



On load balancing strategies for baggage screening at airports



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ARTICLE INFO

Article history:

Received 22 August 2016

Received in revised form

21 February 2017

Accepted 24 February 2017

Keywords:

Aviation baggage screening

Load balancing

Task assignment

Performance evaluation

Discrete-event simulation

ABSTRACT

We study load balancing policies for an airport baggage handling system (BHS). The performance of the screening subsystem is important as it can potentially cause traffic congestion of the whole BHS during peak period. Currently, the round-robin (RR) and the first-available (FA) policies are implemented at airports. This paper presents a simulative approach to evaluate the impact of load balancing policies on the system performance. Using discrete-event simulations, airport practitioners can assess the effectiveness of the policies according to the actual layout of a particular passenger terminal. In addition to the RR and FA, a join-shortest-queue (JSQ) policy is introduced. This scheme can be applied jointly with the RR for daily operations. A case study is presented to illustrate the characteristics of this scheme. Simulation results demonstrate that the RR-JSQ can replace the existing RR-FA for a better balanced load distribution and improve the overall system performance.

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1. Introduction

Baggage handling system (BHS) is a type of logistic system installed at airports, transporting passenger bags automatically from sources to destinations (e.g., from check-in counters to departure areas). The major functionalities of a BHS are baggage check-in, transportation, screening, tracking, sortation, early-storage, etc., and are implemented by various logistical equipment (Yu and Xu, 2010). The carriers to transfer baggage can be conveyors, trays, carts, or their combinations within the system. Recent technological advancement in the BHS is destination-coded vehicle (DCV) where the speed of every bag can be controlled individually (Mao et al., 2015). A BHS is made up by a number of subsystems on the basis of baggage processing flow (van de Laar, 2009). A subsystem is normally comprised of machines that handle the baggage such as screening machines, loading robots, etc., and a number of buffers (e.g., queue conveyors) which are necessary during peak period. A BHS consists of a number of cascaded queueing systems which can potentially cause a bottlenecking problem within the system (de Neufville, 1994; de Neufville and Odoni, 2013).

Therefore, it can be advantageous if practitioners are able to verify the performance of subsystems via simulative analysis ahead of actual system deployment. Solution providers are usually requested to assess their design via simulation and present the

performance results to the airport management when tendering a new BHS project. Hafizogullari et al. highlighted the importance of proactive system-level simulation in (Hafizogullari et al., 2003) with an example of Lambert St. Louis International Airport. A number of simulative studies are available in different aspects of the BHS, such as check-in area (Le et al., 2007), merge area (Johnstone et al., 2015), and especially screening area (Sterchi and Schwaninger, 2015; Dorton and Liu, 2016; Leone and Liu, 2005). Sterchi et al. investigated the effects of screening time and false alarm rate on the baggage throughput of airport security screening checkpoint in (Sterchi and Schwaninger, 2015). Reference (Dorton and Liu, 2016) verified the impacts of baggage volume and false alarm rate on the performance (waiting times and number of queues) by modelling the system using queueing theory. Leone et al. suggested a way to estimate the total number of explosives detection system (EDS) machines required and evaluated also waiting times and queue lengths using discrete-event simulation (Leone and Liu, 2005).

This paper concentrates on a different topic which is the routing strategy in airport baggage screening. Currently, according to the industry standard from Transportation Security Administration of the United State (Transportation Security Administration, 2011), baggage screening subsystems implement the round-robin (RR) and first-available (FA) policies for bag assignment. It is a very simple algorithm which distributes bags in a circular way without knowing anything about the system states. It can be easily implemented by software on a programmable logic controller (PLC) (Haneyah et al., 2013). The RR is the most common practice in the industry. It is the only load balancing policy for screening subsystems as stated in the official bidding document of Charlotte

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Douglas International Airport (Charlotte Douglas International Airport, 2014). In the design document (San Francisco International Airport, 2011; hereafter SFO, 2011) of San Francisco International Airport, the RR can be complemented with the FA. Under the FA scheme, bags are dispatched to the first screening line where the queue conveyors are not full. This strategy requires information from screening lines, and is only used when the queue utilization is extremely high. Both the RR and the FA fall into the category of static routing. The main disadvantage for static routing is the inability to handle variability. At the presence of unbalanced queue lengths (due to variability), neither RR nor FA can react quickly to improve the situation, because of the lack of feedback mechanism. This paper introduces a dynamic policy, namely join-shortest-queue (JSQ), to the airport screening process. It is not a new policy as it has been used in job scheduling in computing, communication theory, and so on (Mukhopadhyay and Mazumdar, 2016; Jiang et al., 2012; Iyengar et al., 2015). This approach relies on the real-time state feedback from queues and servers. A variety of literature demonstrated the optimality of the JSQ policy when the servers follow the first-come-first-serve (FCFS) principle (Winston, 1977; Nelson and Philips, 1993; Akgun et al., 2011).

The contribution of this paper is three-fold. First, this paper presents the first analysis on the load balancing strategy used in airport baggage screening systems. The JSQ policy is introduced in addition to the existing RR and FA. Second, a simulation platform is presented to verify the effectiveness of the load balancing strategies. This platform is easy to configure and can adapt according to actual system parameters at airport terminals. Third, the simulation study demonstrates that the overall screening performance can be considerably improved with a hybrid RR-JSQ load balancing strategy combining advantages from both the RR and JSQ.

The remainder of the paper is organized as follows: Section 2 introduces the background of the BHS, including performance indicators which we evaluate under different load balancing policies. The policies including the hybrid RR-JSQ are elaborated in Section 3. In addition, the model of baggage screening is generalized to facilitate the simulation. Section 4 presents the environment of the discrete-event simulation and the verification of the RR-FA, the JSQ and the RR-JSQ policies. Conclusions and recommendations for further research are given in Section 5.

2. Airport baggage screening system

2.1. System overview

Every bag originated from check-in counters or early-baggage storages is transferred to a screening subsystem to receive mandatory (level-1) security inspection. The layout of a typical screening subsystem is illustrated in Fig. 1(a). A screening subsystem consists of several homogeneous screening lines. The arrived bags are distributed to each screening line according to a load balancing strategy. Each screening line, indexed by $l \in \mathbb{L} = \{1, \dots, m\}$ where m is the total number of lines, is normally comprised of one EDS machine and several queue conveyors. The system state observed by the k -th arriving bag is denoted by $\mathbf{q}^k = (q^{k,1}, q^{k,2}, \dots, q^{k,l}, \dots, q^{k,m})$, where $q^{k,l}$ is the number of bags waiting in EDS line l . We let N_Q^l denote the number of queue conveyors (limited waiting space) at the l -th line. It is obvious that physical constraint $q^{k,l} \leq N_Q^l$ must hold. Screening is carried out on a FCFS basis for each queue. Jockeying amongst queues is not possible. If the screening machine outputs a safe signal, the X-rayed bags are transported to the sortation area. Otherwise, it can be cycled back for a second checking, or transferred to another checkpoint with more stringent inspection (level-2) (Blejcharova et al., 2012). We assume that all checking results are “pass” and only level-1 screening is applicable, i.e., no

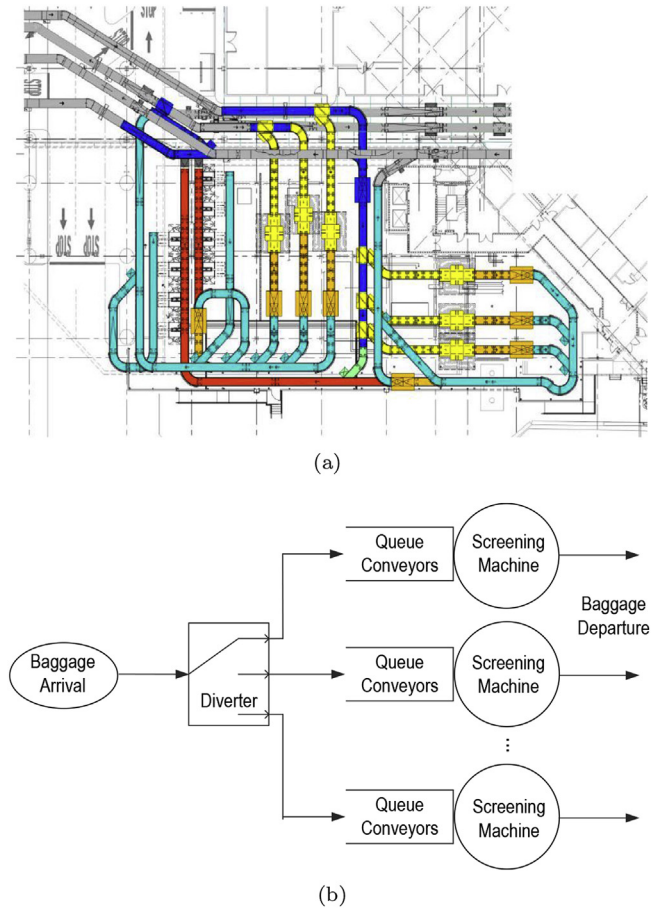


Fig. 1. Baggage screening subsystem: (a) Physical layout; (b) Logical view.

recycle for questionable bags.

In principle, the control logic of any subsystem within a BHS is dealt with by a PLC. The PLC communicates with sensors and actuators to fulfil all the necessary functionalities of baggage handling (Dai and Vyatkin, 2012; Wu et al., 2013). In the case of screening subsystem, the PLC performs a load balancing algorithm to divert each bag to screening line l based on the system states collected from sensors. The start and stop of each queue conveyor is also controlled by the PLC.

In this paper, we focus on the study of load balancing policy (see Fig. 1(b)). The baggage that arrives in screening area is distributed to a specific screening line mechanically by one or more diverters. For a DCV-based system, this is done by route choice control (Tarau et al., 2010). We define operator $\mathcal{R}(k)$ to represent the routing policy for the k -th bag. The output of function $\mathcal{R}(\cdot)$ is EDS line index l . Obviously, $\mathcal{R}(\cdot)$ has direct impact on the baggage arrival on each EDS line. At present, the RR and the FA are the only two algorithms practically implemented in airport screening subsystems as the load balancing strategy.

2.2. Performance indicators

Travel time (in minutes) and throughput (in bags per minute/hour, or bpm/bph) are crucial to airport BHSs (Le et al., 2012).

Total travel time for a bag is made up of transportation time, waiting time, and processing time. The design of a BHS would allow at least 95%, for example, of all checked bags from any check-in counter to the loading area within 10 min (Little Rock National Airport, 2011). Transportation and processing time are the static

part of travel time, and are almost identical to each bag. On the other hand, the time for each bag waiting for its processing by baggage handlers (e.g., EDS machines) is variable according to a number of factors, for instance, system load and capacity. The waiting time of the k -th bag is denoted as w^k . It is no doubt that the average waiting time $E(W)$ is an important performance indicator. The maximum transient waiting time $\max(w^k)$ is also important because it reflects the capability to handle “hot” (urgent) bags.

Reducing mean and transient waiting time is not the only goal for BHS. The processing capacity refers to how many bags the system or subsystem can transfer or process within a certain period. Based on this parameter, airport management can estimate the number of passengers that a terminal or a subsystem can handle. For example, it is stated in (SFO, 2011) that the expected throughput of a screening subsystem at San Francisco International Airport is 3000 bags per hour in year 2017. The load for each screening line can be reflected by $q^{k,l}$ which must be less or equal to the queue capacity N_Q^l . The problem of maximizing system throughput is equivalent to the problem of minimizing possible $\max(q^k)$ during daily operation. We define $|q^k| = \sum_{l=1}^m q^{k,l}$ as the total number of bags queueing in the system. This transient property is important as it is relevant to the stability of the system.

Definition: Similar to the definition given in (Sharifnia, 1997), we give the following statements: A screening system is regarded as unstable if it fails to process all bags using its limited resources (buffers and EDS machines) during daily operation. Mathematically, the system is unstable if the congestion condition is met at the k -th bag instance

$$\max_k (q^{k,l}) > N_Q^l, l \in \mathbb{L} \quad (1)$$

This condition must be avoided during BHS operation as it can lead to system shut-down and consequently financial and reputational loss to the airport.

3. System modelling

3.1. Baggage arrival

We let a^k represent the inter-arrival time between the k -th bag and its subsequent bag. The baggage arrival is partially predictable because it can be, to some extent, scheduled by the airport as each passenger is allocated with a limited period of time to check-in their bags (Abdelghany et al., 2006). Note that baggage separation is a common practice in the BHS to maintain the safety gap between bags (Black and Vyatkin, 2010; Hills, 2009). The control of bag spacing may change the inter-arrival time of bags inside a BHS. As a result, we assume that a^k is generally distributed. At a particular location within a BHS, a^k can be obtained by a photoelectric sensor. The sensor is capable of detecting the time difference between the presence of two consecutive bags. The signals are collected by the PLC where a^k can be then obtained. Average arrival rate and the coefficient of inter-arrival time, represented by λ and $\text{Cov}(a^k)$, respectively, can be also calculated.

3.2. Baggage screening

The EDS machines within a screening system are usually identical, i.e., with symmetric processing capacities. They operate in parallel. We define b^k as the screening time for the k -th bag. The average service time μ is given by the EDS machine manufacturer. The actual screening time each bag spends on an EDS machine can be obtained by the PLC via fieldbus interface (e.g., PROFIBUS) (Morpho, 2016). Parameter b^k generally depends on the job

complexity (what is contained inside the bag) and the computational power of the machine's CPU/GPU. Therefore, variability in b^k is expected. Again we assume that b^k is generally distributed.

3.3. Queueing model

Each screening line consists of an X-ray machine and several queue conveyors located at upstream of each machine for buffering. Based on the above-mentioned analysis, we generalize the system using a G/G/m/ \mathcal{R} /FCFS model (G/G/m queue with load balancing policy \mathcal{R} and FCFS discipline). We let $\rho = \lambda/m\mu$ denote the utilization ratio of the screening system. During a heavy baggage traffic period, it could be possible that the demand rate exceeds the screening rate ($\rho > 1$). The overload condition leads to queueing behaviours and hence delays in baggage delivery. The waiting delays and queue lengths grow non-linearly with system utilization (de Neufville and Odoni, 2013). In the worst-case scenario, it may happen that bags cannot make it to the aircraft on time. Because the subsystems are cascaded, every subsystem could potentially cause blockage, especially when the system is designed without enough simulative verification. The discrete events such as baggage dispatching, queueing and screening can be evaluated via simulation. Our objective is to improve the overall system performance by applying a right load balancing policy \mathcal{R} .

3.4. Load balancing

3.4.1. Round-robin

The RR is widely adopted in the BHS industry due to its simplicity. Bags are dispatched in a cyclic manner to equalize the expected number of bags assigned to parallel EDS machines. The policy can be described as $\mathcal{R}(k) = (k \bmod m) + 1$. That is, the k -th bag is routed to EDS line $(k \bmod m) + 1$. The RR performs open-loop routing, so the PLC does not need any state feedback from EDS lines. The RR policy offers the optimal performance when job size is deterministic (Kuri and Kumar, 1994). In other words, the screening time would be optimal if the complexities of each bag are fixed. The variability in the job size is considerable in actual BHS as suggested in (Leone and Liu, 2011) by Leone et al.

3.4.2. First-available

The FA policy, sometimes referred to as first-non-block queue (FNB), distributes the bag to the first screening line that is not fully loaded, i.e., the algorithm finds the first $l \in \mathbb{L}$ where $q^{k,l} < N_Q^l$ is satisfied. It can be expected that this approach tries to involve as minimal number of EDS machines as possible. A photoelectric sensor should be installed at the most upstream queue conveyor in each screening line. Total m number of sensors should be deployed. The sensor is used to detect if a bag is present on that queue conveyor, i.e., if the buffers are fully occupied. The measurements at the presence of the k -th bag are fed back to the PLC to decide the output of $\mathcal{R}(k)$. This policy must be always implemented jointly with the RR. It is only activated during peak hours (at least one queue is fully occupied) to attain maximum throughput of the system.

Algorithm 1 Load balancing policy RR-FA

- 1: Arrival of the k -th bag
 - 2: **for** $l = 1 : m$ **do**
 - 3: **if** $q^{k,l} = N_Q^l$ **then**
 - 4: **return** $\mathcal{R}(k) \rightarrow FA$
 - 5: **end if**
 - 6: **end for**
 - 7: **return** $\mathcal{R}(k) \rightarrow RR$
-

3.4.3. Join-shortest-queue

This policy has been widely applied in computing and communication theory. We investigate its applicability in baggage screening systems. The algorithm demands the current states of q^k . It thus requires a total of $\sum_{l \in \mathbb{L}} N_Q^l$ photoelectric sensors to be installed on queue conveyors in order to monitor their status. The algorithm searches for candidate l which is of the minimal number of bags waiting in the queue. If there are more than one candidates, the ties can be broken by arbitrarily choosing one of the candidates. The algorithm can be illustrated as

$$\mathcal{R}(k) = \arg \min_{l \in \mathbb{L}} (q^{k,l}) \quad (2)$$

Comparing with the $G/G/m$ -RR system, there are more results obtained by researchers on the $G/G/m$ -JSQ system. The equivalence of $G/G/m$ (one shared queue) and $G/G/m$ -JSQ was established in (Kuri and Kumar, 1994). Nelson et al. boiled down a $G/G/m$ -JSQ system to simple $G/G/1$ queues, and formulated the average waiting time and queue length in (Nelson and Philips, 1993). However, the approximation is only accurate when $\text{Cov}(a^k) \leq 1$ and $\text{Cov}(b^k) \leq 1$. The optimality of the JSQ in case of exponential service time was addressed by a number of literature (Winston, 1977; Koole et al., 1999; Akgun et al., 2011). Whitt, however, suggested in (Whitt, 1986) that the JSQ may not be the optimal load balancing policy when service time is not exponentially distributed. The optimality of the JSQ in our baggage screening application is questionable as the service time does not follow an exponential distribution as analyzed earlier. This can be validated via simulation studies.

The JSQ is expected to outperform the RR in the presence of a heavy traffic and increased variability due to its closed-loop nature (Nelson and Philips, 1993; Hyyti and Aalto, 2016). On the other hand (Whitt, 1986), suggested that the JSP might not be optimal during light traffic. Inspired by both scenarios, together with the fact the policies can be applied in a switching way depending on the system states (as implemented in the RR-FA for example), we propose a hybrid RR-JSQ policy, with expectation that combined advantages can be offered as the policy dynamically shifts between the RR and the JSQ depending on the system queue lengths. The RR is applied during light traffic period. It is taken over by the JSQ when $q^{k,l}$ is larger than a threshold N_Q^l . The algorithm can be illustrated as the following.

Algorithm 2 Load balancing policy *RR-JSQ*

```

1: Arrival of the  $k$ -th bag
2: for  $l = 1 : m$  do
3:   if  $q^{k,l} \geq N_Q^l$  then
4:     return  $\mathcal{R}(k) \rightarrow JSQ$ 
5:   end if
6: end for
7: return  $\mathcal{R}(k) \rightarrow RR$ 

```

The performance of this new policy relies on the modelling of two systems $G/G/m$ -RR and $G/G/m$ -JSQ. Due to the difficulty of obtaining accurate approximation on $G/G/m$ -RR and $G/G/m$ -JSQ systems, and the lack of formulations on transient behaviours, simulative approach can be advantageous on the performance assessment and comparison, and therefore is considered over mathematical formulations in our paper.

4. Simulation study

4.1. Case study description

We explore the policies by making forecast on the short- and long-term behaviours of screening subsystem with an example of San Francisco International Airport (SFO) Terminal 3, boarding area F. The system design is described in (SFO, 2011) in detail. Here we repeat only important information. The system parameters related to the screening area given in the design document are listed in Table 1. There are 5 screening lines running in parallel in the subsystem. The screening rates are symmetric (640 bph for screening machine model CTX 9800). Therefore the combined average service rate for all 5 machines is 3200 bph. The probability distribution of b^k was evaluated in actual BHSs at airports in (Leone and Liu, 2011) and (Leone, 2010) and it was concluded that log-normal distribution fits b^k the best. In our case study, consequently, we make an assumption that b^k follows a log-normal distribution and $\text{Cov}(b^k) = 0.5$.

The average baggage arrival rate is usually set at every 10-min interval (Leone and Liu, 2005) (denoted by $\lambda_{10\text{min}}$). In this case study, $\lambda_{10\text{min}}$ throughout a day is estimated from reference (SFO, 2011). With the assumption that a^k is uniformly distributed with parameters $\lambda_{10\text{min}}$ and $\text{Cov}(a^k)$ within every 10-min interval, a^k is initialized and the event-series of baggage arrival can be generated according to a^k . We let N_B^l denote the number of bags handled at the l -th EDS machine per day. Obviously, bag index $k \in \{1, \dots, \sum_{l \in \mathbb{L}} N_B^l\}$,

where $\sum_{l \in \mathbb{L}} N_B^l$ is the total number of bags handled during a day. The same a^k will be applied to the system under different load balancing policies when comparing the performance of the policies.

Based on observation of (SFO, 2011), the peak hour for the operation in each day is from 11:30 to 12:30. This can be the most challenging period for BHS of a day. We assume the duration from 12:00 to 12:10 as the 10-min peak period during operation. The average baggage input during peak 10-min, or $\lambda_{10\text{min_peak}}$, is estimated at 48.20 bpm in year 2017. The BHS at boarding area F was put into operation in year 2012, and was expected to experience a 1.1%–1.3% annual passenger growth rate. To simplify the simulation and presentation, we assume that the baggage arrival is changed only on a yearly basis, instead of daily, weekly or monthly. Based on the maximum possible annual growth rate of 1.3%, we give forecasts on the total number of handled bags per day $\sum_{l \in \mathbb{L}} N_B^l$ and peak

baggage arrival rate (10-min interval) $\lambda_{10\text{min_peak}}$ for the next 10 years (2017–2027). The traffic estimations are presented in Table 2. Note that the demand rate can exceed the service rate since year 2025 as the system will be overloaded during peak 10-min, i.e., $\rho_{10\text{min_peak}} > 1$. The simulation study is to evaluate how load balancing schemes can impact the system performance over short-term and long-term.

Table 1
Simulation parameters.

Parameters	Value
m	5
N_Q^l	10, $\forall l \in \mathbb{L}$
$\lambda_{10\text{min}}$	Estimated from (SFO, 2011)
$\lambda_{10\text{min_peak}}$	48.20 bpm (year 2017)
$\text{Cov}(a^k)$	0.092
μ	640 bph
$\text{Cov}(b^k)$	0.5

Table 2
Traffic forecast.

Year	$\sum_{l \in L} N_B^l$	ρ	λ_{10min_peak} (bpm)	ρ_{10min_peak}
2017	18739	0.244	48.20	0.904
2018	18972	0.247	48.83	0.916
2019	19221	0.250	49.46	0.927
2020	19468	0.253	50.10	0.939
2021	19724	0.257	50.75	0.952
2022	19987	0.260	51.41	0.964
2023	20242	0.264	52.08	0.977
2024	20506	0.267	52.76	0.989
2025	20784	0.271	53.45	1.002
2026	21047	0.274	54.14	1.015
2027	21310	0.277	54.84	1.028

4.2. Methodology

4.2.1. Simulation environment

The simulation work is carried out on the MATLAB/Simulink platform. Time-series a^k is generated in MATLAB code based on λ_{10min} and $Cov(a^k)$, while event-based diverting, queueing, and screening behaviours are simulated in a Simulink model on the basis of discrete-event toolbox SimEvents (Gray, 2007). EDS machine parameters such as μ and $Cov(b^k)$ are defined in MATLAB code and passed to Simulink. Initially, all queues are empty. Each screening line is encapsulated to a G/G/1 system. Simulation results w^k and $q^{k,l}$ are collected from the Simulink model for each and every bag. The complete simulation platform is presented in Fig. 2.

4.2.2. Load balancing policy

It can be known from document (SFO, 2011) that only the RR-FA is taken into account in the system design. In this simulation study,

we consider the existing RR-FA, standalone JSQ, and the RR-JSQ routing strategies. Parameter N_Q' in the RR-JSQ strategy can be statically defined. We are not able to give any theoretical formulation for the choice of N_Q' at the moment due to the fact that approximated result of G/G/m/JSQ/FCFS is not available from any literature. In this case study $N_Q' = 1$ is chosen, since it could be sufficiently large to bring over the combined benefits.

4.3. Results and discussions

4.3.1. Short-term performance forecast

First, we describe and discuss the performance results on each individual EDS line achieved from selected policy candidates, i.e., the RR-FA, the JSQ and the RR-JSQ, over the peak hour (noon from 11:30 to 12:30). Due to the space constraints, only the performance forecast for a particular year (year 2022, $\lambda_{10min_peak} = 51.41$ bpm) is stated here. Static results are summarized in Table 3, while the dynamic queueing behaviours are presented in Fig. 3. The RR-FA strategy here is equivalent to the RR, since the FA scheme is not expected to be enabled for year 2022 even during peak hour. It can be noticed from Fig. 3(a) that, among all EDS lines, the transient waiting time induced by the RR is relatively uneven, despite the fact that the numbers of bags sent to each EDS machine N_B^l are equal. Bags dispatched to the fifth EDS line are expected to experience an average additional delay 5.28 s than those of the first line during peak hour (11:30–12:30). This behaviour is caused by the variabilities $Cov(a^k)$ and $Cov(b^k)$, which are considerably high in the baggage screening process. In addition, $q^{k,l}$ is also unbalanced. When a queue firstly reaches for its maximum capacity limit during daily operation, other queues are probably not fully occupied. That is to say, it is unlikely to enter the state of $|q^k| = \sum_{l \in L} N_Q^l$ under the

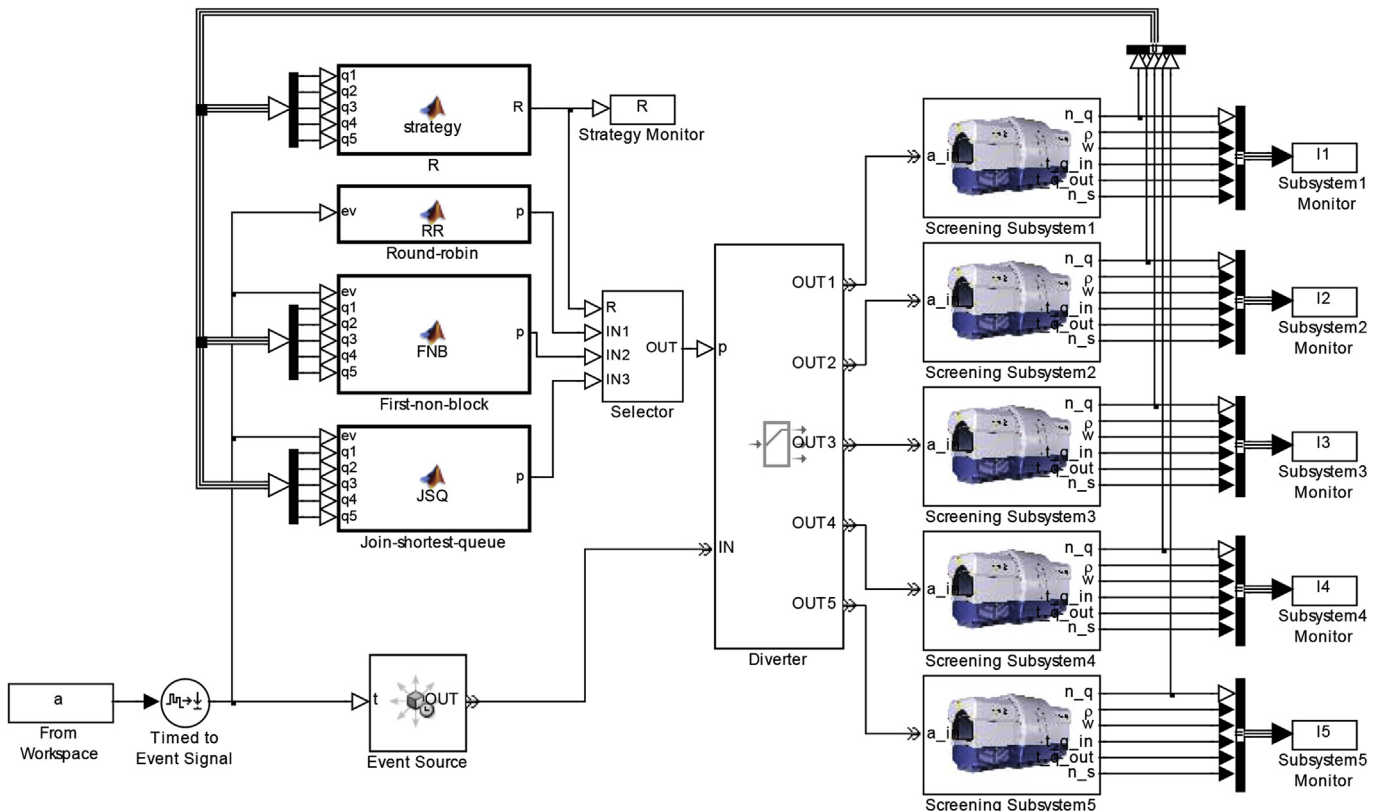


Fig. 2. Simulation environment.

Table 3
Peak-hour simulation results.

Year 2022						
Policy	Results	l				
		#1	#2	#3	#4	#5
RR – FA	$E(W)$ (s)	3.30	3.59	3.60	4.70	8.58
	$\max(w^k)$ (s)	24.86	24.83	25.18	27.47	33.24
	$\max(q^{k,l})$	4	5	5	5	6
	N_B^l	527	527	527	527	527
JSQ	$E(W)$ (s)	3.45	3.29	3.16	3.32	3.43
	$\max(w^k)$ (s)	22.95	18.35	24.08	20.66	27.12
	$\max(q^{k,l})$	2	2	3	2	2
	N_B^l	522	525	540	523	525
RR – JSQ	$E(W)$ (s)	2.94	2.89	2.85	3.13	3.02
	$\max(w^k)$ (s)	19.05	17.71	20.55	23.31	28.33
	$\max(q^{k,l})$	2	2	2	2	2
	N_B^l	541	522	519	534	519

RR. We can anticipate that the maximum allowable baggage volume under the RR is probably lower than the maximum throughput achievable by the system.

The JSQ has better capability to deal with increasing variability (Gupta et al., 2007). From Fig. 3(b) and Table 3, we notice that the JSQ is capable of improving the balance at bag assignments as compared to the RR. Performance variations between EDS lines are minimized. Mean and transient waiting time can be decreased. Another advantage of the JSQ policy is that the buffer consumption $|q^k|$ is significantly reduced. This can be intuitively explained by the fact that the JSQ can dynamically adjust the load distribution according to the state of q^k when q^k is already unbalanced.

The dynamic behaviour of the RR-JSQ strategy is shown in Fig. 3(c). From the figure, we note that the JSQ plays a leading role in the policy during peak hour. One exception is the last 10 min (12:20–12:30) where the RR is mainly activated. The mean waiting time offered by the RR-JSQ is 2.96 s which is 37.7% and 10.8% lower than that of the RR (4.75 s) and the JSQ (3.32 s), respectively. It also gives the better performance in transient waiting time as well as the required queue length. The maximum consumed queue length $\max(q^{k,l})$ are equal $\forall l \in \mathbb{L}$, which implies perfect load balancing. The results demonstrate the combined advantages of the RR-JSQ. To further compare the behaviours under various baggage loads, we forecast long-term system-level performance results using different policies.

4.3.2. Long-term performance forecast

Next, we estimate the system-level performance delivered from all selected polices over the years. The simulation results are presented in Fig. 4. The first impression about the result is that the average waiting time $E(W)$, maximum possible delay $\max(w^k)$ and total required queue length $\sum_{l \in \mathbb{L}} \max(q^{k,l})$ increase non-linearly with years (or the system utilization ρ).

Firstly, we look at the bag waiting delays. Simulation results on mean and maximum waiting times are presented in Fig. 4(a) and (b), respectively. Before year 2023, the RR-FA is expected to still deliver satisfactory performance, and therefore can be adopted. However, its outcome is expected to become unacceptable in year 2024, even though the system is not overloaded (i.e., $\rho_{10\text{min-peak}} < 1$). This is partially because of the stochastic delays built up by the probabilistic fluctuations in baggage inter-arrival and screening rate, i.e., $\text{Cov}(a^k)$ and $\text{Cov}(b^k)$. Stochastic delays can be significant when the inter-arrival rate is lower than but close to

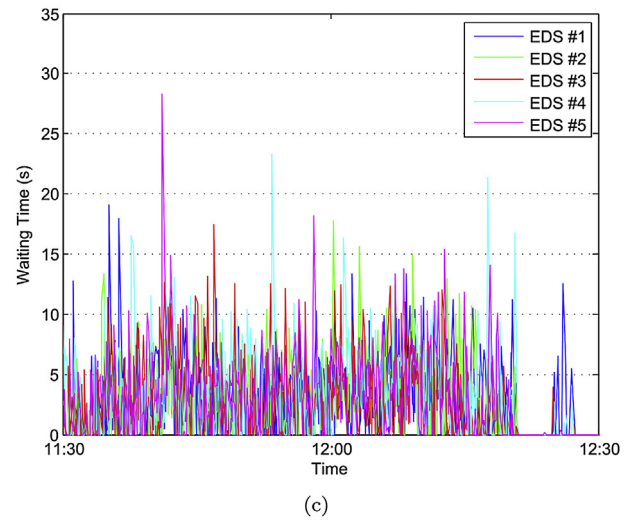
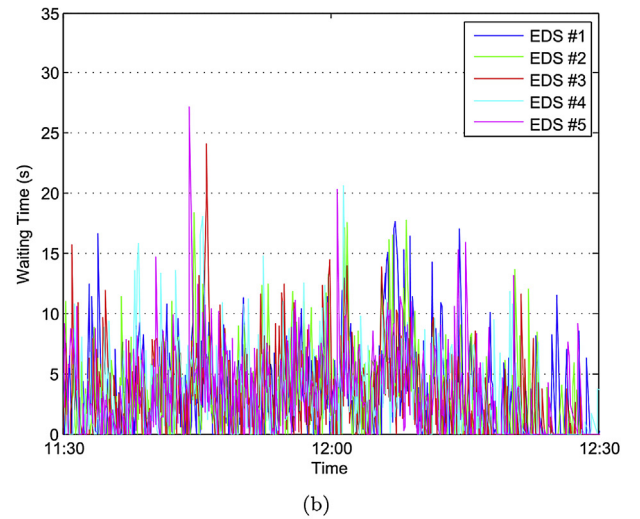
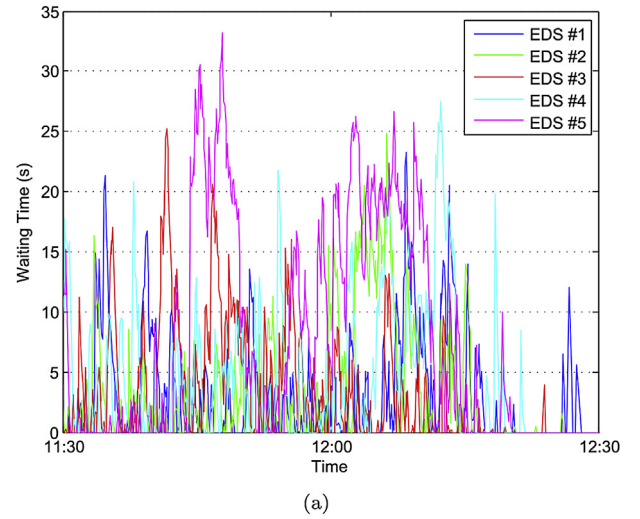


Fig. 3. Short-term behaviours on load balancing policy: (a) RR-FA; (b) JSQ; (c) RR-JSQ.

the screening rate for each EDS line (de Neufville and Odoni, 2013). It is noticeable that the maximum transient waiting time can be as high as 100 s which can be problematic especially when dealing with “hot” bags.

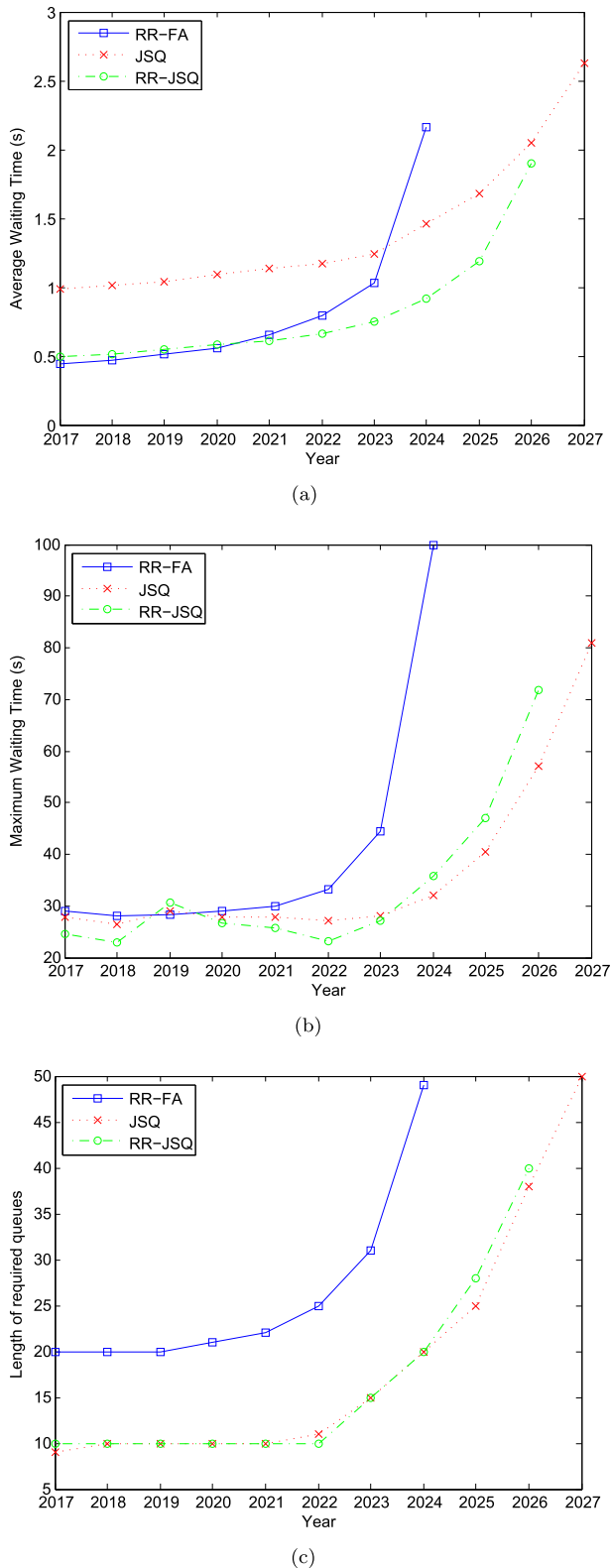


Fig. 4. Long-term results on (a) Mean waiting time; (b) Maximum transient waiting time; (c) Total number of queues required.

From Fig. 4(a), the daily average waiting time achieved by the JSQ is nearly doubled from the RR from year 2017–2020. To explain this, we consider a case when all queues are empty and all machines are idle at the arrival of the k -th bag. The decision of the JSQ

policy is to dispatch that bag randomly. All queues are then still empty, however, with a busy machine. When the $(k + 1)$ -th bag arrives, the decision is still made arbitrarily because the JSQ policy does not take account of the states of EDS machines (elapsed or estimated residual time). The next bag could, with the probability of $1/m$, be routed to the same busy server. Consequently, the waiting time for the next bag could be as high as EDS screening time. This disadvantage is not applicable to heavy traffic condition as we can see from Table 3 that the mean and transient waiting time during peak-hour introduced by the JSQ is less than that of the RR. This is in line with the statement in (Whitt, 1986) where it is demonstrated that the optimality of the JSQ does not exist in light traffic examples. This drawback can be avoided by the RR due to the cyclic assignment. The RR assigns bags “blindly” and cyclically. During a non-peak period, the distribution under the RR could be more balanced than it under the JSQ. Therefore, the JSQ should not be applied on its own during daily operation. It can be used during heavy traffic to complement the RR.

Interestingly, from Fig. 4(a) we observe that the $E(W)$ curve in the case of the RR-JSQ follows that of the RR-FA from year 2017–2021, but later approaches the JSQ from year 2022 onwards. This can be explained by the fact that the JSQ part of the hybrid policy is not much triggered before year 2021 when the baggage traffic is relatively light. However, since year 2022, the JSQ is predicted to start to play more roles in routing as the traffic gains. The combination of the RR and JSQ performs the best overall performance by avoiding the disadvantages from each individual policy. The hybrid policy switches between the RR and the JSQ depending on the states q^k and the pre-defined parameter N_Q . The mean and maximum waiting time of the RR-JSQ are expected to be improved from the RR-FA from year 2021 onwards.

Stability wise, it can be expected that the RR-FA only guarantees system stability until year 2024 (see Fig. 4(c)). In year 2024, it can be predicted that the FA scheme is activated to cope with the shortage of queue capacity. Both the hybrid RR-JSQ and the JSQ can handle the transient overload ($\rho_{10min_peak} > 1$) for year 2025 and 2026. The RR-JSQ, with reduced queue usage, can extend the life of the system for 2 more years. Out of these policies, the JSQ gives the best performance in terms of stability. The system is expected to be operational until year 2027. From year 2028 onwards, all selected policies cannot manage to stabilize the system. Either improving the algorithm, or upgrading existing mechanical and/or electrical configurations (e.g., longer queue, more efficient EDS machines, etc.) is necessary to bring the system to be back into operation.

4.3.3. Simulation summary

From both short- and long-term evaluations, we can conclude that the RR-JSQ policy offers a number of advantages over existing RR-FA. Firstly, it achieves better load balance among EDS lines. Secondly, the mean and transient waiting time can be reduced especially when the system operates under its maximum capacity. Lastly, we predict that it can extend the operation life of the existing system by 2 years.

5. Conclusions and future works

All passenger bags entering a BHS are mandatory to go through security inspection in screening area before loaded onto the aircraft. Load balancing policy plays an important role in the performance of screening subsystem. This paper investigated different load balancing policies including the RR, FA and JSQ and a possible combination RR-FA (existing common practice) and RR-JSQ. A $G/G/m/\infty/FCFS$ queueing model was adopted. Considering the difficulty and accuracy of mathematical formations, a discrete-event simulation platform was developed based on the model to evaluate

policies.

Simulation study demonstrated the effectiveness of selected policies. Our proposed RR-JSQ policy outperforms existing RR-FA policy. With better balanced load distribution, the overall system performance can be considerably improved (reduced waiting times and increased maximum achievable system throughput). It should be noted that the discussions and results given in this paper can be applied to any type of the BHS including conveyors, trays, carts, or the emerging DCV. The hardware and software efforts required for implementing the RR-JSQ policy is simple. We strongly encourage airport BHS practitioners to consider this policy during project planning and design.

One suggested potential study could be the further improvement on the routing algorithm. For example, the elapsed screening time could be measured and considered in the algorithm (Koole et al., 1999). Another topic is the design guideline of parameter N_Q which could be estimated mathematically by comparing the performance of the RR and the JSQ using approximations.

Funding

This work was supported by Singapore Economic Development Board (EDB) [grant number S11-1669-IPP].

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