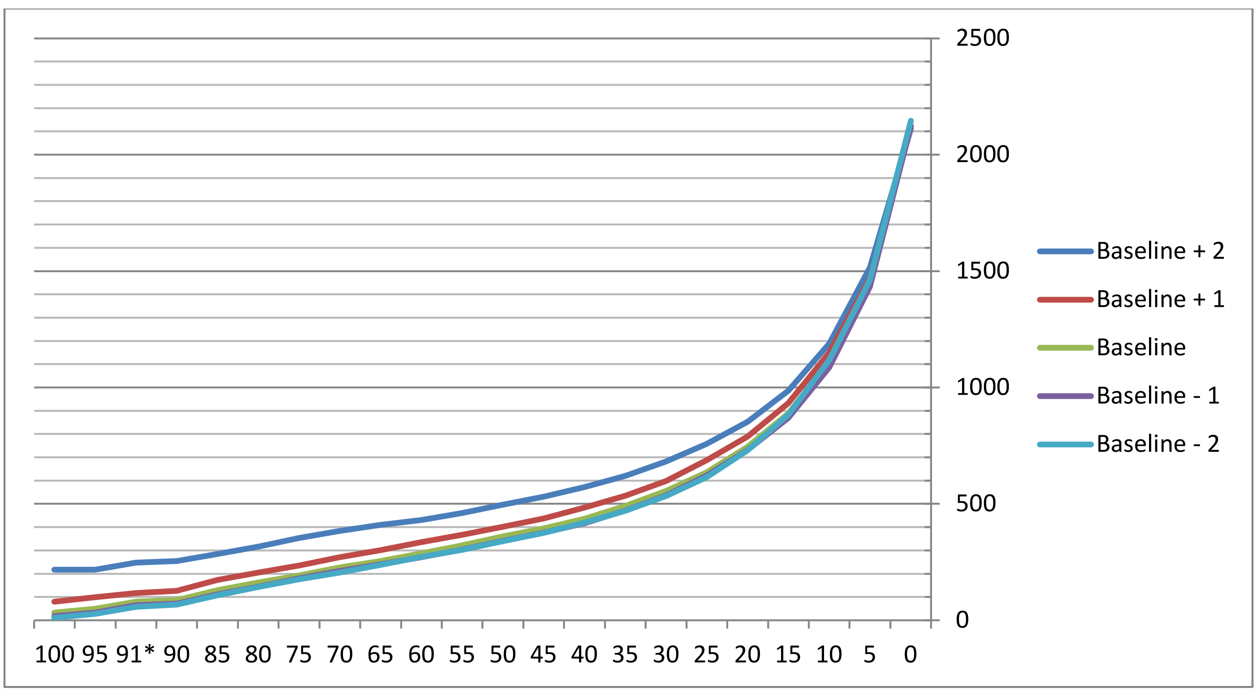


Figure 15. Graphical depiction of PAX cycle time from sensitivity analysis.

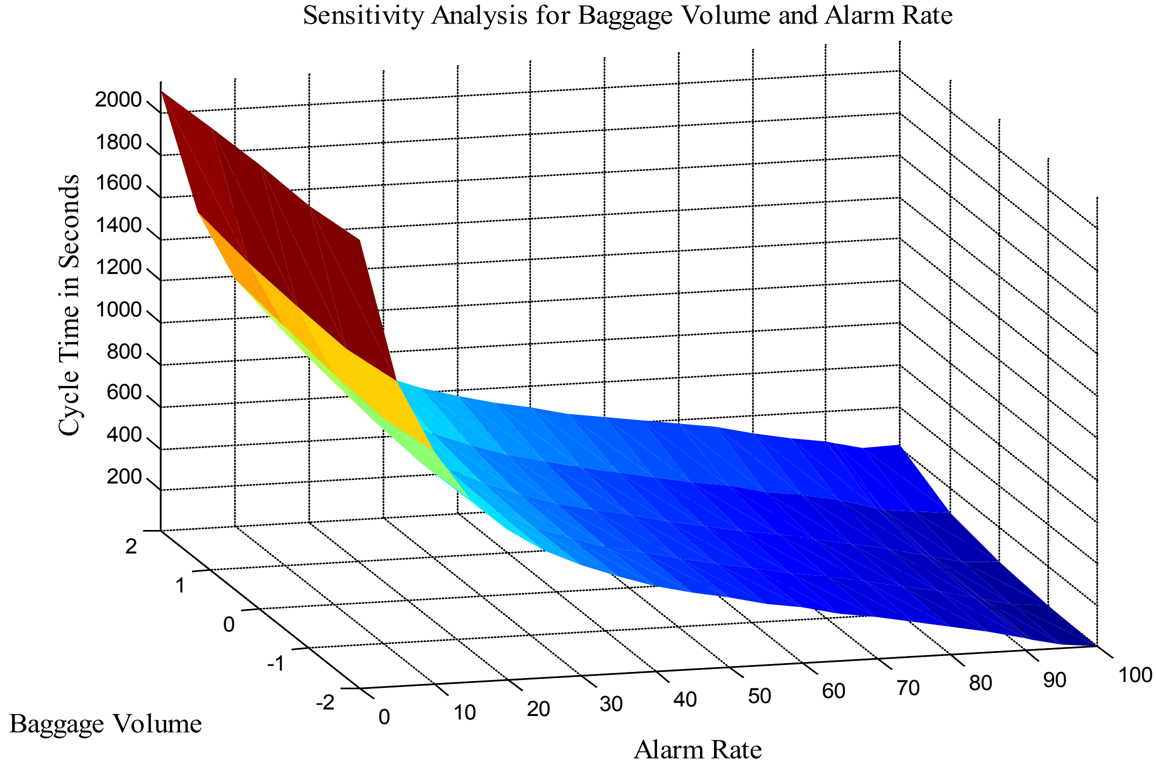


Figure 16. Three dimensional graphical depiction of PAX cycle time from sensitivity analysis.

Despite the large sensitivity of alarm rate on cycle time, the SSCP can still meet TSA and PAX requirements under strenuous conditions. With exception of the baseline + 2 level of baggage volume, TSA requirements for PAX cycle time of 10 minutes or less were fulfilled until the alarm rate exceeded 30%. PAX requirements of 30 minutes or less as defined in Frederick-Recascino et al. (2003) were still met with a 5% alarm rate. A 0% alarm rate is the only alarm rate at which the average PAX cycle time does not meet any requirements. Caution should be used however when assessing these requirements. The average cycle time is only collected for PAX that exit the system; therefore, while cycle time may meet the requirements it is certainly not feasible to have only 67 PAX per hour. Major results, practical applications, and limitations of the study will be discussed in the following section.

Discussion

Discussion of Results

Results from the queuing network provided interesting insight into the accuracy of mathematical modeling, as well as the fragility of the model. As demonstrated, the Jackson open queuing network produced accurate results while it was within the assumption of steady state performance. When it was not in steady state however the results could not converge to a finite solution. This is an inherent characteristic of queuing theory and accounts for the varied results (Blanchard & Fabrycky, 2006; Hopp & Spearmann, 2001; Ross, 1997).

This sensitivity of assumptions has been highlighted throughout not only the classic queuing theory literature, but exemplified by its attempts at being used in a variety of industries. While queuing networks are an accurate and efficient predictor of performance in simple industrial settings, even a modestly complicated system with decision modules and balking can make a queuing network approach futile (Shanthikumar et al., 2007). Aside from manufacturing, the application of queuing networks to SSCP operations has been found to be ineffective because of the limitation of assumptions (Leone & Liu, 2010). The results of the use of mathematical modeling found in this study were concurrent with what is commonly stated in the literature.

One advantage of queuing theory/theoretical approach over a DES/empirical approach is the ease of assessing validity of the method. Using Equation 37 and Equation 39, one can find the limits to which a queuing network is in steady state from knowing either the arrival rate or service time of the system. Conversely, one must spend considerable time in construction of a model, construction of assumptions documentation, verification, and validation of a DES model to know whether it is applicable or a good fit to the system of interest. Verification and validation of a simulation model are iterative processes that take much time and effort to complete. If time or workload is a significant factor, it is tremendously simple to assess the applicability of a theoretical approach to the problem rather than assess the applicability of an empirical approach.

Results from the sensitivity analysis show that there is a high sensitivity to alarm rate with both of the dependent measures, little sensitivity of baggage volume on cycle time, and practically no sensitivity of baggage volume on throughput. The high sensitivity of alarm rate is because manual screening is a long process and the airport being modeled only utilizes one manual screening server. In queuing theory, longer service times and fewer servers are typically causative of lowered performance (Blanchard & Fabrycky, 2006). As shown in Figure 12, there is a delay in the effects of alarm rate on throughput until approximately 85%, which indicates that the effect of alarm rate on the single queue that builds up at the manual screening server exceeds its service capacity. This is a “choke point” of the operation similar to those found in the study by Brown and Madhavan (2010), yet does not affect the SSCP because of the consistently high alarm rate in the actual system. The results of this study compliment the results of the study by Leone (2002) by showing that throughput is not only sensitive to alarm rate in checked baggage, but screened baggage as well.

Baggage volume had only a moderate effect on cycle time and no effect on throughput. The low process times published in Leone and Liu (2010) would only cause a marginal increase in time if baggage were increased, which was reflected in the results of the sensitivity analysis. Because there were two servers and the process times were relatively low, the TRX servers were able to cope with the added baggage volume effectively. Furthermore, as alarm rates increase and more bags are sent to manual screening, the effects of baggage volume become diminished as shown in Figure 15 and Figure 16. With exception of the alarm rate being 30% or 35%, baggage volume had no effect on whether or not cycle time requirements were met. At these levels the cycle time exceeded the TSA requirement of 10 minutes or less once baggage volume exceeded the baseline + 1 level, which resembles a tipping point where queuing network performance has a practical impact. With exception of the two cases of $\beta = 30\%$ and $\beta = 35\%$, the lack of effects on requirements means that the only remaining limit to baggage is spatial requirements of the aircraft.

The dependent measures of throughput and cycle time reacted in an interesting fashion. Throughput is not an exact function of cycle time; however, the two dependent measures are roughly inversely proportional. When entities exhibit a shorter cycle time, a greater throughput is possible in an infinite population queuing system as displayed by the results of this study. Because of this relationship, caution should be taken when assessing the dependent measures as two independent ideas. However, it should be noted that throughput behaved in a linear fashion, while cycle time behaved in a non-linear fashion when independent variables were altered. This difference supports the concept that the two are not directly related to each other. While they are closed related concepts, the cycle time is a measure of customer satisfaction in this study, and behaves differently than throughput, which is used as a measure of system efficiency. The difference in performance as well as the different contextual uses of each dependent measure supports the use of both measures to assess system performance, although they are closely related variables.

Limitations of the Study

While data collection was straight forward, research was performed in corroboration with SMEs, and the model was verified and validated, there are still experimental aspects to consider before applying the results of this study. While the methods used in this study produced a validated simulation model there are identified factors that may have affected the internal validity of the study. Because no data collection access was granted in the actual SSCP, there is no conclusive evidence as to how small children/infants, and disabled persons have on SSCP throughput and cycle time. Descriptive data of PAX with small children and PAX who were disabled (walked with crutches, a walking cane, a visible cast, or were in a wheelchair), as well as the occurrence of PAX with heavy coats are shown in Table 5.

While it has been discussed with SMEs that children can slow down the screening process, the mean occurrence of two per operating session can more than likely rule them out as confounds. Also, PAX who are disabled and require manual searching as deemed by the Americans with Disabilities Act (ADA) are done so explicitly by TSOs who are staffed for that very purpose, ruling out disabled PAX as confounding to the internal validity of the study.

Table 5

Descriptive statistics of possible confounding PAX.

Sample	PAX_{ADA}	Coats	Kids
1	2	14	4
2	0	16	2
3	1	20	2
4	5	22	3
5	3	26	1
6	2	25	1
7	3	16	2
Σ	16	139	15
Mean	2	20	2
St. Dev	1.60	4.71	1.07

Finally, the number of coats counted as extra baggage were counted during data collection to assess the impact of the assumption of considering heavy coats as baggage. While

139 coats may seem like a large quantity at face value, the coats account for merely 7% of baggage. Given the small sensitivity of baggage volume on the dependent measures it is highly unlikely that the coat assumption could have affected internal validity.

Another phenomenon that could have possibly altered the results PAX arrival data was the small quantity of PAX that entered the SSCP by the definitions of this study, then turned around and left without receiving any screening. From observations and collaboration with SMEs this can occur for any number of reasons such as people wishing to eat or drink something before scanning to avoid throwing it out, assisting family members with baggage, or being a "well-wisher", somebody who is seeing a loved one off. The occurrence of this phenomenon was very low, happening roughly once per sample. Also, because of the average arrival of two to three PAX per minute made it fairly easy to keep track of PAX who exited the SSCP after arriving. Because it was a well managed and rare occurrence it is unlikely that it affected arrival data; however, this could pose a serious problem to validity at a larger airport.

Practical Implications

Given the results from the theoretical model, it becomes difficult to place practical applications of queuing networks into a process as frenetic as a SSCP due to the strict limitations on the steady state assumption. Given that the DES model and actual probability distributions for service times had to be subjected to assumptions, and that the queuing network was only accurate if it met the steady state assumption, it should be noted that it should not be a preferred method of assessing SSCP performance. The primary problem with applying queuing networks to SSCP operations at smaller airports is the arrival rate. The queuing network relies on a stationary arrival rate, while SSCPs experience non-stationary scheduled arrivals. The choice to research a peak time inherently implies that the system will not be in a steady state, but in an overloaded state. Therefore, queuing networks should be applied only at SSCPs where flow rate is stationary, or in other aspects of airport operations such as shuttle services or more consistent processes.

One intended application of this study was to investigate the feasibility of incentivizing PAX to check more baggage to increase SSCP performance and allow for more efficient operations. While less carry-on baggage would likely speed up planing and deplaning operations, baggage volume was demonstrated to have little effect on throughput or cycle time. Regardless of alarm rate, approximately 15 seconds would be saved if PAX on average carried two less items each. Depending on financial models of air carriers, it would not seem prudent or feasible to incentivize checking baggage to save such a negligible amount of time and make no impact on throughput.

Another application of this study is an examination of equipage and staffing at small origin and destination airports. As previously stated, equipage and staffing are both heavily regulated by the TSA (Transportation Security Administration, 2009); however, results of this study support the ability of small volume airports to effectively screen PAX with less expensive equipment. Leone (2002) analyzed different screening machines and found that some were much faster, yet limited because of their higher FARs. In a scenario such as the SSCP modeled in this study, a higher alarm rate would be acceptable as long as it did not exceed approximately 75% or lower based on the number of PAX on the scheduled flights. This slightly elevated alarm rate (false or real) would also be buffered by utilizing the manual screening resource in a fashion similar to the paced-system design utilized in the study by Leone and Liu (2010). Any findings with regards to equipage changes must be evaluated with caution, as PAX throughput would drastically change if more flights were scheduled. Currently only three of a total of eight gates are being utilized at the airport being modeled.

Possibly the most noteworthy application of this study would be the possible reinvention of PAX check-in and screening processes. Yildiz et al. (2008) proposes a new concept of screening, where nearly all technology at SSCPs would be altered rather than changing one or two aspects. This method of thinking is known as holistic design, which is contrasted to reductionist thinking in which research or ideas are used to alter a small portion of a system (Vicente, 2006). A similar large scale adjustment could be made with regards to PAX check in and SSCP utilization based on the results of this study. Brown and Madhavan (2010) found that PAX checking in and utilizing a gate agent and checking bags was the largest choke point in airport operations. PAX who utilized a self check in kiosk took only a fraction of time that others did to acquire their travel documentation and check a bag. These findings, in tandem with the findings of this study, can be combined to reinvent the check-in and screening processes.

Because there is no effect of baggage volume on SSCP throughput or cycle time, theoretically PAX could bring all of their baggage through security without affecting throughput and slightly affecting cycle time. This concept could enable airlines to replace traditional check-in counters with automated kiosks and minimal staffing, and allow PAX to pass through security and check their bags at the gate. By checking bags at the gate, there would be no need for large amounts of staffing at check-in, or the entire existing infrastructure of people and equipment to convey baggage from check-in to the airplane. Even a modest increase in cycle time would be more than likely allowable because of the time saved from negating the traditional check in process. While theoretically a unified check in process would save large amounts of time and money, further research would be needed to investigate the legitimacy of such a concept.

Finally, the sensitivity to alarm rate shown in the results of this study offer practical implications. If the national security level is raised, or if a known threat is confirmed, thresholds for supplemental manual screening can be derived from the results of this study. In the case of the SSCP investigated in this study, an alarm rate of 80% still produces acceptable throughput and cycle times. This shows that whether or not there was a TRX alarm, one in every five PAX could be randomly searched during peak times for increased security without disrupting airport operations as a whole. Likewise, during non-peak hours the alarm rate could be decreased to allow for even more PAX to be manually searched. The sensitivity to baggage volume found in this study could allow for SSCP planners to add supplemental manual searching to increase security without disrupting system performance.

Conclusions

As discussed in the previous section, the results of this study lend themselves to applications in SSCP operations. While results of a sensitivity analysis may indicate something is possible, the very nature of simulation is based on the fact if one component is changed, the system as a whole may behave in an unpredictable manner (Kelton et al., 2007). There are a handful of research studies that can and should be conducted to successfully apply the results of this study.

While the queuing network proved to be an effective tool under limited conditions, it has only been speculated whether it would work an airport with more steady PAX flow. Leone and Liu (2010) attempted to use queuing networks at a larger airport than the one in this study, yet were not effective. This study employed a different network than theirs, and was used at a less steady SSCP. Future research could apply the queuing network utilized in this study and apply it to a larger more stable SSCP operation to see if it is an accurate fit. If queuing networks and mathematical modeling proved effective at larger airports, much effort could be saved in SSCP planning.

Likewise, the results of the queuing network were based on a network where nearly every aspect of the system was reduced to an assumption. Arrival times, service times, baggage distribution, and alarm rates were all modified to ensure the network would operate. The results of a sensitivity output from a queuing network may or may not be comparable to results obtained in this study from the DES approach. Because of the ability of DES to more adequately capture the randomness of human systems, one might speculate that DES would be the more accurate method. If access was granted to an extensive amount of throughput data of an SSCP a side by side comparison of DES and queuing network outputs could be performed to assess the accuracy of both. The most valuable research in this area would be to see if one could interpolate the results of actual output as somewhere between results from queuing networks and DES. If such, a correctional coefficient could be applied to mathematical results to correct for missed randomness, while not requiring planners to utilize DES.

As stated in the results section, the performance metric of cycle time is very robust to the effects of alarm rate and even more so to baggage volume. The practical constraint however is that cycle time may be within limits, but the throughput is unacceptable for loading a plane in a timely manner. Further research should be performed to use linear or nonlinear optimization methods to find the practical limit to alarm rate and baggage volume based on the number of scheduled flights. Using the validated times and rates for this airport, further research could show throughput requirements for the SSCP based on the number of gates being utilized.

Graphical representations such as Figure 12 and Figure 15 show that performance metrics of the SSCP behave in linear and nonlinear manners respectively. While simple regression methods are limited to linear models, multiple regression methods may offer valuable insight to predicting SSCP performance (Field, 2009). A well founded regression model would not only allow TSA professionals to be able to predict performance. Also, if research supported other airport SSCPs behaved similarly to the one modeled in this study, a simple switch of the regression coefficients could allow the formula to be applied to any airport that operates in a similar manner.

Other research could be performed to determine the trade-off of manual screening servers and TRX machines. Given the high price of machinery and the recurring costs of maintenance and certification, it would be valuable to investigate the possibility of replacing a two TRX setup with a single TRX setup at smaller airports. The paced design proposed by Leone and Liu (2010) increased throughput by utilizing a seldom used resource. By that concept, staffing and equipping multiple manual screening stations and utilizing them could prove efficient. A study could investigate different levels of paced system parameters as well as number of manual screening servers to see if the SSCP still meets requirements. While the TSA may or may not be receptive to suggestions on equipage, research in this area could increase awareness of alternate possibilities. A large confounding factor with this method would be the high stress placed on heavily utilized manual screeners, necessitating high pay and shift rotation, thereby negating the financial advantage of not using machinery (Wetter et al., 2010).

Finally, rather than concentrating only on the SSCP, further research could help reinvent the entire airport departure process. A concept such as the unified check in would require a vast amount of data collection and experimentation. Different TRXs are used for checked baggage and carry-on baggage so that larger checked bags could be handled. While baggage volume seems to have no effect on performance, the space requirements for introducing TRX machinery to handle larger bags could be violated (Wilson et al., 2006). A large scale simulation would need to be constructed to not concentrate on only the SSCP or only the airport as a whole, but instead model everything to an adequate level to see the effects of SSCP modifications on total system performance. Wetter et al. (2010) have shown that subjective ratings of employees and PAX must be considered when proposing system changes. A major limiting factor to this proposed research would be the amount of data needed to power it. Simulations are only as accurate and reliable as the amount and quality of data put into them, meaning a large scale study to redesign the system would need requisitely large amounts of data (Law, 2006; Kelton et al., 2007). The lack of public access to data pertaining to airport operations may be the single largest factor limiting a study of this scale to take place.

In conclusion, this study utilized information from a vast body of literature and multiple SMEs to investigate important factors of SSCPs. While most studies investigate staffing and equipage factors, this study investigated the effects of baggage volume and alarm rate on SSCP performance with regards to both system performance (throughput) and passenger experience (cycle time). Furthermore, this study revealed under what conditions of baggage volume and alarm rate the SSCP would be able to meet regulatory requirements as well as passenger expectations. In addition to results from the empirical approach of DES, the theoretical method of queuing networks and their applicability were assessed in this study. It was demonstrated that queuing networks are very accurate when the system is in steady state, yet unreliable when it is not. Likewise, the methods of evaluating applicability of both theoretical and empirical methods were compared to show the ease of testing steady state assumption for queuing networks in comparison to verification and validation of DES/empirical models.

As the number of PAX per year continually increases, this field and contributions to optimizing it becoming increasingly important. This study offers valuable insight into SSCP operations and performance, discusses results and practical applications, and entices further research to benefit the betterment of public aviation transportation.

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Appendix A: List of Aviation & Security Acronyms

ADA	Americans with Disabilities Act
ATSA	Aviation Transportation Security Act
CAPPS	Computer-Assisted Passenger Pre-Screening System
CDG	Checkpoint Design Guide
DES	Discrete Event Simulation
DHS	Department of Homeland Security
EDS	Explosive Detection System
ETD	Explosive Trace Detection
FAR	False Alarm Rate
FSP	Federal Screening Personnel
PAX	Passengers
SME	Subject Matter Expert
SSCP	Security Screening Checkpoint
TDC	Travel Document Checker
TSA	Transportation Security Administration
TSO	Transportation Security Officer
WTMD	Walk Through Metal Detector

Appendix B: Data Collection Form

Graduate Thesis Data Collection Form															Date ______________										
Mark number of bags each PAX has on them at time i																									
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Appendix C: Mean Hourly Arrival Rates by Different Scheduling Lengths

<table>
<tr><th>XBar</th><th colspan="5">Xbar</th></tr>
<tr><th>Time</th><th>λ (1)</th><th>λ (3)</th><th>λ (5)</th><th>λ (10)</th><th>λ (15)</th></tr>
<tr><td>5:50</td><td>171.43</td><td rowspan="3">120.00</td><td rowspan="5">145.71</td><td rowspan="10">162</td><td rowspan="10">N/A</td></tr>
<tr><td>5:51</td><td>128.57</td></tr>
<tr><td>5:52</td><td>60.00</td></tr>
<tr><td>5:53</td><td>205.71</td><td rowspan="3">205.71</td></tr>
<tr><td>5:54</td><td>162.86</td></tr>
<tr><td>5:55</td><td>248.57</td><td rowspan="5">178.29</td></tr>
<tr><td>5:56</td><td>180.00</td><td rowspan="3">168.57</td></tr>
<tr><td>5:57</td><td>197.14</td></tr>
<tr><td>5:58</td><td>128.57</td></tr>
<tr><td>5:59</td><td>137.14</td><td>N/A</td></tr>
<tr><td>6:00</td><td>111.43</td><td rowspan="3">114.29</td><td rowspan="5">109.71</td><td rowspan="10">118.29</td><td rowspan="15">130.86</td></tr>
<tr><td>6:01</td><td>68.57</td></tr>
<tr><td>6:02</td><td>162.86</td></tr>
<tr><td>6:03</td><td>111.43</td><td rowspan="3">114.29</td></tr>
<tr><td>6:04</td><td>94.29</td></tr>
<tr><td>6:05</td><td>137.14</td><td rowspan="5">126.86</td></tr>
<tr><td>6:06</td><td>137.14</td><td rowspan="3">114.29</td></tr>
<tr><td>6:07</td><td>120.00</td></tr>
<tr><td>6:08</td><td>85.71</td></tr>
<tr><td>6:09</td><td>154.29</td><td rowspan="3">168.57</td></tr>
<tr><td>6:10</td><td>154.29</td><td rowspan="5">156</td><td rowspan="10">174</td></tr>
<tr><td>6:11</td><td>197.14</td></tr>
<tr><td>6:12</td><td>77.14</td><td rowspan="3">142.86</td></tr>
<tr><td>6:13</td><td>214.29</td></tr>
<tr><td>6:14</td><td>137.14</td></tr>
<tr><td>6:15</td><td>214.29</td><td rowspan="3">222.86</td><td rowspan="5">192</td><td rowspan="10">202.29</td></tr>
<tr><td>6:16</td><td>240.00</td></tr>
<tr><td>6:17</td><td>214.29</td></tr>
<tr><td>6:18</td><td>154.29</td><td rowspan="3">157.14</td></tr>
<tr><td>6:19</td><td>137.14</td></tr>
<tr><td>6:20</td><td>180.00</td><td rowspan="5">190.29</td><td rowspan="5">207.43</td></tr>
<tr><td>6:21</td><td>180.00</td><td rowspan="3">185.71</td></tr>
<tr><td>6:22</td><td>128.57</td></tr>
<tr><td>6:23</td><td>248.57</td></tr>
<tr><td>6:24</td><td>214.29</td><td>194.29</td></tr>
</table>

6:25	180.00				
6:26	188.57				
6:27	265.71		224.57		
6:28	248.57	251.43			
6:29	240.00				
6:30	300.00				
6:31	257.14	257.14			
6:32	214.29		255.43		
6:33	214.29				
6:34	291.43	217.14		228.86	
6:35	145.71				
6:36	240.00				
6:37	145.71	202.86	202.29		213.71
6:38	222.86				
6:39	257.14				
6:40	162.86	208.57			
6:41	205.71				
6:42	240.00		183.43		
6:43	137.14	182.86			
6:44	171.43				
6:45	102.86			162.86	
6:46	171.43	151.43			
6:47	180.00		142.29		
6:48	120.00				
6:49	137.14	134.29			
6:50	145.71				
6:51	111.43				
6:52	60.00	85.71	99.429		101.14
6:53	85.71				
6:54	94.29				
6:55	85.71	85.71		80.571	
6:56	77.14				
6:57	60.00		61.714		
6:58	34.29	48.57			
6:59	51.43				

Appendix D: MATLAB Source Code for Theoretical Model

```
function [Wq, n1, n2, W]=computeWq(k, beta)

lamda=2.7;
mu=7.14;

ES=k/mu;
ESsquare=k/mu^2+(k/mu)^2;
Wq1=(lamda^2*ES*ESsquare);
Wq2=((2-lamda*ES)^2)*((1+lamda*ES)+((lamda*ES)^2/(2-lamda*ES)));
Wq=Wq1/Wq2;

n1=lamda*(Wq+ES);

mu2=0.2857;
lamda2=(1-beta)*lamda
rou2=lamda2/mu2;
n2=rou2/(1-rou2);

n=n1+n2;

W=n/lamda;
```