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

The airport checkpoint security screening system is an important line of defense against the introduction of dangerous objects into the U.S. air transport 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 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.

This research 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.

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).

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. The current paradigm is to have unpaced processes, that is, the TSO has unlimited inspection time. There has never been a time limit placed on the network of screeners looking for prohibited items primarily because 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. Therefore, this study examined 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, in addition to the generation of SIOC curves that show inspection times as a function of the rate of carry-on items cleared and those not-cleared.

LITERATURE REVIEW

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 risk-based 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". 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. 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 OR researchers addressed airline security, focusing primarily on scanning passengers or baggage (Wright, Liberatore, and Nydick, 2006; Leone and Liu, 2003, 2004, 2005). 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. The data revealed that for laptop passengers there is a significant decrease in the detection probability and in the probability of correct rejection.

Investigations of 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). 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.

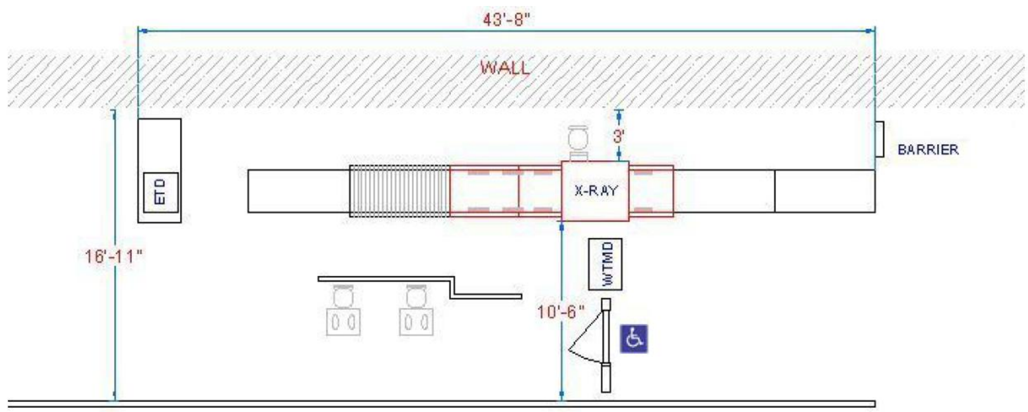
ACSS SYSTEM MODEL AND SCREENING OPERATIONS

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 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).

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.



Source: Transportation Security Administration. (2006).

Figure 1 Study checkpoint physical layout.

Descriptive Model

Figure 2 shows the descriptive model of the single lane ACSS. 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 λ-arrival demand, μ-service rate, and β-rejection rate. Passengers arrive, denoted as λ, 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 μ_1, that is, $(60/\tau)$ represents the time (τ) the TSO spends on inspecting the image searching for prohibited items to when a decision is made to either reject (β) 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 μ_{21} and μ_{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 (α), 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.

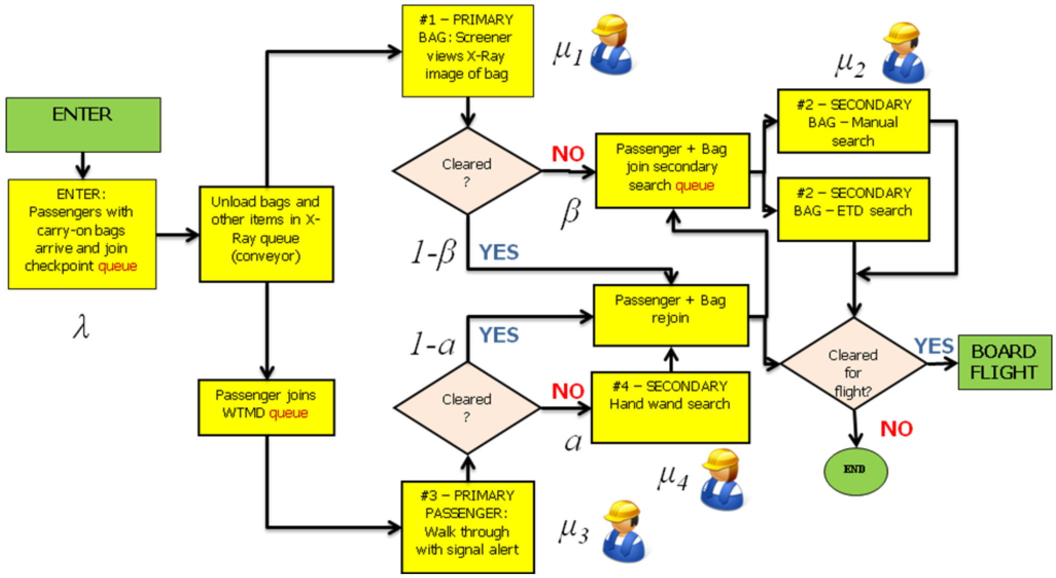


Figure 2 Single lane ACSS descriptive model.

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:

$$T_P = \lambda_1 / \left[\mu_1 \left(\mu_1 - \lambda_1 \right) \right] \tag{1}$$

$$T_S = \lambda_2 / \left[\mu_2 \left(\mu_2 - \lambda_2 \right) \right] \tag{2}$$

$$T = T_P + T_S \tag{3}$$

Where:

T: Total time spent in check point screening
T_P: Time spent in the primary inspection process
T_S: Time spent in the secondary inspection process
λ_1: Initial arrival rate
λ_2: Secondary arrival rate, which is directly related to the rejection rate β
μ_1: Primary inspection service rate
μ_2: Secondary inspection service rate

Data Collection

The Federal Aviation Administration (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 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.

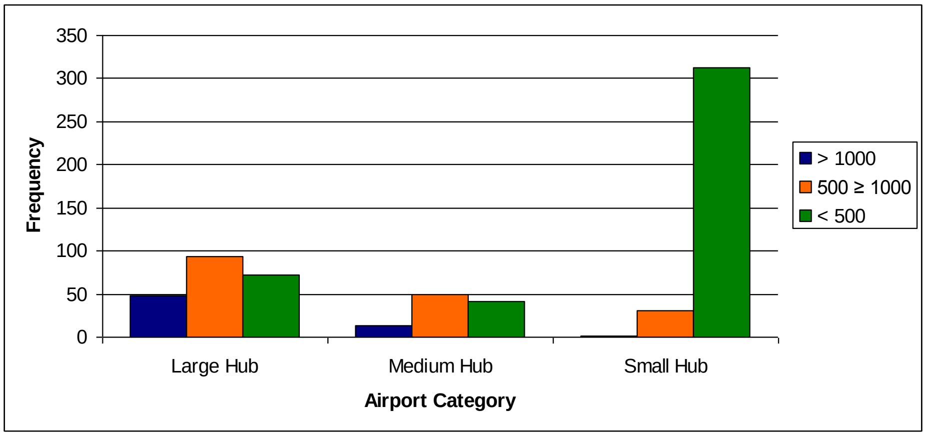


Figure 3 Peak hour passenger demand by airport hub.

Figure 3 also shows that there are 213, 104, and 345 checkpoints within large, medium and small hub airports, respectively. As indicated in Table 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 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". 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 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 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).

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. 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

For items 1, 2, and 3, empirical 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.

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. Other performance measures include staffing per lane, which is 4.25 TSOs per lane, and checkpoint throughput. According to the same GAO report, checkpoint throughput (passengers per lane, per hour (pplph)) is considered to be 200 pplph. In addition to wait time, staffing levels, and throughput, queue length and resource utilization are also used to measure performance in queuing systems.

Descriptive Data and Summary Statistics

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). Table 4 shows the means and standard deviations for X-ray inspection times for the large hub type airports along with the 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.

Table 4 X-ray TSO Inspection Times (in seconds) for ACSSs at Large Hubs by Decision

ACSS	Cleared			Not-Cleared			Total			95% Confidence Interval for Mean				Not-Cleared
ID	N	Mean	SD	N	Mean	SD	N	Mean	SD	L-B	U-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	9%
2	1223	7.64	8.44	158	9.38	12.63	1381	7.84	9.03	7.36	8.31	1	120	11%
3	1247	6.59	4.45	165	6.55	4.20	1412	6.58	4.42	6.35	6.81	1	28	12%
4	1264	6.84	7.28	80	6.29	4.84	1344	6.80	7.16	6.42	7.19	1	72	6%
7	976	6.92	5.38	52	6.56	4.30	1028	6.90	5.33	6.57	7.22	1	42	5%
8	994	6.42	4.99	92	8.82	10.39	1086	6.63	5.68	6.29	6.96	1	67	8%
9	1194	7.87	7.13	111	7.99	8.57	1305	7.88	7.26	7.49	8.27	1	120	9%
10	1136	6.83	4.81	41	6.66	2.29	1177	6.83	4.74	6.55	7.10	1	25	3%
11	1064	6.69	5.31	149	7.68	7.49	1213	6.81	5.63	6.49	7.13	1	66	12%
12	1043	6.71	6.55	136	8.09	7.25	1179	6.87	6.64	6.49	7.25	1	118	12%
Total	11290	6.93	6.18	1093	7.70	8.11	12383	7.04	6.37	6.89	7.11	1	120	9%

Additionally, the mean secondary inspection service times (in seconds) for both physical search and ETD search are shown in Table 5. 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 6 describes the characteristic behavior of the ACSS 1-to-1 Single Lane Design with Wanding Station. More specifically, the passenger arrival demand at the checkpoint (λ_C), in addition to the screening lane (λ_L) per hour values are shown for each checkpoint across the airport hubs. This table also lists the primary inspection times (μ_1) in seconds and the percentages of carry-on items not-cleared.

Table 5 Physical Search and ETD Service Times (in seconds) across Airport Hubs

	Small			Medium			Large			Total		
Type	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

Table 6 ACSS Parameters for All Checkpoints by Airport Hubs

Airport Type	ACSS ID	# of Lanes	Passenger Arrival Rate per Hour at Checkpoint (λ_C)	Passenger Arrival Rate per Hour at Lane (λ_L)	Primary Inspection Time (in seconds) (μ_1)	Percentage Not-Cleared (β)
Large	1	6	1001	167	6.70	9%
	2	6	1387	231	7.84	11%
	3	6	1391	232	6.58	12%
	4	6	1270	212	6.80	6%
	7	6	1113	186	6.90	5%
	8	6	1200	200	6.63	8%
	9	6	1185	198	7.88	9%
	10	6	1261	210	6.83	3%
	11	6	1384	231	6.81	12%
	12	6	1096	183	6.87	12%
	Total	6	1229	205	7.04	9%
Medium	5	5	1267	253	7.43	12%
	6	5	1011	202	7.29	10%
	14	4	720	180	6.92	3%
	15	4	564	141	6.70	2%
	16	4	928	232	5.78	6%
	Total	4	898	202	7.00	7%
Small	13	3	696	232	5.88	10%
	17	2	301	151	5.72	4%
	18	2	275	138	5.72	2%
	Total	2	424	173	5.81	5%

PRIMARY INSPECTION OPERATING CHARACTERISTICS

Combining the data collection periods and collapsing individual checkpoints into the different airport hubs, Figure 4 shows the percentage of the carry-on items cleared and not-cleared as a function of the maximum inspection time for large hub airports. 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 the figure. 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 (ψ_t) that will complete inspection (both cleared and non-cleared) within the maximum allowable inspection time of t seconds. For example, t when ψ_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.

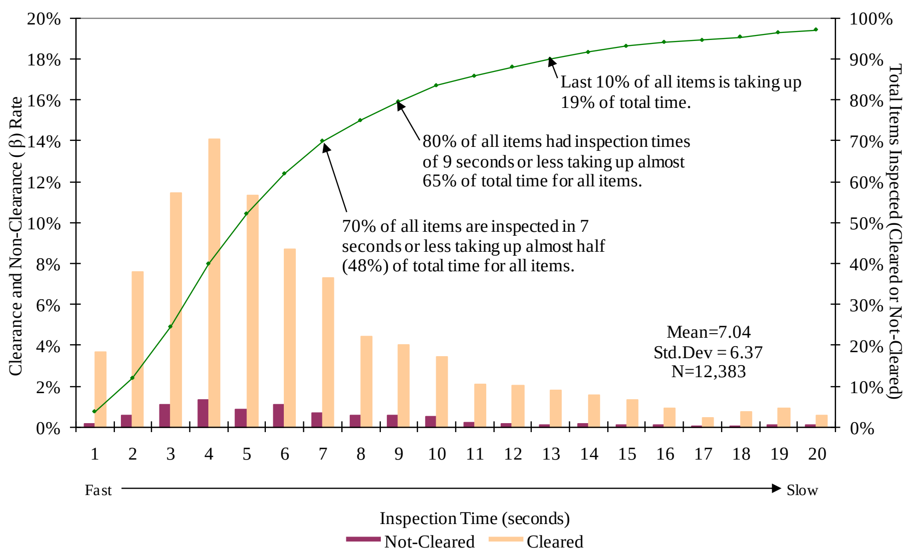


Figure 4 Primary inspection as a function of time at large hub airports combined.

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 β is reduced in the shorter inspections

TYPE B - Improve the decision capability so that β is reduced in the longer inspections

TYPE C - Improve the decision capability at all inspection rates

As shown in Figure 5, 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 carry-on item (bags) per minute or μ=8 seconds. Denoting speed or service rate by μ and the rate at which carry-on items move to secondary inspection by β, μ^{MAX} is introduced as the maximum inspection rate; μ^{MIN} is the slowest inspection rate. At the slowest rate there could possibly be no carry-on items being sent to secondary inspection; β^{MAX}, at the rate sent to secondary inspection corresponding to μ^{MAX}, and β^{MIN}, the rate sent to secondary inspection corresponding to μ^{MIN}, is in many cases this will be 0%. When a maximum inspection time μ^{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 β.

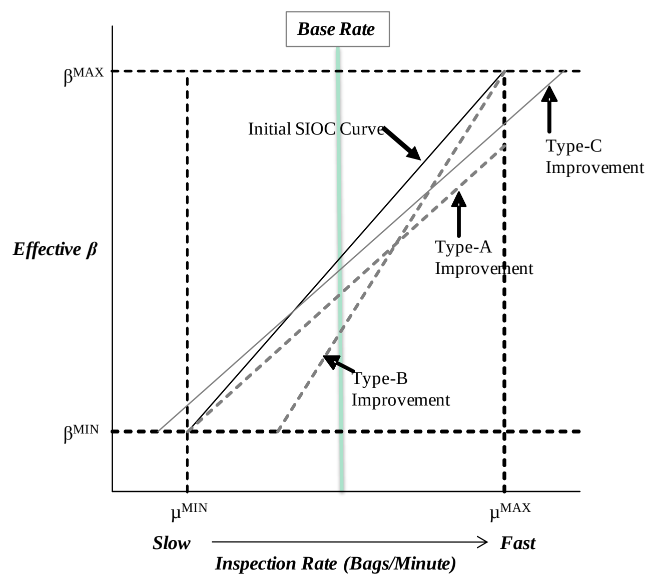


Figure 5 Conceptual SIOC threshold points with improvement strategies.

SIOC curves were generated with the empirical data collected and presented in the previous 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 6 illustrates the SIOC curve for large hub airports. Instead of the inspection time (τ), the service rate (μ), where $\mu=60/\tau$, is plotted on the xaxis to show the rejection rate as a function of time, that is, the number of carry-on items inspected per minute by the TSO.

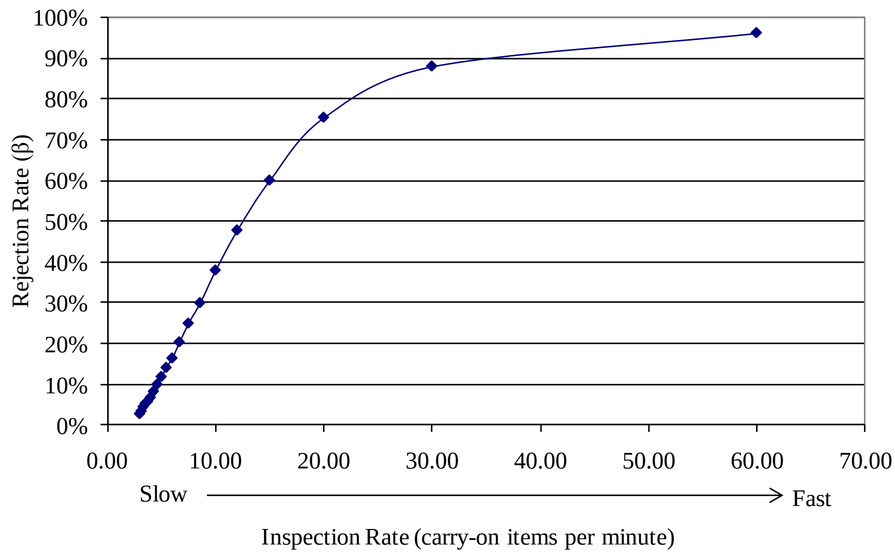


Figure 6 Large hub SIOC curve.

In Figure 6 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 β, labeled as the Rejection Rate is too high. Therefore, setting the thresholds to μ^{MIN} to 3 per minute and μ^{MAX} to 12 per minute; and β^{MIN} at 2.9% and β^{MAX} at 47.8%, the resulting plot is shown in Figure 7. The data shows that the relationship between the Effective β and the maximum inspection rate ($60/\mu^{MAX}$) describes an approximate linear relationship in the 3 to 12 bags per minute range. The equation derived is shown in Figure 7 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 8 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 9. The specific rejection rate values are provided in Table 7. 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. 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.

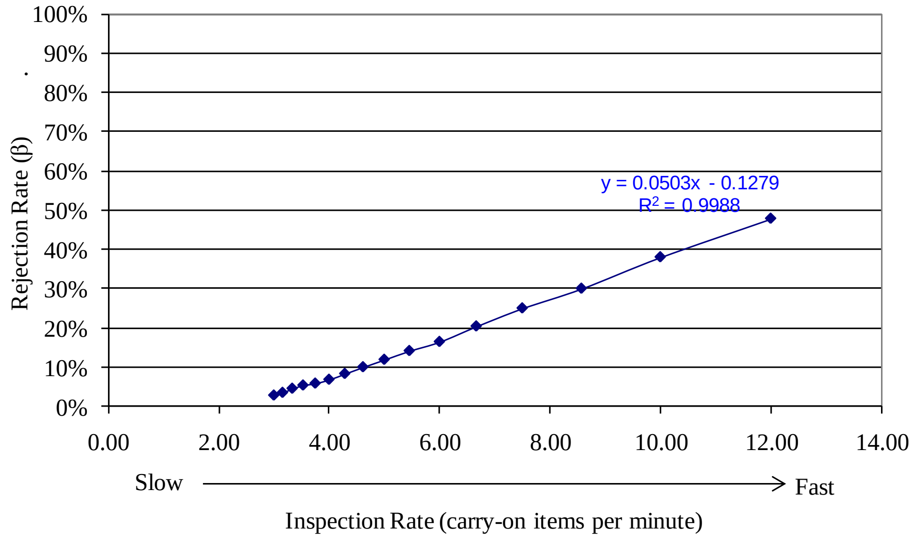


Figure 7 Large hub SIOC curve with threshold points.

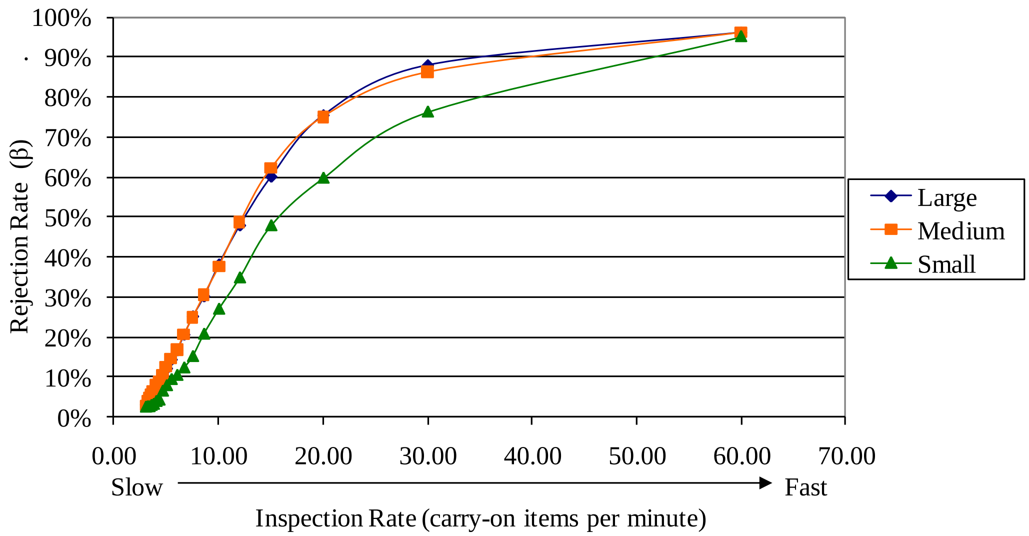


Figure 8 Large, medium and small airport hubs' SIOC curves.

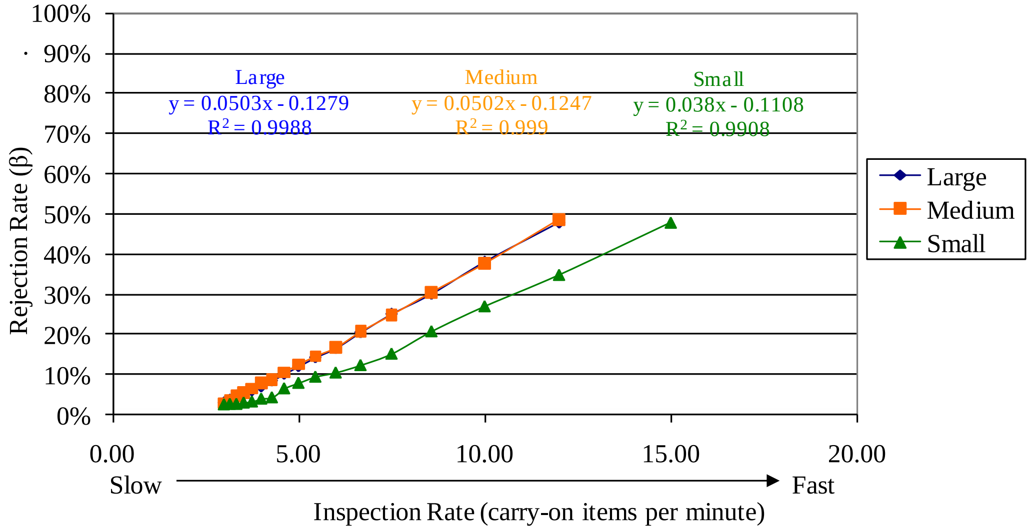


Figure 9 SIOC curve regression for all airport types with threshold points.

Table 7 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%

Hypothesis Testing

To investigate interactions between factors, such as, do cleared items have different mean X-ray TSO image inspection times than not-cleared items, as well as the effects of individual factors, a two-way analysis of variance (ANOVA) (univariate General Linear Model (GLM) 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).

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 8 presents the results obtained to test whether there are differences between inspection times across airports and at different data collection time periods.

Table 8 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*	*F*	*p*	η^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			

***p=<.05*

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.

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

Table 9 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 10. 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 11. 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 9 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 10 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	χ^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 11 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	χ^2 *p*-value	K.S. Statistic
L	0.52	0.01
M	0.52	0.02
S	0.52	0.04

DISCUSSION

Important findings emerged from the analysis. The results showed the interaction of factors 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. 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. Additionally, 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.

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.

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.

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