Simulation-Based Selectee Lane Queueing Design for Passenger Checkpoint Screening *

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Abstract

There are two kinds of passenger checkpoint screening lanes in a typical U.S. airport: a normal lane and a selectee lane that has enhanced scrutiny. The selectee lane is not effectively utilized in some airports due to the small amount of passengers selected to go through it. In this paper, we propose a simulation-based selectee lane queueing design framework to study how to effectively utilize the selectee lane resource. We assume that passengers are classified into several risk classes via some passenger prescreening system. We consider how to assign passengers from different risk classes to the selectee lane based on how many passengers are already in the selectee lane. The main objective is to maximize the screening system's probability of true alarm. We first discuss a steady-state model, formulate it as a nonlinear binary integer program, and propose a rule-based heuristic. Then, a simulation framework is constructed and a neighborhood search procedure is proposed to generate possible solutions based on the heuristic solution of the steady-state model. Using the passenger arrival patterns from a medium-size airport, we conduct a detailed case study. We observe that the heuristic solution from the steady-state model results in more than 4% relative increase in probability of true alarm with respect to current practice. Moreover, starting from the heuristic solution, we obtain even better solutions via a neighborhood search procedure in terms of both probability of true alarm and expected time in system.

Keywords: Passenger checkpoint screening; Selectee lane; Queueing design; Nonlinear binary integer programming; Simulation.

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1 Introduction and Literature Review

With more than 700 million passengers flying in the United States per year [2], the aviation security is crucial to the nation's overall security. The current aviation security system is composed of different layers of defense, including intelligence inputs, passenger prescreening, passenger checkpoint screening, checked baggage screening, air cargo screening, airport access control, airport perimeter security, and in-flight security [25]. The Federal Aviation Administration (FAA) has taken significant steps to enhance each layer in the last 40 years. For example, in response to the increased number of hijackings in the early 1970s, all passengers and their carry-on baggage were demanded to be screened. The Computer-Assisted Passenger Prescreening System (CAPPS), a passenger prescreening system, was implemented in 1998 to classify passengers into two categories: selectees who may pose greater risk and non-selectees who may not [21].

The catastrophic terrorist attacks of September 11, 2001 clearly exposed the vulnerability of the then aviation security system. According to the 9/11 commission report [14], " ... each layer relevant to hijackings — intelligence, passenger prescrening, checkpoint screening, and onboard security — was seriously flawed prior to 9/11. Taken together, they did not stop any of the 9/11 hijackers from getting on board four different aircraft at three different airports". In response to the tragic incidents of 9/11, the Transportation Security Administration (TSA) was created as part of the Aviation and Transportation Security Act and it took over the responsibility for civil aviation security from the FAA. The TSA has enhanced many layers of the aviation security system. Here, we discuss the progress of two layers that are strongly related to this work: passenger prescreening and passenger checkpoint screening.

In response to the act's requirement that a computer-assisted passenger prescreening system be used to evaluate all passengers, TSA proposed the Computer-Assisted Passenger Prescreening System II (CAPPS II). CAPPS II would conduct risk assessments based on the information from both government and commercial databases and categorize each passenger as an acceptable, unknown, or unacceptable risk. Passengers of acceptable risk would be subject to basic checkpoint screening; passengers of unknown risk would be subject to enhanced checkpoint screening; passengers of unacceptable risk would be assessed by law enforcement officials who would determine whether the individual could proceed or not [21]. Due to a variety of concerns [4, 1, 22, 10], the development of CAPPS II was cancelled in August 2004 and the Secure Flight program emerged as the successor. Under Secure Flight, limited information will be collected from each passenger and used for matching the No Fly and the Selectee lists. Correspondingly, each passenger will be classified as no-fly, selectee, or normal [23].

After September 11, 2001, TSA assumed the responsibility for passenger checkpoint screening previously held by private screening companies under contract to the air carriers. Steps have been taken to enhance the important components of the passenger checkpoint screening — people, procedures, and technology [24]. Specifically, actions have been taken to strengthen the performance, management, and deployment of screeners. For example, TSA has expanded the training on threat information and explosive detection. In addition, many changes to the screening procedures have been proposed and implemented to improve the probability of detection or improve the efficiency of screening or both. Moreover, TSA has developed and deployed new technologies to enhance screening.

Due to the potential catastrophic consequence, there is a growing body of literature focusing on improving the effectiveness and efficiency of the aviation security system. Lee et al. [9] provide a detailed survey on such applications of operations research. Here, we focus on literature related to passenger checkpoint screening which is a critical component of the aviation security system. Kobza and Jacobson [7] present probability models based on Type I (false alarm) and Type II (false clear) errors and introduce the concept of controlled sampling, in which passengers may take different paths through the screening system. Jacobson et al. [5] focus on the problem of minimizing the false alarm probability, given a pre-specified false clear rate. Lazar Babu et al. [8] take a different approach and consider how to assign passengers to different combinations of screening stations. Their major conclusion is that passenger grouping is beneficial.

In all models mentioned above, a basic assumption is that every passenger is equally likely to be a terrorist. Poole and Passantino [20] propose a risk-based system which relies on classifying passengers into two or more risk classes with different screening procedures applied to each class according to its risk level. The major finding is that a risk-based system may be more effective than the system where all passengers receive equal scrutiny. Using the risk-based idea, McLay et al. [11] consider the multilevel allocation problem where every passenger is assigned an assessed threat value and assignment of passengers to a given number of classes of checking devices is performed to maximize the true alarm rate. By considering the device allocation problem and the passenger assignment problem together, Nikolaev et al. [17] introduce the sequential stochastic security design problem. The problem is formulated as a two-stage model where the first stage determines the set of screening devices to purchase and install, and the second stage determines how to screen passengers. Nie et al. [15] extend Lazar Babu et al.'s work [8] to incorporate passenger risk levels. They conclude that by taking into account available information on passenger risk attributes, the screening process can be made more efficient. Incorporating the passengers' perceived risk levels, some real-time passenger screening models are proposed, see, for example, [12] and [13].

Due to the advancement of computer technology, simulation has been a powerful tool to model and analyze checkpoint screening systems. Wilson [26] discusses important issues, benefits, and challenges of using simulation tools to improve airport security. She concludes that simulation techniques are beneficial to evaluate new technology advancements, operational concepts, and complex systems. Pendergraft et al. [19] demonstrate a discrete event simulation model for airport passenger security system at Baltimore Washington International Airport. Wilson et al. [27] demonstrate Security Checkpoint Optimizer, a two-dimension discrete event simulation tool, which facilitates security planners to analyze various screening activities graphically. Based on extensive on-site data collection, Paul et al. [18] present a comprehensive simulation model for airport passenger screening system.

In the current risk-based passenger checkpoint screening system, when passengers check in at the airline counter or online, passengers are classified as either a selectee or a non-selectee. A typical U.S. airport has two kinds of screening lanes: a selectee lane (SL) and a normal lane (NL). The SL has enhanced scrutiny and is used to check selectees, while the NLs are used to check non-selectees. Note that some of the assignments made to the SL are not based on risk levels but are random to deter gaming of the screening system. The selectee status is marked on the boarding pass. When a passenger reaches the checkpoint screening area, TSA staff will conduct document verification and direct the individual to join either a SL or NLs depending on his status. The screening procedure in NLs is that the passenger walks through the metal detector while the carry-on baggage goes through the X-ray screening machine. If the metal detector alarms, the passenger is required to clear the items and walk through the detector again. If the alarm sounds off again, hand-wanding or pat-down will be performed to check the alarm. If some suspicious item is found in the carry-on baggage using the image of X-ray machine, the baggage will be searched by hand and samples will be collected from the baggage to identify any traces of explosive. In contrast, at the SL, every passenger goes through the metal detector, hand-wand, and pat-down while all carry-on baggage go through X-ray, hand search, and explosive trace detection.

In the current practice, only selectees are directed to the SL. Although all selectees go through the SL, the SL may not be effectively utilized in some airports [18]. To effectively utilize this screening resource, in this paper, we propose a simulation-based SL queueing design framework to study how to effectively assign passengers to the SL. We assume that passengers are classified into several risk classes via some passenger prescreening system. We consider how to assign passengers from different risk classes to the SL based on how many passengers are already in the SL. The main objective is to maximize the passenger checkpoint screening system's probability of true alarm. The performance of the solution from the proposed simulation-based framework is compared with that of the current practice. Our major conclusion is that our model results in a much higher probability of true alarm.

The remainder of this paper is organized as follows: Section 2 provides the problem description for the SL queueing design. Section 3 propose a steady-state model and Section 4 proposes a rule-based heuristic. A simulation-based optimization framework is reported in Section 5 and a case study is provided in Section 6. Finally, conclusions are offered in Section 7.

2 Problem Description

In this section, we focus on the description of the SL queueing design problem. Here, we assume that there is an effective passenger prescreening system in place and the system classifies passengers into K classes with different risk characteristics, indexed by k, that is, $k = 1, \ldots, K$. Let

$$\alpha_k = Pr(\text{a passenger carries a threat}|\text{he belongs to class } k).$$

Without loss of generality, we assume that $\alpha_1 > \ldots > \alpha_K$, that is, the degree of risk decreases with increasing k.

Because passengers from higher risk classes are more likely to carry a threat, we assume that every passenger from the first b classes will be assigned to the SL no matter how many passengers are currently in the SL. For the $K - b$ remaining classes, passengers could be assigned to the SL only if the number of passengers in the SL is strictly less than C, a threshold for these $K - b$ classes. We assume that both b and C are exogenous. Let j be the number of passengers currently in the SL. For $k \geq b + 1$ and $j \leq C - 1$, let q_{kj} be a binary decision variable, which is 1 if a passenger of class k is assigned to the SL given that there are currently j passengers in the SL when he reaches the screening area and 0 if the individual is assigned to NLs. For NLs, we assume that there is no capacity limit. Under these settings, the flow of a passenger through prescreening and checkpoint screening systems is depicted in Figure 1.

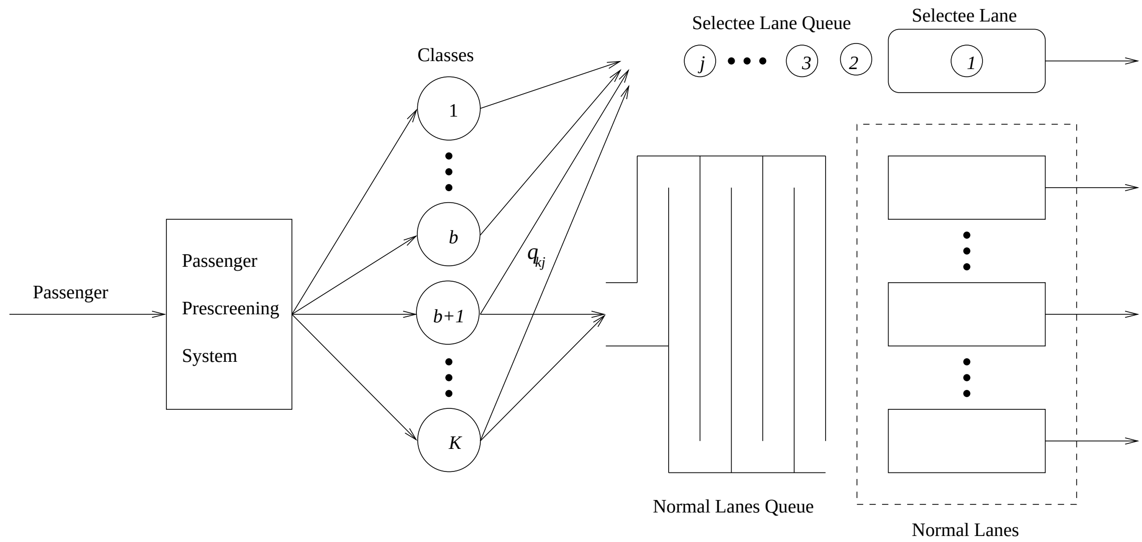

Figure 1: The flow of a passenger through prescreening and screening systems.

The passenger checkpoint screening system consists of one SL and several NLs. After screening each passenger, the checkpoint screening system (either the SL or one NL) will give a clear signal or an alarm. This results in four possible outcomes:

- *True Alarm* (TA) – system gives an alarm and a threat exists;
- *False Alarm* (FA) – system gives an alarm but a threat does not exist;
- *True Clear* (TC) – system gives a clear signal and a threat does not exist;
- *False Clear* (FC) – system gives a clear signal but a threat exists.

Such definitions were first introduced into the checkpoint screening system by Kobza and Jacobson [6, 7] and are used extensively in the literature, see, for example, [15] and [16]. Probabilities of true alarm and true clear are two important performance measures for a screening system; the performance improves as these probabilities increase. True alarms have the potential to avoid fatal consequences, while true clears can reduce inspection delays. In this paper, we are interested in maximizing the checkpoint screening system's probability of true alarm.

Let θ_{SL} be the conditional probability of alarm given that a passenger carrying a threat is assigned to the SL and θ_{NL} be the conditional probability of alarm given that he is assigned to a NL. Since the screening procedure of the SL is stricter than that of NLs, we have that $\theta_{SL} > \theta_{NL}$. In order to determine the checkpoint screening system's probability of true alarm, we define the following two events:

$$\begin{aligned} A &= \text{The checkpoint screening system gives an alarm,} \\ T &= \text{The passenger carries a threat.} \end{aligned}$$

According to the definition of true alarm, we have

$$Pr(TA) = Pr(A \cap T) = Pr(A|T) \times Pr(T).$$

The SL queueing design problem focuses on determining q_{kj} such that the probability of true alarm is maximized.

3 Steady-State Model

Due to different demand patterns from passengers, the flight schedules differ a lot with respect to weekday and time period. For example, most business travelers book early morning flights and most weekend flights are occupied by leisure travelers. This results in the fact that the arrival patterns for checkpoint screening are different depending on the specific date and the time period. These non-stationary arrival patterns are empirically testified by the simulation study of Paul et al. [18] for a medium-size U.S. airport, as shown in Figure 2. According to their simulation study, the passenger arrival pattern for Monday is different from those of Saturday and Sunday, and Tuesday to Friday have similar passenger arrival patterns.

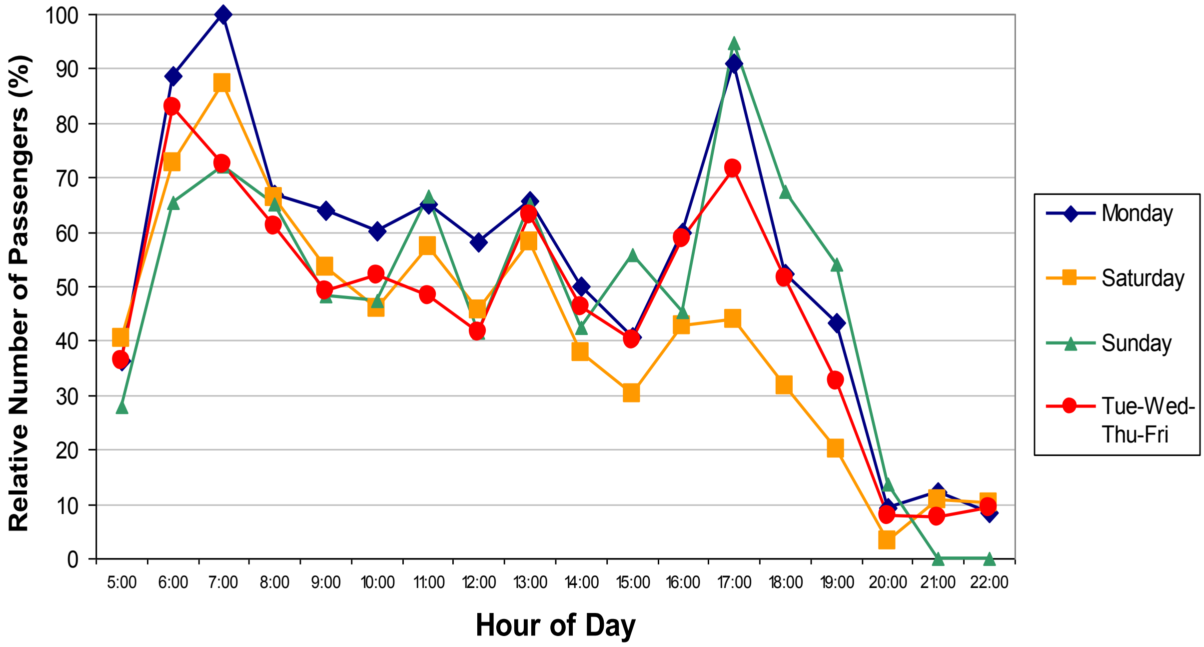

Figure 2: Passenger arrival variability by day pattern (Paul et al. [18]).

To start our analysis, in this section we focus on a steady-state model where we assume that the passenger arrival patterns are the same for different weekdays and different time periods. Through the steady-state analysis, we formulate the SL queueing design problem as a nonlinear binary integer program. The solution derived from the model is used as a starting solution for our simulation-based optimization framework.

In the steady-state model, we assume that passengers of risk class k arrive at the passenger checkpoint screening area according to a Poisson process with arrival rate γ_k. Passengers from different risk classes arrive independently. We assume that the screening time for one passenger in the SL is random and exponentially distributed with rate μ. Because the SL has a stricter checking procedure, this screening time is generally greater than that of a NL. Since our focus is on the SL queue, detailed information about NLs, for example, the number of NLs and the screening rate, are not needed in our steady-state model. The SL queueing system can be modeled as a continuous-time Markov Chain with transition rates λ_j and μ. The transition diagram is shown in Figure 3 and the corresponding λ_j value is calculated as follows:

$$\lambda_j = \begin{cases} \sum_{k=1}^{b} \gamma_k + \sum_{k=b+1}^{K} \gamma_k q_{kj} & 0 \le j \le C-1, \\ \sum_{k=1}^{b} \gamma_k & j \ge C. \end{cases}$$

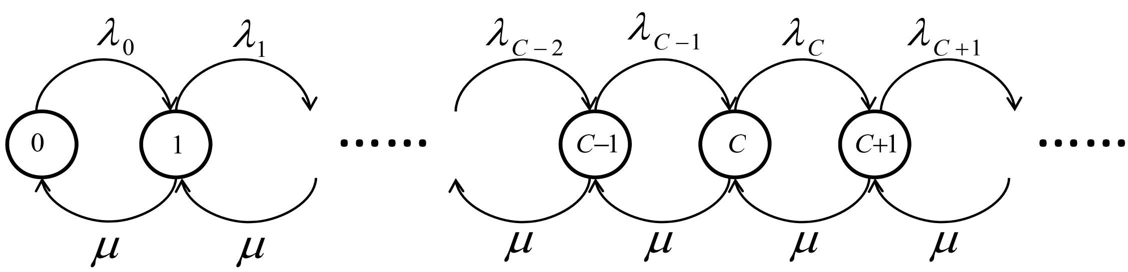

Figure 3: The transition diagram.

We assume that the SL queueing system is in steady-state. Let P_j be the limiting probability that there are j passengers in the SL. Then we have the following set of balance equations:

$$\begin{cases} \lambda_0 P_0 = \mu P_1, \\ (\lambda_j + \mu) P_j = \lambda_{j-1} P_{j-1} + \mu P_{j+1}, \quad j \ge 1. \end{cases}$$

Combining these equations with $\sum_{j=0}^{\infty} P_j = 1$, we obtain that

$$P_0 = \frac{1}{1 + \sum_{j=1}^{\infty} \dfrac{\prod_{0 \le i < j} \lambda_i}{\mu^j}}$$

and

$$P_j = \frac{\prod_{0 \le i < j} \lambda_i}{\mu^j} \times \frac{1}{1 + \sum_{j=1}^{\infty} \dfrac{\prod_{0 \le i < j} \lambda_i}{\mu^j}}, \qquad j \ge 1.$$

Let S_j denote the event that there are j passengers in the SL. Since a passenger can belong to any class k, when he arrives, there may be j passengers in the SL, and he may be assigned to SL or NLs, by using the law of total probability, we have

$$\begin{aligned}
Pr(A|T) &= \sum_{k=1}^{K} Pr(A|T \cap \text{Class } k) Pr(\text{Class } k|T) \\
&= \sum_{k=1}^{b} \theta_{SL} Pr(\text{Class } k|T) + \sum_{k=b+1}^{K} \sum_{j=0}^{\infty} Pr(A|T \cap \text{Class } k \cap S_j) \times \\
&\quad Pr(S_j|T \cap \text{Class } k) Pr(\text{Class } k|T) \\
&= \sum_{k=1}^{b} \theta_{SL} Pr(\text{Class } k|T) + \sum_{k=b+1}^{K} \sum_{j=0}^{C-1} \Big(q_{kj}\theta_{SL} + (1-q_{kj})\theta_{NL}\Big) \times \\
&\quad P_j Pr(\text{Class } k|T) + \sum_{k=b+1}^{K} \sum_{j=C}^{\infty} \theta_{NL} P_j Pr(\text{Class } k|T). \qquad (1)
\end{aligned}$$

During the derivation, we implicitly assume that S_j and $T \cap \text{Class } k$ are independent. This independence is intuitive since the event that there are j passengers in the SL has nothing to do with the event that a passenger from risk class k carries a threat.

For $Pr(\text{Class } k|T)$, via Bayes' formula, we have that

$$Pr(\text{Class } k|T) = \frac{Pr(T|\text{Class } k) Pr(\text{Class } k)}{Pr(T)} = \frac{\alpha_k \gamma_k}{\sum_{k=1}^{K} \alpha_k \gamma_k}.$$

Via the law of total probability, we have

$$Pr(T) = \sum_{k=1}^{K} Pr(T|\text{Class } k) Pr(\text{Class } k) = \sum_{k=1}^{K} \alpha_k \frac{\gamma_k}{\sum_{k=1}^{K} \gamma_k} = \frac{1}{\gamma} \sum_{k=1}^{K} \alpha_k \gamma_k, \qquad (2)$$

where $\gamma = \sum_{k=1}^{K} \gamma_k$.

Hence,

$$\begin{aligned}
Pr(TA) = \frac{1}{\gamma}\Big(\theta_{SL} \sum_{k=1}^{b} \alpha_k \gamma_k + \sum_{k=b+1}^{K} \alpha_k \gamma_k \sum_{j=0}^{C-1} \Big(q_{kj}\theta_{SL} + (1-q_{kj})\theta_{NL}\Big) P_j + \\
\theta_{NL}(1 - \sum_{j=0}^{C-1} P_j) \sum_{k=b+1}^{K} \alpha_k \gamma_k\Big). \qquad (3)
\end{aligned}$$

We consider how to determine q_{kj} value such that the checkpoint screening system's probability of true alarm is maximized. The corresponding problem is formulated as the following nonlinear binary integer program:

$$\begin{aligned}
\text{Max} \quad & Pr(TA) \\
\text{s.t.} \quad & q_{kj} \in \{0, 1\}, \quad k = b+1, \ldots, K, j = 0, \ldots, C-1.
\end{aligned}$$

If we relax the binary constraints of the program, the relaxation problem is a non-concave nonlinear program. Therefore, for small-size problems, the optimal solution can be obtained via total enumeration, but for large-size problems, we have to turn to heuristics.

4 Rule-Based Heuristic for Steady-State Model

To obtain approximate solutions for large-size problems, in this section we propose a rule-based heuristic for solving the steady-state model. The idea of the heuristic is to construct several intuitive rules that good solutions may follow and pick one of the best from the solutions that satisfy these rules. One advantage of our heuristic is that it greatly reduces the search space.

The first rule we construct is that when a passenger from the $(b+1)$th risk class arrives, as long as the number of passengers in the SL is less than the threshold C, he will be assigned to the SL. That is,

Rule 1. $q_{b+1,j} = 1, \; j = 0, \ldots, C-1.$

The intuition of this rule is that since passengers from risk classes 1 to b would be assigned to the SL anyway and passengers from the risk class $b+1$ possess the highest risk for the remaining $K-b$ classes, they need to go through the SL as long as the SL is not fully occupied.

The second rule we construct is that no matter how many passengers are currently in the SL, a passenger from a higher risk class is more likely to be assigned to the SL than a passenger from a lower risk class. That is,

Rule 2. $q_{k,j} \geq q_{k+1,j}, \; k = b+1, \ldots, K-1, j = 0, \ldots, C-1.$

This rule makes sense because the SL resource is more valuable for higher risk passengers than lower risk passengers.

The third rule we construct is that no matter which risk class a passenger comes from, he is more likely to be assigned to the SL if there are fewer passengers in the SL. That is,

Rule 3. $q_{k,j} \geq q_{k,j+1}, \; k = b+1, \ldots, K, j = 0, \ldots, C-2.$

It is intuitive because otherwise when the SL queue is long, passengers from lower risk classes will block passengers from higher risk class to enter the SL.

Based on these three rules, we propose a rule-based heuristic to obtain an approximate solution to the nonlinear binary integer program. The procedure is as follows.

***Rule-Based Heuristic Procedure*:**

Step 1: Construct all feasible solutions that satisfy these three rules.

Step 2: Compute the probability of true alarm for each solution constructed in Step 1.

Step 3: Compare these probabilities of true alarm and choose one solution with the highest true alarm probability.

We focus on calculating the number of possible solutions constructed in Step 1. For a system with SL threshold C and K classes of passengers (the first b classes must go through the SL), we define $Q(C, K, b)$ as the number of feasible solutions which satisfy these three rules. Write one feasible solution as a vector: $\mathbf{q} = (q_{b+1,\cdot}, \ldots, q_{k\cdot}, \ldots, q_{K\cdot})$, where $q_{k\cdot} = q_{k0}, \ldots, q_{k,C-1}$. For each $q_{k\cdot}$, in order to satisfy Rule 3, we have $C+1$ alternatives which are indexed by l, $l = 0, \ldots, C$. These alternatives are shown in each box of Figure 4. Suppose we construct a feasible solution by choosing $q_{k\cdot}$ sequentially. To construct a feasible solution that satisfies Rule 2, each alternative for $q_{k\cdot}$ can only connect to another alternative with lower or equal index for $q_{k+1,\cdot}$ for each $k = b+1, \ldots, K-1$. Then we can construct all those solutions which satisfy Rule 2 and Rule 3. Those solutions are shown in Figure 4.

Suppose we have arrived at $q_{k\cdot}$ and chosen the lth alternative for $q_{k\cdot}$. Let $N(l, k)$ be the number of feasible solutions that satisfy Rule 2 and Rule 3 given that $q_{b+1,\cdot}, \ldots, q_{k\cdot}$ have been fixed. From the current position, we could either go straight right or go up to $q_{k+1,\cdot}$ with lower indexes. If we go straight right, the number of feasible solutions is exactly $N(l, k+1)$. Otherwise, the number of feasible solutions is $N(l-1, k)$. Hence, $N(l, k)$ satisfies the following recursive equation

$$N(l, k) = N(l-1, k) + N(l, k+1),$$

with boundary conditions

$$N(0, k) = 1, \text{ for } k = b+1, \ldots, K, \text{ and } N(l, K) = 1, \text{ for } l = 0, \ldots, C.$$

Moreover, in order to satisfy Rule 1, we can only choose the Cth alternative for $q_{b+1,\cdot}$. Hence, we have that $Q(C, K, b) = N(C, b+1)$, which can be calculated by the recursive equation. For example, for a screening system with $K = 5, b = 2$, and $C = 12$, through the recursive equation, we obtain that $Q(12, 5, 2) = N(12, 3) = 91$. For this example, the total enumeration is not able to find an optimal solution even after several hours of efforts, while our rule-based heuristic needs less than 0.1 second to obtain an approximate solution.

As for the performance of the rule-base heuristic, we test this on several small and medium-size problems for which the total enumeration can obtain optimal solutions within ten minutes. We observe that for all test problems, the optimal solutions satisfy our three rules, that is, our rule-based heuristic obtains optimal solutions for the test problems.

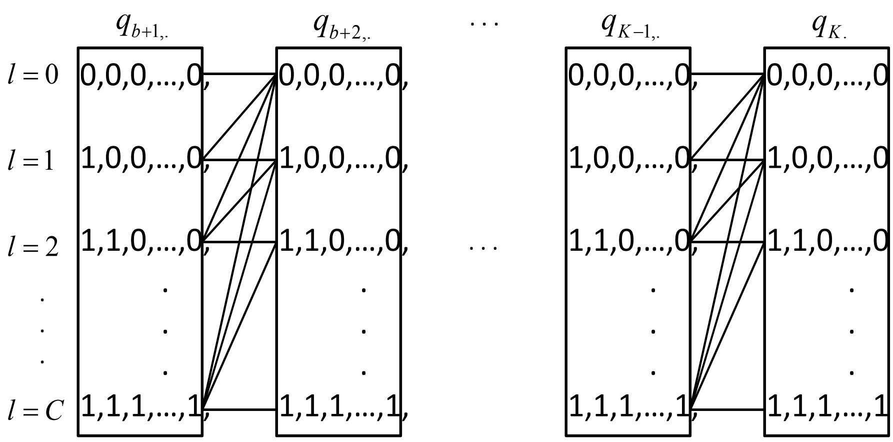

Figure 4: All feasible solutions satisfying Rules 2 and 3.

5 Simulation-Based Optimization Framework

In the steady-state analysis, there are two critical assumptions. The first assumption is that the arrival rate of passengers remains the same for all time periods, while the second assumption is that the continuous-time Markov chain is in steady-state. In real checkpoint screening situations, both assumptions will be violated. In this section, we first propose a simulation framework that could be used to evaluate the performance of different assignment solutions. Then, treating the heuristic solution derived from the steady-state model as an initial solution, we define a neighborhood search procedure to obtain solutions with better performance.

For a given assignment solution, we describe the simulation framework in detail. According to the historical passenger arrival data from the airport record, we obtain the expected arrival rates per hour from 5:00am to 11:00pm for different weekdays (from Monday to Sunday). We model the passenger arrival process for each weekday as a non-stationary Poisson process where the arrival rate for each hour period equals to the observed arrival rate for the corresponding time period. When a passenger arrives, two attributes are specified according to corresponding discrete probability distributions. One attribute is his risk class and the other is if he carries a threat or not. Then, based on his risk class and the number of passengers in the SL, a decision will be made to direct him to a SL or NLs according to the assignment solution. In the simulation model, the service times for SL and NLs follow different triangular distributions. For a passenger carrying a threat, with probabilities θ_{SL} or θ_{NL}, he may cause a system alarm in the SL or NLs, respectively.

When a passenger leaves the screening system, if he carries a threat and the system gives an alarm, we increase the number of true alarms by 1. The simulation process stops when a prespecified number of true alarms is reached. Given the specified number of true alarms and the total number of passenger arrivals, the probability of true alarm can be derived. Moreover, the time in the checkpoint screening system (including waiting time in queue and service time) for each passenger, which is difficult to derive analytically, can be obtained from the simulation. The simulation process is replicated and the statistics regarding to the probability of true alarm and the waiting time are obtained.

The above discussed simulation framework can be applied to any assignment solution. Since the number of all possible solutions are exponentially large, it is not practical to simulate all these alternatives. Thus we need to focus on the generation of a reasonable number of candidate solutions. From the rule-based heuristic for the steady-state case, we obtain an approximate solution. Treating the approximate solution as an initial solution, we propose a neighborhood search procedure. The neighbors of a solution are defined as all those solutions that differ at most one element for each $q_{k.}$ (defined as $q_{k0}, \ldots, q_{k,C-1}$ in Section 4), satisfy Rules 2 and 3 of the rule-based heuristic, and $q_{k0} = 1$ for $k = b+1, \ldots, K$ (that is, if the SL is empty, any passenger will be assigned to the SL no matter which risk class he comes from).

For each neighbor of the initial solution, we run the simulation model several times and obtain the probability of true alarm. For the neighbors with the highest three probabilities of true alarm, we further construct their neighbors and conduct simulation studies on them. The probability of true alarm and the expected waiting time for each solution alternative are then plotted.

6 Case Study

In this section, we illustrate the steady-state model and the simulation-based model using observed passenger arrival patterns from a medium-size airport. For the simulation study, we choose the number of replications to be 25 and the stopping criterion to be 5000 true alarms.

We consider a checkpoint screening system with one SL and two NLs. In our case study, we assume that these lanes are open for the whole day from 5:00am to 11:00pm. Passengers are classified into five risk classes according to some passenger prescreening system. The passenger proportions for the five classes are 1/60, 1/15, 1/6, 1/4, and 1/2, respectively. Given these five risk classes, the conditional probabilities that a passenger carries a threat are 0.18, 0.08, 0.04, 0.016, and 0.004, respectively. According to these values, the probability that a passenger carries a threat, that is, $Pr(T)$, is 0.021, which is in the same magnitude as the data provided by the Bureau of Transportation Statistics [3]. Among these five classes, passengers from the first two classes will be assigned to the SL no matter how many passengers in the SL. The SL threshold for the remaining three classes is 12 persons. If a passenger carrying a threat is assigned to the SL, the probability of alarm is 0.99. The probability of alarm is 0.80 for NLs. All these parameter values are summarized in Table 1.

Assume that the passenger arrival rate in the busiest time period (7:00am to 8:00am) is 1200 passengers per hour, which is reasonable for a typical medium-size airport. According to the passenger flow analysis in Paul et al. [18], we obtain the average numbers of passenger arrivals for different time periods and weekdays, which are listed in Table 2. The screening time for the SL follows a triangular distribution with parameters 10, 12, and 14 seconds, while the parameters for NLs are 8, 10, and 12 seconds.

The arrival rate for the steady-state model is assumed to be 1200 passengers per hour,

Table 1: Checkpoint screening system parameter values

Parameter	Description	Value
K	Number of risk classes	5
b	First b classes go directly to the SL	2
C	SL threshold for the remaining $K-b$ classes	12
θ_{SL}	Cond. prob. of alarm given a threat for SL	0.99
θ_{NL}	Cond. prob. of alarm given a threat for NLs	0.80
$Pr(\text{Class } k)$	Prob. of belonging to class k	(1/60,1/15,1/6,1/4,1/2)
α_k	Cond. prob. of carrying a threat given class k	(0.18,0.08,0.04,0.016,0.004)

Table 2: Average numbers of arrivals by weekday and time period

Time period	Mon	Tue-Fri	Sat	Sun
5:00-6:00	432	432	480	336
6:00-7:00	1068	996	876	780
7:00-8:00	1200	864	1056	864
8:00-9:00	792	732	792	780
9:00-10:00	768	600	648	576
10:00-11:00	720	612	552	564
11:00-12:00	768	588	696	792
12:00-13:00	696	504	552	492
13:00-14:00	780	768	708	756
14:00-15:00	600	564	456	504
15:00-16:00	492	480	372	660
16:00-17:00	720	708	516	540
17:00-18:00	1092	864	528	1128
18:00-19:00	624	624	384	816
19:00-20:00	528	396	240	648
20:00-21:00	120	108	48	168
21:00-22:00	144	96	132	0
22:00-23:00	108	120	120	0

which is the arrival rate for the busiest hour. The service rate of the SL is chosen to be 300 passengers per hour, which is transformed to screening time 12 seconds per passenger. Other parameters are the same as those in Table 1. The heuristic solution is: $q_{3,0} = \ldots = q_{3,11} = 1, q_{4,0} = \ldots = q_{4,9} = 1, q_{5,0} = 1$. The corresponding probability of true alarm is 0.02027. If we run the simulation for the heuristic solution, the resulting probability of true alarm is 0.02022. We observe that even though the steady-state model overestimates the probability of true alarm, the relative deviation is less than 0.25%.

Starting from the heuristic solution (Solution #1), we construct its neighbors according to the neighborhood definition in Section 5. For the heuristic solution, we have 11 neighbors, which are Solution #2 to Solution #12 shown in Table 3. For each neighbor, we run the simulation and obtain the corresponding probability of true alarm and the expected time in system. In Table 3, Base solution is defined as the solution where only passengers from the first two risk classes go through the SL. The Base solution represents the current practice for most U.S. airports. When we compare Solution #1 with the Base solution, we observe that even though Solution #1 requires 25.56 more seconds in the screening system, the relative improvement for probability of true alarm reaches 4.33%. From these 11 neighbors, we observe that Solutions #4, #6, and #11 rank the best three in terms of probability of true alarm. We go one step further and construct all neighbors for these three solutions. The new solutions are Solutions #13 to #30 shown in Table 3. We observe that Solution #13 obtains the highest probability of true alarm 0.02030, which is 0.40% higher than that of the heuristic initial solution.

One advantage of the simulation-based model is that besides the probability of true alarm, the expected time in the screening system, an important performance measure for the screening system, can be estimated. The scatter plot for $Pr(TA)$ vs expected time in the screening system for each solution is provided in Figure 5. From the figure, we observe that the heuristic solution (Solution #1) is outperformed in terms of both $Pr(TA)$ and expected time in system. Moreover, we observe that there are three non-dominated solutions: Solution #13, Solution #21, and Solution #Base, which are available for security authority to choose from. If the authority care more about $Pr(TA)$ than expected time in system, Solution #13 will be recommended.

Table 3: Results for all neighbor solutions

No.	Solution details	$Pr(TA)$	Time (s)
Base	—	0.01938	53.91
1	$q_{3,0} = \ldots = q_{3,11} = 1, q_{4,0} = \ldots = q_{4,9} = 1, q_{5,0} = 1$	0.02022	79.47
2	$q_{3,0} = \ldots = q_{3,11} = 1, q_{4,0} = \ldots = q_{4,10} = 1, q_{5,0} = 1$	0.02014	81.00
3	$q_{3,0} = \ldots = q_{3,11} = 1, q_{4,0} = \ldots = q_{4,10} = 1, q_{5,0} = q_{5,1} = 1$	0.02019	84.48
4	$q_{3,0} = \ldots = q_{3,11} = 1, q_{4,0} = \ldots = q_{4,9} = 1, q_{5,0} = q_{5,1} = 1$	**0.02023**	81.61
5	$q_{3,0} = \ldots = q_{3,11} = 1, q_{4,0} = \ldots = q_{4,8} = 1, q_{5,0} = 1$	0.02022	76.82
6	$q_{3,0} = \ldots = q_{3,11} = 1, q_{4,0} = \ldots = q_{4,8} = 1, q_{5,0} = q_{5,1} = 1$	**0.02025**	80.07
7	$q_{3,0} = \ldots = q_{3,10} = 1, q_{4,0} = \ldots = q_{4,10} = 1, q_{5,0} = 1$	0.02004	81.68
8	$q_{3,0} = \ldots = q_{3,10} = 1, q_{4,0} = \ldots = q_{4,10} = 1, q_{5,0} = q_{5,1} = 1$	0.02013	83.47
9	$q_{3,0} = \ldots = q_{3,10} = 1, q_{4,0} = \ldots = q_{4,9} = 1, q_{5,0} = 1$	0.02020	79.87
10	$q_{3,0} = \ldots = q_{3,10} = 1, q_{4,0} = \ldots = q_{4,9} = 1, q_{5,0} = q_{5,1} = 1$	0.02020	81.01
11	$q_{3,0} = \ldots = q_{3,10} = 1, q_{4,0} = \ldots = q_{4,8} = 1, q_{5,0} = 1$	**0.02028**	76.03
12	$q_{3,0} = \ldots = q_{3,10} = 1, q_{4,0} = \ldots = q_{4,8} = 1, q_{5,0} = q_{5,1} = 1$	0.02016	77.86
13	$q_{3,0} = \ldots = q_{3,10} = 1, q_{4,0} = \ldots = q_{4,7} = 1, q_{5,0} = 1$	**0.02030**	74.35
14	$q_{3,0} = \ldots = q_{3,10} = 1, q_{4,0} = \ldots = q_{4,7} = 1, q_{5,0} = q_{5,1} = 1$	0.02019	76.23
15	$q_{3,0} = \ldots = q_{3,11} = 1, q_{4,0} = \ldots = q_{4,7} = 1, q_{5,0} = 1$	0.02028	74.45
16	$q_{3,0} = \ldots = q_{3,11} = 1, q_{4,0} = \ldots = q_{4,7} = 1, q_{5,0} = q_{5,1} = 1$	0.02026	76.17
17	$q_{3,0} = \ldots = q_{3,9} = 1, q_{4,0} = \ldots = q_{4,8} = 1, q_{5,0} = 1$	0.02021	76.52
18	$q_{3,0} = \ldots = q_{3,9} = 1, q_{4,0} = \ldots = q_{4,8} = 1, q_{5,0} = q_{5,1} = 1$	0.02010	77.64
19	$q_{3,0} = \ldots = q_{3,9} = 1, q_{4,0} = \ldots = q_{4,9} = 1, q_{5,0} = 1$	0.02011	78.38
20	$q_{3,0} = \ldots = q_{3,9} = 1, q_{4,0} = \ldots = q_{4,9} = 1, q_{5,0} = q_{5,1} = 1$	0.02007	80.09
21	$q_{3,0} = \ldots = q_{3,9} = 1, q_{4,0} = \ldots = q_{4,7} = 1, q_{5,0} = 1$	0.02015	73.55
22	$q_{3,0} = \ldots = q_{3,9} = 1, q_{4,0} = \ldots = q_{4,7} = 1, q_{5,0} = q_{5,1} = 1$	0.02023	77.06
23	$q_{3,0} = \ldots = q_{3,11} = 1, q_{4,0} = \ldots = q_{4,9} = 1, q_{5,0} = q_{5,1} = q_{5,2} = 1$	0.02015	83.35
24	$q_{3,0} = \ldots = q_{3,11} = 1, q_{4,0} = \ldots = q_{4,10} = 1, q_{5,0} = q_{5,1} = q_{5,2} = 1$	0.02015	85.86
25	$q_{3,0} = \ldots = q_{3,11} = 1, q_{4,0} = \ldots = q_{4,8} = 1, q_{5,0} = q_{5,1} = q_{5,2} = 1$	0.02021	80.87
26	$q_{3,0} = \ldots = q_{3,10} = 1, q_{4,0} = \ldots = q_{4,9} = 1, q_{5,0} = q_{5,1} = q_{5,2} = 1$	0.02009	83.09
27	$q_{3,0} = \ldots = q_{3,10} = 1, q_{4,0} = \ldots = q_{4,10} = 1, q_{5,0} = q_{5,1} = q_{5,2} = 1$	0.02014	85.74
28	$q_{3,0} = \ldots = q_{3,10} = 1, q_{4,0} = \ldots = q_{4,8} = 1, q_{5,0} = q_{5,1} = q_{5,2} = 1$	0.02021	80.40
29	$q_{3,0} = \ldots = q_{3,11} = 1, q_{4,0} = \ldots = q_{4,7} = 1, q_{5,0} = q_{5,1} = q_{5,2} = 1$	0.02023	78.47
30	$q_{3,0} = \ldots = q_{3,10} = 1, q_{4,0} = \ldots = q_{4,7} = 1, q_{5,0} = q_{5,1} = q_{5,2} = 1$	0.02022	78.11

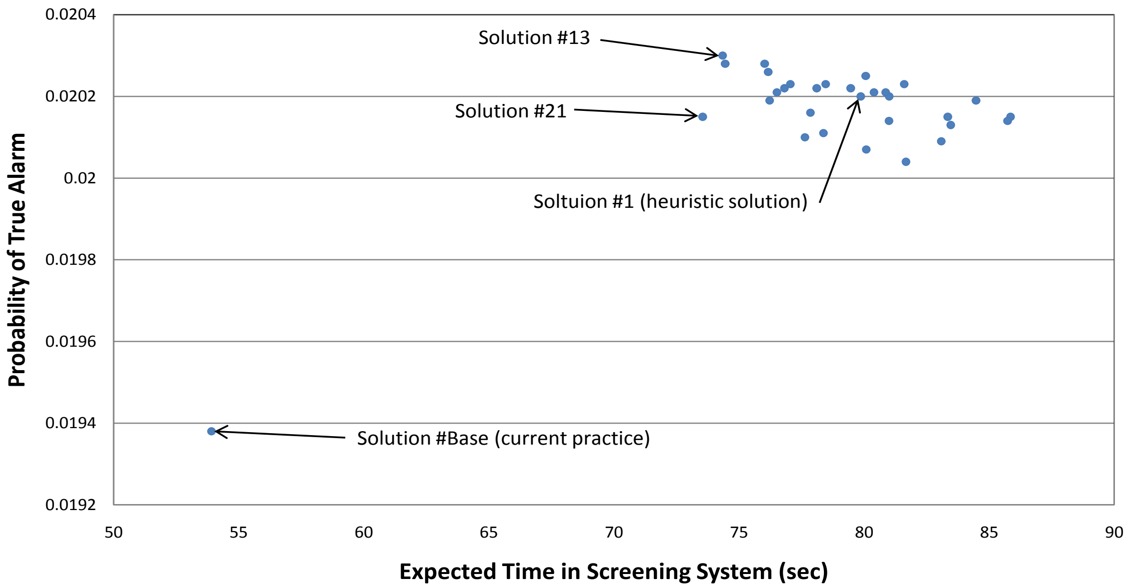

Figure 5: Scatterplot for $Pr(TA)$ vs expected time in system for all neighbors.

7 Conclusions

In this paper, we consider how to effectively utilize the SL for passenger checkpoint screening. Assuming that a passenger prescreening system effectively classifies passengers into several risk classes, we propose a simulation-based SL queueing design framework that assigns passengers from different risk classes to the SL based on how many passengers are already in the SL. Our major conclusion is that incorporating our simulation-based SL queueing design model, the passenger checkpoint screening can be made more effective over the current practice. Specifically, we can achieve higher probability of true alarm while keeping the impact of average time in system reasonable.

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