A sequential stochastic passenger screening problem for aviation security

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A sequential stochastic passenger screening problem for aviation security

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Designing effective aviation security systems has become a problem of national concern. Since September 11th, 2001 passenger screening systems have become an important component in the design and operation of aviation security systems. This paper introduces the Sequential Stochastic Passenger Screening Problem (SSPSP), which allows passengers to be optimally assigned (in real-time) to aviation security resources. Passengers are classified as either selectees or non-selectees, with screening procedures in place for each such class. Passengers arrive sequentially, and a prescreening system determines each passenger’s perceived risk level, which becomes known upon check-in. The objective of SSPSP is to use the passengers’ perceived risk levels to determine the optimal policy for screening passengers that maximizes the expected number of true alarms, subject to capacity and assignment constraints. SSPSP is formulated as a Markov decision process, and an optimal policy is found using dynamic programming. Several structural properties of SSPSP are derived using its relationship to knapsack and sequential assignment problems. An illustrative example is provided, which indicates that a large proportion of high-risk passengers are classified as selectees.

Keywords: Homeland security, Markov decision process, knapsack problems, assignment problems, dynamic programming

1. Introduction

The events of September 11, 2001 led to sweeping nationwide changes in aviation security policy and operations. The piecemeal and reactive nature of many of these changes has resulted in large increases in costs and inconvenience to travelers. The August 2006 arrest in London of several suspected terrorists plotting to blow up ten US-bound transatlantic flights, and the ensuing changes in airport security procedures, serve to further illustrate this point. These experiences suggest the need for new aviation security paradigms that bring together the key security system factors (namely, technology, intelligence and procedures) needed to achieve screening operations that are efficient, cost-effective and non-intrusive.

Aviation security policy and procedures have been abruptly altered several times since September 11, 2001. One policy change was the 100% baggage screening mandate, put forth by the Aviation and Transportation Security Act (ATSA), passed on November 19, 2001, with a deadline of December 31, 2002 (Mead, 2003). Under such a policy, all checked baggage must be screened by Explosive Detection Systems (EDSs) or Explosive Trace Detectors (ETDs), approved by the Transportation Security Administration (TSA). To comply with the ATSA, the TSA began acquiring and deploying EDSs and ETDs in airports throughout the nation, with more than 1400 EDSs and 6600 ETDs deployed since 2001 (US GAO, 2006). Another change included restrictions on carry-on items (such as liquids, as of August 2006).

A major policy change following September 11, 2001 was the development of program Secure Flight. Secure Flight performs a check on passenger information against consolidated Federal terrorist watch lists (US TSA, 2006). Passengers who are permitted to fly by Secure Flight are then prescreened by CAPPS, the Computer-Aided Passenger Prescreening System. CAPPS performs a risk assessment on each passenger and partitions passengers into two classes: non-selectees and selectees, where non-selectees are...
passengers who have been cleared of posing a risk, and selectees are passengers who have not been cleared, based on limited information known about them. A prescreening system such as CAPPS can be used to assign an assessed threat value to each passenger, a scalar value that quantifies the risk associated with the characteristics of the passenger. CAPPS distinguishes selectees and non-selectees by requiring additional screening (such as hand searches) for selectees and their baggage. The selectee and non-selectee classes are each defined by a preassigned subset of devices and a procedure through which passengers are processed prior to boarding an aircraft. CAPPS was refined after September 11, 2001, resulting in a new prescreening system called CAPPS II. However, CAPPS II was eventually dismantled over privacy concerns. At present, an updated version of CAPPS is being used to pre-screen passengers at the nation's commercial airports.

Prescreening systems such as CAPPS are an important layer in aviation security. The use of a prescreening system has operational implications in the screening of passengers with security screening devices and procedures. There are several devices available for screening passengers, where each device is an aviation security technology or procedure used to identify threat items. Threat items are those items prohibited from being carried onto aircraft, as defined by the TSA (note that the TSA periodically redefines what they consider to be threat items; for example, liquids in bottles greater than 3 ounces have been prohibited in carry-on baggage since August 2006). A device screens passengers in one of three ways: (i) checked baggage; (ii) carry-on baggage; or (iii) passengers. At present, all checked baggage is screened for explosives either by an EDS or an ETD. All passengers are screened with a magnetometer and their carry-on baggage is screened with an X-ray machine. Each device has an associated capacity, the upper bound on the number of passengers or bags that a device can screen in a given amount of time. Selectees and their carry-on baggage are differentiated from non-selectees by undergo hand searches by airport screening personnel. In some airports, selectees are screened with hand wands or trace portals and their carry-on baggage is screened by an ETD.

A weakness of any prescreening system, including CAPPS, is that such systems can be gamed through extensive trial-and-error sampling by a variety of passengers passing through the system (Barnett, 2001; Chakrabarti and Strauss, 2002). Martonosi (2005) and Martonosi and Barnett (2006) report that the underlying screening process has a larger impact on reducing successful attacks than an effective prescreening system. Barnett (2004) suggests that CAPPS II may only improve aviation security under a particular set of circumstances and recommends that prescreening systems be transitioned from a security centerpiece to one of many components in future aviation security strategies. The TSA describes prescreening systems as critical components in a layered system for aviation security, including reinforced cockpit doors, bomb sniffing dogs and deploying Federal air marshals on numerous flights (US TSA, 2004).

Aviation security experts suggest that more intense scrutiny of passengers perceived as greater security risks is a more effective approach to aviation security than increasing the screening intensity for all passengers. Barnett (2001) suggests a security policy that increases the level of screening for selectee passengers rather than diminishing the difference between selectee and non-selectee passengers. Butler and Poole (2002) and Poole and Passantino (2003) argue that 100% checked baggage screening is not cost-effective, and suggest that creating multiple levels of security for screening passengers may be more effective than treating all passengers the same.

Integer programming and discrete optimization models have been used to formulate several aviation security problems when a system such as CAPPS is used to pre-screen passengers. Jacobson et al. (2001) provide a framework for measuring the effectiveness of baggage screening security device deployments for screening selectee baggage at a particular airport station. Jacobson et al. (2003) introduce three performance measures for baggage screening security systems and introduce models to assess the security effect for single or multiple airport stations. Jacobson et al. (2005a) formulate problems that model multiple sets of flights originating from multiple airport stations subject to a finite amount of security resources; these problems consider the three performance measures introduced in Jacobson et al. (2003). Examples are presented to illustrate strategies that may provide more robust device allocations across all these performance measures. Jacobson et al. (2005b) construct integer programming models for problems that consider multiple sets of flights originating from multiple airports. Virta et al. (2002) consider the impact of originating and transferring passengers on the effectiveness of baggage screening security systems. Both these papers consider classifying selectees into two types: (i) those at their point of origin; and (ii) those connecting through a hub airport. This is noteworthy since at least two of the hijackers on September 11, 2001 were connecting passengers. Lazar Babu et al. (2006) use linear programming models to investigate the benefit acquired from using multiple risk groups for screening passengers. They conclude that using multiple risk groups is beneficial for security, even when a prescreening system is not used to differentiate passenger risk. Nie et al. (2006) extend this model to consider passenger risk levels, as determined by a passenger prescreening system, and formulate the resulting model as a mixed-integer program. They find that using passenger risk levels results in a more efficient security system.

Other research has focused on the experimental and statistical analysis of risk and security procedures on aircraft. Barnett et al. (2001) report the results of a large-scale, two-week experiment at several airports to identify costs and disruptions that would arise from using positive passenger baggage matching, an aviation security procedure where passengers’ checked baggage is removed from a flight if the
passengers do not board the aircraft. They conclude that using positive passenger baggage matching results in an average delay of one minute per flight, and its implementation costs an additional 40 cents per passenger. Barnett et al. (1979) and Barnett and Higgins (1989) study mortality rates on passenger aircraft and perform a statistical analysis on this data. Czerwinski and Barnett (2006) analyze differences in airlines protecting passengers from death and recovering from emergencies that have occurred. They find no evidence that established airlines are safer than new-entrant airlines.

Optimal risk-based passenger screening must operate in real-time and be dynamic, responding to changes in passenger arrival rates and device utilization. This paper introduces the Sequential Stochastic Passenger Screening Problem (SSPSP) that models passenger screening strategies using Markov decision processes and discrete optimization models. SSPSP assumes that passengers are classified as selectees or non-selectees based on the output of a prescreening system. SSPSP is motivated by McLay et al. (2006, 2007), who introduce the Multilevel Allocation Problem (MAP) and the Multilevel Passenger Screening Problem (MPSP). In these problems, multiple security classes are available for screening passengers, which generalizes the binary paradigm of Secure Flight. Moreover, the set of passengers to be screened at a particular station in an airport in a given period of time is assumed to be known, and hence, the assessed threat values are assumed to be known a priori. This assumption is relaxed by SSPSP, in which passengers check in sequentially, and each passenger’s assessed threat value becomes known only upon check-in. This necessitates a change in the solution methodology since all passenger screening decisions are made simultaneously in MAP and MPSP, whereas passenger screening decisions are made sequentially for SSPSP. MPSP is a static model that does not account for passenger check-in order, whereas SSPSP incorporates the effect of passenger check-in order. Since passengers are classified as selectees or non-selectees upon check-in, it is critical to understand the impact of passenger order on the ability of a screening system to systematically identify high-risk passengers in real-time to focus more effective screening technologies on these passengers. Note that this research assumes that a prescreening system such as CAPPS has been implemented and is effective in identifying passenger risk (i.e., the assessed threat values accurately quantify passenger risk) (Kahn, 2006).

The primary contribution of this paper is to identify a real-time methodology for screening passengers under a binary screening paradigm and to show how this methodology can be used to provide insights into the operation and performance of such real-time systems. This paper focuses on the theoretical issues surrounding this methodology in order to understand its fundamental properties, and the results provide an optimal policy for screening passengers in real-time. Providing strategies to screen passengers is critical in the design and development of next-generation aviation security systems, given the political force being exerted on the aviation security community to react to existing and new terrorist threats.

The paper is organized as follows. Section 2 introduces SSPSP as a Markov decision process model, and shows how the optimal policy for SSPSP can be obtained by dynamic programming. Section 3 provides structural properties of the Markov decision process model and states the relationship between SSPSP, the Dynamic and Stochastic Knapsack Problem and the Sequential Stochastic Assignment Problem. Section 4 analyzes an illustrative example to provide insight into the operation of real-time passenger screening systems. Section 5 discusses implications of optimal screening policies under a binary screening system. Section 6 provides concluding comments and directions for future research.

2. Optimization models

Efficiently and effectively screening passengers using a risk-based system is challenging. SSPSP models a passenger screening problem when passengers are classified as either selectees (s) or non-selectees (ns). This section formulates SSPSP as a stochastic optimization model and uses a Markov decision process model to solve for its optimal policy.

Passengers and their baggage are screened by a sequence of devices, which is set in advance by the TSA for both the selectee and non-selectee classes. Note that each device gives one of two possible responses: an alarm or a clear, and hence, the system gives one of two possible outcomes: an alarm or a clear, which is a function of the device outcomes and can be defined in several ways (see Kobza and Jacobson (1996, 1997) for a discussion on how this can be done). Each passenger is either a threat or a non-threat, where a threat is defined as a passenger carrying a prohibited item (e.g., gun, knife) through a security checkpoint. Ideally, the system yields a clear response for all non-threat passengers and an alarm response for all threat passengers. Although it is not known in advance whether a given passenger will yield an alarm response, it is assumed that there are procedures in place for resolving alarms and that adequate resources are available to resolve all alarms given by the system.

Several assumptions are needed to define SSPSP. First, SSPSP assumes that passengers check in sequentially, and that each passenger is assigned to a class upon check-in (i.e., before the next passenger checks in). Note that the passengers may check in several hours before they arrive at the airport. Therefore, the time period when passengers are assigned to classes may be different than the time period when passengers arrive at the security area in an airport terminal. In practice, a prescreening system such as CAPPS determines which passengers are selectees using information provided by passengers at the point of ticket purchase, and hence, assigning passengers to classes when they check in consistent with existing TSA procedures and practices (US GAO, 2005).
The given time interval for screening passengers can be divided into $T$ stages, where during stage $t$, a passenger checks in with probability $p_t$, $t = 1, 2, \ldots, T$, and hence, with probability $1 - p_t$, no passenger checks in during stage $t$. If the length of each stage is sufficiently small, then it is reasonable to assume that at most one passenger checks in during each stage. Stages are defined to reflect the sequential way passengers check in. The total number of stages during each stage. Stages are defined to reflect the sequential way passengers check in. The probability density function of the assessed threat value of passenger $t$ (a random variable), with value unknown until then, is the capacity of the passenger that checks in during stage $t$.

Let $\mathcal{A}(t)$ denote the assessed threat value of passenger $t$, the assessed threat value of passenger $t$ becomes known upon the passenger’s arrival, taking on value $\alpha(t), t = 1, 2, \ldots, T$. Without loss of generality, define $\alpha(t) = 0$ if no passenger arrives during stage $t$. Passenger $t$ refers to the passenger that checks in during stage $t$ or the dummy passenger with $\alpha(t) = 0$, and hence, SSPSP can be formulated as if $T$ passengers always check in. The capacity of the non-selectee class is defined as $T$; this ensures that there is sufficient capacity to classify all passengers as non-selectees.

SSPSP is formulated as a stochastic optimization problem, where the objective is to determine the optimal policy for assigning passengers to classes as they check in. A policy $\pi$ defines a rule for assigning each passenger to a class, which may change after each passenger assignment is made and after the state changes (i.e., the remaining capacity in the selectee class). A policy may be deterministic (i.e., the policy always assigns a passenger to the same class given the identical time and state) or random (i.e., the policy may assign a passenger to different classes given an identical time and state). It may also be Markovian (i.e., the policy only depends on the current passenger and current state) or history dependent (i.e., the policy depends on the passenger assignments of the previous passengers).

The optimal policy maximizes the expected security subject to assignment and capacity constraints. Security can be defined to capture several criteria, and hence, the objective is defined in a flexible way to potentially address a number of objectives. SSPSP classifies passengers as either selectees or non-selectees. A passenger assignment refers to the class to which a passenger is assigned. SSPSP is formally stated as a discrete optimization problem.

The Sequential Stochastic Passenger Screening Problem (SSPSP)

**Instance:**

- $T$ stages;
- $p_t$, the probability that a passenger checks in during stage $t$, $t = 1, 2, \ldots, T$;
- $f_{\alpha}(\alpha)$, a probability density function that describes the distribution of the passengers’ assessed threat values, $0 < \alpha \leq 1$;
- $c$, the capacity of the selectee class over the entire time interval, (the capacity of the non-selectee class is assumed to be $T$);
- $L_S$, and $L_{NS}$, the security levels associated with the selectee and non-selectee classes.

**Variables:**

- $\mathcal{A}(t)$, the assessed threat value of passenger $t$;
- $x_{S}(t)$, passenger $t$ assignment as either a selectee ($x_{S}(t) = 1$) or a non-selectee ($x_{S}(t) = 0$).

**Objective:** Find the policy $\pi$ that determines passenger assignments $x_{S}(1), x_{S}(2), \ldots, x_{S}(T)$ such that the number of passengers classified as selectees is within capacity (i.e., $\sum_{t=1}^{T} x_{S}(t) \leq c$) and the expected total security is maximized:

$$z = \sup_{\pi \in \Pi} \left\{ E \left[ \sum_{t=1}^{T} L_{S} \mathcal{A}(t) x_{S}(t) + \sum_{t=1}^{T} L_{NS} \mathcal{A}(t) (1 - x_{S}(t)) \right] \right\}.$$  

The realized assessed threat values are determined by a prescreening system such as CAPPS. The details of CAPPS are classified, and the assumptions of how prescreening systems operate are based on information disseminated in the public domain (US GAO, 2005). It is also assumed that each realized assessed threat value is determined independently and in real-time, since the prescreening system is an expert system that outputs the deterministic, realized assessed threat values based on information that passengers provide at the time of ticket purchase.

The security levels can be obtained using information and data available from the TSA. The security level of each class (scaled between zero and one) is based on the effectiveness of security procedures of each device used by the class to screen passengers. Security can be defined in several ways. In this paper, the security levels of the selectee and non-selectee classes are measured as the conditional true alarm probability, the conditional probability that a passenger with a threat item is detected given that they are classified as selectees or non-selectees, respectively. If each assessed threat value is defined as the conditional probability that a passenger carries a threat item, then the resulting expected security maximizes the number of true alarms detected by the system. This objective function is identical to minimizing the expected number of false clears. For simplicity, it is assumed that a passenger carries at most one threat item. Security screening devices are designed to detect one class of threat items; for example, metal detectors are designed to detect guns and knives, while EDSs and ETDs are designed to detect explosives and bombs. Each device is not equally proficient at detecting each type of threat item; however, the formulation is realistic if the parameters are defined to restrict the search to one class of threat item (e.g., explosives).

Security devices may require significant amounts of space in airport lobbies or terminals. SSPSP does not explicitly...
incorporate space requirements of screening devices. Secondary screening is performed for passengers who receive an alarm response. A certain number of alarms will occur, given the capacity of the selectee class, and it is assumed that the necessary security devices are available for resolving these alarms. However, since it is assumed that the capacity of the selectee class is based on the necessary number of screening devices allowed by the physical space available, then space requirements are implicitly captured by SSPSP.

There have been limited research efforts that focus on real-time, risk-based passenger screening strategies given a prescreening system such as CAPPS. SSPSP has similarities to three other types of passenger screening methodologies. First, SSPSP is a particular case of the Sequential Stochastic Multilevel Passenger Screening Problem (SSMSPSP) (McLay et al. 2006), which generalizes the binary paradigm of CAPPS to consider multiple classes for screening passengers. SSMSPSP is NP-hard, and as a result, there are additional challenges in its implementation that do not apply to SSPSP. Therefore, although the more general results for SSMSPSP also apply to SSPSP, the results considered in this paper provide more practical, tailored recommendations for a binary screening system (i.e., selectee and non-selectee passenger classification). Moreover, the analysis of SSPSP provides insights that may be of practical value, since the TSA has repeatedly embraced real-time, risk-based passenger screening strategies given a prescreening system such as CAPPS. SSPSP has similarities to three other types of passenger screening methodologies to obtain different insights into a similar passenger screening problem.

SSPSP is similar to the second stage of a stochastic two-stage model (Nikolaev et al. 2007). The two-stage model uses discrete optimization to determine which security devices to purchase and install as well as a passenger screening strategy that maximizes device utilization. Although there is overlap between SSPSP and the two-stage model presented by Nikolaev et al. (2007), the two-stage model provides insight into issues of long-term device allocation rather than the more immediate issue of how to optimally screen passengers in real-time. Moreover, the analysis in Nikolaev et al. (2007) focuses on the aggregate level, such as analyzing expected system performance, as opposed to focusing on implications of individual passenger screening decisions (see Sections 4 and 5).

Since SSPSP has a sequential structure and makes screening decisions based only on the current state of the system, it is natural to formulate SSPSP as a Markov Decision Process (MDP). This MDP formulation also illustrates how the optimal policy is found. SSPSP can be formulated as an MDP with \( T + 1 \) stages, with the state in stage \( t = 1, 2, \ldots, T \) describing the system before the first \( t \) passengers have been assigned to classes, where stage 1 corresponds to the initial stage, with stage \( T + 1 \) giving the final state after all passengers have been assigned to classes.

Let \( S \) denote the set of states. Let state \( s(t) \in S \) represent the remaining capacity in the selectee class before passenger \( t = 1, 2, \ldots, T \) has been assigned to a class. The initial state corresponds to the initial capacity, \( s(1) = c \), and denotes the state in stage \( t \) as the remaining capacity of the selectee class, \( c \). Therefore, \( |S| = c + 1 \).

For passenger \( t \), there are two actions available: (i) classify the passenger as a selectee, if there is available capacity; or (ii) classify the passenger as a non-selectee. Given state \( s(t) = c \), if \( c > 0 \), then the next passenger may be classified as either a selectee or non-selectee, and if \( c = 0 \), then the next passenger must be classified as a non-selectee, \( t = 1, 2, \ldots, T \), for all \( s(t) \in S \). The transition probabilities, which determine state \( s(t + 1) \) given state \( s(t) \) and the passenger assignment, are defined as

\[
p(s(t + 1)|s(t), x_8(t)) = \begin{cases} 
1, & \text{if } s(t + 1) = s(t) - x_8(t) \\
0 & \text{otherwise}
\end{cases}
\]

for \( t = 1, 2, \ldots, T \).

The objective function value of SSPSP is determined by accruing a reward after each stage in the MDP. Define the reward for classifying passenger \( t \) as a selectee or non-selectee given state \( s(t) \in S \), \( t = 1, 2, \ldots, T \), as

\[
r(s(t), A(t), x_8(t)) = L_S A(t) x_8(t) + L_{NS} A(t) (1 - x_8(t)),
\]

where \( L_S \) and \( L_{NS} \) are the costs associated with selecting a passenger as a selectee or non-selectee, respectively.

The expected total security for SSPSP is determined by policy \( \pi \), which describes the decision rule for selecting an action (i.e., the class to which each passenger is assigned) in each state and at each stage. Let \( S(t) \) denote the random variable corresponding to the state before passenger \( t \) has been assigned to a class, and let \( X_8^T(S(t)) \) denote the random variable corresponding to the class to which passenger \( t \) is assigned given policy \( \pi \). Given that the system is initialized in state \( s(1) \), then the expected total security for SSPSP is defined as

\[
E^\pi(s(1)) = E^\pi\left[ \sum_{t=1}^{T} r(S(t), A(t), X_8^T(S(t))) | S(1) = s(1) \right],
\]

where \( r(S(t), A(t), X_8^T(S(t))) \) is the random variable corresponding to the security obtained in time period \( t \) in state \( S(t) \) with decision variables \( X_8^T(S(t)) \) based on policy \( \pi \). The objective of SSPSP is to find the optimal policy \( \pi^* \) such that \( E^{\pi^*}(s(1)) = \sup_{\pi} \{ E^\pi(s(1)) | \pi \} \).

Define the value function in stage \( t = 1, 2, \ldots, T \) as the optimal expected total security for assigning passenger \( t \) and the remaining \( T - t \) passengers to classes if \( s(t) > 0 \):
for \( t = 1, 2, \ldots, T \), where for SSPSP:

\[
V_i(s(t)) = \max \{ E[L_S \pi(t)|s(t) + L_{NS}(1 - x_s(t)) \\
+ V_{i+1}(s(t) - x_s(t)) \},
\]

(2)

for \( t = 1, 2, \ldots, T \) (that are also known as the optimality equations with boundary conditions)

\[
V_{T+1}(s(t)) = 0, s(t) \in S. \tag{3}
\]

Passenger \( t \) is classified as a selectee if

\[
L_S \alpha(t) + V_{i+1}(s(t) - 1) \geq L_{NS} \alpha(t) + V_{i+1}(s(t)). \tag{4}
\]

The optimal policy \( \pi^* \), which solves the optimality equations, can be found using dynamic programming. The total security of a SSPSP instance, given realized assessed threat values \( \alpha(1), \alpha(2), \ldots, \alpha(T) \) and their assignments \( x_s(1), x_s(2), \ldots, x_s(T) \), is \( \sum_{t=1}^{T} \alpha(t)(L_S x_s(t) + L_{NS} (1 - x_s(t))) \). The optimal expected total security is captured by \( V_i(s(1)) \).

Integration is performed when computing the value functions in Equation (2), since the value function is an expected value. Let \( O(I) \) denote the time complexity required to perform integration at each stage in the recursion. Note that this time complexity is \( O(1) \) if there is a closed-form expression for the integrand, and that, in general, \( I \) depends on the number of grid points if numerical integration is used. If the probability density function is discrete, and each assessed threat value may take on one of \( W \) values, then \( I = W \).

Note that since \( c \) is bounded by \( T \), then the optimal policy can be determined in \( O(T^2 I) \) time and \( O(T^2) \) space.

3. Structural properties

In this section, several structural properties of SSPSP and its MDP formulation are derived, and the relationship between SSPSP and the Dynamic and Stochastic Knapsack Problem (DSKP) and the Sequential Stochastic Assignment Problem (SSAP) are made explicit. First, it is noted that the optimal policy is deterministic and Markovian. DSKP and SSAP are then used to illustrate the remaining structural properties for SSPSP.

**Theorem 1.** This optimal policy for SSPSP is deterministic and Markovian.

**Proof.** Follows from the number of states being finite (Puterman, 1994).

3.1. The DSKP

SSPSP can be formulated as a particular case of DSKP (Papastavrou et al., 1996). In the general instance of DSKP, there is a knapsack with capacity \( c \). There is a time interval with \( T + 1 \) stages, with the probability \( p \) of an item arriving in any of the first \( T \) stages, and a probability of \( 1 - p \) of no item arriving. Each arriving item has weight \( W \) and profit \( R \), which become known upon the item’s arrival. Both \( W \) and \( R \) are independent and identically distributed random variables, and they have probability density functions that are known in advance. If an item arrives, then one of two actions must be taken: (i) either the item is accepted (i.e., placed in the knapsack); or (ii) it is rejected. The objective is to maximize the expected total reward accumulated over the \( T + 1 \) stages, where \( R \) remains feasible. Let \( EV_{t}^c \) denote the optimal expected reward accumulated from (and including) time period \( t \) until time period \( T + 1 \) with remaining capacity \( \bar{c} \), \( t = 1, 2, \ldots, T + 1, \bar{c} = 0, 1, \ldots c \). The optimal expected reward over all stages is given by \( EV_1^c \).

SSPSP is equivalent to the particular case of DSKP when all of the item types have equal weights, with \( w = 1 \) for all arriving item types. In this case, the knapsack capacity is analogous to the capacity of the selectee class and each item’s reward is analogous to the assessed threat values, scaled by the difference between the security levels of the selectee and non-selectee classes:

\[
R = A(t)(L_S - L_{NS}). \tag{5}
\]

Items in the knapsack correspond to passengers classified as selectees. Rejected items correspond to passengers classified as non-selectees. Solving SSPSP by formulating it as a DSKP instance finds the optimal expected additional security acquired from classifying passengers as selectees, compared to classifying all passengers as non-selectees.

The optimal policy for DSKP is a threshold policy, in which arriving items whose weight and value are above (below) a threshold value are accepted (rejected). Define the expected reward from stage \( t + 1 \) until stage \( T + 1 \) with remaining capacity \( \bar{c} \) as \( EV_{t+1}^{\bar{c}} \) in the DSKP formulation, which corresponds to \( V_{i+1}(\bar{c}) \) in the SSPSP formulation. The optimal policy determines a threshold value for each stage and for each remaining capacity:

\[
R_t^c = EV_{t+1}^{\bar{c}} - EV_{t+1}^{\bar{c}-1},
\]

with \( R_t^c \) denoting the critical reward. The optimal policy for the particular case of DSKP \( \pi^*(t, \bar{c}, r) \) is

\[
\pi^*(t, \bar{c}, r) = \begin{cases} 
\text{accept} & \text{if } r \geq R_t^c, \\
\text{reject} & \text{if } r < R_t^c.
\end{cases}
\]

**Proposition 1.** The optimal policy for SSPSP defines a critical assessed threat value \( H_t(\bar{c}) \) at each stage \( t \) and in each state \( s(t) = \bar{c} \), with a passenger whose realized assessed threat value is greater than or equal to this threshold classified as a selectee.

**Proof.** The optimal policy for DSKP with equal weights can be applied to SSPSP, since SSPSP can be transformed into a particular case of DSKP. Given that there are \( \bar{c} \) positions available in the selectee class at stage \( t \), then passenger \( t \) is classified as a selectee if

\[
a(t) \geq H_t(\bar{c}) = \frac{R_t^c}{L_S - L_{NS}}.
\]
Theorem 2 summarizes several results from Papastavrou et al. (1996) applied to SSPSP. Proposition 2 provides two results for SSPSP that can also be applied to the particular case of DSKP with equal weights.

**Theorem 2.** The following results are valid for SSPSP.

1. \( V_t(\bar{c}) \) is a concave non-decreasing function of \( \bar{c} \), \( t = 1, 2, \ldots, T \).
2. \( V_t(\bar{c}) \) is a concave non-increasing function of \( t \), \( \bar{c} = 0, 1, \ldots, c \).
3. \( H_t(\bar{c}) \) is non-increasing with \( \bar{c} \), \( t = 1, 2, \ldots, T \).
4. \( H_t(\bar{c}) \) is non-increasing with \( t \), \( \bar{c} = 0, 1, \ldots, c \).

**Proof.** Follows from Papastavrou et al. (1996), since \( H_t(\bar{c}) = R^c_t/(L_S - L_{NS}) \) and

\[
V_t(\bar{c}) = \max_{x_0(t) \in [0, 1]} \left[ E[(L_S - L_{NS})A(t)x_0(t)]ight. \\
\left. + L_{NS}A(t) + V_{t+1}(s(t) - x_0(t))] \right] \\
= \max_{x_0(t) \in [0, 1]} \left[ E[(L_S - L_{NS})A(t)x_0(t)] + V_{t+1}(s(t) - x_0(t))] \right] \\
= V_t + (T - t + 1)E[L_{NS}A(t)].
\]

**Proposition 2.** The following results are valid for SSPSP.

1. \( V_t(\bar{c}) \) is a concave non-decreasing function of \( \bar{p} \), \( \bar{c} = 0, 1, \ldots, c \), \( t = 1, 2, \ldots, T \).
2. \( H_t(\bar{c}) \) is non-decreasing with \( \bar{p} \), \( \bar{c} = 0, 1, \ldots, c \), \( t = 1, 2, \ldots, T \).

**Proof.** For simplicity, both claims are shown for the particular case of DSKP with equal weights, since the proof of Theorem 2 shows that if true for DSKP, both claims are also true for SSPSP.

1. The claim is shown by induction. Let \( EV_t^{\bar{c}} \) denote the optimal expected reward accumulated from (and including) time period \( t \) given that an item has arrived during time period \( t \). Define \( F(R) \) as the cumulative density function of the item rewards, evaluated at reward \( R \).

By Theorem 2, \( EV_t^{\bar{c}} \) and \( EV_t^{\bar{c}} \) are concave, non-decreasing functions of \( \bar{p} \), \( \bar{c} = 0, 1, \ldots, c \) (where \( EU_t^{\bar{c}} = EV_t^{\bar{c}} \) when \( p = 1 \)). Assume that \( EV_t^{\bar{c}} \) is a concave, non-decreasing function of \( p \) for all \( \bar{c} \) for \( t' = t + 1, t + 2, \ldots, T \). Note that this implies that \( EU_t^{\bar{c}} \) is a concave, non-decreasing function for all \( \bar{c} \) for \( t' = t + 1, t + 2, \ldots, T \), since

\[
EU_t^{\bar{c}} = P(\text{Accept}) EV_t^{\bar{c}} + P(\text{Reject}) EV_t^{\bar{c}} \\
= (1 - F(R_t^{\bar{c}})) EV_t^{\bar{c}} + F(R_t^{\bar{c}}) EV_t^{\bar{c}}.
\]

Therefore, \( EU_t^{\bar{c}} \) is a convex combination of two concave, non-decreasing functions of \( p \), and hence, is a concave, non-decreasing function of \( p \). Then,

\[
EV_t^{\bar{c}} = (1 - p) EV_t^{\bar{c}} + p EU_t^{\bar{c}},
\]

and \( EV_t^{\bar{c}} \) is a convex combination of two concave, non-decreasing functions of \( p \), and hence, \( EV_t^{\bar{c}} \) is a concave, non-decreasing function of \( p \).

2. The claim is shown by induction. Recall that \( R_t^{\bar{c}} = EV_t^{\bar{c}} - EV_t^{\bar{c}} \), with \( R_t^{\bar{c}} = 0 \) for all \( \bar{c} > 0 \) and \( R_t^{\bar{c}} = +\infty \), since all items are rejected if there is no remaining capacity in the knapsack. Assume that \( EV_t^{\bar{c}} - EV_t^{\bar{c}} \) is a concave, non-decreasing function of \( p \), \( t' = t + 1, t + 2, \ldots, T \). Then, \( EU_t^{\bar{c}} - EU_t^{\bar{c}} \) is a concave, non-decreasing function of \( p \), since

\[
EU_t^{\bar{c}} - EU_t^{\bar{c}} = (1 - F(R_t^{\bar{c}})) EV_t^{\bar{c}} + F(R_t^{\bar{c}}) EV_t^{\bar{c}} \\
- (1 - F(R_t^{\bar{c}})) EV_t^{\bar{c}} - F(R_t^{\bar{c}}) EV_t^{\bar{c}} \\
= (1 - F(R_t^{\bar{c}}))(EV_t^{\bar{c}} - EV_t^{\bar{c}}) \\
+ F(R_t^{\bar{c}})(EV_t^{\bar{c}} - EV_t^{\bar{c}}) \\
+ (F(R_t^{\bar{c}}) - F(R_t^{\bar{c}}))(0).
\]

Note that \( R_t^{\bar{c}} \geq R_t^{\bar{c}} \), and hence, \( F(R_t^{\bar{c}}) \geq F(R_t^{\bar{c}}) \). Therefore, \( EU_t^{\bar{c}} - EU_t^{\bar{c}} \) is a convex function of three non-decreasing functions of \( p \), and hence, is a non-decreasing function of \( p \), for \( t' = t + 1, t + 2, \ldots, T \). Then, for \( t' = t \):

\[
EV_t^{\bar{c}} - EV_t^{\bar{c}} = (1 - p) EV_t^{\bar{c}} + p EU_t^{\bar{c}} - (1 - p) EV_t^{\bar{c}} - p EU_t^{\bar{c}} \\
= (1 - p)(EV_t^{\bar{c}} - EV_t^{\bar{c}}) + p(EU_t^{\bar{c}} - EU_t^{\bar{c}}).
\]

Therefore, \( EV_t^{\bar{c}} - EV_t^{\bar{c}} \) is a convex combination of two non-decreasing functions of \( p \), and hence, \( R_t^{\bar{c}} \) is a non-decreasing function of \( p \), for \( \bar{c} = 0, 1, \ldots, c \), \( t = 1, 2, \ldots, T \).
when $p$ is small. Note that whether a high-risk passenger is classified as a selectee depends on the time that the passenger checks in and how many passengers have already been identified. In practice, the capacity can be exceeded in order to classify a small number of extra passengers as selectees; the hybrid model presented in Section 5 addresses this point.

### 3.2. The SSAP

SSSPSP can be formulated as a particular case of the Generalized SSAP (Derman et al. 1972). In SSAP, there are $n$ available people for $n$ jobs, with the values of the people given by $v_1, v_2, \ldots, v_n$, which are treated as known constants. The $n$ jobs arrive sequentially, with the values of the jobs being independent and identically distributed random variables $X_1, X_2, \ldots, X_n$ with cumulative distribution function $F(X)$. Therefore, there are $n$ sequential stages in SSAP, where in stage $t$, a job arrives and its value $x_t$ becomes known, $t = 1, 2, \ldots, n$. The job is matched to a person who has not yet been assigned to an arriving job. Therefore, job $t$ is assigned to person $i_t$, $t = 1, 2, \ldots, n$. The objective is to maximize the expected total reward, given by the expectation of sum of the products of the values of the job and the person to whom it is matched, $E[\sum_{t=1}^{n} X_t v_{i_t}]$. Derman et al. (1972) provide the optimal policy for SSAP.

SSAP can be generalized to consider the number of jobs being different than the number of people. If the number of jobs $m$ is less than the number of people $n$, then the $m$ people with the highest values are assigned to a job. If $m \geq n$, then $n - m$ pseudo-people are created with value zero. If the probability that a job arrives at each stage is less than one, then the optimal policy can be trivially modified by modeling the event that a job does not arrive as a job arriving with value zero, which can be obtained by modifying $F(X)$. This generalization of SSAP to consider a random number of jobs arriving is referred to as the Generalized SSAP (GSSAP).

To formulate SSSPSP as a particular case of GSSAP, first create a set of $T$ people, with $c$ people having value $L_S - L_{NS}$ (corresponding to the spaces available in the selectee class) and $T - c$ people having value zero (corresponding to the spaces available in the non-selectee class). The job arriving at each stage has value zero with probability $1 - p$, corresponding to no one arriving for check-in during stage $t$. With probability $p$, a job arrives, whose value follows the cumulative density function $F(X)$. The objective function is to maximize the expected additional security from classifying passengers as selectees.

Derman et al. (1972) provide an optimal policy for SSAP using dynamic programming. In their approach, in stage $t$, $T - t + 2$ breakpoints are created using the probability density function of the jobs:

$$-\infty = a_{0,t} \leq a_{1,t} \leq \ldots \leq a_{T-t+1,t} = +\infty,$$  

where

$$a_{r,t} = \int_{a_{r-1,t}}^{a_{r,t}} y dF(y) + a_{r-1,t+1} F(a_{r-1,t+1}) \quad + a_{r,t+1} (1 - F(a_{r,t+1})), \quad (7)$$

$t = 1, 2, \ldots, T - 1, t' = 1, 2, \ldots, T - t + 1$, are computed in advance for all $T$ stages, requiring $O(T^2 I)$ time and $O(T^2)$ space (recall that $O(I)$ is the time complexity required to perform integration). When a job arrives during stage $t$, its realized value $x_t$ falls into one of $T - t + 1$ intervals in Equation (6), with each interval corresponding to one of the remaining available people. Job $t$ is assigned to the person with the $i$th smallest value who has not been assigned a job such that $a_{i,t} < x_t \leq a_{i+1,t}$. The policy executes in $O(T \log T)$ time, after the breakpoints (7) are computed. Note that the optimal policy depends on the distribution of the job values, not the values of the available people.

The optimal policy can be generalized for GSSAP by redefining the cumulative density function to take into account the probability of a job not arriving:

$$F_{GSSAP}(X) = (1 - p) + p F(X). \quad (8)$$

The optimal policy for GSSAP is identical to that of SSAP, with $F_{GSSAP}(X)$ replacing $F(X)$ in Equation (7). Note that the DSKP and GSSAP policies are identical, with

$$a_{T-t-c,t-1}(L_S - L_{NS}) = E V^c_t - E V^{c-1}_t = R_t^{c-1},$$

$t - 1 = 1, 2, \ldots, T$. $c = 1, 2, \ldots, c$. The online Appendix contains the optimal policy for a more general case of GSSAP, where the random variables $X_1, X_2, \ldots, X_n$ are not required to be identically distributed.

The breakpoints for GSSAP in Equation (7) provide the critical assessed threat values for SSSPSP, with:

$$H_t(c) = a_{T-t-c+1,t}$$

Since the assessed threat values are between zero and one, then $a_{0,t} = 0$ and $a_{T-t+1,t} = 1, t = 1, 2, \ldots, T$. Proposition 3 shows that the optimal way to assign passengers is to classify the highest-risk passengers as selectees. Proposition 4 indicates that the optimal policy is insensitive to the security levels.

**Proposition 3.** If the passengers and their assessed threat values are known a priori, then the optimal policy is to classify the $c$ passengers with the highest realized assessed threat values as selectees and the remaining passengers as non-selectees.

**Proof.** Follows directly from Hardy’s Lemma in Derman et al. (1972).

**Proposition 4.** The optimal policy for SSSPSP does not depend on the security levels, $L_S$ and $L_{NS}$.

**Proof.** Follows from Equation (7). The optimal policy and the critical assessed threat values depend only on the distribution of the assessed threat values, the number of stages and the remaining capacity in the selectee class.
4. Illustrative example

This section provides an illustrative example for SSPSP. In this example, a total of $T = 2000$ stages are considered, with the probability that a passenger checks in during each stage given by $p = 0.5$, resulting in 1000 passengers expected to check-in during the time interval. The assessed threat values are assumed to follow a truncated exponential distribution with parameter $1/16$. The security level of the selectee and non-selectee classes are $L_S = 0.9$ and $L_{NS} = 0.7$. However, Proposition 4 indicates that the optimal policy does not depend on the security levels, and hence, the insights obtained from the analysis are applicable regardless of the real-world security levels. Resolving alarms by secondary screening is not explicitly considered; rather, it is assumed that the capacity of the selectee class is determined by factoring in the expected number of resources needed to resolve false alarms.

Figures 1, 2 and 3 illustrate the value function and critical assessed threat value thresholds that reflect the monotonicity and concavity results in Theorem 2 and Proposition 2, using a remaining capacity of ten for illustration purposes. For simplicity, they reflect the expected additional security using the knapsack formulation notation ($EV^c_t$). Note that these figures do not illustrate how the optimal policy operates in practice (i.e., how the critical assessed threat value actually changes as passengers check-in) since Fig. 1 illustrates the policy when the remaining capacity and $p$ are fixed, Fig. 2 illustrates the optimal policy when the stage and $p$ are fixed and Fig. 3 illustrates the optimal policy when the remaining capacity and the stage are fixed.

The optimal policy was computed using Matlab on a Pentium D 3.2 GHz processor with 3.5 GB of RAM. The capacity of the selectee class considered was $c = 50, 100$ and 200 passengers, which is consistent with the observation that most passengers are classified as non-selectees (Barnett, 2001). A total of 100 replications were executed for each capacity level. The optimal value functions were computed in advance and were used by all 100 replications. In each replication, a set of passenger arrivals was simulated, and the optimal policy was applied to determine how to screen the passengers as they checked in. The average objective function values were 46.5, 47.7 and 50.1, for $c = 50, 100$ and 200, respectively. These values are within a factor of 0.001 of the optimal screening strategy when all passengers are assumed to be known a priori (see Proposition 3), which indicates that the optimal policy is highly effective at classifying high-risk passengers as selectees. These values are absolute expected total security values, and they can be compared to the expected additional security values in Fig. 2 by adding a constant factor of $p T L_{NS} E(A(t)) = 43.75$ to the values in Fig. 2. Note that the critical assessed threat values were relatively constant until the end of the time interval. Figure 4 illustrates the average critical assessed threat values as a function of passenger arrivals, for $c = 50, 100,$ and 200. When there was no remaining capacity in the selectee class, the critical assessed threat value increased to one until stage $T$, which increases the average critical assessed threat value and forced any additional passengers to be classified
as non-selectees. Figure 5 illustrates the conditional distrib-
utions of the assessed threat values of the passengers who
are classified as selectees and non-selectees as the optimal
SSPSP policy executed for a single replication. Note that the
capacity $c$ decreased and the stage $t$ increased during each
replication, whereas $c$ remained constant in Fig. 1. It shows
that there is very little overlap of the assessed threat values
of the passengers classified as selectees and the passengers
classified as non-selectees, and hence, the optimal policy
was able to consistently identify high-risk passengers.

Once there is no remaining capacity in the selectee class,
any additional passengers that check in are classified as

Fig. 2. Value function and critical assessed threat value as a function of remaining capacity in the selectee class, $t = 1$.

Fig. 3. Value function and critical assessed threat value as a function of $p$, $c = 10$, $t = 1$. 
Fig. 4. Average critical assessed threat value as a function of time.

Fig. 5. Assessed threat value distributions of selectees and non-selectees, $c = 200$. 

non-selectees. This provides a way for passengers to time their arrival at the airport in order to receive less security scrutiny. This issue is compounded by the fact that the optimal SSPSP policy tends to utilize nearly all of the capacity in the selectee class. The entire capacity of the selectee class was used in all but three, six, and eleven of the 100 replications, for $c = 50, 100$ and $200$, respectively. There was only excess capacity when no passengers arrived during the last several stages, and this excess remaining capacity never exceeded two passengers.
To analyze the possibility of passengers arriving at the end of a time interval to avoid being classified as selectees, suppose that there exists a stage $t$ (with $t < T$) at which a passenger was classified as a selectee and effectively used the last selectee class spot. By design, all passengers checking in during stages $t + 1, t + 2, \ldots, T$ must be classified as non-selectees. For $c = 50$, 18.1 passengers on average arrive after there is no remaining selectee class capacity, while for $c = 200$, this average drops to 3.4 passengers. Although several passengers arriving at the end of the time interval could avoid being classified as selectees under the optimal SSPSP policy, this affects only a small fraction of the passengers. Moreover, the time intervals can begin and end at arbitrary times, so there is a level of unpredictability in knowing when a passenger can arrive to maximize the likelihood of being classified as a non-selectee, which reduces the ability of terrorists to game the system.

The effectiveness of the optimal SSPSP policy depends on accurately identifying and predicting the assessed threat value distribution and the probability of a passenger arriving during each stage. To study the sensitivity of the optimal SSPSP policy with respect to this distribution, a different assessed threat value distribution of the passengers arriving to check in was considered and compared to the assessed threat value distribution used to compute the optimal policy. A truncated exponential distribution with parameter $1/16$ was used to generate the optimal policy (i.e., the value functions and critical assessed threat values). The assessed threat values of passengers arriving to check in followed truncated exponential distributions with parameters $\lambda = 0.005, 0.01, \ldots, 0.1$. For each such value of $\lambda$, 100 replications were executed. Figure 6 shows the average total security as a function of $\lambda$, scaled by the sum of the realized assessed threat values. The scaling was performed since the expected assessed threat value increases with $\lambda$, and hence, the total number of threats in the system increased with $\lambda$. The optimal objective function value is maximized when $\lambda = 1/16$.

Figure 7(a) shows the resulting remaining capacity as a function of passenger arrival, for $c = 50$. When the assessed threat value is accurate (i.e., the distribution has parameter $1/16$), the remaining capacity decreases linearly as passengers arrive, with the selectee class being used uniformly over the entire time interval. When the parameter of the assessed threat value distribution increases, passengers have realized assessed threat values that are smaller than expected, and hence, the selectee class is not utilized until the end of the interval, and there is significant excess capacity in the selectee class after all passengers have checked in. Moreover, when the parameter of the assessed threat value distribution decreases, passengers have realized assessed threat values that are higher than expected, and hence, the selectee class is fully utilized at the beginning of the following interval. This suggests that SSPSP is sensitive to the accuracy of the assessed threat value distribution.

The sensitivity of the optimal SSPSP policy was also studied as a function of the probability of passengers arriving during each stage $p^*$. This probability was considered to differ from the probability $p = 0.5$ used to determine the
optimal policy. A passenger arrived for check-in with probability $p^* = 0.4 - 0.6$ during each stage. For each value of $p^*$, 100 replications were executed. Figure 7(b) shows the resulting remaining capacity as a function of $p^*$ with $c = 50$, resulting in either 800 or 1200 passengers expected to check-in during the time interval. Despite the variation in the number of passengers being screened by the system, any excess capacity was used almost uniformly over the time interval, which suggests that SSPSP is less sensitive to changes in the rate of passenger arrival.

Consider a scenario where a group of high-risk, passive terrorists (i.e., terrorists not carrying a threat) check in one after another, so as to disturb the security class assignment rule in such a way that the probability of a later arriving, active terrorist (i.e., terrorist carrying a threat) is assigned to the highest level of screening decreases. The behavior of the security system to this type of gaming strategy may be interpreted as the system response due to an external disturbance.

Consider a group of $\delta$ high-risk passengers, with assessed threat value $\alpha = 1$, that arrive at time stages $t = \tau + 1, \tau + 2, \ldots, \tau + \delta$ within the time interval. These high-risk passengers are considered to arrive in successive stages to maximize their effect on the security system, but a similar effect can also be studied by assuming non-successive stages. The resulting effects on the critical assessed threat values may be analyzed to quantify the vulnerability of the security system to classifying a late arriving, high-risk passenger as a non-selectee. Figure 8(a) and Fig. 8(b) show the critical assessed threat values after a disturbance group of $\delta = 10$ occurs near the beginning ($\tau = 200$) and near the end ($\tau = 1800$) of the time interval, respectively. The selectee and non-selectee classes are under-utilized near the beginning of the time interval, and hence, the disturbance exhibits little effect on the critical assessed threat values. However, if this disturbance occurs late in the time interval, then the probability that a late arriving, high-risk passenger is classified as a non-selectee is significantly increased.

Note that if a large batch of high-risk passengers (more than $c$) arrive in the time interval, some terrorists could be classified as non-selectees, even if SSPSP is modified to account for this run over in capacity, although the execution of the SSPSP optimal policy indicates that it is extremely unlikely that all such passengers would be classified as non-selectees. Note that on September 11, three of the four planes were hijacked by five terrorists whereas the fourth plane was hijacked by four terrorists. If fewer terrorists can get through the security procedures, it is possible that a terrorist attack could be canceled, and hence, it is not always necessary to identify all terrorists as selectees. Note that terrorists classified as non-selectees still undergo security screening, and hence, may be prevented from flying based on base-line security screening.

5. Discussion

SSPSP provides a real-time tool that could be used by the TSA to screen passengers. The SSPSP policy has several operational implications if implemented. First, note that the time interval considered by SSPSP can be defined arbitrarily (e.g., one hour), with each stage corresponding to a small time period (e.g., ten seconds). Therefore, several time intervals would be needed to cover a day, and capacity changes between the time intervals would correspond to changes in security screening personnel staffing and device availability. Passenger arrival rates are variable over the day, but are considered to be constant within each time interval. This is reasonable since the time intervals could be defined to capture shorter periods of time, with different arrival rates.
in different time intervals. SSPSP treats each time interval independently, but they are not entirely independent in an airport. For example, passengers already waiting in security lines may have been classified as selectees or non-selectees during an earlier time interval than passengers currently arriving at the end of security lines. Independence is less of an issue if the capacity of the selectee class in one time interval depends on the length of the security lines when the time interval begins (e.g., capacity of the selectee class in the next time interval could be reduced if the security lines are long).

One implication of SSPSP is that the optimal policy does not depend on the security levels, $L_S$ and $L_{NS}$. That is, passengers would be classified the same way if the security level of the selectee class is either nearly the same or much higher than the security level of the non-selectee class. SSPSP nearly always classifies threat passengers that CAPPS identifies as high-risk as selectees, but CAPPS incorrectly labels some threat passengers as low risk. It has been observed that even if a prescreening system such as CAPPS is effective at identifying threat passengers, a large proportion of threat passengers may still be classified as non-selectees, because the proportion of passengers classified as selectees is small (Barnett, 2004; Martonosi and Barnett, 2006). Therefore, it may be of benefit to improve the quality of the screening of non-selectees rather than that of the selectees (i.e., reducing $L_S - L_{NS}$ rather than increasing $L_S$).

The optimal SSPSP policy can also be modified to allow for all extremely high-risk passengers as selectees, even when there is no remaining capacity in the selectee class. In such a hybrid model, let all passengers with an assessed threat value larger than a prespecified threshold $\theta$ be classified as selectees, which occurs with probability $q = \int_{\theta}^{1} f_{A}(\alpha)\,d\alpha$, given that a passenger arrives. The objective of this hybrid model is to maximize the expected total security of the passengers who are not automatically classified as selectees (i.e., all passengers whose assessed threat values are less than $\theta$). Then, the optimality equations originally given by Equations (2) and (3) become:

$$V_t(s(t)) = \max_{x_S(t)\in[0,1]} \left\{ (1-q) E[L_S A(t)x_S(t) + L_{NS} A(t)(1-x_S(t))|x < \theta] + q V_{t+1}(s(t) - 1) \right\}$$

(9)

$$+ V_{t+1}(s(t) - x_S(t)|x < \theta]) + q V_{t+1}(s(t) - 1)$$

(10)

for $s(t) > 0$ and $V_0(0) = 0$ for $t = 1, 2, \ldots, T$, with boundary conditions:

$$V_{T+1}(s(t)) = 0, \quad s(t) < S.$$

(12)

The resulting capacity on the system is time dependent in the hybrid model. Note that passenger $t$, whose assessed threat value $\alpha(t)$ is no more than $\theta$, is classified as a selectee if

$$L_S \alpha(t) + V_{t+1}(s(t) - 1) \geq L_{NS} \alpha(t) + V_{t+1}(s(t)),$$

which is the same as the criteria in the original model given in Equation (4). Since the assessed threat values range from zero to $\theta$ rather than from zero to one, then the optimal policies given by DSKP and GSSAP are valid for the hybrid model when the probability density function of the assessed threat values $f_{\theta}(\alpha)$ is defined as

$$f_{\theta}(\alpha) = \frac{f_A(\alpha)}{1-q}, \quad 0 \leq \alpha \leq \theta.$$
There are many points of criticism of binary passenger screening systems, as opposed to screening all passengers the same way. In particular, it has been noted that terrorists could probe the system by sending a large number of terrorists through the system prior to carrying out an attack to determine the conditions under which the terrorists would be classified as non-selectees, maximizing the probability of a successful attack (Chakrabarti and Strauss, 2002). It is conceivable that in the future, the TSA could abandon binary screening systems to pursue a more uniform screening strategy. However, the challenges and costs associated with deploying next-generation passenger screening technologies at our nation’s airports indicate that there are long periods of time when there is not sufficient capacity to screen all aviation passengers with new technologies. For example, the 100% baggage screening mandate requires all checked baggage to be screened by EDSs and ETDs. In the 5 years after this measure was enacted (November 19, 2001), over 1400 EDSs and 6600 ETDs were deployed at the nation’s commercial airports in order to meet this objective (US GAO, 2006). Alternative screening methods such as hand searches and positive passenger baggage matching were used to screen checked baggage for explosives until EDSs and ETDs became available. Deploying new security screening technologies (temporarily) creates a binary passenger screening system, even when the intention is to screen all passengers with the new technology. Therefore, SSPSP remains highly relevant even if uniform screening methods are pursued, and its analysis can be used to address questions of how to optimally use limited resources in next-generation passenger screening systems.

6. Conclusions

Passenger screening is a critical component of any aviation security system operation. This paper introduces SSPSP, which models stochastic passenger and baggage screening systems. SSPSP, which considers passengers arriving over time, is formulated as an MDP, where the optimal policy can be computed by dynamic programming. The solution to SSPSP provides a real-time passenger screening methodology, which suggests that SSAP could be part of a tool used by the TSA for screening passengers in real-time. In addition, the relationship between SSPSP, DSKP and SSAP is made explicit, illustrating several theoretical properties of the optimal policy.

An illustrative example was analyzed to study the optimal SSPSP policy. Analysis of the solutions suggests that extremely high-risk passengers are almost certainly classified as selectees, regardless of when these passengers check in. Critical assessed threat values were relatively constant over the time interval. The optimal policy was shown to be more sensitive to the accuracy of the assessed threat value distribution and less sensitive to the probability of passengers checking in during each stage. Several implications of implementing such a policy are discussed. One implication is that the optimal policy does not depend on the security levels, which implies that it may be of benefit to improve the quality of the screening of non-selectees rather than just selectees, which currently receive the most security attention and consideration.

The optimal policy for SSPSP is highly effective in classifying extremely high-risk passengers as selectees. Exceptions occur at the very end of the time intervals and when the assessed threat value distribution is inaccurate. The fact that a small number of high-risk passengers could be classified as non-selectees could be a potential weakness of SSPSP. However, in practice, extremely high-risk passengers would not be classified as non-selectees, even if there is no remaining capacity in the selectee class. For security purposes, it is reasonable to classify one extra passenger as a selectee and have the security lines move slightly slower, and the hybrid model presented in Section 5 can be used to mitigate some of this risk. Therefore, the possibility of terrorists gaming the system by timing their check-ins can be circumvented.

SSPSP addresses the direct effects of passenger screening, such as detecting threat items, not the indirect effects of passenger screening, such as deterrence. Although the implementation of SSPSP does not depend on the security levels, the amount of deterrence is likely to depend on the security levels, and in particular, \( L_S - L_{NS} \) (Martonosi and Barnett, 2006). One extension to this paper is the development of models that capture the indirect effects of the security levels on system security.

There are several other possible directions to extend the research results presented. First, considering screening costs can give insight into the design of cost-effective screening strategies. Second, understanding how the optimal policy can be manipulated by terrorists wishing to be screened by less secure classes would be of interest to the aviation security policy community. In particular, modeling how terrorists could take advantage of how optimal policies operate in real-time as well as manipulating the passenger pool (e.g., flooding the airport with decoys) may provide the impetus for designing robust heuristics and algorithms. Work is in progress to address all these extensions.

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Biographies

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in several journals, including *IIE Transactions*, *Operations Research* and *Transportation Science*, among others, and has been recognized with several awards, including the Aviation Security Research Award and a Guggenheim Fellowship. His research has been supported by the National Science Foundation and the Air Force Office of Scientific Research. The research in this article is part of a long term research agenda designed to rethink the way aviation security is implemented in the United States, and identify new paradigms for such systems.

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