Security and Performance Analysis of a Passenger Screening Checkpoint for Mass-transit Systems

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Abstract—**During the past decade, the international community has witnessed several attacks on forms of mass transportation such as train stations and subways. The Department of Homeland Security requested that we develop methods to assess the security of mass transit in order to mitigate the vulnerability of the nation's public transportation systems. We present a methodology to quantify the impact of imposing screening on mass transit, which considers both security and delays incurred on the traveling public. We demonstrate the approach through a case study, the Fairfield Metro Station in Fairfield, Connecticut. Our results indicate that rigorous aviation-style screening will slow the flow of passengers drastically. We also show how to use the approach to identify where faster screening technologies can improve passenger throughput while ensuring security. The approach can thus be used to identify areas where investments in technology improvement would most effectively enhance security and convenience.**

Keywords-mass-transit; passenger screening; security; performance;

I. Introduction

Screening is critical to ensure the security of every mode of transit in the nation's transportation infrastructure. Both aviation and port security employ screening to minimize the chance that airplanes and boats carry illegal or dangerous items and individuals. Domestic mass transit systems such as railroads and subways, however, cannot impose rigorous security procedures because the time incurred in screening will produce a noticeable drag on the smooth flow of large volumes of passengers. The inconvenience and high cost of screening rail and subway passengers is undesirable, however, in the past decade, these modes of transportation have been the targets of several terrorist attacks throughout the world [1]. Moreover, it is public knowledge that terrorist organizations such as Al-Qaeda plan to perpetrate such attacks. Mass-transit may also be an attractive terrorist target because of the widespread attention and public fear such acts inspire. Therefore, although the screening delays inconvenience passengers and harm profitability, protecting people and assets remains a significant concern. This suggests that advances in the speed of screening technologies are necessary before such comprehensive screening can be implemented for mass-transit systems.

Prevalent research focuses on the engineering of security technologies rather than exploring their performance. For example, Burgoon *et al.* [2] automate techniques to detect deceptive behavior in individuals at border crossings. Tambe [3] has applied game theoretic techniques to security problems, including screening of cars entering Los Angeles International Airport, scheduling Federal Air Marshals on flights with potentially dangerous passengers, and randomized Coast Guard patrols to detect terrorism and drug trafficking. Most of these works focus on how existing screening technologies can be used effectively to improve security. However, there is very little research [4] on whether these technologies balance security and performance when employed at checkpoints. Therefore, such screening can be reasonably employed only when the volume of passengers is low, such as at airports. They do not scale to mass transit systems, which usually experience extremely high volumes of traffic. Therefore, to enhance the security of mass transit systems through passenger screening, methods which assess both the security and performance of a checkpoint are needed to determine if specific design and technologies exhibit desired levels of threat detection while maintaining acceptable passenger throughput.

This paper presents a methodology to quantify the security and performance of a screening checkpoint in terms of the security and performance metrics of its constituent technologies and their organizational layout. We demonstrate our approach using the case study of the Fairfield Metro Station, which is the first railroad station to be built in Connecticut in over 90 years. The methodology allows us to quantify the probability that a threat will be detected as it passes through the checkpoint, along with the degradation in passenger throughput caused by screening. Our results indicate that imposing rigorous aviation-style screening will slow the flow of passengers drastically. Therefore, unless screening technologies can be made faster they will be too cumbersome for mass-transit. Our approach can thus systematically identify checkpoint designs and technology improvements that can balance the security and performance concerns, to enable their use in securing the mass transit infrastructure.

The paper is organized as follows: Section 2 outlines the challenges in quantifying security and performance with an example. Section 3 proposes the modeling approaches. Section 4 demonstrates these approaches. Section 5 summarizes lessons learned and offers suggestions for enhancements. Conclusions and future research are offered in Section 6.

II. Problem Formulation

This section describes the challenges in assessing performance and security of screening checkpoints for mass transit systems using the layout of the security turnstiles in the lobby of Fairfield Metro Center (FMC), as shown in Fig. 1 Passengers arrive at the station at rate $\lambda(t)$. This arrival process is a function of time because travelers rely on mass transit systems for their daily commute. Hence, higher volumes may be expected during the rush hour, with lighter traffic at other times. Next, the passengers walk down a hallway to insert their ticket into one of three turnstiles for scanning, where a computer records the time and outputs the voided ticket before opening a gate to allow them to pass. The passengers then proceed to the platform of their departing train.

To enhance passenger throughput, these turnstiles are placed side-by-side to create multiple parallel lanes. A passenger typically selects the turnstile with the shortest line. When passenger volume is high, however, the lines at all turnstiles are approximately equal. Therefore, we set the probability of selecting a particular turnstile equal ($x_1 = x_2 = x_3 = 1/3$). The process of inserting a ticket and passing through the turnstile requires approximately three seconds.

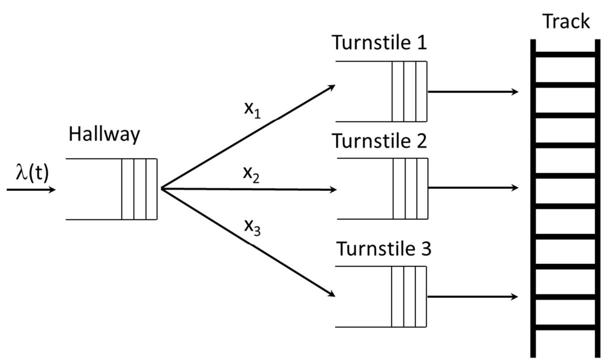

Figure 1. Fairfield Metro Center turnstile configuration.

To understand the impact of introducing airport screening into mass-transit, Fig. 2 shows the primary components and key decision points in a simple checkpoint. These components could replace the turnstiles within FMC without requiring major modifications to the interior of the building.

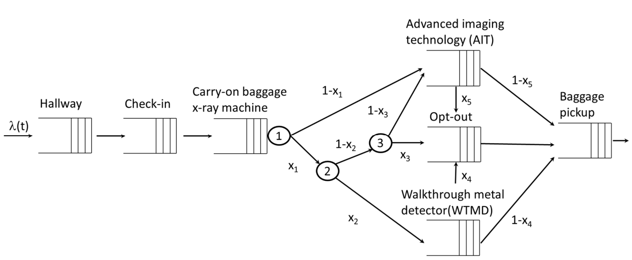

Figure 2. Passenger screening checkpoint.

In this layout, passengers arriving at the screening checkpoint must first check-in by providing their ticket and identification to a security officer. Next, they must divest themselves of their carry-on baggage and other personal items to be placed on a conveyor belt for x-ray screening. After this step, there are several decision points. First, a passenger may choose to undergo scanning by an Advanced Imaging Technology (AIT) machine or the older but more popular Walkthrough Metal Detector (WTMD). We assume that the probability of WTMD screening, denoted x_1, is greater than that of AIT screening ($1 - x_1 = \bar{x}_1$) because AIT exposes passengers to radiation and passengers believe that it generates revealing images. The second branch occurs because an attending officer has the authority to ask a passenger to undergo AIT scanning ($\bar{x}_2$), even if the passenger prefers WTMD. This leads to the third decision point because passengers have the right to *opt-out* of AIT and request alternative screening procedures (x_3), involving a pat down inspection. Some passengers passing through WTMD forget to remove metal items and may also be asked to undergo a pat down (x_4). AIT may also fail to ascertain the absence of concealed items, in which case a pat down will be requested (x_5). Once passengers clear the screening stations, they proceed to retrieve their carry-on baggage, shoes, and other personal items. Subsequently, they will exit the screening checkpoint and continue to the platform from which their train will depart.

The types of technologies in Fig. 2 include several implicit security policies employed at mass-transit checkpoints. They also reflect existing policies. For example, passengers' identities are verified manually at check in. Such manual screening may be acceptable for high-speed rail, but will be extremely labor-intensive for subways. x-ray screening of carry-on baggage assumes that passengers will be required to submit their luggage for inspection. Finally, although WTMD and opt-out show limited effectiveness for detecting concealed threats, these alternative forms of screening continue to be retained because these forms may be necessary to respect the passengers' privacy by offering them these choices.

WTMD and opt out cannot be eliminated; in fact, a large fraction of passengers may prefer these slower forms, leading to underutilization of AIT and long lines for WTMD, requiring passengers to arrive for their trip earlier. Moreover, these alternative screening methods are laborious; suggesting that passenger preference for them will influence performance. It will also have a negative impact on security, because they have a lower probability of detecting concealed non-metal items. Thus, these technologies hinder the implementation of screening in mass-transit. Inclusion of AIT assumes that future mass-transit screening will consist primarily of this modern technology and that older less effective ones such as WTMD, opt-out, and unattended turnstiles will be phased out.

In summary, the goal of modeling mass-transit screening is to assess the impact of passenger preference and the detection probabilities of the screening technologies on the security and performance of the screening checkpoint. A method to quantify tradeoffs between the security and performance will identify improvements that can reduce the waiting time while simultaneously ensuring the protection of people and assets.

III. Modeling Approach

This section describes our approach to quantitatively assess the impact of imposing screening on mass transit. Security and performance of a checkpoint are analyzed as a function of the organization of the screening technologies and flow of passengers through the machines and checkpoint.

A. Security Analysis

Security is defined as the probability that a screening technology or a checkpoint successfully detects a threat. We refer to our approach as architecture-based analysis because it expresses the checkpoint security in terms of the security of the screening stations comprising the checkpoint and the probabilistic flow of passengers through these stations. Let n denote the number of screening stations in the checkpoint. We represent the layout of these screening stations in terms of the one-step transition probability matrix of an absorbing DTMC [5] $\mathbf{P}_{n \times n}$, where $p_{i,j}$ denotes the probability that a passenger moves to station j after passing through station i. Without loss of generality, we assume that screening begins at station 1 and completes after station n. Thus, station 1 is designated as the initial state, and station n is the final or the absorbing state of the DTMC. The entry $p_{n,n}$ of $\mathbf{P}$ is set to 1.0.

We augment the DTMC with two absorbing states D and F, where D corresponds to successful threat detection and the failure state F is reached if a threat escapes the checkpoint undetected. From each station i, a transition (i,D) with probability s_i is added, which is the likelihood that the station detects the threat. The original transition probability $p_{i,j}$ between stations i and j is revised to $\bar{s}_i p_{i,j}$, where $\bar{s}_i = (1 - s_i)$. This indicates that a passenger moves to station j only if station i does not detect a threat. Finally, a transition is added from station n to state D with probability $p_{n,D} = s_n$ and to state F with probability $p_{n,F} = \bar{s}_n$. Thus, the checkpoint fails if a threat is undetected at all stations the passenger visits. The process of composing the layout of the checkpoint with stations' detection probabilities assumes that the transitions among the stations are independent and that the detection of a threat at any station implies that the checkpoint is successful. We refer to the resulting model as the 'composite model' because it offers an integrated representation of the layout of the checkpoint and the detection capabilities of the stations.

Once the composite model is built, the following sequence of operations can be performed to obtain an expression, S, for the security of the checkpoint.

- Set $\mathbf{P}_{n,n}$=0.
- Define diagonal matrix $\mathbf{M}_{n \times n}$ with $m_{i,i} = \bar{s}_i$.
- Let $\mathbf{Q}_{n \times n}$=$\mathbf{M} \cdot \mathbf{P}$.
- Compute $\mathbf{V}_{n \times n}$=$(\mathbf{I} - \mathbf{Q})^{-1}$.
- Set $\bar{S} = v_{1,n} s_n$.
- Then $S = 1 - \bar{S}$.

The matrix $\mathbf{V}_{n \times n}$ contains visit statistics, where $v_{i,j}$ represents the mean number of times a passenger visits station j given that they enter the checkpoint at station i. Because an absorbing state can only be visited zero or one time during the screening of a passenger, it is a Bernoulli random variable with average probability of success given by $v_{i,n} \leq 1.0$. Thus, $v_{1,n}$ represents the probability of reaching the baggage pickup station starting from the check-in station with no threat detected. Therefore, $v_{1,n}$ multiplied by $\bar{s}_n$, the probability station n fails to detect a threat, represents the probability the checkpoint fails to detect a threat $\bar{S}$. Thus, checkpoint security is simply $S = 1 - \bar{S}$.

B. Performance Analysis

Traditional performance models [5] quantify the number of passengers screened per unit time. In this paper, we quantify performance as the percentage of passengers that can clear a security checkpoint before their train departs. Performance is commonly assessed using queuing theory, which is efficient and effective for such analysis. However, it requires restrictive assumptions that are often violated in practice. For example, the passenger arrival process needs to follow the well-known exponential distribution which implies a constant arrival rate. Passenger arrivals at mass transit, however, may not follow the exponential distribution. Passenger arrivals will exhibit temporal variations, often peaking during the rush hour, and waning at other times. Analytical queuing models cannot flexibly characterize such variations, and hence, cannot produce accurate estimates of screening performance.

We develop a simulation model to consider time-varying trends in passenger arrivals. In this approach, passengers can arrive at a checkpoint consisting of n screening stations according to an arbitrary stochastic process $\lambda(t)$. Similar to the security model, the one-step transition probability matrix $\mathbf{P}$ of the DTMC controls the flow of passengers among stations, which is determined by the checkpoint layout and the decision probabilities $\mathbf{X}$. The vector $\boldsymbol{\mu}$, with element μ_i represents an arbitrary service time distribution describing the wait time of a passenger at station i. We denote m as the total number of passengers that will arrive at a checkpoint for a particular train. Fig. 2 shows the steps of the simulation procedure:

- Step 1 simulates the vector of arrival times $\mathbf{T}^a$ according to the arrival process [6].
- Step 2 enqueues all m passengers at station one within the checkpoint.
- Step 3 checks the completion time of the passenger at the front of each queue $1 \leq i \leq n$ to determine the passenger that moves next.
- Step 4 removes this next passenger k from the front of queue i.
- Step 5 determines the station j to which passenger k moves after finishing at station i according to the transition probability matrix $\mathbf{P}$.
- Step 6 tests if the destination station j is an absorbing station.
- Step 7 simulates t_k^j, the time at which passenger k will depart station j as follows. If there are no other passengers at station j, the completion time of the passenger is simply the time at which they completed service at station i, t_k^i, plus the randomly generated time sampled from μ_j for the time spent waiting at station j. However, if other passengers are at station j the completion time of passenger k is the randomly

generated time sampled from μ_j plus the completion time of the passenger at the end of queue *j*.

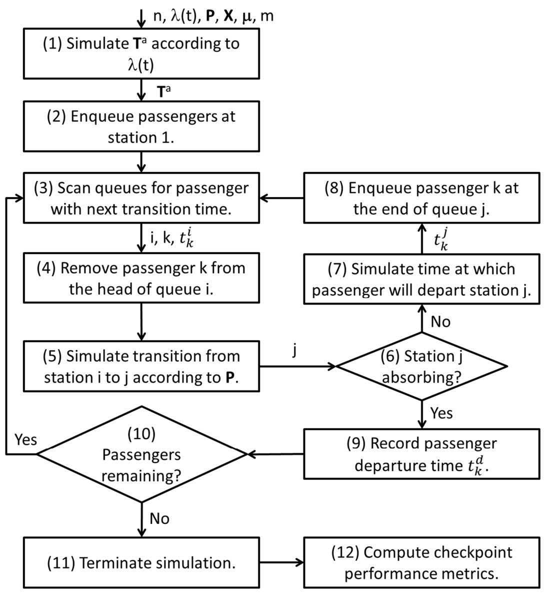

Figure 3. Checkpoint simulation procedure.

- Step 8 enqueues passenger *k* at the end of queue *j* and returns to Step 3 to determine the next passenger to move.
- Step 9 records t_k^d, the time passenger *k* departs the checkpoint after having completed screening.
- Step 10 checks to see if all *m* passengers have departed the checkpoint and returns to Step 3 if passengers remain. If no passengers remain, Steps 11 and 12 terminate the simulation and compute performance metrics of the checkpoint, which are described below.

By tracking the vector of passenger arrival times $\mathbf{T}_a = \langle t_1^a, \ldots, t_m^a \rangle$, the times at which passengers depart their present screening station t_k^i, and the vector of times at which the passengers depart the screening checkpoint $\mathbf{T}_d = \langle t_1^d, \ldots, t_m^d \rangle$, it is possible to calculate the number of passengers at each station at time *t* and the number of passengers in the checkpoint at time *t*. We can also determine the time spent in the queue by computing the difference $t_k^d - t_k^a$ for each passenger and then plot completion times as a function of the arrival times. We compute the fraction of passengers that miss their train because they fail to pass through the checkpoint in a timely manner.

IV. Illustrations

This section demonstrates the security and performance assessment techniques through a series of examples. For both attributes, we initially demonstrate how to quantify the metric, followed by an illustration of how the sensitivity of the metric to various parameters of the layout and constituent technologies can be analyzed.

A. *Security Analysis*

This example quantifies the security of the station layout shown in Fig. 1, using the transition matrix **P** in Table I, where element *(i,j)* denotes the probability that a passenger moves to station j, upon the completion of screening at station *i*.

TABLE I. Transition Probabilities Among Stations

i\j	c	x	a	o	w	P
(c) Check-in	0	1.	0	0	0	0
(x) x-ray	0	0	$\bar{x}_1 + x_1\bar{x}_2\bar{x}_3$	$x_1\bar{x}_2x_3$	x_1x_2	0
(a) AIT	0	0	0	x_5	0	$\bar{x}_5$
(o) Opt-out	0	0	0	0	0	1.
(w) WTMD	0	0	0	x_4	0	$\bar{x}_4$
(p) Pickup	0	0	0	0	0	0

Here x_i correspond to the decision points described in Section II. The sequence of matrix operations from Section 2 produces the following expression for checkpoint security.

$$S = 1 - \big((x_1x_3 + x_1x_2x_3)\bar{s}_c\bar{s}_x\bar{s}_o + (\bar{x}_1 + x_1\bar{x}_2\bar{x}_3)(1 - x_5 + x_5\bar{r}_4)\bar{s}_c\bar{s}_x\bar{s}_a + x_1x_2(1 - x_4 + x_4\bar{s}_4)\bar{s}_c\bar{s}_x\bar{s}_w\big)\bar{s}_p. \quad (1)$$

Equation (1) expresses checkpoint security in terms of the decision points and detection probabilities of the stations. Thus, it is possible to evaluate checkpoint security for different types of threats and decision probabilities. For example, when a passenger conceals an object under clothing, the check-in, carry-on baggage x-ray machine, and baggage pickup stations have no chance of detecting this threat. Hence, s_c, s_x, and s_p are set to *0*. AIT will be the most effective at detecting this hidden threat, followed by manual screening at the opt-out station, while the WTMD will exhibit the lowest probability of detection. Thus, the securities of these three stations are set to s_a=*0.9999*, s_o=*0.99*, and s_w=*0.9* to reflect their relative effectiveness. We set the probabilities of the five decision parameters to nominal values shown in Table II.

TABLE II. Decision Parameters

(i) Decision	Probability (x_i)
(1) Passenger selects WTMD	0.90
(2) Officer allows WTMD	0.85
(3) Passenger opts-out of AIT	0.30
(4) WTMD passenger undergoes pat down	0.10
(5) AIT passenger undergoes pat down	0.05

Table II indicates that most passengers prefer and are allowed to undergo WTMD screening. Approximately *30%* of passengers selected for AIT screening opt out. Furthermore, one in ten passengers screened by WTMD will also be screened manually, but only one in twenty passengers going through AIT require manual screening. These values are chosen solely for the sake of illustration. In practice, detection and transition probabilities may be determined from measurements made in transportation security laboratories and operational environments. For these parameters, Equation (1) computes that the threat detection probability is *0.9306*. This illustrates that even though the AIT machine can detect threats with a higher probability, passenger preference for WTMD can significantly lower checkpoint security.

Realistically, the detection probabilities of certain technologies cannot be improved beyond a certain threshold. For example, WTMD may have inherently low detection probability for most concealed, non-metal threats. Thus, Equation (1) suggests that an alternative method to improve security is to boost the probability that passengers select modern screening technologies. We thus analyze the sensitivity of checkpoint security to decision parameters using Equation (1). These parameters include the probability that a: (i) passenger selects WTMD (x_1); (ii) security officer allows a passenger to undergo WTMD screening (x_2), and (iii) passenger selected for AIT screening opts-out (x_3). These probabilities were varied individually in the range (0,1), while holding all the other parameters at their values in Table II.

Fig. 4 illustrates that a significant improvement in checkpoint security could be obtained by eliminating the possibility passengers choose WTMD ($x_1 = 0$), which increases detection probability to *0.9999* (4 nines). A strategy that selects every passenger wishing to undergo WTMD for AIT screening increases detection probability to *0.9972* (2 nines) [7] while eliminating passenger opt out shows the smallest improvement of 0.*9311*. This analysis quantitatively confirms that passenger preference for WTMD over AIT lowers checkpoint security significantly. Therefore, passenger aversion to AIT must be decreased, which may be achieved using two possible strategies. The first approach is to mitigate health and privacy concerns through public education. A second method is to select more passengers for AIT screening (decreasing x_2), to create a learning effect through passenger familiarity.

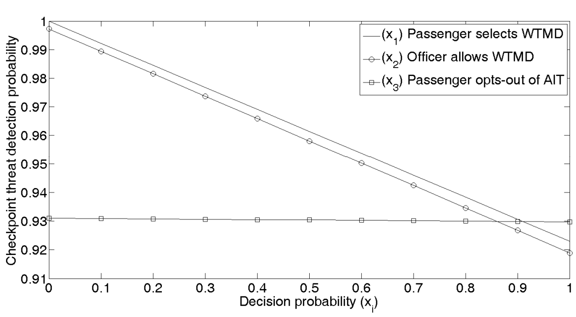

Figure 4. Sensitivity of security to decision parameters.

B. *Performance Analysis*

This example compares the performance of the current turnstile configuration in Fig. 1 with the rigorous passenger screening checkpoint in Fig. 2 using the simulation model. We consider *m=100* passengers arriving for an 8:00am train according to a normal distribution with mean μ = *-20* and standard deviation σ = *6*. The mean indicates that the passengers arrive on an average *20* minutes prior to the departure of the train, while the standard deviation accommodates passengers arriving more conservatively, *30* minutes or more in advance of the departure time. It also accounts for late and seasoned passengers who arrive just minutes before departure. According to these parameters, approximately *99%* of the passengers will arrive sometime in the interval $\mu \pm 3\sigma$ = *(7:22am,7:58am)*. Although we use the normal distribution for illustration, it can be determined empirically based on the data collected by the turnstiles while stamping tickets.

We assume that *80* passengers ($\mu_h = 80$) can walk down the hallway leading to the turnstiles per minute, passengers get in line at one of the three turnstiles with equal probability ($x_i = 1/3$, $i = \{1, 2, 3\}$), and the time required for the computer to read and stamp the ticket follows an exponential distribution with an average time of *3* seconds, or twenty passengers per minute ($\mu_t = 20$). The decision parameters of the passenger screening checkpoint are set to the values in Table II, while Table III provides the service rates of the passengers per minute for each station in the security checkpoint.

TABLE III. CHECKPOINT STATION RATE PARAMETERS

(i) Station	Rate (μ_i)	(i) Station	Rate (μ_i)
(h) Hallway	80.0	(o) Opt-out	3.0
(c) Check-in	6.0	(w) WTMD	4.0
(x) x-ray	4.0	(p) Pickup	5.0
(a) AIT	7.5		

Fig. 5 shows the results of a single experiment. The first passenger arrives approximately 35 minutes early, while the last passenger arrives just five minutes before the train departs. We fed the same sequence of arrival times to the simulation models of both the turnstile and screening checkpoint. The completion times under the turnstile model indicate that passengers quickly pass through and continue on to the train. A small slowdown can be seen slightly after 7:40am. The arrival distribution reaches its maximum at that time causing many passengers to arrive about twenty minutes before departure waiting at the turnstiles. However, the maximum wait time never exceeds 1 minute and no passengers miss the train. Under the screening checkpoint model, however, the last passenger clears the checkpoint over an hour after the train departure and only *40* of the *100* passengers can clear the checkpoint to board the train.

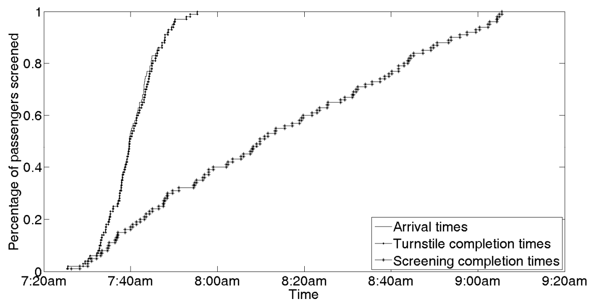

Figure 5. Comparison of turnstile and screening completion times.

The difference between the arrival and wait time grows because the time needed for passengers to clear the checkpoint is greater than their arrival rate. This is consistent with a well-known tenet from queuing theory [5], which states that the queue will be bounded only if arrival rate at the checkpoint is greater than its service rate. This property is not satisfied because the time-varying arrival process peaks at 20 minutes prior to the train's departure.

Fig. 6 shows the length of the line at the check-in station as a function of time, revealing that this check-in desk is the bottleneck. The arrival rate at *7:30am* is not sufficiently high for the queue to grow unbounded. However, the queue begins to grow in the interval between *7:30am* and *7:35am* because passengers begin to arrive faster than they can be checked in. The increase in the queue length accelerates in the time interval *(7:35am,7:45am)* since the normal distribution characterizing passenger arrivals peaks at *7:40am*. As the rate of arrival decreases in the interval *(7:45am, 7:50am)*, the queue length levels off. However a delay with one passenger at *7:50am* causes the queue to grow yet again. After *7:55am*, all passengers have arrived and the queue empties at an approximately constant rate.

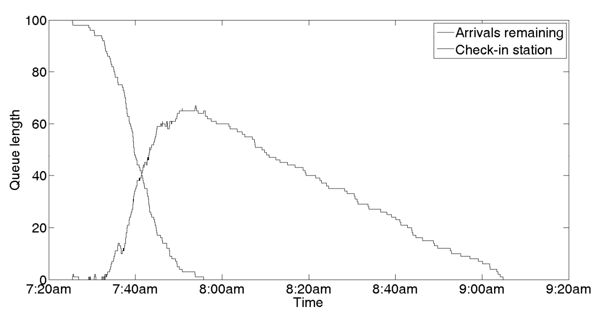

Figure 6. Passenger check-in queue length.

The bottleneck created by the check-in desk suggests that manual verification of passengers' identities is infeasible. Moreover, as noted earlier, introducing additional check-in stations is not feasible because of its cost. Thus, in order to avoid eliminating identity verification, faster technologies such as biometrics can be used. An experiment which removed the check-in station from Fig. 1 and allowed passengers to proceed directly to the baggage station shifted the bottleneck to the baggage station, suggesting that baggage scanning also needs to be expedited.

The results of the above experiment revealed that imposing rigorous aviation security screening on mass-transit could create serious delays. Next, we demonstrate how the approach could be used to quantitatively compare the impact of improvements in individual stations. Usually, a single simulation experiment does not provide metrics with sufficient accuracy, so it is customary to compute the average metrics over several runs. We thus repeated the simulation with the station parameters in Table III 10,000 times, which indicated that on an average 34 passengers (approximately one third) can be cleared before the train departure. Having established this baseline, we next doubled the completion rate of each station in Table III one at a time and estimated the average number of passengers that would be cleared before departure. Table IV reports the results of this analysis for each station in the checkpoint and ranks the improvements according to the increase in the number of passengers that make their train.

TABLE IV. SENSITIVITY OF STATION PERFORMANCE

Station	Increase	Rank	Station	Increase	Rank
Check-in	2.298	1	Opt-out	0.067	6
x-ray	0.377	2	WTMD	0.290	3
AIT	0.170	5	Pickup	0.226	4

This analysis quantitatively confirms that accelerating check-in would produce the greatest improvement in passenger throughput followed by the x-ray machine, WTMD, and pickup stations respectively. Examining Fig. 2, all passengers must pass the check-in, x-ray, and pickup stations, potentially creating bottlenecks. Intuitively, Table III might suggest that the x-ray machine is the biggest bottleneck because it can service only four passengers per minute. The simulation results, however, indicate that the check-in desk creates the greatest slowdown because it is the first one in the network of stations. This causes the long line in Fig. 6 suggesting that the earlier stations are more critical to checkpoint performance. Improvements in WTMD rank higher than AIT because a larger percentage of the passengers will prefer and ultimately undergo WTMD inspection. AIT ranks higher than opt out for similar reasons. Substituting the probabilities from Table II into the transition matrix in Table I indicates that on an average 76 of the 100 passengers go through the WTMD, while the AIT station and opt-out stations are visited by 19 and 5 passengers respectively. Thus, the criticality rankings given in Table IV are influenced by the service rates of the stations given in Table III and the average number of passengers visiting a station. The approach can therefore quantify the impact of each station on the performance of the checkpoint despite these complex factors influencing a station's importance.

V. POLICY RECOMMENDATIONS

This section offers policy recommendations based on our observations and lessons to improve security and balance performance for mass-transit screening. Specifically:

- Introducing aviation-style screening checkpoints into mass-transit could dramatically slow passengers causing several passengers to miss their train.
- Including alternative technologies like WTMD and opt out can significantly lower security.
- Increasing passenger acceptance of AIT will offer the highest improvement in security.
- Technologies to verify passengers' identity and screen baggage must be accelerated.

These lessons suggest that, to make mass transit screening effective and efficient, older screening methods such as WTMD and opt out must be phased out by increasing acceptance of AIT. Improved education to mitigate health and privacy concerns and selecting a larger number of passengers for AIT screening to increase their familiarity may accelerate this acceptance.

VI. Conclusions and Future Research

This paper presents techniques to quantify the security and performance of passenger screening checkpoints and applied them to assess the impact of imposing screening on mass-transit. The results reveal that the performance of screening technologies must be improved and passenger aversion to newer and faster technologies must be addressed to ensure the feasibility of screening for mass-transit. Our future research will enrich the security and performance assessment techniques by developing sophisticated modeling capabilities. For example, the model may be enhanced to incorporate batch or grouped arrivals of passengers, such as a family traveling together. To enhance the scalability of the approach and improve the accuracy of the metrics, more efficient data structures will be explored. We will use these enhanced simulation techniques as the basis of an optimization framework to identify investments in technology improvement offering the greatest improvements in security and performance.

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Disclaimer

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