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### **ABSTRACT**

### OPERATING CHARACTERISTICS OF PASSENGER SCREENING PROCESSES AND THE DEVELOPMENT OF A PACED INSPECTION SYSTEM

### by Geraldine Kelly Leone

The airport checkpoint security screening (ACSS) system is an important line of defense against the introduction of dangerous objects into the U.S. aviation system. Recently, there has been much interest in modeling these systems and to derive operating parameters which optimize performance. In general there are two performance measures of interest (i) the waiting time of the arriving entities, and (ii) the allocated screening resources and its utilization. Clearly, the traveling public would like a zero waiting time, while airports are limited both in terms of space and resource capital. The arrival and exit entity in the ACSS system are passengers. On arrival, passengers split into two subentities (i) bags or other carry-on items and (ii) passenger body and the two must rejoin prior to exit. There is a 1:M ratio between passengers and carry-on items with M≥0. The existing knowledge base related to the operating characteristics of ACSS processes is very limited. Almost all screening systems have a human interpretive component, as a result the screening behavior is highly variant and difficult to predict.

This dissertation studies the operating characteristics of the security screening process to develop proven relationships between inspection times and clearance rates. A descriptive model of the screening system, which identifies the design variables, operational parameters and performance measures, is defined. Screening data was collected from 18 U.S. airports (10 high volume, 5 medium volume, and 3 low volume). The data sets captured (i) passenger arrival times, (ii) X-ray inspection times, (iii)

clearance decision, (iv) passenger physical inspection times, and (v) secondary carry-on item inspection times. An empirical analysis was used to generate a speed of inspection operating characteristic (SIOC) curve for each of the inspection processes. Mean inspection times are found to be much larger than what is frequently assumed in the literature. The findings showed that the inspection rate increases linearly with inspection time until the 7 second point, after which it describes a negative growth. The behavior of these relationships under different operating conditions was studied using a set of hypothesis. These include performance differences between airport types, between checkpoints within an airport, as well as the effect of increased passenger arrival rates.

Reliable data describing the operating characteristics of security inspection processes are now available. This data can be used to design and analyze ACSS systems with much greater accuracy and detail. The results will in effect reduce the dependence on trial-and-error experiments at the site. A greater understanding of the statistical behavior of the inspection process is known and validated. The SIOC curves provide a standard against which new and alternative ACSS designs can be evaluated and benchmarked. Paced ACSS systems are demonstrated as a viable alternative with potentially higher performance.

### OPERATING CHARACTERISTICS OF PASSENGER SCREENING PROCESSES AND THE DEVELOPMENT OF A PACED INSPECTION SYSTEM

by Geraldine Kelly Leone

A Dissertation
Submitted to the Faculty of
New Jersey Institute of Technology
in Partial Fulfillment of the Requirements for the Degree of
Doctor of Philosophy in Transportation

**Interdisciplinary Program in Transportation** 

January 2010

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### **APPROVAL PAGE**

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One cannot forget about all the men and women fighting the war against terrorism. This work is dedicated to them.

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### **CHAPTER 1**

#### INTRODUCTION

The airport checkpoint security screening (ACSS) system and screeners who operate them are the most important line of defense against the introduction of dangerous objects into the aviation system (National Commission on Terrorist Attacks upon the United States, 2004 [9/11 Commission]; U.S. General Accountability Office, 2000 [GAO], 2007a). Over 2 million commercial aviation passengers are screened in the United States each day for weapons and dangerous articles prior to boarding an airplane (Airports Council International - North America, 2008). During 2006, Transportation Security Administration (TSA) security officers (TSOs) intercepted 13.7 million prohibited items at security checkpoints, of which 11.6 million were lighters and 1.6 million were knives (TSA, 2006a). However, these inspections have resulted in significant operational costs and passenger delays. TSA also reported that during 2006 the average peak wait time for passengers was 11.76 minutes, which is more than the established performance goal of 10-minutes (Mineta, 2002).

Trading off security for mobility is clearly problematic. Since the TSA assumed responsibility for conducting passenger screening at over 400 commercial airports in the United States, it has spent billions of dollars and implemented wide ranges of initiatives to enhance its passenger screening operations. Despite the attention to passenger screening operations, however, concerns about the effectiveness of the screening system remain. In the post 9/11-era detection rates continued to decline despite federalizing the screener workforce and deploying new security equipment (GAO, 2004, 2005, 2007d).

### 1.1 Statement of the Problem

Recently, there has been much interest in modeling security screening systems and to derive operating parameters which optimize performance. In general there are two performance measures of interest (i) the waiting time of the arriving entities, and (ii) the allocated screening resources and its utilization. Clearly, the travelling public would like a zero waiting time, while airports are limited both in terms of space and resource capital. The arrival and exit entity in the ACSS system are passengers. On arrival, passengers split into two sub-entities (i) bags or other carry-on items and (ii) passenger body and the two must rejoin prior to exit. There is a 1:M ratio between passengers and carry-on items with M≥0. The existing knowledge base related to the operating characteristics of ACSS processes is very limited. Almost all screening systems have a human interpretive component, as a result the screening behavior is highly variant and difficult to predict.

### 1.2 Purpose of the Study

This dissertation studies the operating characteristics of the security screening process to develop proven relationships between inspection times and clearance rates. A descriptive model of the screening system, which identifies the design variables, operational parameters and performance measures, is defined. Screening data was collected from 18 U.S. airports (10 high volume, 5 medium volume, and 3 low volume). The data sets captured (i) passenger arrival times, (ii) X-Ray inspection times, (iii) clearance decision, (iv) passenger physical inspection times, and (v) secondary carry-on item inspection times. An empirical analysis was used to generate a speed of inspection operating characteristic (SIOC) curve for each of the inspection processes. The purpose of the

SIOC curves is to identify how much time the X-ray TSO spends on inspecting an image of a passenger's carry-on item to when a decision is made to either clear the item, that is, no prohibited items are found, or send it to secondary inspection for further scrutiny.

The current ACSS paradigm is to have unpaced processes, that is, the TSO has unlimited inspection time. Thus, another research objective is to evaluate the advantages of paced systems in which the primary inspection time is capped at a maximum, following which the entity is forwarded to the secondary inspection process. A simulation model is developed to conduct a range of experiments.

### 1.3 Significance of the Study

Despite its importance, minimal changes to the passenger screening checkpoints occurred only incrementally in the past 30 years, often in response to a crisis or loss of an aircraft. For example, there has never been a time limit placed on the network of screeners looking for prohibited items. A paced inspection approach would require major operational changes from existing practices. Limiting the time in primary inspection would dramatically increase the number of secondary inspections. While secondary inspections areas frequently appear to operate at small fraction of their physical capacity, additional stations and staffing is likely to be costly to keep up with the increased demand. Thus, knowing how much performance, that is, passenger wait times, is improved if the system was paced without introducing significant operational delays and costs could lead to how checkpoints are designed in the future.

### **CHAPTER 2**

### LITERATURE REVIEW

### 2.1 Evolution of Airport Security Screening

The security system in place today for screening passengers before boarding hasn't changed much since the 1970's. The system originated after three series of events in our nation's aviation history. The first event was the rise in acts of hijacking during the late 1960s and early 1970s, which resulted in the establishment of the Federal Government's anti-hijacking program ("Anti-hijacking", 1974). The air carriers voluntarily cooperated with the Federal Aviation Administration (FAA), who was the regulatory body overseeing civil aviation security, to screen passengers for potential hijack weapons just prior to boarding the aircraft.

When airplane hijackings continued, President Richard Nixon ordered air carriers to deploy surveillance equipment and techniques to all appropriate airports in the United States. The President further instructed the Departments of Defense and Transportation to work with the U.S. air carrier industry to determine if metal detectors and X-ray devices used by the military could assist in preventing hijackings. The Air Transportation Security Act ("Anti-hijacking", 1974) provided the statutory basis for a rule the FAA issued requiring air carriers to use a screening system, acceptable to the FAA that would require screening all passengers by one or more of the following systems: behavioral rule, magnetometer, identification check, or physical search. These requirements established the baseline for the passenger screening checkpoint of today.

The second major event was the bombing and destruction of Pan Am Flight 103 on December 21, 1988 over Lockerbie, Scotland killing all 259 passengers and crew aboard. This tragic event significantly elevated the FAA's response to the threat of hijacking and of explosives concealed in luggage. For example, when the threat expanded to include improvised explosive devices (IEDs) designed to destroy the aircraft, the FAA promulgated a number of security directives setting forth procedures including the use at passenger checkpoints of explosives trace detection (ETD) devices.

Also, in response to Pan Am 103, the President's Commission on Aviation Security and Terrorism was created by Executive Order 12686. Its objective was to conduct a comprehensive study and appraisal of practices and policy options to prevent terrorist acts against civil aviation with particular reference to the destruction of Pan Am 103. The Commission's report was issued on May 15, 1990, and following its recommendations, the Federal Government returned to an area not visited since the height of the hijacking threat in the mid-1970: the capital purchase of security equipment for use by private sector air carriers to enhance their ability to screen passengers and items effectively and efficiently prior to boarding.

Under the Aviation Security Improvement Act ("Aviation Security Improvement Act", 1990), the FAA established the Security Equipment Integrated Product Team to acquire and deploy advanced security equipment through "non-competitive contracts or cooperative agreements with air carriers and airport authorities, which provide for the FAA to purchase and assist in installation of advanced security equipment for the use of such entities." The Federal Government for the first time subsidizes air carriers' capital expenses related to security improvements. All major air carriers assumed operations

costs for installed equipment and other technologies and paid maintenance costs upon expiration of warranties and initial maintenance periods. According to the National Research Council Committee on Commercial Aviation Security (1996) this act has been described to be the most comprehensive, far-reaching legislative initiative designed to improve all aspects of aviation security. It mandated many regulatory actions affecting several agencies, required new reports, created new organizations and staffing requirements, and empowered the FAA to promote and strengthen aviation security through an expedited, more focused research and development program.

The third major event occurred on the morning of September 11, 2001, when 19 terrorist hijackers commandeered 4 commercial aircraft and succeeded in destroying the World Trade Center, damaging the Pentagon, and killing almost 3,000 people. The events on 9/11 significantly altered the nation's views on how to secure and protect the people, borders, and assets of the United States, and dramatically highlighted the need to take immediate actions to reduce the likelihood of future attacks of this magnitude taking place on U.S. soil. In an effort to strengthen the security of commercial aviation, President G.W. Bush signed the Aviation and Transportation Security Act on November 19, 2001, which created the Transportation Security Administration ("ATSA", 2001).

### 2.2 Security System Design Studies

In detecting threats—particularly explosives, the challenge is to design a system that has acceptable detection probability but does not unduly inconvenience travelers. Thus, choosing a practical architecture to provide the best possible security system design is an important challenge.

The Committee on Science and Technology for Countering Terrorism (2000) and the 9/11 Commission (2004) essentially called for an increased use of operations research analysis in (aviation) security policy when it recommended that "the U.S. government should identify and evaluate the transportation assets that need to be protected, set riskbased priorities for defending them, select the most practical and cost-effective ways of doing so, and then develop a plan, budget, and funding to implement the effort". Some work has already been done using operations research, in evaluating the costeffectiveness of certain policies (Chow et al., 2005; Jacobson, Virta, Bowman, Kobza, and Nestor, 2003), in pointing out potential weaknesses in proposed measures (Barnett, 2004; Chakrabarti and Strauss, 2002; Martonosi, 2005; Martonosi and Barnett, 2004) and policies (Waugh, 2004), in assessing performance of multi-tiered security processes (Jacobson, Kobza, and Easterling, 2001; Kobza and Jacobson, 1996, 1997; Leone and Liu, 2003, 2004), and in assessing the equipment speed and detectability (Leone, Thompson, and Olson, 2004; Transit Cooperative Research Program, 2002, 2004). The commonest screening equipment used in the U.S. and European airports is conventional X-ray technology or Computed Tomography X-ray (CTX) (International Air Transport Association, 2003; Leone and Liu, 2005; Rhykerd, Hannum, Murray, and Parmeter, 1999). The challenge is not the speed of the equipment, but rather in bag handling, multiple stages of screening, and sample acquisition by the screener. U.S. experts have found that if the sampling process is not done systematically, detections will be missed.

Singh and Singh (2003) point out that many optimization techniques have been used to model the security screening process and strategy. McLay et al., (2006) introduced the multilevel allocation problem for modeling the screening of passengers

and baggage in a multilevel aviation security system, Olapiriyakul and Das (2007) used a queuing model to derive the optimal design, Yoo and Choi (2006) considered an analytic hierarchy process approach for identifying factors to improve passenger security checks and showed that the most important to raise the performance of screening would be human resources, and others for optimizing the application of security measures to different classes of passengers (Jacobson, Bowman, and Kobza, 2001; Jacobson, Virta, Bowman, Kobza, and Nestor, 2003; Virta, Jacobson, and Kobza, 2002, 2003).

Other salient research using modeling and simulation for security screening has indicated that although many operations research techniques such as linear/integer programming, stochastic programming, and queuing theory provide valuable insights. they often fail to represent problems that arise in airport terminal design due to poor scalability or excessive computational burden (Hafizogullari, Bender, and Tunasar, 2003). Many are choosing discrete event simulation modeling as the major tool in addressing the requirements. Leone (2001, 2002), Leone and Kukulich (2002), and Wilson (2005) show that modeling and simulation offers a non-intrusive and cost effective way to examine the security problem and provide decision-makers with a better understanding of the impact of their decisions. Also, Saetta and Tiacci (2005) proposed a new approach to line balancing of security inspection lines with a combination of simulation of metaheuristics and modeling and simulation. However, Odoni (1991) noted that an essential pre-requisite for the use of the simulation models is the availability of a complete, reliable, and consistent set of data needed to calibrate the simulation model for the specific airport and scenario analyzed.

Investigating the trade-offs between speed and accuracy of the screeners has also been an important focus of researchers seeking to improve inspection performance. According to Schwaninger (2005), average inspection times of X-ray images often are in the range of 3–5 seconds under conditions of high passenger flow. Thus, recognition of threat objects is a fast process occurring within the first few seconds of image inspection. The task of screening passengers' carry-on items was seen and investigated as being similar to a general inspection task (Chi and Drury, 1998; Ghylin, Drury, and Schwaninger, 2006). In the view of paced inspections and economics optimal stopping time models have been presented (Baveja, Drury, Karwan, and Malon, 1996; Drury and Chi, 1995; Morawski, Drury, and Karwan, 1992).

Operations research (OR) has had a long history of work in aviation security. Gilliam (1979) employed queuing theory to design a passenger X-ray screening facility at an airport. Since then, many OR researchers addressed airline security, focusing primarily on scanning passengers or baggage (Wright, Liberatore, and Nydick, 2006). Within these studies the information pertaining to the customer (average number of customers in the system/queue, average time customer spends in the system/queue) and server information are assumed to be independent.

As human behavior is present in customers and servers, the idea that servers may also adapt their behavior was as studied by Green and Kolesar (1987) giving an example of where congestion is severe, servers may cut corners in order to speed up service, thereby reducing the quality of service rendered. In their study, they raised concepts but offered no observational evidence explaining the phenomenon using Parkinson's Law

(Parkinson, 1958), which states that work expands to fill the time available for its completion.

No papers have been found since Green and Kolesar (1987) that apply Parkinson's Law to queuing phenomena until recently when Marin, et al., (2007) performed an observational study to examine airport security queuing system for server behavior in response to queue length. It was found that X-ray screeners (servers) did speed up with longer queue lengths for one type of item, laptop computers. In the study the impact of speed-up in screening was further explored by examining the speed-accuracy trade-off (SATO). The data revealed that for laptop passengers there is a significant decrease in the detection probability and in the probability of correct rejection.

Since many studies have addressed the behavior of customers in the queues, but not the consequences of changes in server behavior, the opportunities for more research, such as this one where placing a time limit on the X-ray screener, is examined remain numerous.

### **CHAPTER 3**

### **ACSS SYSTEM MODEL AND SCREENING OPERATIONS**

This chapter addresses the first research objective, that is, to develop a descriptive model of the ACSS system, and is separated into four sections. The first section presents the physical layouts of typical checkpoints including the configuration under study, and describes the screening process. The second section includes the descriptive model of the ACSS developed where the design variables, parameters and performance measures for the screening process are defined. The third section provides information on checkpoints at airports throughout the nation describing their numbers, different types, and operational characteristics. It also discusses the empirical data required for the major variables of interest and collected from different type checkpoints at various airports. The data collected represents behaviors of multiple checkpoints over multiple days at airports across the nation. The last section provides summary information and descriptive statistics generated for the major variables, along with an analysis of the differences between checkpoints across airports.

### 3.1 Checkpoint Layout and Screening Operations

According to the TSA's Security Checkpoint Layout Design / Reconfiguration Guide (2006b), there are nine approved physical layouts. Each airport's unique characteristics determine which layout serves as the "best fit". This study uses the 1-to-1 Single Lane Design with Wanding Station layout depicted in Figure 3.1. The configuration is a standard design for a single screening lane. The elements of a single lane consists of one

walk-through metal detector (WTMD), one X-ray unit with roller extensions, one ETD device, one bag search table, and one hand wanding and holding station. As of October 2006 there were 2,002 single lanes in the U.S. (GAO, 2007b).

Figure 3.1 also shows the associated minimum spacing requirements between respective equipment and furniture pieces. A wanding station is created by placing glass partitions parallel to an existing airport wall. An advantage of this design is that passengers can easily be diverted to the wanding station, in addition to co-location of the ETD machine and bag search table. One slight disadvantage is the amount of width needed to accommodate the wanding station.

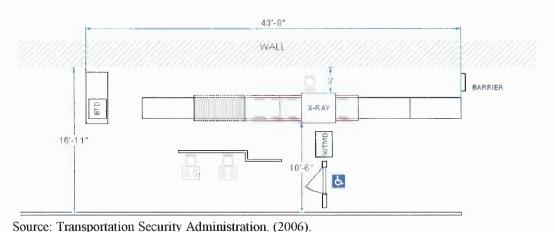
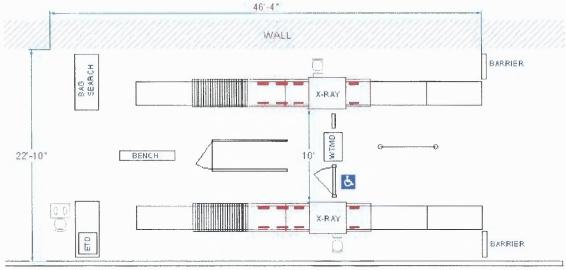


Figure 3.1 Study checkpoint physical layout.

Figure 3.2 illustrates a different layout, which is the 2-to-1 Design with Holding Station configuration. This configuration consists of one WTMD centered between two X-ray units and is a standard design that is prevalent throughout most airports. To match heavy passenger demand, airports typically add multiple configurations. For example, at T.F. Green Airport in Providence, Rhode Island there are three of this type side-by-side for a total of six screening lanes. In the layout the holding station is centered 4 feet from

the WTMD, and is used as a containment area until a TSO becomes available to conduct secondary screening. The advantage of this design is the fact that overall width is only 22 feet. This design also allows greater flexibility for TSOs to work among checkpoint lanes. One slight disadvantage is the slightly increased depth needed for the secondary screening area.



Source: Transportation Security Administration. (2006).

Figure 3.2 Standard checkpoint physical layout.

Regardless of the design, there are four screening functions at checkpoints:

- X-ray screening of carry-on items
- WTMD screening of individuals
- Hand-wand or pat-down screening of individuals
- Physical search of passenger's carry-on items or inspection with an ETD

According to the GAO (2007c) passengers whose carry-on items are deemed suspicious by the X-ray TSO as having prohibited items, who alarm the WTMD, or who are designated as selectees, that is, passengers selected by the Computer-Assisted Passenger Prescreening System (CAPPS) or other TSA-approved processes to receive additional

screening, are inspected by hand-wand or by pat-down, or by trace portals that are installed at a limited number of airports, and have their carry-on items screened for explosives traces or physically searched.

ETDs work by detecting vapors and residues of explosives. The TSOs collect samples by rubbing swabs along the interior and exterior of an object that the TSOs determine to be suspicious, and place the swabs in the ETD machine, which then chemically analyzes the swab to identify any traces of explosive materials. Additionally, at some airports TSOs are specially trained to detect suspicious behavior in individuals approaching the checkpoint. These Behavior Detection Officers may refer the individual for individual screening or to a law enforcement officer (GAO, 2007b).

### 3.2 Descriptive Model

Figure 3.3 shows the block diagram of the single lane ACSS with foundational parameters noted that are salient to the research objectives. The model considers the screening of carry-on items and the passengers themselves at the WTMD or Hand Wand stations. In the model the parameters that govern the behavior are  $\lambda$ -arrival demand,  $\mu$ -service rate, and  $\beta$ -rejection rate. Passengers arrive, denoted as  $\lambda$ , at the checkpoint screening lane and proceed to the X-ray unit where an image of the carry-on item is taken. A service rate  $\mu_1$ , that is,  $(60/\tau)$  represents the time  $(\tau)$  the TSO spends on inspecting the image searching for prohibited items to when a decision is made to either reject  $(\beta)$  it and send to secondary inspection for further scrutiny or clear  $(1-\beta)$  it, meaning that no suspicious items were detected. At secondary inspection the service rate is represented as  $\mu_{21}$  and  $\mu_{22}$  for ETD and hand search inspections, respectively. After the

passenger unloads their carry-on items at the X-ray unit, they proceed to the queue for the WTMD. If a passenger alarms the WTMD, denoted as the Greek letter alpha ( $\alpha$ ), then they move to secondary inspection by hand wand. After clearing either the WTMD (1- $\alpha$ ), or the Hand Wand search, the passenger is rejoined with their carry-on items. Once clearing all primary and secondary inspections, the passenger can board the aircraft. Otherwise, boarding is not permitted and the passenger is escorted out of the system by a TSO. A very small percentage of passengers are not allowed to board.

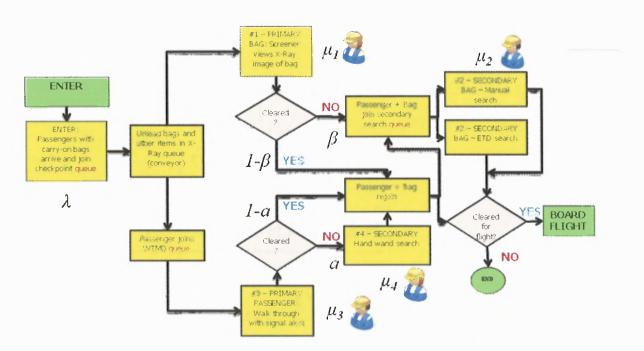


Figure 3.3 Single lane ACSS descriptive model.

Since the above performance measures are components of a queuing system, each inspection station can be modeled as an M/M/1 system and the average time a passenger spends at each inspection can be described from standard queuing theory equations.

For example, let  $T_p$  be the time a bag spends in the queue and inspection process, then:

$$T_{P} = \lambda_{1} / \left[ \mu_{1} \left( \mu_{1} - \lambda_{1} \right) \right] \tag{3.1}$$

$$T_s = \lambda_2 / \left[ \mu_2 \left( \mu_2 - \lambda_2 \right) \right] \tag{3.2}$$

$$T = T_p + T_s \tag{3.3}$$

Where:

T: Total time spent in check point screening

T<sub>P</sub>: Time spent in the primary inspection process

T<sub>S</sub>: Time spent in the secondary inspection process

 $\lambda_1$ : Initial arrival rate

 $\lambda_2$ : Secondary arrival rate, which is directly related to the rejection rate  $\beta$ 

 $\mu_1$ : Primary inspection service rate

μ<sub>2</sub>: Secondary inspection service rate

Using the rejection rate as an indicator of accuracy, Olapiriyakul and Das (2007), applied the speed and accuracy operating characteristic (SAOC) curve for the two stage inspection process as depicted in Equations 3.4 and 3.5:

$$\alpha_{\mu l} = f\{\mu^{Max}, \mu^{Min}, \beta^{Max}, \beta^{Min}\}$$
 (3.4)

and considered a linear curve of the form:

$$\alpha_{\mu 1} = (\mu 1 - \mu^{Min}) \{ (\beta^{Max} - \beta^{Min}) / (\mu^{Max} - \mu^{Min}) \}.$$
 (3.5)

They assumed that  $\beta^{Min}=0$  for different types of inspection methods, that is, X-ray scanning or chemical trace, since often less intrusive processes used in stage-1 inspections tend to have  $\beta^{Min}>0$ .

In the problem they considered, an optimal formula for a two-stage tandem inspection system was proposed. Following their formula, the notation used here is I is 1 and 2, serial inspection stages, N is the number of entities (e.g., passengers with their

carry-on items) in the system,  $S_I$  is number of parallel servers at stage I,  $\lambda_I$  is arrival rate at stage I,  $\mu_I$  is service rate of stage I inspection process,  $\beta_I$  is rejection (or alarm) rate of the stage I inspection process,  $\rho_I$  is utilization factor at stage I, and  $W_E$  is average waiting time for an entity in the system.

Since cost is a factor in any queuing design analysis, the total inspection system cost was derived as:

$$C_{TOTAL} = C_W \lambda_1 W_E + \sum C_i S_i$$
 (3.6)

where,  $C_W$  is unit waiting time cost for an entity (\$/h), and  $C_i$  is inspection process cost per server at stage I (\$/h). The waiting or queuing cost accounts for all  $\lambda$  passengers in the system during the hour, and the congestion penalty involves just the waiting time because passengers resent the wait, not the time receiving service. In the model the operating cost for each the primary inspection and the secondary inspection stages consist of the salary for the TSO plus the equipment and operations and maintenance (O&M) costs. In fiscal year 2009, the average annual salary for a full performance level TSO is \$36,113 (TSA, 2009) and 1 TSO works 2080 hours per year. The cost of an X-ray unit is \$45,000 with annual O&M costs of \$3,000 (U.S. General Services Administration, 2009). Additionally, the cost of an ETD is \$48,864 with O&M at \$10,974. It is assumed that the waiting time cost is \$10 per hour. These costs cover the main focus of the study inspection of carry-on items. However, nodes where passenger inspections occur must also be considered when calculating total system costs. As such, a WTMD cost is \$3,700 and a hand-held wand is \$150. There are 4.25 screeners per screening lane; one each at primary and secondary inspection nodes, one for the WTMD, and one and a quarter is assigned to the Hand Wanding node to comply with gender specific screening policies.

The service rate for primary inspection is  $\mu_1$  and is considered to be a decision variable. The arrival rate of entities at secondary inspection is given by  $\beta_1\lambda_1$ . In this system  $W_E = W_1 + W_2$ , where  $W_1 + W_2$  are the primary inspection and secondary inspection waiting times, and can be derived as:

$$W_{\rm E} = \frac{1}{\mu_1 - \lambda_1} + \frac{1}{\mu_2 - \lambda_2} \tag{3.7}$$

Since  $\lambda_2 = \beta_1 \lambda_1$ , and  $\beta_1 = \alpha_{\mu 1}$  which was defined in (3.5), then substituting in (3.7):

$$W_{E} = \frac{1}{\mu_{1} - \lambda_{1}} + \frac{\mu^{Max} - \mu^{Min}}{\mu_{2}(\mu^{Max} - \mu^{Min}) - \mu_{1}\lambda_{1}(\beta^{Max} - \beta^{Min}) + \mu^{Min}\lambda_{1}(\beta^{Max} - \beta^{Min})}$$
(3.8)

For secondary inspection the limiting constraint is  $\mu_2 = \mu^{Min}$ . Further it is assumed that  $\beta^{Max} = 0\%$ , then letting:

$$A = \mu^{Min} (\mu^{Max} - \mu^{Min}) + \mu^{Min} \lambda_1 \beta^{Max},$$

$$B = \lambda_1 \beta^{Max},$$

$$D = (\mu^{Max} - \mu^{Min}).$$

Eq. (3.8) can be simplified to:

$$W_{\rm E} = \frac{1}{\mu_{\rm l} - \lambda_{\rm l}} + \frac{D}{A - B\mu_{\rm l}}.\tag{3.9}$$

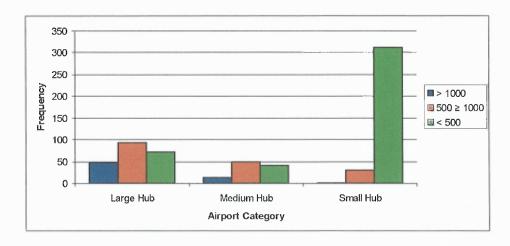
The total inspection system operating cost is then derived by substituting Eqs (3.9) in (3.6). As noted earlier for the two-stage system  $S_1 = S_2 = 1$ . Hence the send part of Eq (3.6) is a constant and  $C_{TOTAL}$  is a convex function of  $\mu_1$ . The optimal primary inspection service rate ( $\mu_1$ \*) is therefore prescribed by differentiating  $W_E$  in terms of  $\mu_1$ . Setting the derivative  $\delta W_E/\delta \mu_1 = 0$  and solving gives:

$$\mu_1^* = \frac{-2B(A - \lambda_1 D) \pm \sqrt{4B^2(A - \lambda_1 D)^2 - 4B(D - B)(\lambda_1^2 BD - A^2)}}{2B(D - B)}$$
(3.10)

Applying the model, the characteristic behavior of the ACSS 1-to-1 Single Lane Design with Wanding Station can be examined in a systematic and general manner. The research examines these measures in terms of average and variability, that is, maximum and minimum, experimenting with a simulation model to understand the behavior of the ACSS system under varying conditions. Specific relationships and performance levels are derived and evaluated once a particular data set is implemented in the model, which is demonstrated in the next chapters.

#### 3.3 Data Collection

The FAA places commercial service airports into five different categories: Large, Medium and Small hubs, Non-hubs and Non-primary based on annual enplanements. For example, in 2006 Large Hub airports accounted for 70% of a total of 738,364,097 million annual passenger enplanements, whereas Medium and Small Hubs account for only 20% and 8%, respectively (FAA, 2006). As shown in Figure 3.4 these large hub airports contain checkpoints with high volumes of passenger arrivals during peak hours, that is, demand is greater than 1000 passengers per hour (pph). In addition to enplanements data, the TSA collects and maintains airport sizing information, such as, the number of checkpoints and lanes, in their Performance Management Information System (PMIS).



**Figure 3.4** Peak hour passenger demand by airport hub.

Figure 3.4 also shows that there are 213, 104, and 345 checkpoints within large, medium and small hub airports, respectively. As indicated in Table 3.1 the majority of checkpoints see passenger demand of less than 500 pph (64.50%) with moderate and large demand volumes at 26.13% and 9.37%, respectively. While the number of checkpoints that process low volumes of passengers is considerably more, typically these checkpoints are located in small hub airports, which account for only 8% of total annual passenger activity. These airports also have average peak hour wait times below the 10-minute maximum wait time for processing passengers as shown in Table 3.2. Yet, from 2005-2007 average peak wait times at the nation's larger airports (large and medium hub) generally exceeded the wait time standard, overall (TSA, 2007). In FY 2008, the times are at 15 minutes (Hawley, 2008). Thus, the focus of the study was on high-volume and medium-volume checkpoints at large and medium hub airports.

A total of 18 checkpoints were chosen for the study where 10 of them are located in airports the FAA categorizes as "large hubs". Table 3.3 shows the number of checkpoints within airport hubs indicating the study sample size across each type. Non-

hubs and Non-primary airports were excluded from the study because passenger boardings are much more limited and sporadic at these locations. Data from five of the remaining eight checkpoints came from medium hub airports where demand is between 500–1000 pph, and the rest from small hubs that typically see less than 500 pph.

 Table 3.1
 Distribution of Checkpoints by Peak Hour Demand (pph)

Demand	Frequency	Percentage
> 1000	62	9.37%
500 ≥ 1000	173	26.13%
< 500	427	64.50%
Total	662	100.00%

Source: Transportation Security Administration. (2007).

**Table 3.2** Average Peak Wait Times in Minutes by Airport Hub for 2005-2007

Fiscal Year	Large Hub	Medium Hub	Small Hub
FY 2005	12.0	11.2	8.5
FY 2006	12.6	11.8	8.3
FY 2007	14.6	10.4	7.7

Source: Transportation Security Administration. (2007).

 Table 3.3
 Distribution of Checkpoints by Airport Hub with Sample Size

Airport Type	No. of Checkpoints	Sample Size
Large Hub	213	5%
Medium Hub	104	5%
Small Hub	345	1%

The empirical data for this research were obtained from archival sources collected by TSA for only two of the four screening functions—that is, X-ray screening of carry-on items and physical search of carry-on items and trace detection for explosives. As shown in Figure 3.5 performance data was collected in five separate areas from multiple days across airport types, typically during peak hours (e.g., weekdays between 5:00–8:00 A.M. and 3:00–7:00 P.M.)

- 1. Passenger arrival times to the checkpoint
- 2. X-ray TSO image inspection times
- 3. Decision type (cleared or not-cleared)
- 4. Physical search of carry-on items service times
- 5. Trace detection for explosives service times

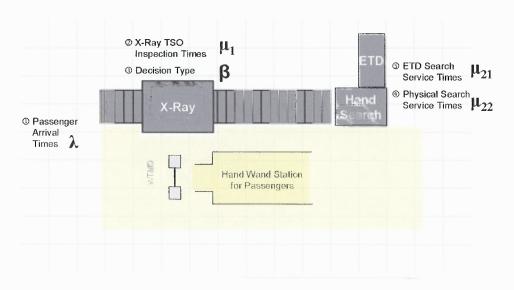


Figure 3.5 Checkpoint data collection areas.

For items 1, 2, and 3, data was obtained from each of the 18 ACSSs. For the secondary inspection service times, TSA provided 500 samples from each airport type, which could have come from the 18 ACSSs or other sites. Because of the nature and

method of data collection, as well as restrictions imposed by TSA, data were not collected to indicate the specific outcome of any carry-on items that were flagged suspicious and sent to secondary inspection, that is, if any prohibited items were actually discovered or not. Additionally, TSA agreed to provide the data after the researcher made necessary provisions to ensure protection of sensitive security information, such as, masking airport names with a coded system. All data were referenced by a unique identification number randomly created to maintain integrity across multiple airports and checkpoints and collection periods while ensuring the confidentiality of all information.

The empirical data is collected by TSOs located at airports and maintained by the Office of Security Operations within TSA headquarters. Throughout any given calendar year TSA collects data on checkpoint performance through observation techniques, various surveys, and automation. Since all data are recorded electronically and submitted directly by individual airport TSOs, such electronic data collection reduced potential errors of second-party data entry and recording, and enhanced the integrity and interpretability of submitted data. Upon completion of data collection, all data were analyzed and cleaned to remove invalid or erroneous data. In accordance with TSA policies, all archival data obtained were devoid of all identifiable information, thus ensuring the maximum level of confidentiality for airports and screeners on whom data were collected. All data collected and maintained were stored in accordance with applicable policies.

### **Measures of Performance**

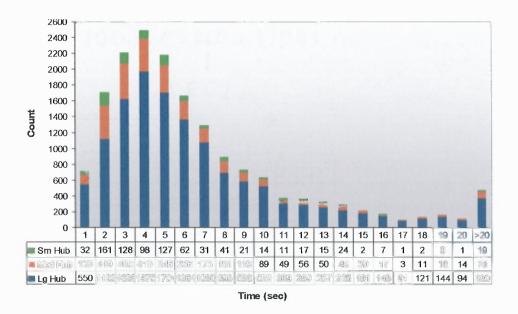
TSA uses passenger processing wait times as a primary measurement for checkpoint performance, and their goal is 10 minutes or less (Hawley, 2008). Yet, the average peak wait times at the nation's larger airports generally exceeded the wait time standard (Airports Council International - North America, 2003).

Passenger processing wait time is defined as the amount of time passengers have to wait to undergo screening at the security checkpoint (GAO, 2007b). TSA collects wait time data every 30 minutes during peak hours and every hour during non-peak periods of time. During each data collection period, a TSO stamps wait time cards with the current time, provide the cards to the last three passengers in line during off-peak periods and the last four passengers during peak periods. The TSO records the time on the card and at the end of the day enters the wait time data into the PMIS. Other performance measures include staffing per lane, which is 4.25 TSOs per lane, and checkpoint throughput. According the same GAO report, checkpoint throughput (passengers per lane, per hour (pplph)) is considered to be 200 pplph since this is what TSA uses in its simulation studies.

In addition to wait time, staffing levels, and throughput, queue length and resource utilization are also used to measure performance in queuing systems. The study examines these measures, both the average and variability, that is, maximum and minimum, experimenting with a model to understand the behaviour of the ACSS system under varying conditions.

## 3.4 Descriptive Data and Summary Statistics

Figures 3.6 and 3.7 show the combined number of carry-on items inspected from across all airport types along with the time TSOs took to decide for items to be "cleared" and "not-cleared", respectively. TSOs made a decision whether to clear the item or not most (80%) of the time within 10 seconds or less. Overall, small hub airports had lower (faster) X-ray TSO image inspection times (M=5.81) than medium hubs (M=7.00) and large hubs (M=7.04) as shown in Tables 3.4 through 3.6. These tables show the means and standard deviations for X-ray inspection times separately for the three airport types and two decision types combining the different data collection periods. The average percentage of items requiring secondary inspection ranges from 3–9% with checkpoints at large hub airports having the greatest rates.



**Figure 3.6** No. items cleared combining ACSSs by airport hub.

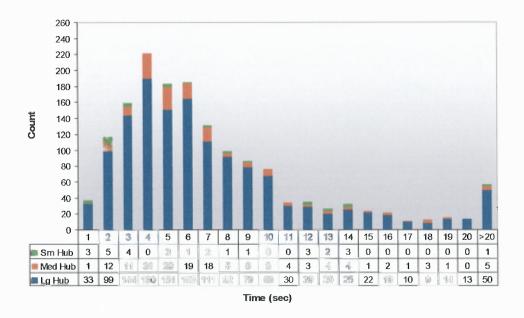


Figure 3.7 No. items not-cleared combining ACSSs by airport hub.

The mean secondary inspection service times (in seconds) for both physical search and ETD search are shown in Table 3.7. It was determined that physical search takes 2–5 minutes per carry-on items and these times do not vary across airport types. It was also determined that ETD search times are similar across airports and it takes 2–2.5 minutes per carry-on items.

Table 3.4 X-ray TSO Inspection Times (in seconds) for ACSSs at Large Hubs by Decision

			Cleared		Ž	Not-Cleared	pa		Total		95% Cc	Confidence	Interv	al for	Not-
Airport	ACSS											Mean	-		Cleared
Type	А	z	Mean	SD	Z	Mean	SD	Z	Mean	SD	<b>L-B</b>	<b>U-B</b>	Min	Max	%
	1	1149	6.64	5.54	109	7.31	7.76	1258	6.70	5.76	6.38	7.02	1	72	%6
	7	1223	7.64	8.44	158	9.38	12.63	1381	7.84	9.03	7.36	8.31	_	120	11%
	3	1247	6.59	4.45	165	6.55	4.20	1412	6.58	4.42	6.35	6.81	-	28	12%
	4	1264	6.84	7.28	80	6.29	4.84	1344	6.80	7.16	6.42	7.19		72	%9
Large	7	926	6.92	5.38	52	6.56	4.30	1028	6.90	5.33	6.57	7.22	<del></del>	42	2%
	∞	994	6.42	4.99	95	8.82	10.39	1086	6.63	5.68	6.29	96.9	_	29	%8
	6	1194	7.87	7.13	111	7.99	8.57	1305	7.88	7.26	7.49	8.27		120	%6
	10	1136	6.83	4.81	41	99.9	2.29	1177	6.83	4.74	6.55	7.10	-	25	3%
		1064	69.9	5.31	149	7.68	7.49	1213	6.81	5.63	6.49	7.13	<del></del>	99	12%
	12	1043	6.71	6.55	136	8.09	7.25	1179	6.87	6.64	6.49	7.25	_	118	12%
	Total	11290	6.93	6.18	1093	7.70	8.11	12383	7.04	6.37	68.9	7.11		120	%6

X-ray TSO Inspection Times (in seconds) for ACSSs at Medium Hubs by Decision Table 3.5

			Cleared		Z	Not-Cleared	eq		Total		%56	95% Confidence Interval	nce Inte	rval	Not-
Airport	ACSS											for Mean	ean		Cleared
Type	А	z	Mean	SD	Z	Mean	SD	Z	Mean	SD	L-B	N-B	Min	Max	%
	5	1074	1074 7.39 6.83	6.83	151	7.73	7.18	1225	7.43	6.87	7.05	7.81	1	120	12%
	9	1090	7.02	5.01	126	9.56	14.21	1216	7.29	6.63	6.92	7.66	_	120	10%
Medium	14	792	68.9	5.81	24	8.00	4.60	816		5.77	6.52	7.32	-	20	3%
	15	778	6.70	5.51	18	6.94	4.72	962	6.70	5.49	6.32	7.08	Н	42	2%
	16	441	5.71	4.27	28	98.9	5.77	469	5.78	4.38	5.38	6.18	7	33	%9
	Total	4175	68.9	5.72	347	8.30	10.06	4522	7.00	6.18	6.82	7.18	_	120	%8

Table 3.6 X-ray TSO Inspection Times (in seconds) for ACSSs at Small Hubs by Decision

			Cleared		~	Not-Cleared	eq		Total		95%	Confide	nce Int		Not-
Airport	ACSS											for M	<b>[ean</b>		Cleared
Type	О	z	Mean	SD	Z	Mean	SD	Z	Mea	SD	L-B	U-B	Min		%
	13	884	884 5.70 7.33	7.33	86	7.52	l	982	5.88	7.43	5.42	6.34	1		10%
Small	17		607 5.68 5.81	5.81	24	6.79	5.61	631	5.7	5.80	2 5.80 5.27 6.17	5.27 6.17 1 72	1		4%
	18		5.67	3.78	5	7.80	4.38	212	5.72	3.79	5.21	6.23	7		2%
	Total	1698	5.69	6.46	127	7.39	7.56		5.81	6.55	5.51	6.11	_	8	7%

Table 3.7	Physical	Search	and	ETD	Service	Times	(in	seconds)	across
Airport Hub	S								

		Small			Mediun	1		Large			Total	
Туре	N	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD
Physical	500	191.6	38.9	511	191.3	39.3	506	208.5	44.4	1517	197.1	41.7
ETD	500	133.6	6.1	500	133.9	6.1	500	148.9	12.1	1500	138.82	11.18

As shown in Figure 3.8, a large variation in primary inspection times was observed ranging from 1–120 seconds. The lengthy "right tail" of the lognormal distribution indicates that a small number of complicated, time-consuming cases are contributing disproportionately to overall inspection times. If these cases were diverted earlier to secondary inspections, then this would improve the throughput of the primary inspection process, although naturally this would require that more resources be devoted to secondary inspections.

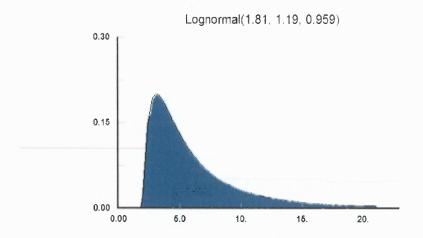


Figure 3.8 Lognormal distribution for benchmark data.

The next two tables describe the characteristic behavior of the ACSS 1-to-1 Single Lane Design with Wanding Station. More specifically, the passenger arrival demand at the checkpoint ( $\lambda_C$ ), in addition to the screening lane ( $\lambda_L$ ) per hour values are shown in Table 3.8 for each checkpoint across the airport hubs. This table also lists the primary inspection times ( $\mu_1$ ) in seconds and the percentages of carry-on items not-cleared. Table 3.9 summarizes the information combining ACSSs into the three hubs but also includes the service rates at secondary inspection for both ETD inspection ( $\mu_{21}$ ) and physical hand search ( $\mu_{22}$ ).

Table 3.8 ACSS Parameters for All Checkpoints by Airport Hubs

			Passenger Arrival	Passenger	Primary	
			Rate per Hour at	Arrival Rate per	Inspection	Percentage
Airport	ACSS	# of	Checkpoint	Hour at Lane	Time (in	Not-Cleared
Type	О	Lanes	(%)	$(\lambda_{\!\scriptscriptstyle  m L})$	seconds) (μ <sub>1</sub> )	(B)
	-	9	1001	167	6.70	%6
	7	9	1387	231	7.84	11%
	m	9	1391	232	6.58	12%
	4	9	1270	212	98.9	%9
	7	9	1113	186	9.90	2%
Large	∞	9	1200	200	6.63	%8
)	6	9	1185	198	7.88	%6
	10	9	1261	210	6.83	3%
	11	9	1384	231	6.81	12%
	12	9	1096	183	6.87	12%
	Total	9	1229	205	7.04	%6
	5	5	1267	253	7.43	12%
	9	\$	1011	202	7.29	10%
;	14	4	720	180	6.92	3%
Medium	15	4	564	141	6.70	2%
	16	4	928	232	5.78	%9
	Total	4	868	202	7.00	7%
	13	3	969	232	5.88	10%
Small	17	7	301	151	5.72	4%
	18	7	275	138	5.72	2%
	Total	7	424	173	5.81	2%

 Table 3.9
 Summary Behavior Characteristics for a 1-to-1 Single Lane Design ACSS

	Passenger Arrival	Passenger Arrival	Primary Inspection	Secondary	Secondary Inspection	
	Rate per Hour at	Rate per Hour at		Time (in	seconds)	Not
Type	Checkpoint (Ac)	Lane $(\lambda_L)$		$\mathrm{ETD}(\mu_{21})$	$ETD(\mu_{21})$ Hand( $\mu_{22}$ )	
Large	1229	205	7.04	148.9	208.5	
Medium	868	202		133.9	191.3	
Small	424	173	5.81	133.6	191.6	5%

### **CHAPTER 4**

#### PRIMARY INSPECTION OPERATING CHARACTERISTICS

The efficiency of an inspection process is commonly described by the speed and accuracy operating characteristic curve, where very fast responses can be performed with chance accuracy and accuracy will increase as responding slows down. Due to security concerns and the inherent difficulties in quantifying prohibited items not detected by the X-ray TSO, there is little information publicly available on how effective inspections are as a function of time. The next sections in this chapter address the second research objective, where more detail information is provided on the primary inspection process as a function of time followed by the speed of inspection characteristic curves that were generated. In addition to the curves, regression analysis results are presented.

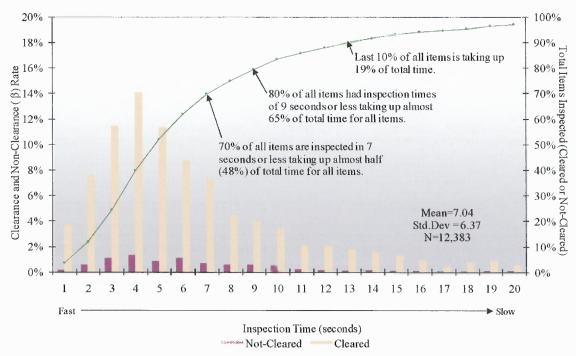
# 4.1 Primary Inspection Service Time Statistics

Combining the data collection periods and collapsing individual checkpoints into the three different airport hubs, Figures 4.1 through 4.3 show the percentage of the carry-on items cleared and not-cleared as a function of the maximum inspection time for large, medium and small hubs, respectively. Additionally, the total (both cleared and not-cleared combined) carry-on items inspected (cumulative percentage) is plotted on the second Y-axis for the different time intervals.

Two key pieces of information can be drawn from Figures 4.1 through 4.3. First, is the *operating characteristic curve*, which is defined as the relationship between a system decision for a given system input. It is commonly used in quality control to

project the acceptance rate for a specific actual defect rate. These curves can be an effective method for representing the behavior of security inspection systems. Secondly, there is the SIOC curve, which specifies the cumulative percent of entities ( $\psi_t$ ) that will complete inspection (both cleared and non-cleared) within the maximum allowable inspection time of t seconds. For example, t when  $\psi_t$  is 80% = 9.12 seconds for large hub airports.

A large variation in primary inspection times was observed ranging from 1 to 120 seconds. The lengthy "right tail" of the distribution indicates that a small number of complicated, time-consuming cases are contributing disproportionately to overall inspection times. If these cases were diverted earlier to secondary inspections, then this would improve the throughput of the primary inspection process, although naturally this would require that more resources be devoted to secondary inspections. The data also suggests that inspection times beyond 13 seconds for both large and medium hubs should result in carry-on items being automatically diverted to secondary inspection, and 10 seconds for small hubs. Additionally, at both large and medium hub airports, 70% of all carry-on items are inspected in 7 seconds or less taking up almost half (48%) of the total time for inspecting all carry-on items. Inspection times at small hub airports are faster, where 70% of the carry-on items are inspection in 6 seconds or less. Additionally, the data reveals that at all airport types the last 10% of carry-on items is taking up approximately 20% of the total inspection time.



**Figure 4.1** Primary inspection as a function of time at large hub airports combined.

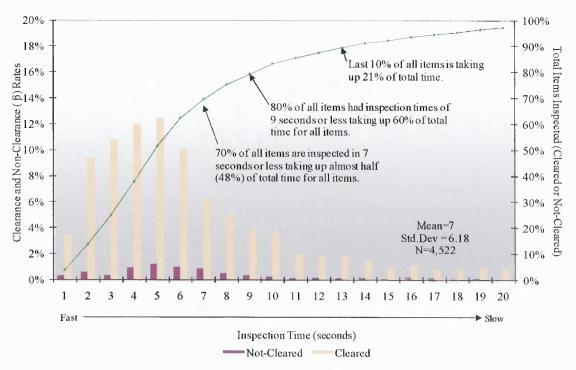


Figure 4.2 Primary inspection as a function of time at medium hub airports combined.

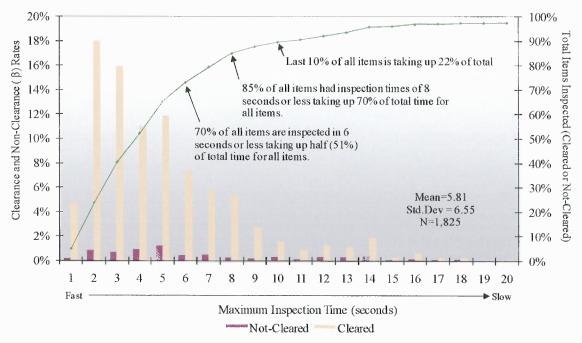


Figure 4.3 Primary inspection as a function of time at small hub airports combined.

## 4.2 Speed of Inspection Operating Characteristic Curves

In evaluating different technology options for the security inspection process there are three strategic improvement options:

TYPE A - Improve the decision capability so that  $\beta$  is reduced in the shorter inspections

TYPE B - Improve the decision capability so that  $\beta$  is reduced in the longer inspections

TYPE C - Improve the decision capability at all inspection rates

As shown in Figure 4.4, a strategy is characterized by the type and improvement at the base rate. For example: Type-A 20% implies a 20% reduction at the base rate of 7 carryon item (bags) per minute or  $\mu$ =8 seconds. Denoting speed or service rate by  $\mu$  and the rate at which carry-on items move to secondary inspection by  $\beta$ ,  $\mu^{MAX}$  is introduced as the

maximum inspection rate;  $\mu^{MIN}$  is the slowest inspection rate. At the slowest rate there could possibly be no carry-on items being sent to secondary inspection;  $\beta^{MAX}$ , at the rate sent to secondary inspection corresponding to  $\mu^{MAX}$ , and  $\beta^{MIN}$ , the rate sent to secondary inspection corresponding to  $\mu^{MIN}$ , is in many cases this will be 0%. When a maximum inspection time  $\mu^{MAX}$  is allowed then entities flowing to the secondary inspection include (i) those not-cleared, and (ii) those for which the inspection was incomplete. The sum of these two is the Effective  $\beta$ .

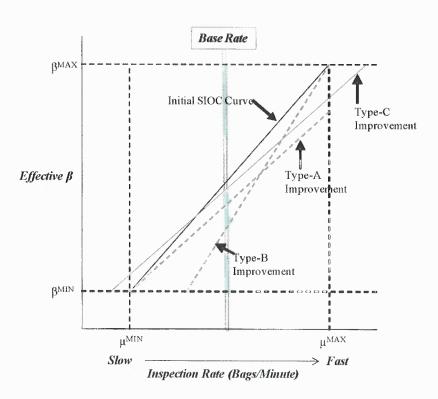


Figure 4.4 Conceptual SIOC threshold points with improvement strategies.

In following their concept, SIOC curves were generated with the empirical data collected and presented in the previous section's charts, which showed primary inspection as a function of time. These SIOC curves characterize the effect of inspection

speed on the rejection rate, that is, whether the TSO determines that a carry-on item does not contain any prohibited item and is cleared or rejects it for further scrutiny at secondary inspection.

Figure 4.5 illustrates the SIOC curve for large hub airports. Instead of the inspection time ( $\tau$ ), the service rate ( $\mu$ ), where  $\mu$ =60/ $\tau$ , is plotted on the x-axis to show the rejection rate as a function of time, that is, the number of carry-on items inspected per minute by the TSO.

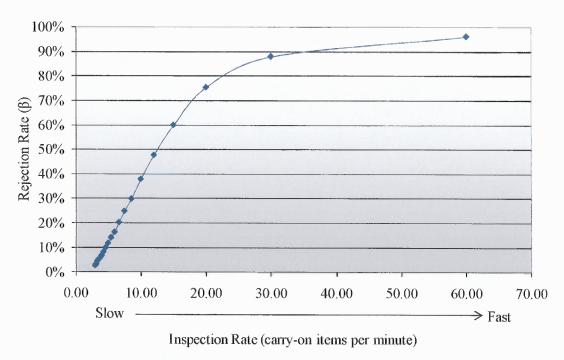


Figure 4.5 Large hub SIOC curve.

In Figure 4.5 the full range of rates from 3 to 60 carry-on items per minute is plotted. From the data, rates above 12 per minute are unreasonable since too few bags are cleared and the Effective  $\beta$ , labeled as the Rejection Rate is too high. Therefore, setting the thresholds to  $\mu^{MIN}$  to 3 per minute and  $\mu^{MAX}$  to 12 per minute; and  $\beta^{MIN}$  at 2.9% and  $\beta^{MAX}$  at 47.8%, the resulting plot is shown in Figure 4.6. The data shows that the

relationship between the Effective  $\beta$  and the maximum inspection rate  $(60/\mu^{MAX})$  describes an approximate linear relationship in the 3 to 12 bags per minute range.

Simple regression was conducted to investigate how well the frequency of X-ray TSO inspection times can be predicted for all carry-on items screened. Interestingly, just as Olapiriyakul and Das (2007) assumed, the graph is linear. The equation derived is also shown in the figure and the regression result was significant, where F(1,14) = 11211.18, p < .001. The adjusted R squared value was .99, which indicates that 99% of the frequency was explained by the inspection times. According to Cohen (1988) this is a large effect.

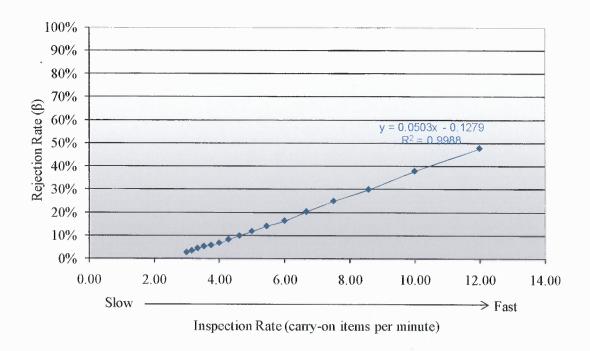


Figure 4.6 Large hub SIOC curve with threshold points.

Figure 4.7 plots the SIOC curve data for the full range of rates for all three airport hubs and the results of the regression analysis are shown in Figure 4.8. The specific rejection rate values are provided in Table 4.1. The data shows that for medium airport

hubs the thresholds are similar to large airports, while for small airport hubs rates above 15 carry-on items per minute result in too few being cleared along with high rejection rates.

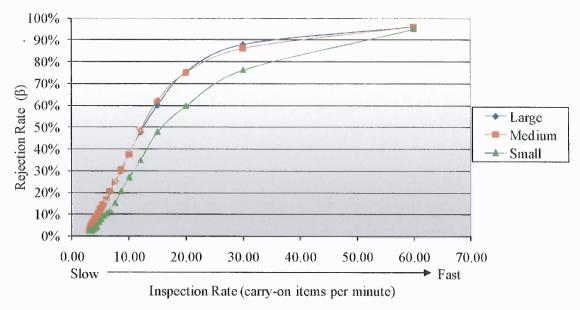
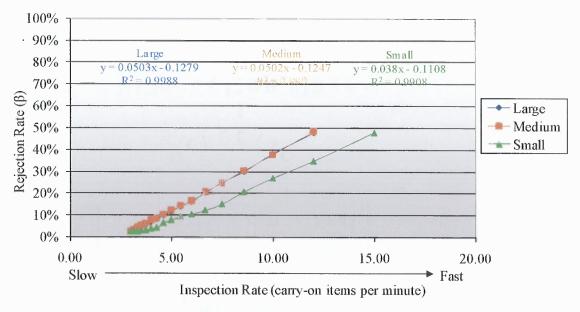


Figure 4.7 Large, medium and small airport hubs' SIOC curves.



**Figure 4.8** SIOC curve regression for all airport types with threshold points.

As with large airports, the results were significant for medium and small airport types, where F(1,15) = 13630.9, p < .001, and F(1,16) = 1616.67, p < .001, respectively. The adjusted R squared value for both medium and small hubs was 0.99. This indicates that over 90% of the frequency was explained by the inspection times. Again, this is a large effect. Additional analysis of the curve data incorporating the possible improvement strategies presented by Olapiriyakul and Das is part of the experimentation conducted in this study and presented in Chapter 6.

 Table 4.1
 SIOC Curve Parameter Values for All Airport Types

Inspection Time (τ) sec	Inspection Rate (μ) per hour	Large Hub Rejection Rate (β)	Medium Hub Rejection Rate (β)	Small Hub Rejection Rate (β)
1.00	60.00	96.15%	96.17%	95.12%
2.00	30.00	87.98%	86.25%	76.27%
3.00	20.00	75.44%	75.12%	59.73%
4.00	15.00	60.06%	62.21%	47.84%
5.00	12.00	47.84%	48.58%	34.79%
6.00	10.00	38.04%	37.59%	26.96%
7.00	8.57	30.06%	30.45%	20.71%
8.00	7.50	25.05%	24.83%	15.12%
9.00	6.66	20.46%	20.65%	12.27%
10.00	6.00	16.52%	16.65%	10.41%
11.00	5.45	14.21%	14.53%	9.37%
12.00	5.00	11.98%	12.52%	7.84%
13.00	4.61	10.09%	10.55%	6.47%
14.00	4.28	8.40%	8.82%	4.22%
15.00	4.00	6.91%	7.81%	3.89%
16.00	3.75	5.94%	6.50%	3.18%
17.00	3.52	5.45%	5.59%	2.90%
18.00	3.33	4.64%	4.73%	2.58%
19.00	3.15	3.59%	3.69%	2.58%
20.00	3.00	2.90%	2.85%	2.47%

### **CHAPTER 5**

#### INVESTIGATION OF CHECKPOINT DIFFERENCES

Chapter 5 reports on the results pertaining to the third research objective where an analytical investigation of the differences between checkpoints within airport types was conducted. Additionally it includes a description of the simulation model developed and presents the results of the simulation investigation of the performance sensitivity to passenger arrival rates and inspection times.

## 5.1 Hypothesis Testing

The following questions guided the statistical analyses and interpretation of collected data.

- Does inspection time affect the outcome of the inspection?
- Are there differences in mean X-ray TSO image inspection times at different airport types?
- Is the passenger waiting time affected by the TSO performance at the primary inspection stage?

To answer the questions posed above, a series of hypotheses test to accept or reject each null hypothesis was conducted. For example, the null hypothesis is that TSO's rate of inspecting X-ray images is not associated with passenger wait times. Hence, the alternative hypothesis is that average wait times can be improved upon by limiting the TSO's time to inspect the image.

## Hypothesis Test I

In order to determine the effect of X-ray TSO inspection times on decision type the question was posed: Does speed influence decision type? (Do cleared items have different mean X-ray TSO image inspection times than not-cleared items?) The hypothesis here is that cleared items have lower (faster) X-ray TSO image inspection times than items that are not-cleared.

To investigate interactions between factors as well as the effects of individual factors, a two-way analysis of variance (ANOVA) (univariate General Linear Model procedure) was used. The research experiment involves mixed designs with unbalanced groupings. The mixed design has one within-subject variable X-ray TSO image inspection times (speed) with two levels (peak hour period 1 vs. peak hour period 2) and two between-subject variables, the first (airport type) with three levels (small, medium and large), and the second (decision type) with two levels (cleared vs. not-cleared). The outcome variable (dependent variable) for this study was the X-ray TSO image inspection times. The timing of when an X-ray image is displayed in addition to the response (cleared or not-cleared) of the TSO is recorded by the X-ray systems. In addition there were two key independent variables within this study; the first (airport type) with three levels (large, medium and small), and the second (decision type) or response of the screener with two levels (cleared vs. not-cleared).

Statistical analyses were conducted using the Statistical Package for the Social Sciences (SPSS 15.0) and other appropriate software. For all statistical analyses presented and discussed in this chapter, a two-tailed probability level of p < .05 was used as the criterion for statistical significance.

Table 5.1 presents the results obtained from a two-way ANOVA test using the General Linear Model (GLM) procedure for X-ray TSO image inspection times as a function of decision type, in addition to airport type and peak hour period to test whether there are differences between inspection times across airports and at different data collection time periods.

**Table 5.1** Analysis of Variance for Operator X-ray Image Inspection Times as a Function of Airport Hub, Decision Type and Data Collection Period

Variable and source	df	MS	$\overline{F}$	p	$\eta^2$
X-ray TSO image inspection times					- #
Airport	2	151.80	3.78**	.023	.000
Decision	1	269.65	6.71**	.010	.000
Period	1	33.91	.84	.358	.000
Airport*Decision	2	7.315	.18	.834	.000
Airport*Period	2	33.79	.84	.431	.000
Decision*Period	1	61.76	1.54	.215	.000
Airport*Decision*Period	2	43.58	1.08	.338	.000
Error	18718	40.18			

The results show there was a significant main effect obtain for decision type F(1, 18718)=6.71, p=.010. However, this was a small difference (Partial Eta Squared = .000), thus not supporting the conclusion that cleared items have different mean X-ray TSO image inspection times rates than items that are not cleared.

Does the mean X-ray TSO image inspection time change across the different data collection periods? The null hypothesis here is that there is no difference between X-ray TSO image inspection times as the time of day changes. The results obtained, also shown in Table 5.1, indicated that there was not a significant main effect of time of day on X-ray TSO image inspection times (F(1,18718)=.84, p=.358), thus supporting the conclusion that the mean X-ray TSO image inspection times do not change across different time periods.

## Hypothesis Test II

Since TSA uses passenger processing wait times as a primary measurement for checkpoint performance, an investigation of the effects of passenger volumes on inspection performance was performed. More specifically, are there differences in mean X-ray TSO image inspection times between high, medium and low volume passenger arrivals? It is proposed that the TSO speeds up their inspection of the X-ray image as the number of passengers arriving and waiting increases.

An investigation of passenger interarrival times was first conducted to determine any differences between passenger interarrival times across data collection periods within the different airport types. For the investigation a two-tailed Independent Samples t Test was used. A probability level of p < .05 was used as the criterion of statistical significance.

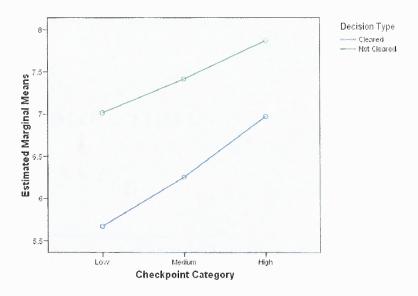
It was determined that passenger interarrival times did not differ significantly across data collection periods for 7 of the 10 checkpoints at large hub airports. However, the t Test revealed a significant difference between the data collection periods for checkpoints 8 (p=0.012), 10 (p=0.024) and 11 (p=0.000). Because the t was statistically

significant, the effect size and the 95% Confidence Interval of the Mean Difference were calculated. The effect size "d" (Cohen, 1988) was computed from the value of the *t* Test of the differences between the two groups (Rosenthal and Rosnow, 1991). The results show in each case the effect size is smaller than typical, where for checkpoints 8, 10 and 11, d=0.103, d=-0.090 and d=-0.177, respectively. Additionally, the analysis shows that the difference between the means in all cases is approximately 2 seconds at a 95% confidence interval.

Within medium hub airports, passenger interarrival times did not differ significantly across data collection periods for any of the five checkpoints, where p=0.621, p=0.403, p=0.935, p=0.872, and p=0.123 for checkpoints 5, 6, 14, 15, and 16, respectively. Also, times did not differ significantly for the three checkpoints within small hub airports, where p=0.629, p=0.410, and p=9.12 for checkpoints 13, 17 and 18, respectively.

The two way ANOVA results obtained, also shown in Table 5.1, indicate a significant main effect of airport type on X-ray TSO image inspection times F(2,18718)=3.78, p=.023, revealing that checkpoints at small hubs had significantly lower (faster) X-ray TSO image inspection times (M=5.81) than at medium hub (M=7.00) and at large hub (M=7.04) checkpoints, and it is statistically significant. However, this was a small difference (Partial Eta Squared = .000). Thus, the hypothesis proposed that as passenger volumes increase, the X-ray TSO inspection times get lower (faster) was not supported. Although the hypothesis was not supported, the result could be of practical importance because X-ray inspection times increase moving from low-volume to high-volume checkpoints, (M=5.81s, 7.00s, and 7.04s, respectively).

As shown in Figure 5.1 X-ray TSO image inspection times for cleared items are lower (faster) regardless of whether there was low, medium or high-volumes of passenger arrivals. The lines are nearly parallel, and supported by post hoc test using Games-Howell adjustments for multiple comparisons, there was no significant difference in estimated marginal means of X-ray TSO image inspection times between the two decision types (cleared vs. not-cleared) across the different airports.



**Figure 5.1** X-ray TSO image inspection times and decision across ACSSs within airport hubs.

### 5.1.1 Distribution Fitting

Tests were performed on passenger arrivals and primary inspection service times to determine whether the empirical data could have come from among the five alternative theoretical probability distributions checked (exponential, Erlang, Gamma, lognormal, and Weibull). Exponential gave the best fit for the passenger interarrival times, and lognormal distributions for the service times. Distribution fitting was conducted with the

chi-square and Kolmogorov-Smirnov goodness-of-fitness tests. Goodness-of-fit tests were run for checking the hypothesis in the form:

 $H_0$ : Passenger arrivals are exponentially distributed.

 $H_1$ : Passenger arrivals are not exponentially distributed.

 $H_0$ : Service times are lognormal distributed.

 $H_1$ : Service times are not lognormal distributed.

In all cases, an alpha value of 0.05 was used for the hypothesis test.

Table 5.2 presents the descriptive data for the interarrival times of passengers to the checkpoints across the two data collection periods by airport type. The exponential distribution for the passenger interarrival times proved to be a very good fit as seen in Table 5.3. The chi-square goodness-of-fit test and the nonparametric Kolmogorov-Smirnov test did not reject the null hypothesis that the passenger interarrival times take on an exponential distribution. Likewise, the lognormal distribution for the primary inspection service times proved to be a very good fit as seen in Table 5.4. The high *p*-values for the chi-square goodness-of-fit test and very low Kolmogorov-Smirnov test statistic, which measures the maximum distance from the actual data to the expected exponential distribution, demonstrate excellent fit.

Table 5.2 Inter-arrival Rates (in seconds) by Airport Hub

Interarrival Time						
Airport	N	Mean	SD	Sites		
Large	1000 - 1391	11.12 - 14.50	10.25 - 13.64	10		
Medium	564 - 928	12.98 - 15.41	11.52 - 13.89	5		
Small	275 - 301	9.59 - 16.06	8.88 - 15.45	3		

**Table 5.3** Chi-square Goodness-of-Fit Test *p*-values and the K-S Test Statistics for an Exponential Distribution of Interarrival Times by Airport Hub

Airport	$\chi^2 p$ -value	K.S. Statistic	Parameter (λ)
Large	0.71 - 0.98	0.01 - 0.01	10.12 - 14.38
Medium	0.65 - 0.99	0.01 - 0.02	11.98 - 14.41
Small	0.84 - 0.90	0.01 - 0.04	8.59 - 15.06

**Table 5.4** Chi-square Goodness-of-Fit Test p-values and the K-S Test Statistics for a Lognormal Distribution of Primary Inspection Service Times by Airport Hub

Airport	$\chi^2 p$ -value	K.S. Statistic
L	0.52	0.01
M	0.52	0.02
S	0.52	0.04

#### 5.2 Simulation Model

An investigation of the performance sensitivity to passenger arrival rates and inspection times was conducted with a simulation model. Using the Extend<sup>TM</sup> simulation software tool package the ACSS was constructed. Extend<sup>TM</sup> is a general-purpose simulation tool available from Imagine That, Inc. (Krahl, 2008). It has been applied to a wide range of areas including high-speed manufacturing, supply chain, chemical processing and transportation. In the most basic terms, the simulation first generates the numbers of arriving passengers based on actual observations collected at airports nation-wide. Secondly, the model simulates the transit of passengers and their carry-on items through the screening process and lastly provides values for specific criteria or performance measures, such as, the average wait times for passengers at primary inspection.

Figure 5.2 illustrates the overall structure of the Extend™ ACSS model. In the Extend™ modeling environment blocks are pulled from libraries into the model. Each block describes a calculation or a step in the process. In the ACSS model, as detail was added, the number of blocks increased. As a result, using hierarchy, the model is represented by the system's most basic elements: (1) the arrival of passengers, (2) the queue of passengers waiting to drop off their carry-on items at the X-ray machine, (3) the X-ray inspection of carry-on items, and (4) secondary inspection of carry-on items deemed suspicious by the X-ray TSO using either ETD or physical hand search.

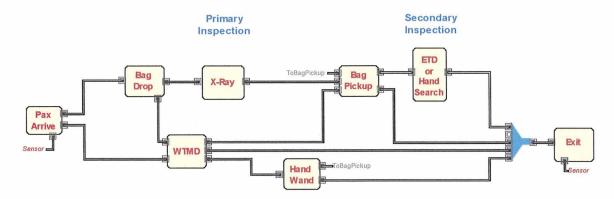


Figure 5.2 Block diagram of Extend™ ACSS model.

While the study's primary focus is on investigating only the performance of inspecting carry-on items, the simulation model was enhanced beyond the conceptual model to simulate the movement of passengers through the system after they drop off their carry-on items at the X-ray machine. Thus, two other elements were added including the movement of passengers through the WTMD after dropping off their carry-on items, and then, if necessary, on to the Hand-Wanding station for secondary inspection, in addition to, matching passengers back up with their carry-on items at the pickup station before moving on to secondary inspection or exiting the system.

Double clicking on any one of the hierarchical blocks opens a new window displaying the sub-model. Figure 5.3 shows the sub-model for the block labeled "Pax Arrive". The sub-model includes the Generator block that generates passengers with a specified arrival rate. The model is set to use an exponential distribution to simulate the time between passenger arrivals to the inspection area. For example, according to the empirical data collected at large hub airports the passenger arrival rate to the screening lane is 205 passengers per hour. Therefore, the mean interarrival time is set to 0.293 minutes in the Generator block.

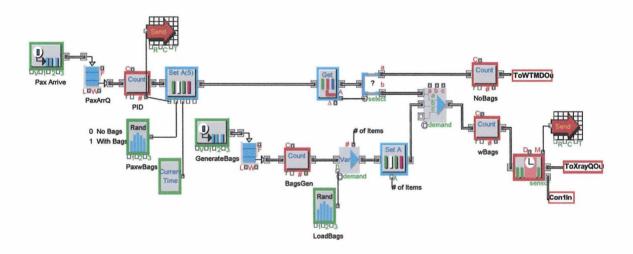


Figure 5.3 PaxArrive sub-model.

Since not all individuals who enter the checkpoint have carry-on items, attributes were used to differentiate between the two types. The Set Attribute Block adds an attribute called "type" to each individual. It randomly sets the value of this attribute to 0 (no bags) or 1 (with bags) using the Input Random Number Block. The block generates random numbers according to an empirical table distribution with values set to 10% of individuals having no bags (carry-on items) and 90% with bags (carry-on items).

While specific data on the number of carry-on items was not collected at part of this study, TSA typically states that the average number of carry-on items per passenger is two and one-half. Also, in a review of airport websites passengers are advised carry-on baggage is limited to one bag plus a personal item per passenger. Yet, more than two items per passenger pass through the X-ray machine when you consider that shoes are put into bins separately, as well as plastic bags containing liquids. Leone and Kukulich (2002) reported the number of carry-on items per passenger to be two and one-half, as well.

Another Generator block is placed in the sub-model to provide units that represent carry-on items. The Batch (Variable) block is used to determine the load size of one to four carry-on items per passenger and to keep track of the number of carry-on items within a load. The load size is generated using the Input Random Number Block. The block generates random numbers according to an empirical table distribution with probability values set to: 1:0.03; 2:0.55; 3:0.40; 4:0.02. To keep track of the number of carry-on items a load is composed of, an attribute is assigned to each load and the attribute value is set to be the number in the load. Subsequently, the value is used as the "n" input in the Unbatch (Variable) block to unbatch that same number of carry-on items in the BagDrop sub-model.

A load of carry-on items is then joined to a passenger using the Batch block. Constructing the sub-model this way facilitates wanting to batch carry-on items with passengers only temporarily; this is called binding. Then, rejoining passengers with their carry-on items before they exit the system or have to move onto secondary inspection of their carry-on items. Passengers, who do not have carry-on items, exit the sub-model by

going directly to the WTMD sub-model; those passengers with carry-on items proceed to the BagDrop sub-model, which is illustrated in Figure 5.4.

Upon entering the BagDrop sub-model, passengers join a First-In, First-Out (FIFO) queue. This queue, in front of the X-ray unit, is where passengers wait to send their carry-on items and personal belongings into the X-ray.



Figure 5.4 BagDrop sub-model.

The "BagDropQ" Queue block holds the passengers, and releases them FIFO. Upon release, the passengers and carry-on items are separated using an Unbatch block simulating passengers sending their carry-on items through the X-ray and moving to the WTMD. An important feature in this sub-model is the use of the Unbatch (Variable) block to unbatch or unload the same number of carry-on items originally associated with a passenger. Each passenger may have carried anywhere from one to four items. The value of the load is used as the "n" input in the block.

There are two Activity Delay blocks in the X-ray sub-model shown in Figure 5.5. The first generates a delay time representing the divestiture of carry-on items into bins and the transit of bins on the conveyor belt into the aperture of the X-ray unit. A uniform distribution was used to output a real (decimal) number greater than or equal to the value of 5 seconds and less than or equal to the value of 10 seconds. In this distribution, all the values between the minimum and maximum are equally likely to occur. For instance,

this distribution is used to indicate "best case/worst case" scenarios, or that the least a carry-on item would take to move into the X-ray machine is 5 seconds and the most it would take would be 10 seconds.

The second Activity Delay block processes the carry-on items for a specified time or delay that is the amount of time it takes an X-ray TSO to inspect an X-ray image and make a decision to either clear the carry-on item or to send it to secondary inspection for further scrutiny.

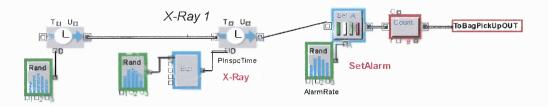


Figure 5.5 X-ray sub-model.

A random processing or delay time is set by connecting an Input Random Number block to the "D" connector of the Activity block. In the dialog of the Input Random Number block, the required distribution is selected, and the value of the parameters specified. For example, based on the empirical data, a LogNormal distribution is used with a mean of 7.04 seconds and standard deviation of 6.37 seconds as the baseline for large hub airports. The Equation block outputs the results of an equation entered in the dialog. The equation limits the inspection time to a minimum time specified to simulate a paced condition.

The checkpoint model is a simple example of serial processing, where carry-on items move from primary inspection to, if necessary, secondary inspection. However, the X-ray sub-model is constructed to allow for parallel processing varying the number of

primary inspection stations from one up to three for experimentation. In the figure only one station is illustrated. Each station works in parallel, representing the same task being performed.

To specify whether or not a carry-on item requires secondary inspection, the item is assigned an attribute with a yes-or-no value using the Input Random Number block connected to a Set Attribute block, as shown in the sub-model. For example, Beta (β) or the percentage of carry-on items that are routed to secondary inspection during a simulation run for the baseline of large hub airports would be defined by the Empirical distribution in the Input Random Number block as 92% of the carry-on items do not require checking (0 for attribute value) and 8% do (1 for attribute value). The attribute value is read in the Bag Pickup sub-model and the carry-on item is routed to secondary inspection or not.

The Bag Pickup sub-model shown in Figure 5.6 uses a Matching Queue block to reassemble carry-on items with passengers and to ensure that the items and passengers are correctly matched with each other. Items are released only if the specified attribute match. The attributes compared for matching (the Match attributes) are identified by name and checked in the dialog. Specifically, the block searches passengers and carry-on items entering the queue to find the attributes "# of Items" and "PaxwBags". The quantity of carry-on items required for each matched batch is the value of the attribute identified as the Demand attribute, that is, "# of Items" attribute. When the required demand is met, a batched item representing the matched set of passenger and carry-on items is released.

The Bag Pickup sub-model also checks for the attribute assigned in the X-ray sub-model which defined whether or not a carry-on item requires secondary inspection, and then routes it appropriately. Before reaching their assigned destination, exit or secondary inspection, a passenger encounters an Activity (Multiple) Delay block, which holds many items and passes them out based on the delay and arrival time for each item. The item with the smallest delay and earliest arrival time is passed out first. This block is used to represent varying walking speeds of passengers traversing from the Bag Pickup area to their next destination. A delay of 10 seconds is used.

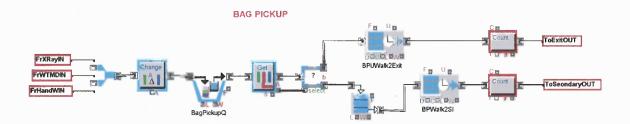


Figure 5.6 Bag Pickup sub-model.

Those carry-on items that were flagged by the TSO to be sent to secondary inspection are processed in the Secondary Inspection sub-model shown in Figure 5.7. In the sub-model passengers with their carry-on items enter a queue waiting for the TSO to pick up their bags and carry them over to either the ETD or physical hand search table. Since there is only one TSO performing secondary inspections the number of passengers allowed into the section of the model is restricted. The Gate block allows only one passenger with their carry-on items at a time to be in the restricted section.

Additionally, in the sub-model the Select block is used to determine which type of secondary inspection is conducted. The dialog sets a random probability of 80% for carry-on items to undergo ETD processing leaving a 20% probability that carry-on items

will undergo physical hand search. These percentages reflect TSA standard operating procedures indicating more emphasis on using ETD to find explosives in carry-on items.

The Secondary Inspection sub-model is constructed to allow for parallel processing varying the number of stations from one up to two for experimentation. In the figure only one station is illustrated. Each station works in parallel, representing the same task being performed.

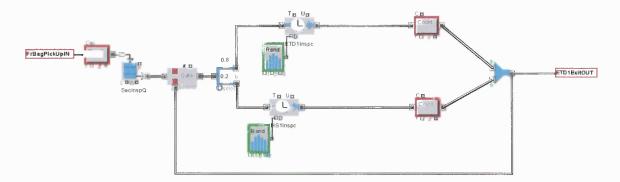


Figure 5.7 Secondary Inspection sub-model.

In the WTMD sub-model shown in Figure 5.8, an Activity Delay block is used to simulate the movement of passengers through the WTMD. A uniform distribution was used to output a real (decimal) number greater than or equal to the value of 1 second and less than or equal to the value of 3 seconds. In this distribution, all the values between the minimum and maximum are equally likely to occur. For instance, this distribution is used to indicate "best case/worst case" scenarios, or that the least a passenger would take to move through the WTMD is 1 second and the most it would take would be 3 seconds.

An Input Random Number is used to set the alarm rate to 16% (Merrill, 2006) requiring passengers to undergo hand wanding or pat down search. A Select block is used in the sub-model to direct passengers with carry-on items to the Bag Pickup sub-

model or to exit the system if they did not have any carry-on items. Additionally, a Multiple Activity Delay block is used to represent the transgression of passengers from the WTMD area to either one of three options, that is, to exit, to pick up their carry-on items, or to proceed to the hand wanding station. This block holds many passengers and passes them out based on the delay and arrival time for each. The passenger with the smallest delay and earliest arrival time is passed out first. The delay time of 10 seconds is specified in the dialog box. For example, this block represents the situation where passengers arrive at different times and take a varying amount of time to proceed to their next stop. Passengers who arrive earlier or only take a little while will leave first; passengers who arrive later or take a long time will leave last.

Those passengers who alarm the WTMD proceed to the Hand Wanding station and are processed in the HandWand sub-model shown in Figure 5.9. Similar to the WTMD sub-model, there is an Activity Delay block to represent the time to inspect a passenger with the hand wand. A uniform distribution was used to output a real (decimal) number greater than or equal to the value of 10 seconds and less than or equal to the value of 20 seconds. In this distribution, all the values between the minimum and maximum are equally likely to occur. For instance, this distribution is used to indicate "best case/worst case" scenarios, or that the least a TSO would take to inspect a passenger is 10 seconds and the most it would take would be 20 seconds.

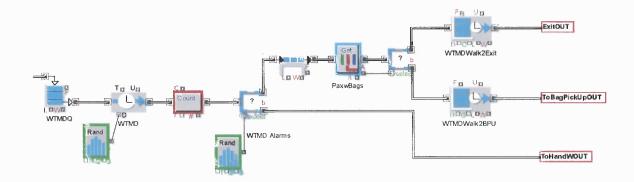


Figure 5.8 WTMD sub-model.

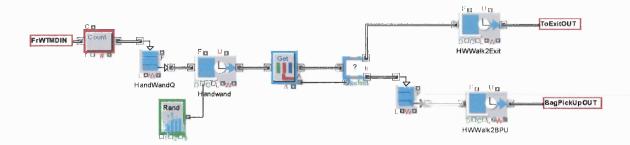


Figure 5.9 HandWand Station sub-model.

Additionally, a Multiple Activity Delay block is used to represent the transgression of passengers from the hand wand station area to either one of two options, that is, to exit, or to pick up their carry-on items. This block holds many passengers and passes them out based on the delay and arrival time for each. The passenger with the smallest delay and earliest arrival time is passed out first. The delay time of 10 seconds is specified in the dialog box. For example, this block represents the situation where passengers arrive at different times and take a varying amount of time to proceed to their next stop. Passengers who arrive earlier or only take a little while will leave first; passengers who arrive later or take a long time will leave last.

#### 5.2.1 Model Verification and Validation

After the model was built, verification that the operational model was performing properly took place as a continuing process. There are numerous validation techniques (Banks, 1998; Hu, San, and Wang, 2001) available to consider in assuring that the computer programming and implementation of the conceptual model—the mathematical/logical representation (mimic) of the system is correct in addition to the degree to which a model is an accurate representation of the real world from the perspective of the intended uses of the model. Given the lack of publicly available information in this area, and the sparse nature of detailed data for passenger security inspections, full validation was not possible. However, at least partial validation was possible using the empirical data collected.

A single measure of performance was selected for this analysis. This measure is the primary inspection service time. The definitive test of model validity is determining whether the simulation times in the system closely resemble that from the actual system. For this purpose, empirical service times from checkpoints at large hub airports were compared with simulation system times. The Mann-Whitney test showed that the difference in means between the two samples was not statistically significant (U=8100, P=0.687).

#### 5.2.2 Sensitivity Analysis

Sensitivity analysis was performed to determine how sensitive the inspection system is to changes in the interarrival time of passengers. For this the arrival times from checkpoints at large hub airports was used as a benchmark with only the interarrival times changing. As expected when passengers appear more frequently (lower interarrival time) utilization

increases and average waiting time increases. As the interarrival time decreases the maximum waiting time dramatically increased.

**Table 5.5** Effects of Interarrival Times on Primary Inspection Queue Waiting Times

Interarriva Chan		Average System Utilization	Average Waiting Time	Max Waiting Time
%	(minutes)	%	(minutes)	(minutes)
- 20	2.73	73	1.04	4.18
- 10	3.08	83	2.01	6.09
Benchmark	3.41	88	2.48	6.92
+ 10	3.76	91	3.93	9.24
+ 20	4.10	96	5.91	12.43

Using the simulation model, the average time a passenger spends waiting for and being inspected at each screening node was also generated and summed. The results shown in Figure 5.10 illustrate the mean waiting time cost as a function of the primary inspection times.

Since, another key performance issue in security inspections is how the system will perform during periods of peak arrivals or even low arrivals, Figure 5.11 plots the passenger waiting time behavior as the arrival rate changes. While the data collected reflects passenger arrivals during peak demand periods, there are fluctuations that coincide with clusters of departures throughout the day.

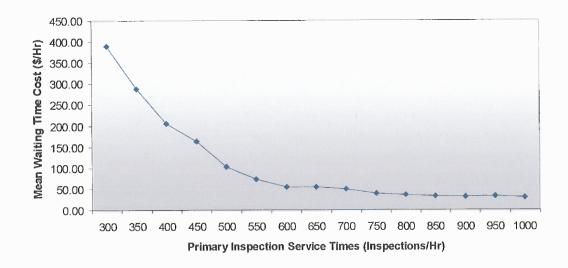


Figure 5.10 Waiting time cost as a function of  $\mu_1$ .

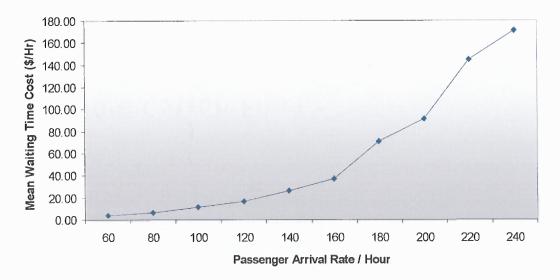


Figure 5.11 Waiting time cost as a function of  $\lambda_1$ .

#### **CHAPTER 6**

#### SIMULATION EXPERIMENTATION AND RESULTS

This chapter addresses the fourth and final research objective describing and reporting on the experiments conducted of different design strategies using a paced inspection system approach to improve performance of the ACSS system. The simulation is operated in the self-paced mode (Koenig, Nickles, Kimbler, Melloy, and Gramopadhye, 2006), where if the TSO completes the inspection before the maximum time has expired he/she can advance to the next carry-on item. Using the ACSS simulation model constructed, three primary sets of simulation experiments were conducted. The first set includes three experiments with multiple scenarios.

## **Experiment 1A:**

An evaluation of a paced ACSS system with a single inspector each at primary and secondary inspection stations. A series of eight scenarios were run for all three airport types where the primary inspection services times and percentages of carry-on items sent to secondary inspection are varied according to the SIOC curve data. All other experiments' performance results are compared to those found in this set.

# **Experiment 1B:**

An evaluation of the relative benefits of a Type-A SIOC curve improvement strategy where there is a 20% reduction in beta or the percentage of carry-on items sent to secondary inspection.

# **Experiment 1C:**

An evaluation of the relative benefits of a Type-B SIOC curve improvement strategy where there is a 20% reduction in beta or the percentage of carry-on items sent to secondary inspection.

In experiments 1B and 1C the reduction is not in beta-max but in beta-base, which is set to  $\tau$ =8 seconds for both large and medium airport types since the global inspection mean is a little more than 7 seconds. For small airports the base is set to 6 seconds. The argument is that a vendor will promise a reduction in the average inspection time.

The second set of experiments repeats experiment 1A, but varies the number of TSOs and stations at both primary and secondary inspection. The performance results are compared to those found in experiment 1A. The second set also includes three experiments with multiple scenarios each.

## **Experiment 2A:**

An evaluation of a paced ACSS system with two primary inspection stations and a single secondary inspection station. In this experiment the arrival rate ( $\lambda$ ) is set to twice the base rate used in experiment 1A.

#### **Experiment 2B:**

An evaluation of a paced ACSS system with two primary inspection stations and two secondary inspection stations.

# **Experiment 2C:**

An evaluation of a paced ACSS system with three primary inspection stations and two secondary inspection stations. In this experiment the arrival rate ( $\lambda$ ) is set to three times the base rate used in experiment 1A.

The third experiment is a full scale evaluation of a paced ACSS system. This experiment also repeats the same set of scenarios run in experiment 1A, but adds realistic passenger screening service times and alarm rates at the WTMD and Hand Wanding stations. In all previous experiments, the WTMD and Hand Wand service rates were set very high in addition to a zero alarm rate so as to not be a hindrance to the flow of carryon item inspections.

The ACSS simulation model is a terminating system, where the system is studied only for a period of peak demand. In airports, there is typically a three-hour morning and evening peak period on weekdays between 5:00–8:00 A.M. and 3:00–7:00 P.M. Therefore, each simulation is set up to last for 3 hours or 180 minutes, and a simulation runs the 180 minute model for 100 repetitions using different random seeds for each run.

The number of replications required for each alternative simulation was based on the sequential stopping procedure specified by Law and Kelton (1991) to achieve a 95% confidence level. This procedure utilizes the equation:

$$\frac{t_{n-1,1-\alpha/2}(s)}{\overline{X}(\sqrt{n})}\tag{6.1}$$

where,  $\overline{X}$  = grand mean of individual replication means; n = number of replications; s = standard deviation of individual replication means;  $\alpha$  = alpha = 0.05; and t = t-value for n-1 degrees of freedom. Replications were conducted until the desired relative precision of 0.10 was obtained. A 95% confidence interval (CI) of the expected average passenger time in the system was then calculated based on the following:

95% CI = 
$$\bar{X} \pm t_{n}$$
, 0.975 $(\frac{s}{\sqrt{n}})$  (6.2)

The model's global time unit is in minutes. The results are fed to an Excel spreadsheet that keeps track of the performance measures of interest over repeated trials.

There were five performance measures of interest including the passenger wait times, the average and maximum queue length at both primary and secondary inspection stations, and the utilization of resources at both primary and secondary inspection. These performance measures were then used in determining system costs. The next sections provide greater detail on the input parameters used for each of the experiments in addition to reporting the performance results.

# 6.1 Evaluating a Paced ACSS System Design

Referring to the SIOC curve data plotted (see Figure 4.7) a small number of complicated, time-consuming cases are contributing disproportionately to overall inspection times. If these cases were diverted earlier to secondary inspections, then this would improve the throughput of the primary inspection process, although naturally this would require that more resources be devoted to secondary inspections.

To evaluate the approach quantitatively, three experiments, that is, 1A, 1B and 1C were set-up representing the different paced system design strategies mentioned above. Within each experiment are eight scenarios. Each scenario places a different maximum time limit for primary inspections of carry-on items in addition to varying the number of those diverted to secondary inspection. Additionally, each of the three experiments is run for all three airport hub types resulting in a total of seventy-two experimental runs (3 experiments x 8 scenarios x 3 airport hub).

The rest of this section is divided into three sub-sections. The first discusses the input parameter values and provides the results from experiment 1A. The second sub-section reports on the same for experiments 1B and 1C. The final sub-section reports on the comparison of experiment 1A with 1B and 1C, and describes any difference in the performance results between them.

# 6.1.1 Experiment 1A

Table 6.1 provides the input parameters values for the primary inspection paced inspection service time  $(\tau)$  and for the rejection rate  $(\beta)$  that was derived from the empirical SIOC curve data (refer to Table 4.1) for each scenario across all three airport hubs. For all other parameter values used in the simulation model see Appendix—Simulation Model Parameters.

The performance results for passenger wait times at both the primary and secondary inspection queues are shown in Table 6.2. The primary inspection average and maximum wait time data (in minutes) is generated by the simulation model. In the simulation, passengers join a FIFO queue upon entering the BagDrop sub-model (refer to Figure 5.4). This queue, in front of the X-ray unit, is where passengers wait to send their carry-on items and personal belongings into the X-ray. Each simulation is run 100 times, and at the end of each run the wait time data is captured and fed into an Excel spreadsheet. The results reported in the table are the average value calculated from all 100 runs.

The secondary inspection average and maximum wait time data (in minutes) is also generated by the simulation and calculated in the same manner as the primary inspection wait times. In the Secondary Inspection sub-model (refer to Figure 5.7)

passengers with their carry-on items enter a queue waiting for the TSO to pick up their bags and carry them over to either the ETD or physical hand search table. Since there is only one TSO performing secondary inspections the number of passengers allowed into the section of the model is restricted.

 Table 6.1
 Experiment 1A Input Parameter Values

Airport Type	Scenario ID	Inspection Time (sec) $(\tau)$	Rejection Rate (β)
	LT5	5.00	47.84%
	LT6	6.00	38.04%
	LT7	7.00	30.06%
Large	LT8	8.00	25.05%
Large	LT10	10.00	16.52%
	LT13	13.00	10.09%
	LT17	17.00	5.45%
	LT20	20.00	2.90%
	MT5	5.00	48.58%
Medium	MT6	6.00	37.59%
	MT7	7.00	30.45%
	MT8	8.00	24.83%
	MT11	11.00	14.53%
	MT13	13.00	10.55%
_	MT17	17.00	5.59%
	MT20	20.00	2.85%
	ST3	3.00	59.73%
	ST4	4.00	47.84%
	ST5	5.00	34.79%
Small	ST6	6.00	26.96%
Siliali	ST8	8.00	15.12%
	ST10	10.00	10.41%
	ST16	16.00	3.18%
	ST20	20.00	2.47%

Table 6.2 also shows the mean average wait time ( $W_E$ ) and the mean waiting cost ( $C_W$ ), where the unit waiting time cost for a passenger is assumed to be \$0.17 per minute (\$/min) or \$10 per hour. In this system the mean average wait time is derived as  $W_E = W_1 + W_2$ , where  $W_1 + W_2$  are the primary inspection and secondary inspection average waiting times. The mean waiting cost reported in the table does not include the cost of service. It is derived by multiplying together the assumed waiting cost (\$10/Hour), the arrival rate ( $\lambda$ ), and the mean average wait time ( $W_E$ ).

As shown in Figures 6.1 through 6.3 the results were plotted for each of the airport hubs. From the figures it can be seen that at lower (faster) paced inspection times the average primary inspection wait times are less than the 10 minute goal. However, because more carry-on items are diverted to secondary inspection, the overall performance of the system results in higher waiting costs. Limiting the primary inspection maximum time to 5 seconds results in a 39% cost increase over a maximum inspection time of 13 seconds, and 80% at 20 seconds at for both large and medium hub airports. In the case of small airports, none of the paced inspection times resulted in average primary inspection wait times above 10 minutes. However, because more carry-on items are diverted to secondary inspection at faster inspection times as in both large and medium hub airports, the system costs are also much higher at lower (faster) paced inspection times. Limiting the primary inspection maximum time to 3 seconds results in a 51% cost increases over a maximum inspection time of 10 seconds, and a 96% increase at 20 seconds.

 Table 6.2
 Experiment 1A Passenger Wait Times with Mean Waiting Costs Results

	•	Waiting	Cost (\$/Hr)	\$1,257.34	\$982.87	\$774.91	\$659.74	\$502.51	\$438.99	\$426.39	\$440.26	\$1,248.55	\$947.75	\$767.38	\$630.58	\$443.03	\$425.45	\$398.59	\$436.74	\$1,278.43	\$1,010.13	\$697.23	\$513.75	\$234.08	\$122.53	\$43.61	\$59.15
Mean Average Wait	Time at PI and SI Qs	Combined	(minutes)	36.80	28.77	22.68	19.31	14.71	12.85	12.48	12.89	37.09	28.15	22.79	18.73	13.16	12.64	11.84	12.97	44.34	35.03	24.18	17.82	8.12	4.25	1.51	2.05
SI Queue	Maximum	Wait Time	(minutes)	149.91	144.48	138.91	133.13	113.62	74.69	17.34	5.59	149.66	144.62	139.29	131.80	103.99	78.64	18.11	5.40	148.61	146.60	137.87	130.49	102.94	72.59	6.47	4.57
SI Queue	Average	Wait Time	(minutes)	74.69	71.85	69.36	66.33	56.46	36.37	6.94	1.09	74.42	71.93	69.23	65.49	51.67	39.11	7.29	1.06	74.05	72.98	69.02	65.22	51.52	35.78	1.39	0.82
PI Queue	Maximum	Wait Time	(minutes)	6.32	6.82	7.28	9.37	14.44	21.68	27.22	28.36	5.99	6.01	7.23	8.67	14.52	20.26	25.21	27.74	2.58	2.42	2.50	2.80	2.86	3.64	5.67	6.79
PI Queue	Average	Wait Time	(minutes)	2.05	2.32	2.62	3.59	6.44	10.21	12.80	13.24	1.81	1.78	2.46	3.28	6.61	9.51	12.11	13.32	0.27	0.23	0.26	0.32	0.39	0.59	1.52	2.08
	•	Scenario	П	LTS	LT6	LT7	LT8	LT10	LT13	LT17	LT20	MT5	MT6	MT7	MT8	MT11	MT13	MT17	MT20	ST3	ST4	ST5	ST6	ST8	ST10	ST16	ST20
	•	Airport	Type				_	Large				•			A C. J	Medium				1			Small				

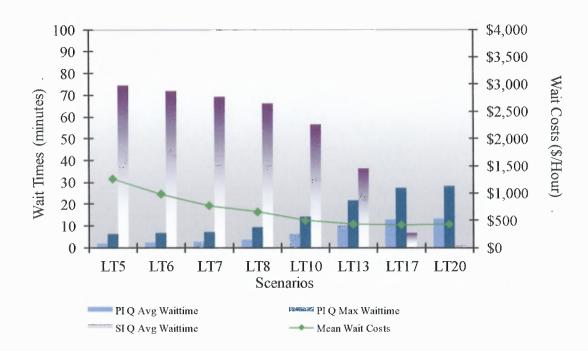


Figure 6.1 Experiment 1A passenger wait times for large hub airport.

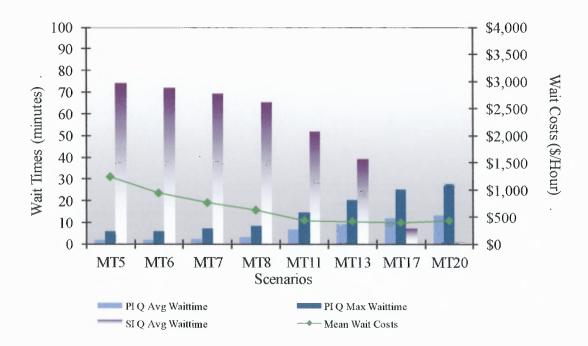


Figure 6.2 Experiment 1A passenger wait times for medium hub airport.

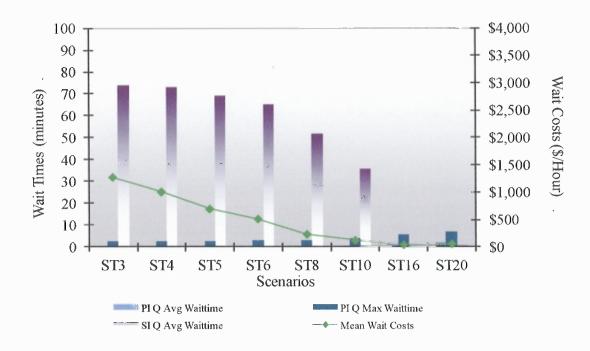


Figure 6.3 Experiment 1A passenger wait times for small hub airport.

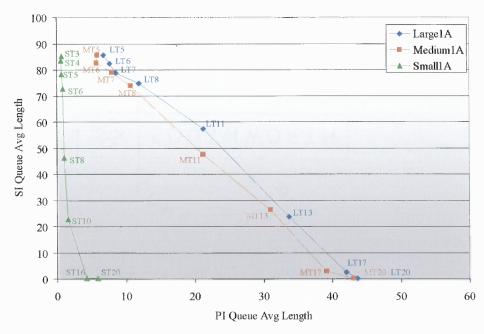
The data also suggests as was noted earlier (refer to Figure 4.1 and 4.2) that inspection times beyond 13 seconds for both large and medium hubs should result in carry-on items being automatically diverted to secondary inspection, and 10 seconds for small hubs primarily because the last 10% of carry-on items is taking up approximately 20% of the total inspection time.

The performance results for average and maximum queue lengths are shown in Table 6.3. As with the wait times, the primary and secondary inspection average and maximum queue length data is also generated by the simulation model using the same FIFO queue block in both the BagDrop sub-model (refer to Figure 5.4) and in the Secondary Inspection sub-model (refer to Figure 5.7). All results shown were calculated in the same manner by averaging the numbers from all 100 simulation runs.

**Table 6.3** Experiment 1A Average and Maximum Queue Lengths at Primary and Secondary Inspection

		PI Queue Average	PI Queue Maximum	SI Queue Average	SI Queue Maximum
Airport Type	Scenario ID	Length	Length	Length	Length
	LT5	6.80	21.98	85.72	100.00
	LT6	7.69	23.50	82.46	100.00
	LT7	8.60	24.42	78.75	100.00
T	LT8	11.92	31.49	74.78	100.00
Large	LT10	21.23	47.51	57.40	99.62
	LT13	33.70	71.65	23.87	49.58
	LT17	42.06	89.11	2.53	7.37
	LT20	43.63	94.69	0.22	2.63
•	MT5	5.95	20.35	85.57	100.00
	MT6	5.80	20.63	82.51	100.00
	MT7	8.09	24.70	79.03	100.00
Modium	MT8	10.72	28.72	73.85	100.00
Medium	MT11	21.28	47.21	47.64	94.18
	MT13	31.01	65.66	26.24	53.13
	MT17	39.15	81.83	2.74	7.70
	MT20	43.11	88.49	0.21	2.39
	ST3	0.75	9.02	85.14	100.00
	ST4	0.65	8.36	83.56	100.00
	ST5	0.73	8.72	78.29	100.00
Small	ST6	0.91	9.55	72.70	100.00
	ST8	1.09	9.53	46.35	91.34
	ST10	1.64	11.71	22.88	47.77
	ST16	4.27	17.19	0.30	2.88
	ST20	5.91	20.07	0.14	2.14

The results were plotted as shown in Figure 6.4 for each of the airport hub types. The figure shows secondary inspection average queue length as a function of primary inspection average queue length. Not surprisingly, at lower (faster) paced inspection times, the average secondary inspection queue length is large compared to those at higher (slower) inspection times because more carry-on items are diverted to secondary inspection.



**Figure 6.4** Experiment 1A queue length results for all airport types.

Table 6.4 shows the overall resource utilization, the percentage of time the TSO at the X-ray machine in the simulation was in use over the course of the simulation run. The primary inspection average utilization data is collected in the X-ray sub-model (refer to Figure 5.5) in the Activity Delay block, which processes the carry-on items for a specified time or delay that is the amount of time it takes an X-ray TSO to inspect an X-ray image and make a decision to either clear the carry-on item or to send it to secondary inspection for further scrutiny.

The percentage of time the TSO is busy at secondary inspection represents the average for both ETD and Hand Search processing combined since only one passenger with their carry-on items at a time are restricted in this section. The information is captured in the Secondary Inspection sub-model (refer to Figure 5.7). In the sub-model the Select block is used to determine which type of secondary inspection is conducted. The dialog sets a random probability of 80% for carry-on items to undergo ETD

processing leaving a 20% probability that carry-on items will undergo physical hand search. These percentages reflect TSA standard operating procedures indicating more emphasis on using ETD to find explosives in carry-on items.

 Table 6.4
 Experiment 1A Resource Utilization Results

		PI Average	SI Average	
		Utilization	Utilization	
Airport Type	Scenario ID	(minutes)	(minutes)	
	LT5	0.513	0.996	
	LT6	0.570	0.995	
	LT7	0.614	0.995	
Taras	LT8	0.646	0.994	
Large	LT10	0.684	0.991	
	LT13	0.703	0.985	
	LT17	0.716	0.876	
	LT20	0.721	0.500	
•	MT5	0.513	0.996	
Medium	MT6	0.572	0.996	
	MT7	0.618	0.995	
	MT8	0.650	0.994	
	MT11	0.696	0.990	
	MT13	0.710	0.988	
	MT17	0.721	0.876	
	MT20	0.727	0.489	
•	ST3	0.275	0.997	
	ST4	0.336	0.996	
	ST5	0.384	0.995	
Small	ST6	0.425	0.994	
	ST8	0.477	0.991	
	ST10	0.513	0.985	
	ST16	0.570	0.543	
	ST20	0.587	0.417	

The data reveals that as the primary inspection times increase from lower (faster) to higher (slower), the TSO's utilization gradually increased from 50% to 70% never moving beyond 72% for both large and medium airports. For small airports the average utilization rate is between 27% and 58%. Additionally, for all airport types, the TSO at

secondary inspection is busy almost (98%) all the time except at the highest (slowest) paced primary inspection time, that is, 20 seconds. Utilization rates are an important factor in checkpoint design. While not a part of this study, it is believed that TSO performance improvement can be achieved because there is opportunity for the TSOs to move between primary and secondary inspection stations. Thus, shorter periods of time at one station could increase vigilance in addition to preventing fatigue problems noted in the literature to be an issue as a result of viewing X-ray images for long periods of time.

In analyzing the different design alternatives, system throughput was also considered as an important performance measure. System throughput is defined as the number of passengers the system completes per unit time. For example, during the observation period of length T, in this case equal to 1 hour, the system completes C passengers, throughput X is measured as C/T. The simulation model captures the number of passengers completing the process in the Exit sub-model after each simulation run, which is then fed to the Excel spreadsheet.

Table 6.5 reports the average system throughput number from all 100 simulation runs, in addition to showing the percentage of improvement in cost (\$/Hour) over betabase for each of the three different airport types. The system throughput numbers are plotted in Figure 6.5 as a function of costs for the different airport types.

The data reveals a significant increase (73–76%) in throughput moving from the lower (faster) base scenario of  $\tau$ =8 seconds to higher (slower) primary inspection times and a gradual increase in cost savings (10–77%). Interestingly, for all three airport types, the best overall throughput was not achieved at the highest (slowest) paced inspection time, but at the next level up. For example, at  $\tau$ =17 and  $\tau$ =20 seconds, the throughput at

large hub airports was 173 and 172 pphpl, respectively. TSA's goal is to increase the average throughput to 200 pphpl (Boggus and Frankel, 2007).

**Table 6.5** Experiment 1A System Throughput and Total Cost Results for All Airport Types

A:	C : -	System	Total		0/
Airport	Scenario	Throughput	System Cost	Cost	%
Type	<u>ID</u>	(Pax/Hour)	(\$/Hour)	Reduction	Change
	LT5	75	\$1,339.55	-\$597.60	-80.54%
	LT6	95	\$1,065.07	-\$323.12	-43.55%
	LT7	114	\$857.12	-\$115.17	-15.52%
Large	LT8	127	\$741.95	n/a	n/a
Large	LT10	150	\$584.72	\$157.23	21.19%
	LT13	165	\$521.20	\$220.75	29.75%
	LT17	173	\$508.60	\$233.35	31.45%
	LT20	172	\$522.46	\$219.48	29.58%
_	MT5	73	\$1,330.76	-\$617.98	-86.70%
	MT6	95	\$1,029.95	<b>-\$</b> 317.17	-44.50%
	MT7	112	\$849.58	-\$136.80	-19.19%
Medium	MT8	127	\$712.78	n/a	n/a
Mediuiii	MT11	152	\$525.24	\$187.54	26.31%
	MT13	163	\$507.65	\$205.13	28.78%
	MT17	173	\$480.79	\$231.99	32.55%
	MT20	172	\$518.94	\$193.84	27.19%
_	ST3	52	\$1,360.63	-\$764.68	-128.31%
	ST4	67	\$1,092.34	-\$496.38	-83.29%
	ST5	91	\$779.43	-\$183.47	-30.79%
Small	ST6	109	\$595.96	n/a	n/a
	ST8	141	\$316.28	\$279.68	46.93%
	ST10	155	\$204.73	\$391.23	65.65%
	ST16	170	\$125.81	\$470.15	78.89%
	ST20	169	\$141.35	\$454.61	76.28%

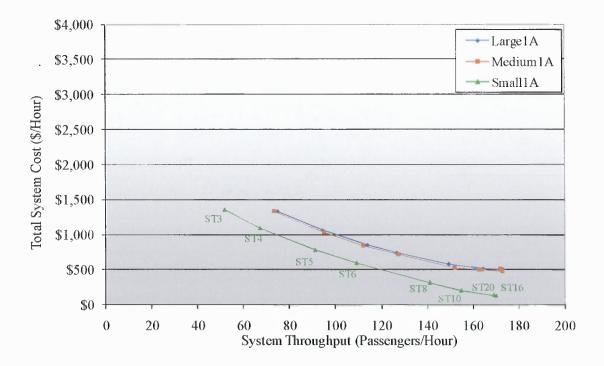


Figure 6.5 Experiment 1A total system costs as a function of system throughput for all airport types.

# 6.1.2 Experiments 1B and 1C - Relative Benefits of Improving Service Rates with SIOC Curve Data

The visualization of the interrelationship between the inspection speed and rejection rate was facilitated by the use of the SIOC curve (refer to Figure 4.7). Accordingly, the regression functions fitted (refer to Figure 4.8) are considered here for possible improvement strategies of the SIOC curve data.

In experiments 1B and 1C, an evaluation of the relative benefits of Type-A and Type-B improvement strategies (refer to Figure 4.4) is performed. However, a 20% reduction in the percentage of carry-on items sent to secondary inspection is considered in beta-base rather than in beta-max reflecting a more probable situation where one looks at reducing the average inspection time. Since the global inspection mean is a little more

than 7 seconds for both large and medium airport types, beta-base is set to  $\tau$ =8 seconds. For small airports the base is set to 6 seconds. Strategy A should be better at higher inspection rates or smaller  $\tau$ , while Strategy B should be better at slower rates or higher  $\tau$ . Using the fitted regression function, the model rejection rate ( $\beta_r$ ) was derived as:

$$\beta_r = A + (B*Rate) \tag{6.3}$$

Where:

 $\beta_r$  = regression model rejection rate

A =the regression model intercept

B = the regression coefficient or slope

The Rate is the inspection rate ( $\mu$ ), which is defined at  $60/\tau$ . The Type-A and Type-B rejection rates ( $\beta_b$  and  $\beta_c$ ), respectively, shown in Table 6.6 were then derived as:

$$\mathbf{R}_{\mathrm{BB}} = 0.8 * \beta_{\mathrm{r}} \tag{6.4}$$

and,

$$\beta_b \text{ or } \beta_c = R_{BB} + ((\mu_i - \mu_{BB}) * L)$$
 (6.5)

Where:

 $\mu_i$  = rate at inspection time interval i

 $\mu_{BB}$  = rate at beta-base

L = linear slope

The linear slope was derived as:

$$L = (R_{BB} - R_m)/(\mu_i - \mu_{BB})$$
 (6.6)

Where:

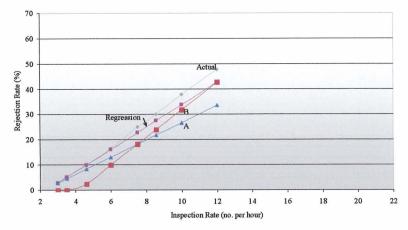
 $R_m$  = regression model rejection rate

For Type-A the rejection rate  $(R_m)$  is set at  $\tau$ =20 seconds, and at  $\tau$ =3 seconds for the Type-B strategy. Using the generated linear model of the SIOC curve data improvement cured for the two strategies—Type A and B—were also generated. For

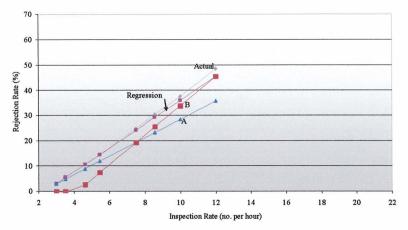
example, for large hub airports the linear model would be  $\beta=0.051(60/\mu)-0.128$ . Figures 6.6 through 6.8 plot the SIOC curves for the actual, regression model, and Type-A and B improvement strategies that were generated from the calculations showing the rejection rates as a function of inspection rates.

 Table 6.6
 Experiment 1B and 1C Input Parameter Values

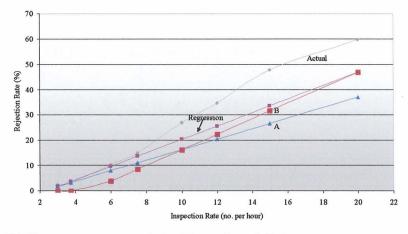
Airport	Scenario	Inspection	•	1C - Rejection
Type	ID	Time $(\tau)$ sec	Rate (β <sub>b</sub> )	Rate (β <sub>c</sub> )
	LT5	5.00	33.58%	42.70%
	LT6	6.00	26.76%	31.83%
	LT7	7.00	21.89%	24.06%
Largo	LT8	8.00	18.23%	18.23%
Large	LT10	10.00	13.11%	10.08%
	LT13	13.00	8.39%	2.55%
	LT17	17.00	4.69%	0.00%
	LT20	20.00	2.88%	0.00%
Medium	MT5	5.00	35.77%	45.47%
	MT6	6.00	28.48%	33.87%
	MT7	7.00	23.28%	25.59%
	MT8	8.00	19.38%	19.37%
	<b>M</b> T11	11.00	11.92%	7.52%
	MT13	13.00	8.87%	2.65%
	MT17	17.00	4.91%	0.00%
	MT20	20.00	2.98%	0.00%
<del></del> -	ST3	3.00	37.04%	46.92%
Small	ST4	4.00	26.66%	31.60%
	ST5	5.00	20.43%	22.41%
	ST6	6.00	16.28%	16.28%
Sillali	ST8	8.00	11.09%	8.62%
	ST10	10.00	7.89%	4.02%
	ST16	16.00	3.31%	0.00%
	ST20	20.00	1.75%	0.00%



**Figure 6.6** SIOC curves generated for Type-A and B improvement strategies for large hub airports.



**Figure 6.7** SIOC curves generated for Type-A and B improvement strategies for medium hub airports.



**Figure 6.8** SIOC curves generated for Type-A and B improvement strategies for small hub airports.

The performance results for experiments 1B and 1C for passenger wait times at both the primary and secondary inspection queues are shown in Tables 6.7 and 6.8, respectively. These tables report  $W_E$  and  $C_W$ , where the unit waiting time cost for a passenger is assumed (imputed cost of waiting) to be \$0.17 per minute (\$\frac{1}{2}\text{min}) or \$10 per hour as it was in experiment 1A. Additionally, in these experiments, the mean average wait time is derived the same as was in experiment 1A, that is,  $W_E = W_1 + W_2$ , where  $W_1 + W_2$  are the primary inspection and secondary inspection average waiting times.

The results were plotted as shown in Figures 6.9 through 6.11 for each of the airport hub types. From the figures it can be seen that at lower (faster) paced inspection times the average primary inspection wait times are less than the 10 minute goal. However, as in experiment 1A, the overall performance of the system results in higher costs because more carry-on items are diverted to secondary inspection. Limiting the primary inspection maximum time to 5 seconds, results in a 47% and 43% cost increases over a maximum inspection time of 13 seconds for both large and medium hub airports, respectively, and 78% and 80% at 20 seconds in experiment 1B. In the case of experiment 1C, there is an 18% cost reduction moving from faster inspection speeds to slower inspection speeds. Thus, suggesting that a Type-A strategy performed better at higher inspection rates, while better performance is shown at slower rates for Type-B.

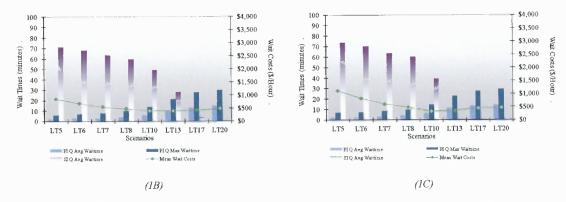
For small airports, none of the paced inspection times resulted in average primary inspection wait times above 10 minutes. However, because more carry-on items are diverted to secondary inspection at faster inspection times as in both large and medium hub airports, the overall performance of the system results in higher costs at faster inspection times.

Table 6.7 Experiment 1B Passenger Wait Times and Mean Waiting Cost Results for All Airport Types

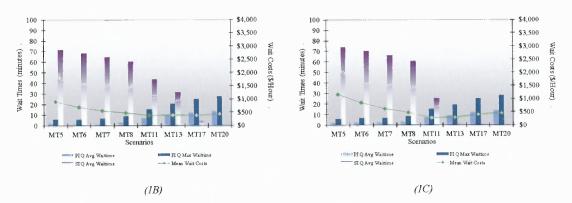
Airport Scenario  Type ID  LT5  LT6  LT7  Large LT8  LT10  LT110  LT117  LT17  LT17  LT17  LT17  LT17	Average io Wait Time (minutes) 1.86 2.70 2.91 4.05 6.11	Maxi	Average Wait Time (minutes) 71.21	Maximum Wait Time	Time at PI and SI Qs	Waiting
t a	· 1		Time (minutes)	Time	Combined	
ω			(minutes)			Cost
			71.21	(minutes)	(minutes)	(\$'Hour)
				142.61	25.14	\$859.12
			67.93	136.11	20.15	\$688.61
			63.64	128.15	16.20	\$553.54
			59.60	119.62	14.18	\$484.35
LT13 LT17 LT20 MT5 MT6			49.23	99.25	11.76	\$401.93
LT17 LT20 MT5 MT6			27.92	56.30	11.70	\$399.70
LT20 MT5 MT6		27.64	4.00	12.30	12.56	\$429.19
MTS MT6		30.34	1.04	5.32	14.18	\$484.50
MT6		6.07	71.53	143.88	26.80	\$902.41
MT7		5.73	68.20	137.20	20.64	\$694.83
TTAT		92.9	64.87	130.48	16.74	\$563.50
Medium MT8		8.79	60.18	121.97	14.38	\$484.23
MTI		15.32	43.86	89.25	11.35	\$382.27
MT13		20.76	31.65	63.24	11.65	\$392.38
MT17		25.18	4.29	12.78	11.38	\$383.23
MT20		27.71	1.09	5.33	12.94	\$435.58
ST3		2.48	70.07	140.78	26.12	\$753.12
ST4		2.54	64.96	130.12	17.53	\$505.41
STS		2.38	58.14	117.38	12.08	\$348.28
Small ST6		2.60	54.14	108.43	90.6	\$261.15
ST8		2.85	39.02	78.59	4.65	\$134.01
ST10		3.52	22.38	45.24	2.28	\$65.69
ST16		5.51	1.37	6.34	1.45	\$41.67
ST20		6.70	0.51	3.20	2.04	\$58.70

 Table 6.8
 Experiment 1C Passenger Wait Times and Mean Waiting Costs Results for All Airport Types

	PI Queue	PI Queue	SI Queue	SI Queue	Mean Average Wait	
	Average	Maximum	Average	Maximum	Time at PI and SI Qs	Waiting
Scenario	Wait Ime	Wait Time	Wait Time	Wait Time	Combined	Cost
	2.45	7.01	72 70	147.02	22.01	(4/110til)
	0.4 0.4 0.4 0.4 0.4 0.4	7.13	70.75	147.65	34.91	\$1,124.33 \$021.63
1 T7	2. <del>1</del> 5	8.30	63.80	128 50	CT 7.1	\$605.30
	7.7	90.0	50.05	120.15	17.72	6467.10
	4.07	7.70	39.90	70.13	14.20	01.70
$\overline{}$	6.41	14.56	39.30	79.36	9.73	\$332.40
~	10.97	22.93	0.99	5.12	10.71	\$366.10
_	13.13	27.80	0.00	0.00	13.13	\$448.65
	13.94	29.40	0.00	0.00	13.94	\$476.27
		5.91	73.94	148.10	34.58	\$1,164.26
		9.90	70.57	141.55	25.37	\$854.03
_	2.17	69.9	66.30	133.11	18.58	\$625.51
		8.28	60.75	122.13	14.33	\$482.31
<del></del>		15.65	25.30	50.29	8.47	\$285.18
3		19.36	1.03	5.33	8.76	\$294.97
7		25.45	0.00	0.00	12.04	\$405.44
0		28.55	0.00	0.00	13.73	\$462.31
		2.36	72.66	145.55	34.22	\$986.79
		2.34	67.62	135.54	21.52	\$620.55
		2.57	60.72	121.98	13.82	\$398.38
	0.30	2.67	53.16	106.63	8.91	\$256.82
	0.50	3.37	27.90	55.76	2.86	\$82.60
_	0.57	3.50	2.70	69.6	0.65	\$18.88
	1.60	5.93	0.00	0.00	1.60	\$46.17
_	2.30	7.10	00.00	0.00	2.30	\$66.40



**Figure 6.9** Passenger wait times at large hub airports for experiments 1B and 1C.



**Figure 6.10** Passenger wait times at medium hub airports for experiments 1B and 1C.

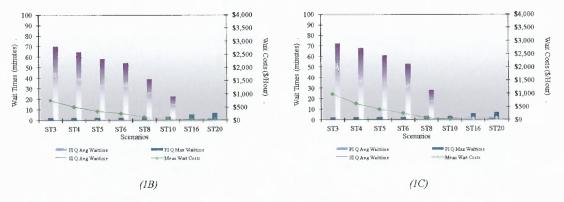


Figure 6.11 Passenger wait times at small hub airports for experiments 1B and 1C.

The data also suggests as was noted earlier that paced inspection times beyond 13 seconds for both large and medium hubs should result in carry-on items being automatically diverted to secondary inspection because the primary inspection average wait times increase above the 10-minute wait goal, and 10 seconds for small hubs.

The performance results for the average and maximum queue lengths for experiments 1B and 1C are shown in Table 6.9 and 6.10, respectively, and plotted in Figures 6.12 and 6.13 for each of the airport hub types. As with experiment 1A, all results shown were calculated in the same manner by averaging the numbers from all 100 simulation runs.

Figures 6.12 and 6.13 also show secondary inspection average queue length as a function of primary inspection average queue length. Not surprisingly, at lower (faster) paced inspection times, the average secondary inspection queue length is large compared to those at higher (slower) inspection times because more carry-on items are diverted to secondary inspection.

**Table 6.9** Experiment 1B Average and Maximum Queue Lengths at Primary and Secondary Inspection for All Airport Types

		PI Queue	PI Queue	SI Queue	SI Queue
Airport	Scenario	Average	Maximum	Average	Maximum
Type	ID	Length	Length	Length	Length
	LT5	6.16	20.99	81.30	100.00
	LT6	9.03	25.15	76.84	100.00
	LT7	9.66	26.87	71.00	100.00
Larga	LT8	13.51	34.13	63.53	100.00
Large	LT10	20.10	45.46	42.32	85.03
	LT13	33.64	71.37	15.29	31.74
	LT17	42.82	91.21	1.28	5.08
	LT20	47.88	98.46	0.20	2.38
	MT5	6.22	20.80	81.98	100.00
	MT6	5.52	19.51	77.61	100.00
	MT7	6.92	23.25	72.69	100.00
Medium	MT8	11.09	29.20	65.53	100.00
Medium	MT11	22.48	49.77	34.25	71.87
	MT13	31.80	68.12	18.42	37.49
	MT17	38.24	81.94	1.44	5.48
	MT20	43.31	90.97	0.22	2.40
	ST3	0.74	8.69	79.75	100.00
	ST4	0.82	8.83	72.29	100.00
	ST5	0.71	8.13	61.93	100.00
Small	ST6	0.82	9.08	50.48	95.96
	ST8	1.01	9.39	26.61	53.99
	ST10	1.56	11.36	11.25	23.66
	ST16	4.10	16.76	0.30	2.85
	ST20	5.84	19.73	0.06	1.53

Table 6.10 Experiment 1C Average and Maximum Queue Lengths at Primary and Secondary Inspection for All Airport Types

		PI Queue	PI Queue	SI Queue	SI Queue
Airport	Scenario	Average	Maximum	Average	Maximum
Type	ID	Length	Length	Length	Length
	LT5	8.19	25.09	84.42	100.00
	LT6	8.25	24.44	80.21	100.00
	LT7	10.38	28.57	71.08	100.00
T	LT8	13.56	33.49	64.27	100.00
Large	LT10	21.24	48.52	27.15	55.84
	LT13	36.31	74.40	0.18	2.29
	LT17	43.44	91.43	0.00	0.00
	LT20	45.95	97.17	0.00	0.00
	MT5	5.79	20.53	84.71	100.00
	MT6	7.35	23.85	80.72	100.00
	<b>M</b> T7	7.10	22.68	74.85	100.00
3.5.11	MT8	10.37	27.74	66.02	100.00
Medium	MT11	23.08	50.96	13.08	26.54
	MT13	29.15	63.47	0.19	2.44
	MT17	39.12	82.95	0.00	0.00
	MT20	44.52	90.73	0.00	0.00
	ST3	0.69	8.40	83.10	100.00
	ST4	0.63	8.12	76.41	100.00
	ST5	0.76	8.92	65.84	100.00
Small	ST6	0.86	9.16	50.19	95.90
	ST8	1.44	11.26	15.35	31.84
	ST10	1.60	11.28	0.75	4.22
	ST16	4.55	18.14	0.00	0.00
	ST20	6.58	21.20	0.00	0.00

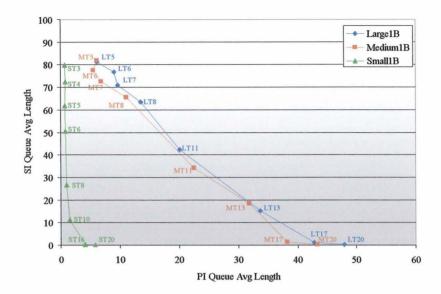


Figure 6.12 Experiment 1B queue length results for all airport types.

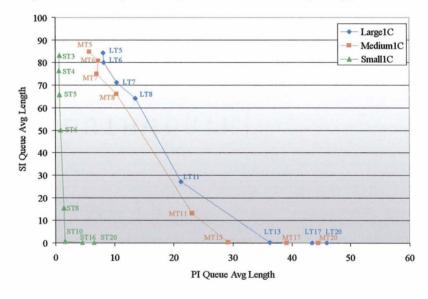


Figure 6.13 Experiment 1C queue length results for all airport types.

Table 6.11 shows the overall resource utilization results for both experiments 1B and 1C. The utilization data is collected and calculated in the same manner as in experiment 1A. Similar to experiment 1A, the data reveals that as the primary inspection times increase from lower (faster) to higher (slower), the TSO's utilization gradually increased from 50% to 70% never moving beyond 72% for both large and medium

airports. For small airports the average utilization rate is between 27% and 58%. The TSO at secondary inspection is also busy almost (99%) in the case for all three airport types except at the highest (slowest) paced primary inspection time, that is, 20 seconds. In the case of experiment 1C, since none of the carry-on items are rejected, the utilization rate is zero.

Table 6.11 Resource Utilization Results for Experiments 1B and 1C at All Airport Types

		Experin	nent 1B	Experin	nent 1C
		PI Average	SI Average	PI Average	SI Average
Airport	Scenario	Utilization	Utilization	Utilization	Utilization
Type	ID	(minutes)	(minutes)	(minutes)	(minutes)
	LT5	0.514	0.995	0.515	0.996
	LT6	0.572	0.995	0.571	0.995
	LT7	0.615	0.995	0.619	0.994
т	LT8	0.649	0.993	0.647	0.993
Large	LT10	0.686	0.989	0.685	0.986
	LT13	0.704	0.980	0.704	0.456
	LT17	0.716	0.784	0.718	0.000
	LT20	0.723	0.483	0.720	0.000
-	MT5	0.516	0.995	0.511	0.996
	MT6	0.570	0.995	0.575	0.995
	MT7	0.617	0.993	0.617	0.995
Medium	MT8	0.651	0.993	0.650	0.994
Medium	MT11	0.696	0.986	0.697	0.975
	MT13	0.710	0.979	0.708	0.474
	MT17	0.720	0.807	0.720	0.000
	MT20	0.726	0.498	0.726	0.000
-	ST3	0.274	0.995	0.275	0.996
	ST4	0.338	0.995	0.333	0.996
	ST5	0.383	0.993	0.383	0.994
Small	ST6	0.421	0.992	0.422	0.991
	ST8	0.476	0.986	0.483	0.981
	ST10	0.515	0.970	0.515	0.685
	ST16	0.572	0.557	0.571	0.000
	ST20	0.583	0.293	0.587	0.000

Table 6.12 reports the system throughput number for both experiments 1B and 1C for each of the different airport types. The results were calculated as was in experiment 1A by taking the average from all 100 simulation runs. This table also shows the percentage of improvement in cost (\$/Hour) over beta-base. The system throughput numbers are plotted in Figures 6.14 and 6.15 as a function of costs for the different airport types. For experiment 1B, the data reveals a 17% increase in throughput moving from the lower (faster) base scenario of  $\tau$ =8 seconds to higher (slower) speed at  $\tau$ =20 seconds with a gradual increase in cost savings (12–72%). For experiment 1C, there is an earlier cost savings from 27–75% moving from the base scenario to slower speeds with about the same percentage increase in throughput as in experiment 1B.

Table 6.12 Cost Results for both Experiments 1B and 1C across all Airport Types

Airport Scenario Throughput  Type D (Pax/Hour)  LT5 106  LT6 124  LT7 137  LT7 137  LT13 147  LT13 171  LT13 171  LT17 174  MT7 117  MT7 111  ST3 86  ST4 111  ST5 125  ST6 138  Small ST8 153  ST10 164		Experiment 1B	nt 1B			Experiment 1C	nt 1C	
D LT5 LT6 LT10 LT10 LT11 LT20 MT5 MT7 MT7 MT11 MT11 MT11 MT12 ST3 ST4 ST8 ST10 ST16		Total System	Cost	%	Throughput	Total System	Cost	%
LT5 LT6 LT7 LT8 LT10 LT113 LT17 LT20 MT5 MT6 MT7 MT7 MT11 MT11 MT111 MT112 ST3 ST4 ST5 ST6 ST8 ST16	ပိ	Cost (\$/Hour)	Reduction	Change	(Pax/Hour)	Cost (\$/Hour)	Reduction	Change
LT6 LT7 LT8 LT10 LT113 LT117 LT120 MT5 MT7 MT7 MT11 MT111 MT111 MT120 ST3 ST4 ST5 ST6 ST8 ST16		\$941.32	-\$374.76	-66.15%	85	\$1,206.74	-\$637.43	-111.97%
LT7 LT10 LT110 LT113 LT17 LT20 MT5 MT7 MT7 MT111 MT111 MT111 MT120 ST3 ST4 ST5 ST6 ST6 ST16 ST16		\$770.81	-\$204.26	-36.05%	110	\$903.83	-\$334.52	-58.76%
LT10 LT13 LT17 LT20 MT5 MT6 MT7 MT7 MT11 MT11 MT11 MT112 ST3 ST4 ST5 ST6 ST8 ST16 ST16		\$635.75	-\$69.19	-12.21%	138	\$687.60	-\$118.29	-20.78%
LT10 LT13 LT17 LT20 MT5 MT6 MT7 MT7 MT11 MT11 MT113 MT120 ST3 ST4 ST5 ST6 ST8 ST16 ST16		\$566.56	n/a	n/a	147	\$569.30	n/a	n/a
LT13 LT17 LT20 MT5 MT6 MT7 MT7 MT11 MT11 MT11 MT120 ST3 ST4 ST5 ST6 ST8 ST16		\$484.13	\$82.43	14.55%	171	\$414.60	\$154.70	27.17%
LT17 LT20 MT5 MT6 MT7 MT11 MT11 MT13 MT13 MT17 ST3 ST4 ST5 ST6 ST8 ST16 ST16		5481.90	\$84.66	14.94%	181	\$448.30	\$121.00	21.25%
LT20 MT5 MT6 MT7 MT11 MT11 MT11 MT20 ST3 ST3 ST4 ST5 ST6 ST8 ST16		\$511.39	\$55.17	9.74%	174	\$530.85	\$38.45	6.75%
MT5 MT6 MT7 MT8 MT11 MT13 MT20 ST3 ST4 ST5 ST6 ST8 ST16		\$566.71	-\$0.15	-0.03%	172	\$558.48	\$10.82	1.90%
MT6 MT7 MT11 MT111 MT113 MT17 MT20 ST3 ST4 ST5 ST6 ST7 ST10 ST16		\$984.61	-\$418.17	-73.83%	79	\$1,246.47	-\$681.95	-120.80%
MT7 MT8 MT11 MT11 MT13 MT17 MT20 ST3 ST4 ST5 ST6 ST76 ST16 ST16		\$777.04	-\$210.60	-37.18%	104	\$936.24	-\$371.72	-65.85%
MT11 MT113 MT17 MT20 ST3 ST4 ST5 ST6 ST8 ST10 ST16		6645.70	-\$79.26	-13.99%	126	\$707.71	-\$143.20	-25.37%
MT11 MT13 MT20 ST3 ST4 ST5 ST6 ST8 ST10 ST16		5566.44	n/a	n/a	143	\$564.51	n/a	n/a
MT13 MT20 ST3 ST4 ST5 ST6 ST8 ST10 ST16		\$464.48	\$101.96	18.00%	178	\$367.38	\$197.13	34.92%
MT20 ST3 ST4 ST5 ST6 ST8 ST10 ST16		\$474.58	\$91.86	16.22%	181	\$377.18	\$187.34	33.19%
MT20 ST3 ST4 ST5 ST6 ST8 ST10 ST16		3465.44	\$101.00	17.83%	175	\$487.64	\$76.87	13.62%
ST3 ST4 ST5 ST6 ST6 ST8 ST8 ST10		\$517.78	\$48.66	8.59%	172	\$544.51	\$20.00	3.54%
ST5 ST6 ST6 ST8 ST10 ST16		\$835.32	-\$491.96	-143.28%	69	\$1,068.99	-\$729.96	-215.31%
ST5 ST6 ST8 ST10 ST10		\$587.62	-\$244.26	-71.14%	76	\$702.75	-\$363.72	-107.28%
ST6 ST8 ST10 ST16		\$430.49	-\$87.13	-25.38%	121	\$480.59	-\$141.56	-41.76%
ST8 ST10 ST16		\$343.36	n/a	n/a	138	\$339.03	n/a	n/a
		\$216.21	\$127.14	37.03%	163	\$164.81	\$174.22	51.39%
		\$147.90	\$195.46	56.93%	170	\$101.09	\$237.94	70.18%
	170	\$123.88	\$219.48	63.92%	170	\$128.38	\$210.65	62.13%
ST20 168		\$140.91	\$202.45	28.96%	169	\$148.60	\$190.43	56.17%

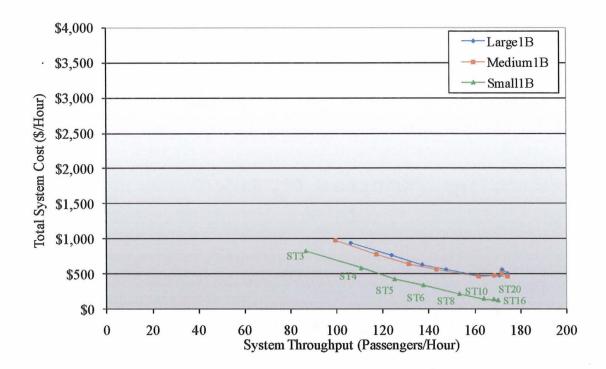


Figure 6.14 Experiment 1B total system costs as a function of system throughput for all airport types.

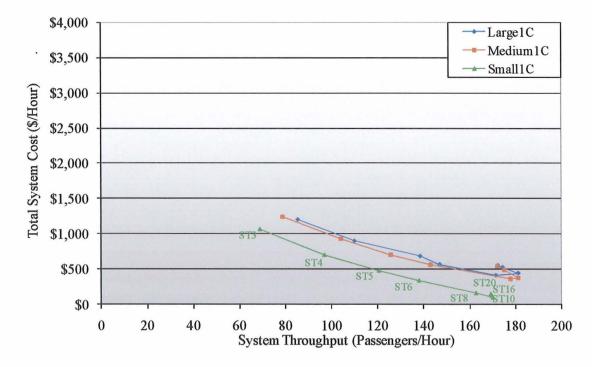


Figure 6.15 Experiment 1C total system costs as a function of system throughput for all airport types.

#### 6.1.3 Comparison of Results

This sub-section reports on the examination of performance results between experiment 1A and experiments 1B and 1C, where different strategies using SIOC curve data are simulated to determine improvements in the ACSS system design. The experiments completed using the simulation model constructed evaluated a paced ACSS system design. The base experiment, that is, 1A included a series of eight scenarios where the primary inspection times and percentages of carry-on items sent to secondary inspection were varied with a single inspector each at the primary and secondary inspection stations. The performance results are used to compare all other experiments results.

Table 6.13 shows the performance results in terms of total system costs (\$/Hour) across experiments 1A, 1B and 1C. It also shows the cost reduction and % change from that in experiment 1A for the different pace inspection times across all airports.

The results are plotted in Figures 6.16 and 6.17 for only large and small airports, respectively. Since they so closely match those of large hub airports, the results for medium hub airports are not shown. The figures plot the primary inspection queue average wait time (in minutes) as a function of the maximum allowable paced inspection time. The data reveals that the secondary inspection queue waiting time is most sensitive to an increasing inspection rate. There is also a sharp drop in the primary inspection queue waiting tie as the pace increases ( $\mu^{MAX}$ ) from 14 to 7 seconds. The overall waiting time is relatively flat in the 10 to 13 second range, so potentially a solution in this range is attractive.

The most significant difference in costs is shown at the paced primary inspection time of  $\tau=13$  seconds for both large and medium airports. For example, at  $\tau=13$  seconds a passenger's average wait time at primary inspection is 10.21 minutes for both experiments 1A and 1B, and 10.97 minutes under experiment 1C, while the total system costs is \$521.20, \$481.90 and \$448.30 for experiments 1A, 1B and 1C, respectively. There is an 8% cost improvement between experiment 1A and 1B, and 14% cost improvement between 1A and 1C. Thus, overall improvements to the ACSS system can be achieved by limiting the inspection time, especially at  $\tau=13$  seconds. Limiting the inspection time to  $\tau=13$  seconds not only resulted in a cost savings while still meeting TSA's wait time goal at primary inspection of 10 minutes or less. A 70% cost savings could be achieved if the percentage of carry-on items sent to secondary inspection can be reduced from 8.4% to 2.6% at both large and medium type airports. Additionally, passenger wait times at small airports did not exceed the 10-minute threshold, but a 34% cost savings results in limiting the inspection time to  $\tau$ =10 seconds. An 84% savings could be achieved if the percentage of carry-on items sent to secondary inspection can be reduced from 8% to 4%.

As shown in Figure 6.17 both improvement strategies had a significant effect on reducing the overall waiting time. Convexities also appear revealing an optimal pace.

Table 6.13 Comparison of Cost Performance Results for Experiment 1 Sub-Experiments across All Airport Hubs

	%	Change	9.91%	15.14%	19.78%	23.27%	29.09%	13.99%	-4.38%	%68.9-	6.33%	9.10%	16.70%	20.80%	30.05%	25.70%	-1.42%	-4.93%	21.43%	35.67%	38.34%	43.11%	47.89%	50.62%	-2.04%	-5.13%
Experiment 1C	Cost	Reduction	\$132.81	\$161.24	\$169.52	\$172.65	\$170.12	\$72.89	-\$22.25	-\$36.01	\$84.29	\$93.72	\$141.87	\$148.27	\$157.86	\$130.48	-\$6.85	-\$25.57	\$291.64	\$389.59	\$298.84	\$256.93	\$151.47	\$103.64	-\$2.57	-\$7.25
Ex	Total Cost	(\$/Hour)	\$1,206.74	\$903.83	\$687.60	\$569.30	\$414.60	\$448.30	\$530.85	\$558.48	\$1,246.47	\$936.24	\$707.71	\$564.51	\$367.38	\$377.18	\$487.64	\$544.51	\$1,068.99	\$702.75	\$480.59	\$339.03	\$164.81	\$101.09	\$128.38	\$148.60
	%	Change	29.73%	27.63%	25.83%	23.64%	17.20%	7.54%	-0.55%	-8.47%	26.01%	24.56%	24.00%	20.53%	11.57%	6.51%	3.19%	0.22%	38.61%	46.21%	44.77%	42.39%	31.64%	27.76%	1.54%	0.31%
Experiment 1B	Cost	Reduction	\$398.23	\$294.26	\$221.37	\$175.39	\$100.59	\$39.29	-\$2.79	-\$44.24	\$346.15	\$252.91	\$203.88	\$146.34	\$60.76	\$33.07	\$15.36	\$1.16	\$525.31	\$504.72	\$348.95	\$252.60	\$100.07	\$56.83	\$1.93	\$0.44
Ex	Total Cost	(\$/Hour)	\$941,32	\$770.81	\$635.75	\$566.56	\$484.13	\$481.90	\$511.39	\$566.71	\$984.61	\$777.04	\$645.70	\$566.44	\$464.48	\$474.58	\$465.44	\$517.78	\$835.32	\$587.62	\$430.49	\$343.36	\$216.21	\$147.90	\$123.88	\$140.91
Experiment 1A	Total Cost	(\$/Hour)	\$1,339.55	\$1,065.07	\$857.12	\$741.95	\$584.72	\$521.20	\$508.60	\$522.46	\$1,330.76	\$1,029.95	\$849.58	\$712.78	\$525.24	\$507.65	\$480.79	\$518.94	\$1,360.63	\$1,092.34	\$779.43	\$595.96	\$316.28	\$204.73	\$125.81	\$141.35
	Scenario	О	LT5	LT6	LT7	LT8	LT10	LT13	LT17	LT20	MT5	MT6	MT7	MT8	MT11	MT13	MT17	MT20	ST3	ST4	ST5	ST6	ST8	ST10	ST16	ST20
	Airport	Type				1	Large							Modina	Moduli							Small				

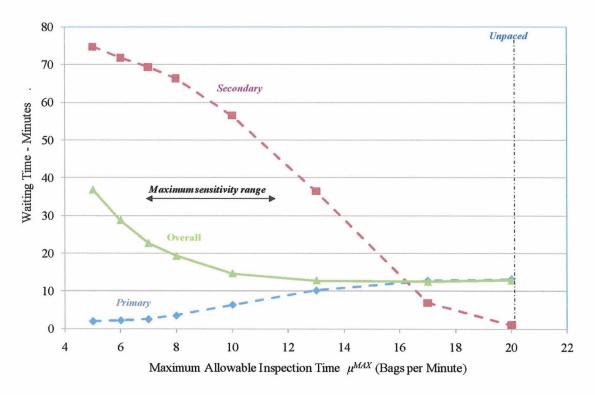


Figure 6.16 Summary of experiment 1A results for large hub airports.

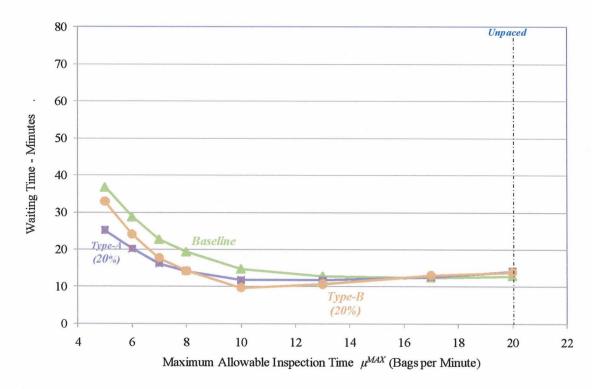


Figure 6.17 Comparison of experiments 1A, 1B and 1C results for large hub airports.

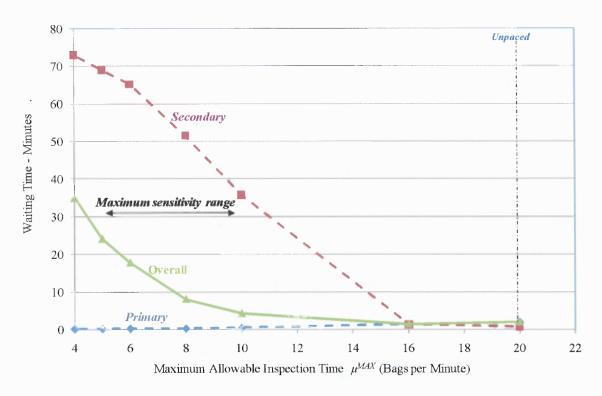


Figure 6.18 Summary of experiment 1A results for small hub airports.

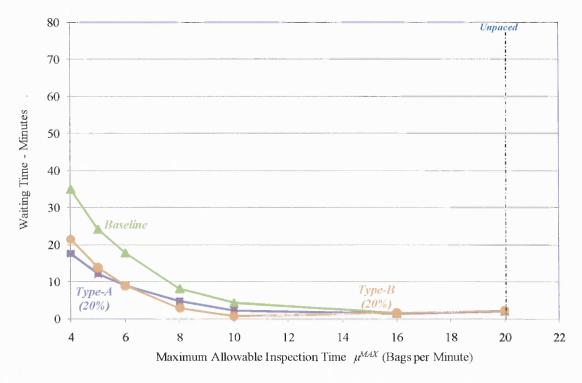


Figure 6.19 Comparison of experiments 1A, 1B and 1C results for small hub airports.

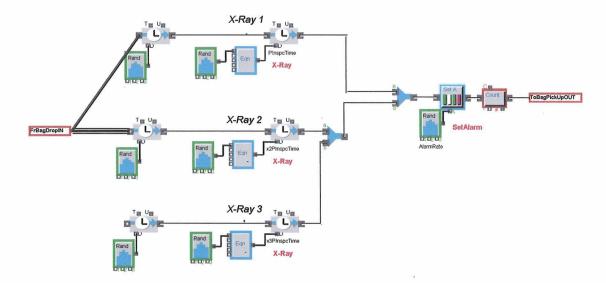
## 6.2 Evaluating a Paced ACSS System Design with Multiple Inspection Stations

In second set of experiments, the number of stations at both primary and secondary inspection is varied. There are three sub-experiments that explore different multiple station configurations, and the performance results of each were then compared to those found in experiment 1A. For example, in experiment 2A there are two primary inspection stations and a single secondary inspection station. In this experiment the arrival rate  $(\lambda)$  is set to twice the base rate used in experiment 1A. That is, instead of an arrival rate of 205, 202 and 173 pph for large, medium and small airports, respectively, the arrival rate was set to 410, 404 and 346 pph. Also, by adding a second primary inspection station the number of TSOs required in this experiment increases from four to five.

Figure 6.20 shows how the multiple primary inspection station design was implemented in the simulation model. In the simulation X-ray sub-model, a second and third X-ray inspection process was constructed to allow for parallel processing varying the number of primary inspection stations from one up to three for experimentation. Multiple primary inspection stations are activated by simply adding a connection line to the Activity Delay block at the beginning of each X-ray process. Each station works in parallel, representing the same task being performed with identical processing parameters.

Each primary inspection station feeds into the Input Random Number block to specify whether or not a carry-on item requires secondary inspection, the item is assigned an attribute with a yes-or-no value using the connected to a Set Attribute block, as shown in the sub-model. The primary inspection paced times and the beta (β) values used or the

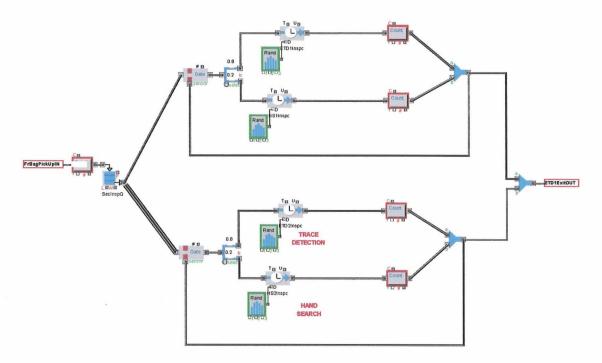
percentage of carry-on items that are routed to secondary inspection during a simulation run are the same as those in run in Experiment 1A (refer to Table 6.1).



**Figure 6.20** Experiment 2 multiple primary inspection station sub-model configuration.

In experiment 2B, the system design is modified by adding another secondary inspection station while keeping the two primary inspection stations. Figure 6.21 shows how the additional secondary inspection station was constructed in the simulation model. As with the multiple primary inspection stations, each secondary inspection station works in parallel, representing the same task being performed with identical processing parameters. In this configuration the number of TSOs required is six.

Experiment 2C is an evaluation of a paced ACSS system with three primary inspection stations and two secondary inspection stations. In this experiment the arrival rate ( $\lambda$ ) is set to three times the base rate used in experiment 1A, that is, 615, 606 and 519 for large, medium and small airports, respectively. In this configuration the number of TSOs required is seven.



**Figure 6.21** Experiment 2 multiple secondary inspection station sub-model configuration.

# 6.2.1 Experiments 2A, 2B and 2C Performance Results

The performance results for passenger wait times at both the primary and secondary inspection queues are shown in Tables 6.14, 6.15 and 6.16 for experiments 2A, 2B and 2C, respectively. The primary inspection average and maximum wait time data (in minutes) is generated by the simulation model exactly the same as in all previous experiments, specifically 1A, at the queue in the BagDrop sub-model (refer to Figure 5.4). This queue, conceptually, in front of the X-ray stations, is where passengers wait to send their carry-on items and personal belongings into the X-ray. Similarly, each simulation is run 100 times, and at the end of each run the wait time data is captured and fed into an Excel spreadsheet. The results reported in the table are the average value calculated from all 100 runs.

Furthermore, the secondary inspection average and maximum wait time data (in minutes) is also generated by the simulation and calculated in the same manner. The data is generated in the Secondary Inspection sub-model (refer to Figure 5.7) at the queue shown in Figure 6.21 where passengers wait for the TSO from either of the two inspection stations to pick up their bags and carry them over to either the ETD or physical hand search table associated with each station. Since there is only one TSO performing secondary inspections at each station the number of passengers allowed into a station is restricted.

Not surprisingly, the data plotted in Figures 6.22 through 6.24 for large, medium and small airports, respectively, shows that at faster inspection speeds across all experiments the passenger wait times do not exceed the 10 minue wait goal. However, there are large wait times at secondary inspection. Overall, experiment 2C with three primary inspection stations and two secondary inspection stations had the highest waiting costs. While the slowest inspection speeds resulted in much lower costs, the average passenger wait time at primary inspection exceeded the 10 minute goal.

The data also suggests as was noted earlier (refer to Figure 4.1 and 4.2) that inspection times beyond 13 seconds for both large and medium hubs should result in carry-on items being automatically diverted to secondary inspection, and 10 seconds for small hubs.

Table 6.14 Experiment 2A Passenger Wait Times with Mean Waiting Costs Results

	Waiting	Cost	(\$/Hr)	\$2,720.02	\$2,147.81	,743.05	\$1,460.78	\$1,144.24	\$1,038.03	\$982.83	\$959.80	\$2,703.18	\$2,088.97	\$1,696.38	\$1,419.84	\$1,073.08	\$961.21	\$883.92	\$883.28	\$2,815.67	\$2,224.74	\$1,583.99	\$1,202.39	\$613.12	\$384.85	\$72.37	\$75.19
Wait				\$2	\$2	\$1	\$1	\$1	\$			\$2	\$2	\$1	\$1	\$1				\$2	\$2	\$1	\$1	• 1	• 3		
Mean Average Wait	Time at PI and SI Qs	Combined	(minutes)	40.00	31.59	25.63	21.48	16.83	15.27	14.45	14.11	40.25	31.10	25.26	21.14	15.98	14.31	13.16	13.15	48.97	38.69	27.55	20.91	10.66	69'9	1.26	1.31
SI Queue	Maximum Wait	Time	(minutes)	164.19	161.65	158.95	155.40	145.63	126.01	81.49	20.66	164.03	161.53	158.59	155.12	141.71	128.34	82.75	21.93	163.91	161.92	158.29	154.36	139.32	125.19	29.15	13.24
SI Queue	Average Wait	Time	(minutes)	82.07	80.30	79.33	77.31	72.62	62.81	40.72	20.6	81.88	69.08	78.98	77.15	70.90	64.06	40.65	9.23	81.91	80.74	78.95	77.21	09.69	62.11	13.62	4.54
PI Queue	Maximum Wait	Time	(minutes)	4.32	5.00	6.44	7.00	12.46	20.67	26.45	29.51	3.61	4.20	5.03	6.46	14.08	17.42	23.77	26.88	1.41	1.45	1.49	1.52	1.62	2.08	3.58	4.30
PI Queue	Average Wait	Time	(minutes)	1.41	1.68	2.56	2.82	5.79	9.93	12.94	14.27	0.91	1.23	1.74	2.64	6.64	8.44	11.53	13.27	0.11	0.12	0.12	0.13	0.16	0.25	0.85	1.23
			Type ID	LT5	LT6	LT7	LT8	LT10	LT13	LT17	LT20	MT5	MT6	MT7	MT8	MT11	MT13	MT17	MT20	ST3	ST4	STS	ST6	ST8	ST10	ST16	ST20
		Airport (	Type					Large				1				Medium				1		Small					

Table 6.15 Experiment 2B Passenger Wait Times with Mean Waiting Costs Results

;		ri Kucuc				200	
		Average	Maximum	Average	Maximum	Time at PI and SI Qs	
Airport	Scenario	Airport Scenario Wait Time	Wait Time	Wait Time	Wait Time	Combined	Waiting
Type	D	(minutes)	(minutes)	(minutes)	(minutes)	(minutes)	Cost (\$/Hr)
	LT5	1.37	4.48	73.86	135.48	36.05	\$2,451.49
	LT6	1.57	4.89	72.41	135.08	28.52	\$1,939.10
	LT7	2.09	5.50	69.26	135.03	22.28	\$1,514.94
1	$\Gamma$ 18	3.06	7.32	69.99	132.46	19.00	\$1,291.81
Large	LT10	5.88	12.84	56.62	114.02	14.26	8969.90
	LT13	9.46	19.81	37.27	75.51	12.26	\$833.93
	LT17	9.15	18.53	4.12	12.09	8.87	\$603.49
	LT20	10.07	20.73	0.36	3.09	9.79	\$665.86
	MT5	1.05	3.78	74.11	135.29	36.55	\$2,454.62
	MT6	1.23	4.25	72.11	134.91	27.88	\$1,872.46
	MT7	1.66	4.93	69.62	134.51	22.35	\$1,501.34
Madina	MT8	2.62	09.9	20.99	132.27	18.37	\$1,234.15
Mediui	<sup>1</sup> MT11	6.65	14.12	52.28	105.57	13.28	\$891.91
	MT13	8.84	18.16	39.34	78.88	12.06	\$810.08
	MT17	7.90	16.23	5.48	13.80	7.77	\$521.78
	MT20	9.44	19.12	0.36	3.07	9.18	\$616.44
	ST3	0.12	1.52	73.97	134.94	44.23	\$2,543.21
	ST4	0.12	1.48	72.60	134.74	34.80	\$2,000.77
	ST5	0.12	1.49	69.07	134.14	24.11	\$1,386.26
Small	ST6	0.14	1.60	65.04	130.78	17.64	\$1,014.26
	ST8	0.18	1.76	50.97	102.40	7.86	\$451.82
	ST10	0.28	2.09	35.60	72.04	3.96	\$227.44
	ST16	0.82	3.52	0.53	3.67	0.81	\$46.79
	ST20	1.17	4.22	0.29	2.66	1.15	\$66.06

Table 6.16 Experiment 2C Passenger Wait Times with Mean Waiting Costs Results

		,	, •	,	,	)	
		Average	Maximum	Average	Maximum	Time at PI and SI Qs	Waiting
	Scenario	Wait Time	Wait Time	Wait Time	Wait Time	Combined	Cost
Type	А	(minutes)	(minutes)	(minutes)	(minutes)	(minutes)	(\$/Hr)
	LTS	1.34	4.00	17.60	136.00	37.82	\$3,895.34
	LT6	1.55	4.42	76.58	135.16	30.09	\$3,099.54
	LT7	2.26	5.49	74.88	135.05	24.09	\$2,480.99
)-	LT8	3.36	7.58	73.26	135.32	20.87	\$2,149.77
Large	LT10	6.85	14.02	67.28	133.13	16.83	\$1,733.93
	LT13	10.72	21.48	54.05	108.77	15.09	\$1,554.38
	LT17	13.81	27.82	25.71	52.14	14.46	\$1,489.64
	LT20	14.84	30.11	1.57	7.07	14.46	\$1,489.32
•	MT5	0.91	3.28	77.55	135.35	38.14	\$3,852.15
	MT6	98.0	3.11	76.36	135.30	29.24	\$2,952.95
	MT7	1.25	3.77	75.09	135.21	23.73	\$2,396.83
W. C 13	MT8	2.03	5.14	72.95	134.69	19.64	\$1,983.42
Medium	MT11	6.55	13.69	64.29	128.84	14.94	\$1,508.72
	MT13	8.77	18.13	55.25	111.17	13.68	\$1,381.37
	MT17	12.39	25.45	26.56	54.07	13.19	\$1,331.78
	MT20	13.36	27.44	1.28	6.04	13.02	\$1,314.66
•	ST3	0.08	1.11	77.43	135.40	46.28	\$4,026.67
	ST4	0.00	1.15	16.67	135.24	36.73	\$3,195.18
	STS	60.0	1.11	74.97	135.30	26.14	\$2,274.09
Small	ST6	0.09	1.18	72.80	135.34	19.69	\$1,713.42
	ST8	0.14	1.40	63.79	127.90	9.76	\$849.40
	ST10	0.20	1.66	53.29	107.42	5.72	\$497.96
	<b>ST16</b>	99.0	2.82	2.34	8.59	0.71	\$62.05
	ST20	1.00	3.61	0.87	5.01	1.00	\$87.03

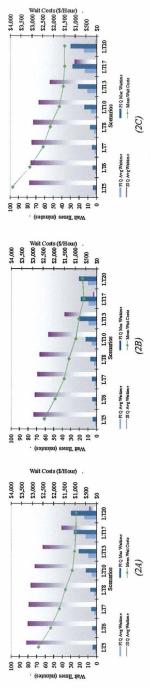
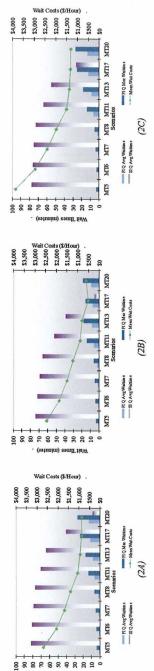


Figure 6.22 Passenger wait times at large hub airports for experiments 2A, 2B and 2C.



Wait Times (minutes)

Figure 6.23 Passenger wait times at medium hub airports for experiments 2A, 2B and 2C.

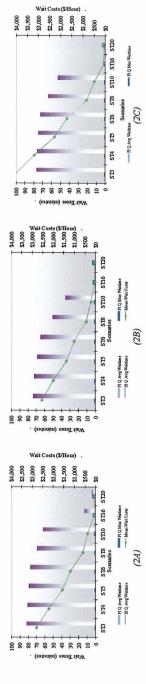


Figure 6.24 Passenger wait times at small hub airports for experiments 2A, 2B and 2C.

The performance results for the average and maximum queue lengths for experiments 2A, 2B and 2C are shown in Tables 6.17 through 6.19, respectively. As with experiment 1A, all results shown were calculated in the same manner by averaging the numbers from all 100 simulation runs.

**Table 6.17** Experiment 2A Average and Maximum Queue Lengths at Primary and Secondary Inspection for All Airport Types

		PI Queue Average	PI Queue Maximum	SI Queue Average	SI Queue Maximum
Airport Type	Scenario ID	Length	Length	Length	Length
	LT5	9.28	29.62	93.30	100.00
	LT6	11.08	33.95	92.14	100.00
	LT7	16.87	43.43	90.64	100.00
Tamaa	LT8	18.54	47.29	88.86	100.00
Large	LT10	37.85	82.71	83.17	100.00
	LT13	64.86	135.86	68.64	100.00
	LT17	84.10	171.47	28.40	57.30
	LT20	93.37	191.47	3.43	8.80
	MT5	5.90	24.73	93.30	100.00
	MT6	7.99	28.47	92.02	100.00
	MT7	11.24	33.72	90.55	100.00
Madissas	MT8	17.10	43.11	88.61	100.00
Medium	MT11	42.68	91.07	80.40	100.00
	MT13	53.82	111.74	70.79	100.00
	MT17	74.08	153.42	29.23	60.43
	MT20	84.98	171.77	3.50	9.10
	ST3	0.62	9.81	93.26	100.00
	ST4	0.68	10.09	92.31	100.00
	ST5	0.68	10.18	90.41	100.00
Small	ST6	0.71	10.22	88.22	100.00
	ST8	0.91	10.80	79.18	100.00
Small	ST10	1.40	13.40	67.50	100.00
	<b>S</b> T16	4.75	21.46	5.67	12.92
	ST20	6.84	25.40	1.51	5.74

**Table 6.18** Experiment 2B Average and Maximum Queue Lengths at Primary and Secondary Inspection for All Airport Types

		PI Queue Average	PI Queue Maximum	SI Queue Average	SI Queue Maximum
Airport Type	Scenario ID	Length	Length	Length	Length
	LT5	9.00	30.45	92.58	100.00
	LT6	10.38	33.06	91.44	100.00
	LT7	13.68	36.87	89.17	100.00
Larga	LT8	19.97	48.33	87.19	100.00
Large	LT10	38.60	84.03	78.19	100.00
	LT13	61.58	130.23	48.22	94.20
	LT17	56.34	114.32	2.98	9.65
_	LT20	61.96	126.99	0.14	2.70
_	MT5	6.84	25.59	92.71	100.00
	MT6	8.07	29.17	91.24	100.00
	MT7	10.80	32.81	89.29	100.00
Medium	MT8	16.89	43.28	86.66	100.00
Medium	MT11	42.95	91.00	73.45	100.00
	MT13	56.65	117.27	52.07	97.79
	<b>M</b> T17	48.16	100.25	4.11	11.22
	MT20	57.56	115.97	0.13	2.71
•	ST3	0.68	10.44	92.62	100.00
	ST4	0.68	10.18	91.67	100.00
	ST5	0.66	10.19	88.96	100.00
Small	ST6	0.79	10.87	86.02	100.00
	ST8	0.99	11.62	71.63	100.00
	ST10	1.54	13.31	44.93	88.54
	ST16	4.57	20.92	0.22	3.18
	ST20	6.51	24.95	0.09	2.37

**Table 6.19** Experiment 2C Average and Maximum Queue Lengths at Primary and Secondary Inspection for All Airport Types

		PI Queue Average	PI Queue Maximum	SI Queue Average	SI Queue Maximum
Airport Type	Scenario ID	Length	Length	Length	Length
	LT5	13.30	40.82	95.40	100.00
	LT6	15.47	45.28	94.55	100.00
	LT7	22.28	55.11	93.32	100.00
T	LT8	33.31	75.39	92.20	100.00
Large	LT10	67.70	138.98	87.71	100.00
	LT13	105.02	210.66	75.48	100.00
	LT17	136.08	274.52	27.08	55.45
	LT20	146.13	298.75	0.90	5.71
•	MT5	8.82	33.19	95.27	100.00
	MT6	8.28	31.47	94.43	100.00
	MT7	12.06	37.52	93.44	100.00
Medium	MT8	19.65	50.84	91.91	100.00
Medium	<b>MT</b> 11	63.30	132.38	85.22	100.00
	MT13	84.46	174.73	76.76	100.00
	MT17	120.20	247.69	28.68	59.32
	<b>MT2</b> 0	129.12	263.78	0.72	4.96
	ST3	0.71	11.49	95.29	100.00
	ST4	0.75	11.84	94.74	100.00
	ST5	0.71	11.44	93.36	100.00
Small	ST6	0.79	12.21	91.74	100.00
	ST8	1.16	13.98	84.75	100.00
Sinan	ST10	1.64	15.83	74.61	100.00
	ST16	5.53	25.09	1.51	7.02
	ST20	8.39	31.63	0.43	4.17

The results were plotted as shown in Figure 6.25 and 6.27 for each of the airport hub types. The figures show secondary inspection average queue length as a function of primary inspection average queue length. Not surprisingly, at lower (faster) paced inspection times, the average secondary inspection queue length is large compared to those at higher (slower) inspection times because more carry-on items are diverted to secondary inspection.

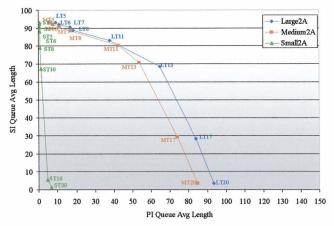


Figure 6.25 Experiment 2A PI and SI average queue lengths across all airport types.

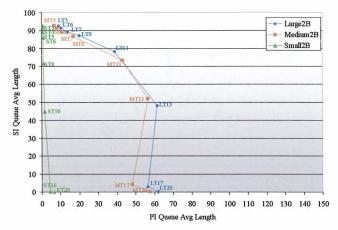


Figure 6.26 Experiment 2B PI and SI average queue lengths across all airport types.

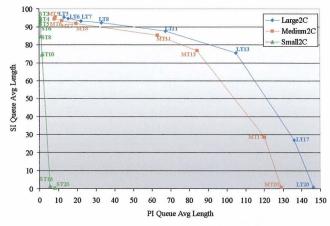


Figure 6.27 Experiment 2C PI and SI average queue lengths across all airport types.

Table 6.20 shows the overall resource utilization results for experiments 2A, 2B and 2C. The utilization data is collected and calculated in the same manner as in experiment 1A. Similar to experiment 1A, the data reveals that as the primary inspection times increase from lower (faster) to higher (slower), the TSO's utilization gradually increased from 50% to 70% never moving beyond 72% for both large and medium airports. For small airports the average utilization rate is between 27% and 58%. The TSO at secondary inspection is also busy almost (98%) in the case for all three airport types except at the highest (slowest) paced primary inspection time, that is, 20 seconds.

Table 6.21 reports the system throughput number for experiments 2A, 2B and 2C for each of the different airport types. The results were calculated as was in experiment 1A by taking the average from all 100 simulation runs. Additionally, Table 6.22 shows the percentage of improvement in cost (\$/Hour) over beta-base. The system throughput numbers are plotted in Figures 6.28 through 6.30 as a function of costs for the different airport types. The data reveals a significant increase (42–48%) in throughput moving from the lower (faster) base scenario of  $\tau$ =8 seconds to higher (slower) primary inspection times across all three experiments and airport types. There is also a gradual increase in cost savings (2–98%) moving from the base rate to slower speeds at primary inspection, while decreasing as primary inspection times get faster but more carry-on items are sent to secondary inspection.

**Table 6.20** Resource Utilization Results for Experiments 2A, 2B and 2C at All Airport Types

		Experi	ment 2A	Exper	iment 2B	Experi	ment 2C
		PI Avg	SI Avg	PI Avg	SI Avg	PI Avg	SI Avg
Airport	Scenario	Util	Util	Util	Util	Util	Util
Type	ID	(min)	(min)	(min)	(min)	(min)	(min)
	LT5	0.519	0.997	0.514	0.997	0.522	0.998
	LT6	0.577	0.997	0.575	0.997	0.582	0.997
	LT7	0.624	0.996	0.621	0.997	0.628	0.997
Laras	LT8	0.652	0.996	0.654	0.996	0.658	0.997
Large	LT10	0.686	0.995	0.689	0.995	0.690	0.996
	LT13	0.708	0.993	0.707	0.992	0.708	0.994
	LT17	0.718	0.988	0.717	0.911	0.719	0.989
	LT20	0.724	0.899	0.722	0.582	0.725	0.781
	MT5	0.514	0.997	0.516	0.997	0.519	0.998
	MT6	0.573	0.997	0.576	0.997	0.578	0.997
	MT7	0.623	0.997	0.623	0.997	0.627	0.997
Medium	MT8	0.656	0.996	0.654	0.996	0.660	0.997
Mediuiii	MT11	0.701	0.995	0.699	0.994	0.702	0.996
	MT13	0.711	0.994	0.712	0.992	0.712	0.994
	MT17	0.724	0.988	0.718	0.922	0.725	0.989
	MT20	0.727	0.899	0.725	0.567	0.730	0.770
	ST3	0.275	0.997	0.276	0.997	0.268	0.998
	ST4	0.336	0.997	0.336	0.997	0.328	0.998
	ST5	0.381	0.997	0.382	0.997	0.371	0.997
Small	ST6	0.421	0.996	0.425	0.997	0.411	0.997
	ST8	0.476	0.995	0.476	0.995	0.468	0.996
	ST10	0.512	0.993	0.513	0.991	0.507	0.994
	<b>ST</b> 16	0.575	0.927	0.575	0.625	0.573	0.845
	ST20	0.589	0.806	0.588	0.507	0.592	0.692

**Table 6.21** System Throughput Results for Experiments 2A, 2B and 2C at All Airport Types

		System Th	roughput (	pass/hour)
Airport Type	Scenario ID	Exp-2A	Exp-2B	Exp-2C
	LT5	128	150	205
	LT6	169	190	264
	LT7	207	228	323
Lamas	LT8	233	254	363
Large	LT10	278	301	430
	LT13	310	330	475
	LT17	332	368	508
	LT20	344	365	517
	MT5	124	146	199
	MT6	168	191	264
	MT7	203	225	317
Medium	MT8	232	254	362
Medium	MT11	286	307	441
	MT13	304	327	469
	MT17	331	367	505
	MT20	343	364	517
	ST3	81	104	134
	ST4	113	134	182
	ST5	160	182	253
Small	ST6	196	219	306
	ST8	260	281	406
	ST10	289	311	449
	ST16	338	342	517
	ST20	339	339	515

Table 6.22 Cost Results for Experiments 2A, 2B and 2C across all Airport Types

		6 Change	-75.83%	-41.26%	-14.39%	n/a	18.07%	25.87%	28.68%	28.69%	-87.51%	-45.40%	-19.36%	n/a	22.23%	28.19%	30.51%	31.32%	-124.00%	-79.43%	-30.05%	n/a	46.32%	65.15%	88.52%	87.18%
Experiment 2C	Cost	Reduction % Change	\$4,047.43 -\$1,745.57	-\$949.77	-\$331.22	n/a	\$415.84	\$595.39	\$660.13	\$660.45	\$4,004.24-\$1,868.73	-\$969.53	-\$413.41	n/a	\$474.70	\$602.05	\$651.63	\$668.76	\$4,178.75-\$2,313.24	\$3,347.27 -\$1,481.76	-\$560.67	n/a	\$864.02	\$1,215.46	\$1,651.37	\$1,626.39
Exp	Total Cost	(\$/Hour)	\$4,047.43	\$3,251.63	\$2,633.07	\$2,301.86	\$1,886.01	\$1,706.47	\$1,641.73	\$1,641.41	\$4,004.24	\$3,105.04	\$2,548.92	\$2,135.51	\$1,660.81	\$1,533.45	\$1,483.87	\$1,466.75	\$4,178.75	\$3,347.27	\$2,426.18	\$1,865.51	\$1,001.49	\$650.05	\$214.14	\$239.12
		% Change	-81.61%	-45.55%	-15.70%	n/a	22.65%	32.22%	48.44%	44.05%	-89.52%	-46.82%	-19.60%	n/a	25.10%	31.10%	52.25%	45.31%	-133.71%	-86.27%	-32.53%	n/a	49.19%	68.81%	84.61%	82.92%
Experiment 2B	Cost	Reduction % Change	\$1,159.69	-\$647.30	-\$223.13	n/a	\$321.91	\$457.87	\$688.32	\$625.94	\$1,220.46	-\$638.31	-\$267.18	n/a	\$342.24	\$424.08	\$712.37	\$617.72	\$1,528.95	-\$986.51	-\$372.00	n/a	\$562.44	\$786.82	\$967.47	\$948.20
Exp	Total Cost	(\$/Hour)	\$2,580.74-\$1,159.69	\$2,068.35	\$1,644.19	\$1,421.05	\$1,099.15	\$963.18	\$732.73	\$795.11	\$2,583.86-\$1,220.46	\$2,001.71	\$1,630.58	\$1,363.40	\$1,021.16	\$939.32	\$651.03	\$745.68	\$2,672.45-\$1	\$2,130.02	\$1,515.51	\$1,143.51	\$581.07	\$356.69	\$176.04	\$195.31
		% Change	-80.42%	-43.88%	-18.03%	n/a	20.22%	27.00%	30.52%	31.99%	-84.16%	-43.88%	-18.13%	n/a	22.74%	30.08%	35.15%	35.19%	-123.39%	-78.19%	-29.19%	n/a	45.07%	62.53%	86.43%	86.21%
Experiment 2A	Cost	Reduction %	\$1,259.24	-\$687.03	-\$282.27	n/a	\$316.54	\$422.76	\$477.95	\$500.98	\$1,283.33	-\$669.12	-\$276.54	n/a	\$346.76	\$458.63	\$535.92	\$536.56	۱	\$1,022.35	-\$381.60	n/a	\$589.27	\$817.54	\$1,130.02	\$1,127.21
Exp	Total Cost	(\$/Hour)	\$2,825.07-\$1,259.24	\$2,252.86	\$1,848.10	\$1,565.83	\$1,249.29	\$1,143.07	\$1,087.88	\$1,064.85	\$2,808.22-\$1,283.33	\$2,194.01	\$1,801.43	\$1,524.89	\$1,178.13	\$1,066.26	\$988.97	\$988.33	\$2,920.72-\$1,613.28	\$2,329.79-\$1,022.35	\$1,689.04	\$1,307.44	\$718.17	\$489.90	\$177.42	\$180.23
	Airport Scenario	Д	LTS	LT6	LT7	LT8	LT10	LT13	LT17	LT20	MT5	MT6	MT7	MT8	MT11	MT13	MT17	MT20	ST3	ST4	ST5	ST6	ST8	ST10	ST16	ST20
	Airport	Type				-	Large				E			:	Medium				1			Small				

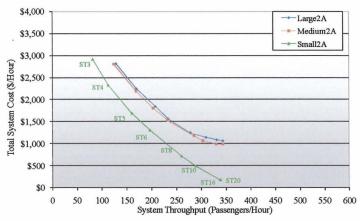


Figure 6.28 Experiment 2A total system costs as a function of system throughput for all airport types.

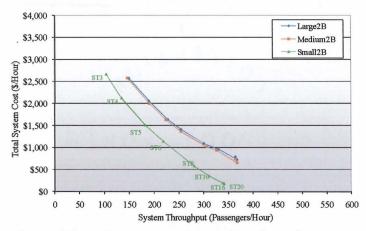


Figure 6.29 Experiment 2B total system costs as a function of system throughput for all airport types.

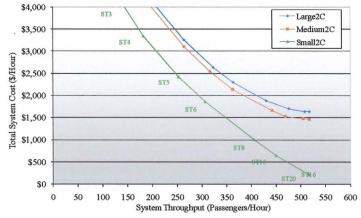


Figure 6.30 Experiment 2C total system costs as a function of system throughput for all airport types.

#### 6.2.2 Comparison of Results for ACSS with Multiple Stations

In this set of experiments, the ACSS system was modified by adding resources at both the primary and secondary inspection stations. Table 6.23 shows the cost performance results for experiment 2A, 2B and 2C as compared to experiment 1A. The data is plotted in Figures 6.31 and 6.32 for again only large and small airports, respectively.

For large hub airports, the results show an improvement but about the same in passenger wait times at primary inspection across experiments as compared to 1A. However, adding additional resources at primary and secondary inspection stations resulted in overall higher costs as compared with experiment 1A for large and small airports. In the case of small airports, the results show significant benefit after 10 seconds. However, there is 40 to 70% increase in costs between the baseline and scenarios 2A, 2B, and 2C. Also of note is that passenger wait times' (13.36 minutes) exceeded the 10 minute goal.

Table 6.23 Comparison of Experiments 2A, 2B and 2C Cost Results with Experiment 1A across All Airport Hubs

	%	Change	-49.68%	-24.29%	-3.60%	%98.9	15.48%	-1.96%	-116.98%	-187.01%	-51.17%	-21.11%	-2.12%	10.93%	18.76%	10.81%	-101.81%	-158.97%	-87.80%	-52.63%	-16.66%	5.40%	36.57%	42.51%	-29.09%	-44.02%
Exp - 2C	Cost	Reduction	-\$1,343.30	-\$635.42	-\$91.59	\$169.45	\$345.54	-\$32.88	-\$885.10	-\$1,069.51	-\$1,355.49	-\$541.13	-\$52.97	\$262.16	\$383.46	\$185.81	-\$748.59	-\$900.37	-\$1,953.67	-\$1,154.17	-\$346.41	\$106.48	\$577.27	\$480.70	-\$48.26	-\$73.09
	Total Cost	(\$/Hour)	\$4,047.43	\$3,251.63	\$2,633.07	\$2,301.86	\$1,886.01	\$1,706.47	\$1,641.73	\$1,641.41	\$4,004.24	\$3,105.04	\$2,548.92	\$2,135.51	\$1,660.81	\$1,533.45	\$1,483.87	\$1,466.75	\$4,178.75	\$3,347.27	\$2,426.18	\$1,865.51	\$1,001.49	\$650.05	\$214.14	\$239.12
	%	Change	4.56%	20.94%	35.31%	42.50%	50.75%	42.45%	3.16%	-39.03%	2.45%	21.93%	34.67%	43.14%	50.05%	45.36%	11.46%	-31.66%	-20.11%	2.88%	27.13%	42.01%	63.19%	68.46%	-6.13%	-17.63%
Exp - 2B	Cost	Reduction	\$123.39	\$547.86	\$897.30	\$1,050.25	\$1,132.41	\$710.41	\$23.89	-\$223.21	\$64.89	\$562.20	\$865.37	\$1,034.26	\$1,023.11	\$779.94	\$84.25	-\$179.31	-\$447.37	\$63.08	\$564.26	\$828.48	\$997.70	\$774.07	-\$10.16	-\$29.28
1	Total Cost	(\$/Hour) F	\$2,580.74	\$2,068.35	\$1,644.19	\$1,421.05	\$1,099.15	\$963.18	\$732.73	\$795.11	\$2,583.86	\$2,001.71	\$1,630.58	\$1,363.40	\$1,021.16	\$939.32	\$651.03	\$745.68	\$2,672.45	\$2,130.02	\$1,515.51	\$1,143.51	\$581.07	\$356.69	\$176.04	\$195.31
	%	Change	-4.47%	13.89%	27.28%	36.64%	44.02%	31.70%	-43.78%	-86.20%	-6.02%	14.43%	27.83%	36.40%	42.37%	37.98%	-34.50%	-74.50%	-31.26%	-6.23%	18.79%	33.70%	54.51%	56.68%	-6.96%	-8.56%
Exp - 2A	Cost	Reduction	-\$120.94	\$363.36	\$693.38	\$905.48	\$982.27	\$530.52	-\$331.26	-\$492.95	-\$159.47	\$369.89	\$694.53	\$872.77	\$866.14	\$653.00	-\$253.68	-\$421.95	-\$695.64	-\$136.69	\$390.73	\$664.55	\$860.59	\$640.85	-\$11.54	-\$14.20
	Total Cost	(\$/Hour)	\$2,825.07	\$2,252.86	\$1,848.10	\$1,565.83	\$1,249.29	\$1,143.07	\$1,087.88	\$1,064.85	\$2,808.22	\$2,194.01	\$1,801.43	\$1,524.89	\$1,178.13	\$1,066.26	\$988.97	\$988.33	\$2,920.72	\$2,329.79	\$1,689.04	\$1,307.44	\$718.17	\$489.90	\$177.42	\$180.23
Exp - 1A	Total Cost	(\$/Hour)	\$1,339.55	\$1,065.07	\$857.12	\$741.95	\$584.72	\$521.20	\$508.60	\$522.46	\$1,330.76	\$1,029.95	\$849.58	\$712.78	\$525.24	\$507.65	\$480.79	\$518.94	\$1,360.63	\$1,092.34	\$779.43	\$595.96	\$316.28	\$204.73	\$125.81	\$141.35
	Scenario		LTS	LT6	LT7	LT8	LT10	LT13	LT17	LT20	MT5	MT6	MT7	MT8	MT11	MT13	MT17	MT20	ST3	ST4	STS	9LS	ST8	ST10	ST16	ST20
	Airport	Type				; ;	Large								Medium							Small				

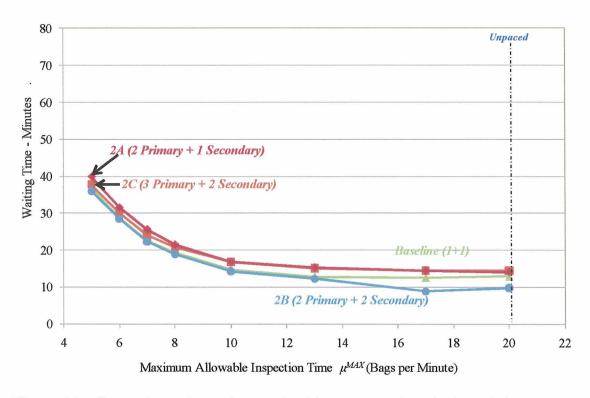


Figure 6.31 Comparison of experiment 1A with 2A, 2B, and 2C for large hub airports.

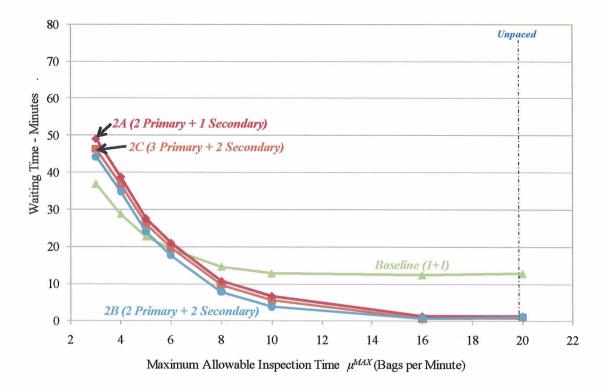


Figure 6.32 Comparison of experiment 1A with 2A, 2B, and 2C for small hub airports.

### 6.3 Full Scale Paced ACSS System Design

The third experiment is a full scale evaluation of a paced ACSS system that adds realistic passenger screening service times and alarm rates at the WTMD and Hand Wanding stations. In all previous experiments, the WTMD and the Hand Wand service rates were set very high in addition to having a zero alarm rate. This was so that passengers would not be delayed at these stations which could possibly result in a hindrance to the flow of carry-on item inspections. In this experiment the same set of scenarios run in experiment 1A were repeated and their performance results compared to each other.

#### 6.3.1 Full Scale Model Performance Results

The performance results for passenger wait times at both the primary and secondary inspection queues are shown in Table 6.24, and plotted in Figures 6.33 through 6.35. Again, the primary inspection average and maximum wait time data (in minutes) is generated by the simulation model exactly the same as in all previous experiments. Each set of scenarios is also run 100 times, and at the end of each run the wait time data is captured and fed into an Excel spreadsheet. The results reported in the table are the average value calculated from all 100 runs.

The performance results for the average and maximum queue lengths are shown in Table 6.25. As with experiment 1A, all results shown were calculated in the same manner by averaging the numbers from all 100 simulation runs.

The data also suggests as was noted earlier (refer to Figure 4.1 and 4.2) that inspection times beyond 13 seconds for both large and medium hubs should result in carry-on items being automatically diverted to secondary inspection, and 10 seconds for small hubs.

Table 6.24 Full Scale Model Passenger Wait Times with Mean Waiting Costs Results

		PI Queue	PI Queue	SI Queue	SI Queue	Mean Average Wait	
		Average Wait	Maximum	Average Wait	Maximum	Time at PI and SI Qs	Waiting
Airport	Scenario	Time	Wait Time	Time	Wait Time	Combined	Cost
Type		(minutes)	(minutes)	(minutes)	(minutes)	(minutes)	(\$/Hr)
	LTS	2.49	7.12	74.71	150.06	37.04	\$1,265.46
	$\Gamma$ L	2.51	7.29	72.60	145.37	29.17	\$996.74
	LT7	3.11	8.14	69.63	139.95	23.11	\$789.51
1	LT8	4.00	9.78	96.56	133.65	19.67	\$672.22
rai ge	LT10	6.44	14.34	56.53	114.15	14.72	\$502.80
	LT13	89.6	20.39	36.17	74.25	12.35	\$421.90
	LT17	13.73	29.24	6.92	17.91	13.36	\$456.43
	LT20	14.36	29.78	1.12	5.53	13.97	\$477.36
	MT5	2.04	6.28	74.42	149.10	37.20	\$1,252.43
	MT6	2.13	6.42	72.11	144.95	28.44	\$957.37
	MT7	2.46	7.31	69.27	138.81	22.81	\$767.78
Modium	MT8	3.24	8.42	20.99	132.62	18.84	\$634.27
IMEGINI	MT11	6.79	15.47	51.06	103.35	13.22	\$445.12
	MT13	9.35	19.70	38.64	78.08	12.44	\$418.79
	MT17	11.86	25.28	7.41	18.08	11.62	\$391.04
İ	MT20	12.74	26.96	1.11	5.59	12.41	\$417.67
	ST3	0.27	2.49	74.83	149.60	44.80	\$1,291.86
	ST4	0.27	2.61	72.74	146.20	34.94	\$1,007.44
	ST5	0.24	2.42	69.02	138.51	24.17	\$696.95
Small	ST6	0.28	2.42	65.33	130.70	17.81	\$513.66
	ST8	0.32	2.60	50.87	101.95	7.97	\$229.69
	ST10	0.58	3.61	35.80	72.61	4.24	\$122.33
	ST16	1.49	5.64	1.42	6.38	1.48	\$42.77
	ST20	1.93	6.41	0.89	4.60	1.91	\$54.95

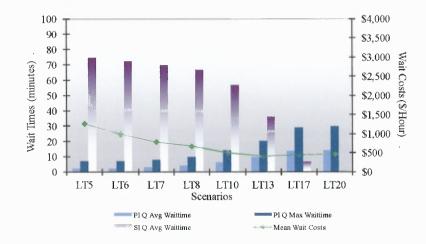


Figure 6.33 Full scale model passenger wait times at large hub airports.

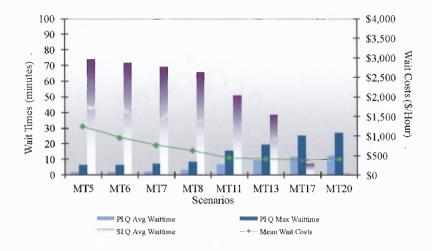


Figure 6.34 Full scale model passenger wait times at medium hub airports.

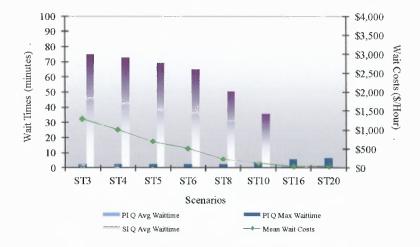


Figure 6.35 Full scale model passenger wait times at small hub airports.

**Table 6.25** Full Scale Model Average and Maximum Queue Lengths at Primary and Secondary Inspection for All Airport Types

		PI Queue	PI Queue	SI Queue	SI Queue
		Average	Maximum	Average	Maximum
Airport Type	Scenario ID	Length	Length_	Length	Length
	LT5	8.27	24.87	85.71	100.00
	LT6	8.41	24.94	83.19	100.00
	LT7	10.27	27.37	79.49	100.00
T	LT8	13.20	32.32	75.15	100.00
Large	LT10	21.18	47.52	57.50	99.99
	LT13	31.45	67.02	23.63	48.73
	LT17	45.97	97.27	2.59	7.68
	LT20	47.11	97.89	0.22	2.47
	MT5	6.69	21.58	85.40	100.00
	MT6	6.99	21.85	82.77	100.00
	MT7	8.07	24.80	78.89	100.00
Madium	MT8	10.57	27.88	74.32	100.00
Medium	MT11	22.17	51.08	47.27	94.15
	MT13	30.33	64.44	26.10	53.44
	MT17	38.79	82.37	2.75	7.48
	MT20	41.45	88.91_	0.22	2.56
	ST3	0.76	8.74	85.63	100.00
	ST4	0.76	8.97	83.30	100.00
	ST5	0.68	8.51	78.21	100.00
Small	ST6	0.78	8.41	72.74	100.00
	ST8	0.91	8.95	45.19	89.74
	<b>ST</b> 10	1.61	11.84	23.00	47.13
	ST16	4.18	17.02	0.30	2.91
	ST20	5.45	18.82	0.15	2.17

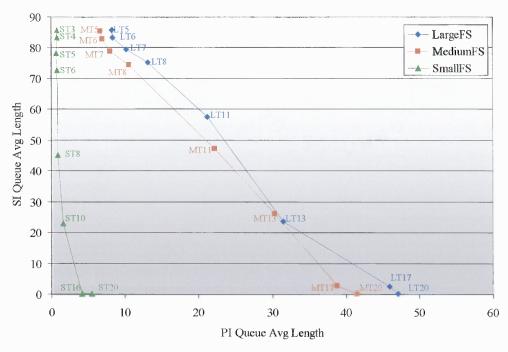


Figure 6.36 Full scale model queue length results for all airport types.

Table 6.26 shows the overall resource utilization. The data reveals much the same as in previous experiment results that as the primary inspection times increase from lower (faster) to higher (slower), the TSO's utilization gradually increased from 50% to 70% never moving beyond 72% for both large and medium airports. For small airports the average utilization rate is between 27% and 58%. Additionally, for all airport types, the TSO at secondary inspection is busy almost (98%) all the time except at the highest (slowest) paced primary inspection time, that is, 20 seconds.

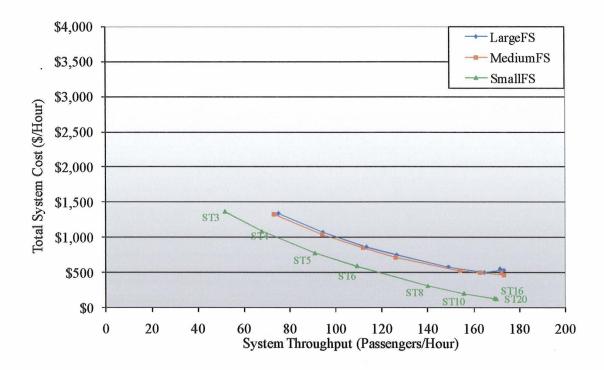
Table 6.27 reports the average system throughput number from all 100 simulation runs, which are then plotted in Figure 6.37 as a function of costs for the different airport types. The data reveals a significant increase (73%-76%) in throughput moving from the lower (faster) base scenario of  $\tau$ =8 seconds to higher (slower) primary inspection times and a gradual increase in cost savings (4–10%).

Table 6.26 Full Scale Model Resource Utilization Results

		PI Average	SI Average	
		Utilization	Utilization	
Airport Type	Scenario ID	(minutes)	(minutes)	
P	LT5	0.516	0.996	
	LT6	0.572	0.995	
	LT7	0.618	0.995	
_	LT8	0.650	0.994	
Large	LT10	0.686	0.992	
	LT13	0.706	0.985	
	LT17	0.717	0.871 0.482	
	LT20	0.722		
-	MT5	0.515	0.996	
	MT6	0.573	0.996	
	MT7	0.617	0.995	
<b>3</b>	MT8	0.647	0.994	
Medium	MT11	0.699	0.991	
	MT13	0.711	0.988	
	MT17	0.720	0.885	
	<b>MT20</b>	0.725	0.489	
-	ST3	0.277	0.996	
	ST4	0.336	0.996	
	ST5	0.382	0.995	
Small	ST6	0.422	0.995	
	ST8	0.474	0.990	
	ST10	0.512	0.984	
	ST16	0.569	0.524	
	ST20	0.587	0.416	

**Table 6.27** Full Scale Model System Throughput and Total Cost Results for All Airport Types

		System	Total		
Airport	Scenario	Throughput	System Cost		
Type	ID	(Pax/Hour)	(\$/Hour)	Cost Reduction	% Change
	LT5	75	\$1,347.67	-\$593.25	-78.64%
	LT6	94	\$1,078.95	-\$324.53	-43.02%
	LT7	113	\$871.72	-\$117.30	-15.55%
Lonco	LT8	126	\$754.42	n/a	n/a
Large	LT10	149	\$585.00	\$169.42	22.46%
	LT13	165	\$504.11	\$250.31	33.18%
	LT17	173	\$538.63	\$215.79	28.60%
	LT20	172	\$559.57	\$194.85	25.83%
	MT5	73	\$1,334.63	-\$618.15	-86.28%
	MT6	94	\$1,039.57	-\$323.09	-45.09%
	MT7	112	\$849.98	-\$133.50	-18.63%
Madium	MT8	126	\$716.48	n/a	n/a
Medium	MT11	154	\$527.32	\$189.16	26.40%
	MT13	163	\$500.99	\$215.49	30.08%
	MT17	173	\$473.25	\$243.23	33.95%
	MT20	172	\$499.88	\$216.60	30.23%
	ST3	52	\$1,374.06	-\$778.20	-130.60%
	ST4	68	\$1,089.65	-\$493.78	-82.87%
	ST5	91	\$779.15	-\$183.28	-30.76%
Small	ST6	109	\$595.87	n/a	n/a
	ST8	140	\$311.90	\$283.97	47.66%
	ST10	156	\$204.54	\$391.33	65.67%
	ST16	170	\$124.98	\$470.89	79.03%
	ST20	169	\$137.16	\$458.71	76.98%



**Figure 6.37** Full scale model total system costs as a function of system throughput for all airport types.

### 6.3.2 Comparison of Results

In this set of experiments, the ACSS system was modified by adding realistic service times and alarm rates at the WTMD and Hand Wanding stations. Table 6.28 shows the cost performance results for the full scale experiment as compared to experiment 1A. The data is plotted in Figures 6.38 through 6.40 for large, medium and small airports, respectively. The results show little discernable differences in passenger wait times and costs across scenarios as compared to 1A.

**Table 6.28** Full Scale Model Cost Performance Results Compared with Experiment 1A across All Airport Hubs

		Experiment 1A	F	Full Scale	
Airport	Scenario	<b>Total Cost</b>	Total Cost	Cost	%
Type	ID	(\$/Hour)	(\$/Hour)	Reduction	Change
Large	LT5	\$2,704.13	\$1,347.67	\$1,356.46	50.16%
	LT6	\$2,616.21	\$1,078.95	\$1,537.27	58.76%
	LT7	\$2,541.48	\$871.72	\$1,669.76	65.70%
	LT8	\$2,471.31	\$754.42	\$1,716.89	69.47%
	LT10	\$2,231.56	\$585.00	\$1,646.56	73.79%
	LT13	\$1,673.59	\$504.11	\$1,169.48	69.88%
	LT17	\$756.63	\$538.63	\$218.00	28.81%
	LT20	\$571.90	\$559.57	\$12.33	2.16%
_	MT5	\$2,648.75	\$1,334.63	\$1,314.11	49.61%
Medium	MT6	\$2,563.91	\$1,039.57	\$1,524.33	59.45%
	MT7	\$2,495.95	\$849.98	\$1,645.97	65.95%
	MT8	\$2,397.66	\$716.48	\$1,681.18	70.12%
	MT11	\$2,044.27	\$527.32	\$1,516.94	74.20%
	MT13	\$1,719.26	\$500.99	\$1,218.27	70.86%
	MT17	\$735.28	\$473.25	\$262.04	35.64%
	MT20	\$566.38	\$499.88	\$66.50	11.74%
_	ST3	\$2,225.08	\$1,374.06	\$851.02	38.25%
Small	ST4	\$2,193.10	\$1,089.65	\$1,103.45	50.31%
	ST5	\$2,079.77	\$779.15	\$1,300.61	62.54%
	ST6	\$1,971.99	\$595.87	\$1,376.12	69.78%
	ST8	\$1,578.76	\$311.90	\$1,266.87	80.24%
	ST10	\$1,130.75	\$204.54	\$926.22	81.91%
	ST16	\$165.88	\$124.98	\$40.90	24.66%
	ST20	\$166.03	\$137.16	\$28.87	17.39%

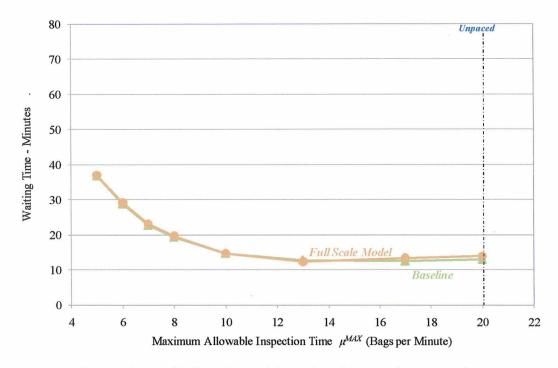


Figure 6.38 Comparison of full scale model results with experiment 1A for large hub airports.

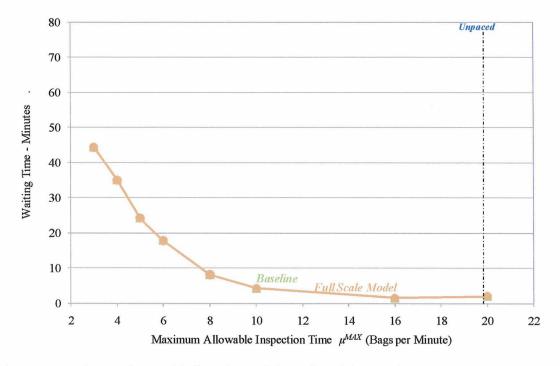


Figure 6.39 Comparison of full scale model results with experiment 1A for small hub airports.

#### **CHAPTER 7**

#### DISCUSSION

### 7.1 Synopsis of Findings

Important findings emerged from the analysis. The results showed the interaction of factors as seen in Table 5.1 as not significant, meaning that the effect of airport hub, decision type and data collection time period on X-ray TSO image inspection times is not different, but about the same for security checkpoints across the three different hubs. However, as demonstrated by the simulation analysis even seconds count in screening of passengers' carry-on items to reduce longer than necessary wait times at airport checkpoints.

Reliable data describing the operating characteristics of security inspection processes are now available. This data can be used to design and analyze ACSS systems with much greater accuracy and detail. The results will in effect reduce the dependence on trial-and-error experiments at the site.

Most importantly, the findings revealed that a paced X-ray TSO was an improvement over the performance of the current un-paced process as shown in Figures 7.1 and 7.2. The SIOC curves provide a standard against which new and alternative ACSS designs can be evaluated and benchmarked. These also make it easier to determine the value of Type-A, B or C improvements of potential vendor technologies. The observed data revealed mean X-ray TSO inspection times of M=5.81, M=7.00, and M=7.04 seconds at current un-paced ACSSs within small, medium and large airport hubs, respectively, with average wait times at primary inspection across large and medium

airports more than the established 10-minute or less goal. Under paced conditions for large and medium hubs, a maximum paced inspection time of 13 seconds reduces mean waiting times from 14-minutes to the 10-minute waiting goal while increasing costs by about 58% because more passengers' carry-on items are sent to secondary inspection. Yet, referring more carry-on items to secondary inspection where screening is more intrusive and accurate has the added benefit of improving the probability of detecting a prohibited item.

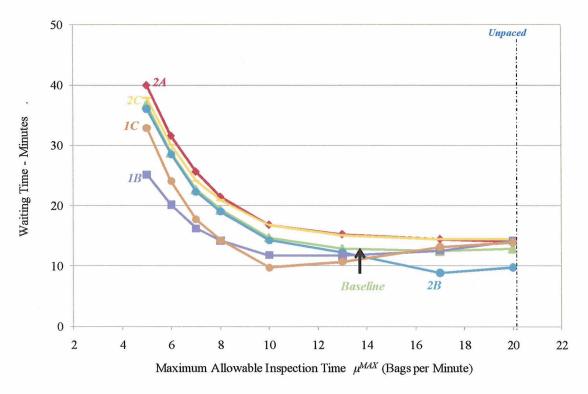


Figure 7.1 Comparison of all experiments for large hub airports.

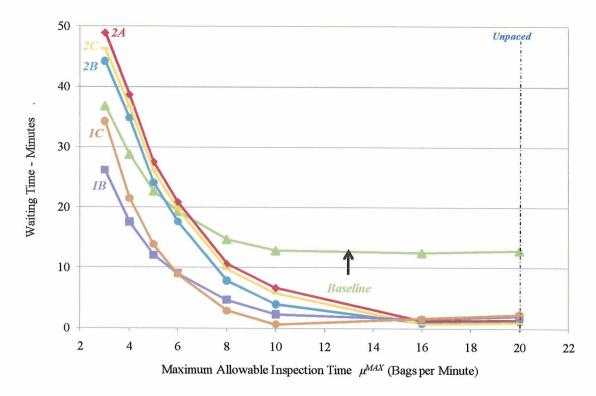


Figure 7.2 Comparison of all experiments for small hub airports.

## 7.2 Limitations and Future Research

While the evidence and analyses in this study reveal that X-ray TSO inspection times are not influenced by different volumes of passenger or during different peak hour periods, limitations of any research must be considered when interpreting the data and resultant findings, and are particularly useful in designing future studies to help bolster previous findings. Towards this end, the study's limitations and potential solutions of the limitations are as follows:

(a) Data were collected from only 5% of the nations' larger checkpoints (high and medium hub categories). Data collection from additional sites would add to the research findings even further.

- (b) X-ray inspection times may not be entirely a product of the TSO's decision time. The TSO may have had to wait to move onto the next X-ray image until the TSO who would perform secondary inspection was available. Additional observations on primary and secondary screener interactions taken from checkpoint sites may be more useful in future studies.
- (c) The study focused on two of the four checkpoint screening functions. Future studies would benefit by including observations of WTMD screening of individuals in addition to hand-wand or pat-down screening of individuals rates and service times to examine impacts on overall waittimes.
- (d) The study focused on only a small number of variables of interest. As with any research, additional variables are always possible and would add tremendous information to the interpretation of findings. For instance, variables such as ticket checker processing times or varying levels of clutter within X-ray images as it relates to inspection times and decisions could certainly mediate or moderate the findings, and could have important impacts on the waittimes at checkpoints.
- (e) To further understand why average inspection times are lower at some faxcilities than other, future increstigation could consider other faxtors such as layout, work schedules, noise, etc.
- (f) Development of new ACSS designs using existing technology, to improve system performance.

Regardless of the limitations presented above, findings from the present study are important in providing useful information relative to checkpoint security screening operations and TSO performance improvements.

# APPENDIX SIMULATION MODEL PARAMETERS

 Table A.1
 Simulation Model Parameters

	Simulation Model Parameters				
Name	Description	Nominal Value			
$\lambda_{\mathrm{C}}$	Passenger per checkpoint arrival rate (ppc)	L - Exp(0.049)			
		M - Exp(0.067)			
		S - Exp(0.142)			
$\lambda_{ m L}$	Passenger per screening lane arrival rate	L - Exp(0.293)			
	(ppl)	M - Exp(0.297)			
		S - Exp(0.347)			
τ <sub>P</sub>	Primary inspection service time (in	L - LogNorm(7.00, 6.37)s			
	seconds)	M - LogNorm(7.00, 6.18)s			
		S - LogNorm(5.81, 6.55)s			
$ au_{ ext{SE}}$	Secondary inspection service time for ETD Equipment (in seconds)	Triangular(47,150,47)s			
$ au_{ m SH}$	Secondary inspection service time for Hand Search (in seconds)	Triangular(120,300,120)s			
$ au_{ m WTMD}$	Inspection service time for Walk through Metal Detector (in seconds)	Uniform(1,3)s			
$ au_{ m HW}$	Inspection service time for Hand Wand (in seconds)	Uniform(10,20)s			
$ au_{\mathrm{CON}}$	Delay time for divestiture of carry-on items into bins and movement into X-ray	Uniform(5,10)s			
	opening				
$\beta_{WTMD}$	Alarm rate for Walk through Metal	16%			
	Detector				
μΡ	Primary inspection service rate (bags per hour)	60/τ <sub>P</sub>			
μ <sub>SE</sub>	Secondary inspection ETD service rate (bags per hour)	$60/ au_{ m SE}$			
μѕн	Secondary inspection Hand Search service rate (bags per hour)	$60/ au_{ m SH}$			

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