International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 8 Issue 2 Ser. I ǁ 2020 ǁ PP. 24-36

A Comparative Simulation Study for the Adoption of a New Smart Check-In Cart in Airports

Mokhtar Kamel*, Aly El-Domiaty and Khaled Ramzy*
Department of Mechanical Engineering, Suez Canal University, Ismailia, Egypt

Abstract: *The work presented in this paper intended to study the usability reflected in the probable time gains, for the passengers and check-in systems, of using a new suggested type of smart carts in airports. A discrete-event simulation model is presented in this study for several currently adopted alternatives of airports' check-in methods in addition to the new suggested smart cart, through various policies. The suggested cart is a smart check-in substitute to the self-check-in booths in airports. A literature review is covered to show in depth the different policies of passenger intake flow of random, round robin (RR), First Available (FA), and join shortest queue (JSQ). About 65 Simulation runs were performed using a specialized simulation package through varying the different policies with altering the number of servers, using different check-in methods. Each run had 2 self-check-in methods and one traditional manned counter. Self-Service-Check-in (SSCI) and smart carts were the self-check-in used methods which were followed by self-bag drop (SBD) station to deliver the baggage. In addition, traditional manned counters were used as the other available alternative to SSCI to perform both functions of check-in and baggage drop in one step. Systems were tested for a period of an accelerated 24 hours to mimic the actual airport working hours. Results revealed that smart carts were the highest utilized among different check-in systems through various policies. Particularly, RR showed the highest utilization percentages among all policies, which is also the most recommended policy regarding the time spent in the system. This could lead to a conclusion that the adoption of the new suggested smart carts, as a predominate check-in system, using the RR policy would lead to the best flow of passengers and minimum queue waiting times.*

Date of Submission: 14-03-2020 Date of acceptance: 31-03-2020

I. INTRODUCTION

Several system alternatives for the process of check-in are available in airports. It includes traditional manned check-in counters, online check-in systems using computers/mobile phones, short messaging services check-in systems using mobile phones, and Self-Service-Check-in (SSCI) booths at the terminal itself (Lee, Kim and Choi 2018), (Lee, et al. 2014), (Chalupníčková and Kejmarová 2016) & (Adamčík, et al. 2017). All the precedent methods of check-in, except the traditional, are considered part of SSCI systems, where passengers do the check-in process themselves and required to do a complementary step of baggage drop either through the traditional manned counter or self-bag drop systems (SBD) (Ng, et al. 2014), (Lee, et al. 2014) & (Lee, Kim and Choi 2018). Traditional manned counters have been praised for being reliable and convenient; therefore, most passengers tend to use it. However, the noticeable increase in airlines' traffic lead to a vast increase in passengers' number; therefore, more waiting time in traditional check-in queues (Lee, Kim and Choi 2018). Besides, counter staff should build rapport with passengers during the process of traditional check-in due to the fact that otherwise passengers are known to balk and renege; therefore, more time is needed for the process leading to probable increased waiting time and longer queues (Nõmmik and Antov 2017). Increased queue waiting times has been regarded as one of the main contributors affecting passengers' satisfaction and airports' service quality (Aguilera-Venegas, et al. 2014) & (Hemdi, et al. 2016). Consequently, the rise of SSCI booths and other SSCI methods, as a viable alternative, was very noticeable. It is a global trend in airports all over the world seen to have led to a clear minimization in traditional check-in queues, improvement in airport quality and service level (Lee, et al. 2014), (Lee, Kim and Choi 2018), (Chalupníčková and Kejmarová 2016) & (Adamčík, et al. 2017).

The use of SSCI has many advantages to passengers, airports, and airline companies. Passengers would save a lot of time when using SSCI, as no waiting queues at traditional counters are required. Therefore, they would spend their time in recreational and leisure areas in airports such as shopping and other fun areas, leading to a probable expenditure and therefore increase in airport's profit. On the other hand, airline companies would save a lot of money in terms of variable costs in the rental and wages of the supposed manned traditional counters, when adopting SSCI systems. Only small booths are needed for each SSCI and SBD to perform the processes (Chalupníčková and Kejmarová 2016) & (Adamčík, et al. 2017). On the other hand, a common problem that might arise from using these systems is that every issue relevant to passengers will be moved from the check-in booths to the location of aircrafts' gates, where time to resolve any issue would be very limited (Chalupníčková and Kejmarová 2016). Another issue accompanied with SSCI is presented by Lu et al. who defined several parameters showing personal self-perceptions of passengers' readiness to use self-service technology, which included the perceived insecurity as a major pillar along with the observed discomfort (Lu, Choi and Tseng 2011). It is worth noting that other obsolete check-in methods, such as the offsite check-in, were shutdown of almost all offsite check-in in the United States in the 1980's mainly due to perceived insecurity (Goswami, Miller and Hoel 2011). In addition, a concern of reliability of SSCI systems is discussed by de Neufville, where several issues were revealed from using new systems which might not be properly tested and evaluated. Other redundant alternatives were recommended to be also available, to mitigate any failure occurrence (de Neufville 1994).

II. CHECK-IN SYSTEM OF WORK

The system of work of check-in using any available method in airports could be divided into three main steps (Kim, Kim and Chae 2017), (Ng, et al. 2014), (Lee, et al. 2014) & (Lee, Kim and Choi 2018):

1. Joining the check-in queue or system directly (traditional manned check-in system or SSCI).
2. Accomplishing the check-in processing either by employee at the check-in manned counter or by passenger himself using any of the SSCI methods.
3. Weighing and labelling baggage on check-in conveyor either by employee at the check-in manned counter or by passenger himself using SBD.

Step 1: Joining the queue

The first step in check-in process starts with a passenger joining the check-in queue to be served. The system intended to be explained in this part could be any of the current available airport systems of traditional manned check-in or SSCI booths. They both share the fact that a passenger might join a queue before being served. It is a typical queuing system which is either represented in literature using a mathematical or simulation model. The approach of joining a queue could vary from a passenger to the other, where the literature presented many approaches based on human variable behavior; which is typically mimicked using simulation. It is a very tricky subject due to the complexity of modeling human behavior, and the choice of joining a queue is no exception. There are always limitations in any simulation software to reach that level of complex human context (Veronese, et al. 2016). Whatever the accuracy of the results obtained from any simulation software, it is not an actual realistic reflection of the real-life human behavior. There will always be ignored human elements in any modeled system (Brailsford, Harper and Sykes 2012). On the other hand, when modeling the system; passengers are dealt with as entities required to be assigned to queues. An entity in simulation is defined by MathWorks, the huge mathematical computing software company, as a discrete item in a discrete-event simulation passing through a network of queues and servers during simulation. Entities could be people traveling in elevators, computational tasks or jobs, airplanes waiting for access to runway, or any other arrivals waiting to be served (MathWorks 2019). The approach or the policy adopted by an entity joining a queue using simulation, known as load balancing or dispatching policy, has been covered in literature in diverse areas (Hyytiä and Righter 2019). There are various approaches adopted in literature of load balancing policies for entities. The main common ones are the elementary Bernoulli split (random), Round-Robin (RR), Join Shortest Queue (JSQ), and First Available (FA) (Wu and Xie 2017), (Hyytiä and Righter 2019), (Hyytiä and Aalto 2016) & (Hyytiä and Righter 2016). The adoption of any of these systems in this study is based on dispatching arriving entities/passengers to multiple parallel servers. Whereas, systems requiring frequent used services, adopt a set parallel servers to get the job done. Many current applications nowadays such as Facebook and Google search in technology field, supermarket queues, call centers, check-in counters at airports, and many others require parallel servers (Hyytiä and Aalto 2016). The various policies are covered in more depth as follow.

Random

As the name says it is the random method of assigning arrivals to queues. It is referred also as random split; it is a load balancing system where arriving entities/passengers are uniformly assigned to random servers. Service times are usually exponential distributed in this case (Hyytiä and Righter 2019)

First Available (FA):

It is known sometimes as first-non-block queue. In the first-available (FA) policy, entities/passengers are assigned to the first seen server that is not full (Wu and Xie 2017). It is based on logic of first availability of servers ready to receive an entity (Flexsim 2019). It is known to be used in cases of extreme extraordinary queue utilization (Wu and Xie 2017).

Round-Robin (RR):

The round robin is another load balancing system. It works through the assignment of arriving entities/passengers to the queues in a fixed sequential order e.g. 1, 2, 3… K; where K is the maximum number of available counters. Hyytiä and Righter explained that the arrival process is regulated when using RR, leading to an enhancement of the performance of the system, where arrival is based on Poisson distribution with an inter-arrival rate of Erlang distribution (Hyytiä and Righter 2019) & (Hyytiä and Aalto 2016). RR policy has been extensively utilized in the baggage handling systems in airports, as a result of being simple and easy to adopt. Using RR, the parallel servers are assigned with an equal number of entities to be served. Typically, the best results could be obtained out of RR when the job size is known; in other words, when complexity of each arriving entity is the same, whereas problematic entities might cause system disturbance (Kuri and Kumar 1994) & (Wu and Xie 2017). Consequently, RR was described to be the most adopted approach for the BHS load balancing. It is the official used approach for the screening subsystems in Charlotte Douglas International Airport. It is applied using discrete-event simulation by airport practitioners to evaluate the workability of policies referring to the actual terminal's data. It is also adopted in San Francisco International Airport during the low arrival rates, where it is accompanied with the FA approach during the peak arrival rates to reach the maximum throughput. However, RR is disadvantageous along with FA for being a static routing system, where any unexpected variation in the system, resulting for unbalanced system for example, would lead to low and inefficient situation handling (Wu and Xie 2017).

Join Shortest Queue (JSQ):

Join Shortest Queue or Join-the-shortest-queue (JSQ) is a vastly adopted load balancing policy in many applications, particularly in computing and communication theory (Wu and Xie 2017). JSQ as the name entitles works by assigning the entity/passenger to a chosen queue with the least entities/passengers. (Hyytiä and Righter 2019). The only know information about the system is the number of entities/passengers in queue, whereas no jockeying is allowed (Johri 1989). Ties are resolved here either by looking at the server having the fastest service rate, or resolved randomly. JSQ policy lead to minimized expected waiting times for the arriving entities/passengers (Hyytiä and Righter 2019). Typically, JSQ assumes exponential distribution for the inter-arrival rate of entities/passengers and servers were assumed to be homogenous (Hyytiä and Aalto 2016). JSQ has proven in many cases in literature to show appropriate solutions, in case of parallel servers; moreover, optimality was achieved in other occasion through reaching average delay time minimization (Hyytiä and Aalto 2016) & (Lin and Raghavendra 1992). Another paper agrees with this finding when arriving entities adopts interchangeable routing policies and Poisson distributed and processing times follow an exponential distribution (Menich and Serfozo 1991). A paper explains the application of JSQ in the same area of concern of this study. The authors explain the adoption of JSQ in check-in stations in airports. Arriving passengers are dealt with individually. Each one is allocated to various counters through their assignment to the shortest queue, referring to his/her class, Airline Company, and flight number. Ties are dealt with through picking up a random choice (Roanes-Lozano, Laita and Roanes-Macias 2004).

Step 2: Check-in processing

The second step is the when the passenger reaches either the traditional check-in manned counter or the SSCI booth. If a passenger chooses the traditional counter, the check-in counter employee does the process of checking his/her passport, tickets, and information; consequently, the assignment of a seat on the plane (boarding), and finally printing the boarding pass (Kim, Kim and Chae 2017). If SSCI booth is chosen, check-in processing is done by passengers through using a touch screen interface at the booth to scan their IDs or passports, provide ticket information or scan the ticket barcode, add all relevant required additional personal or baggage information, and select their chosen seats. The boarding pass and baggage label are printed then and passengers proceed to the next step of baggage drop (Ng, et al. 2014), (Lee, et al. 2014)& (Lee, Kim and Choi 2018).

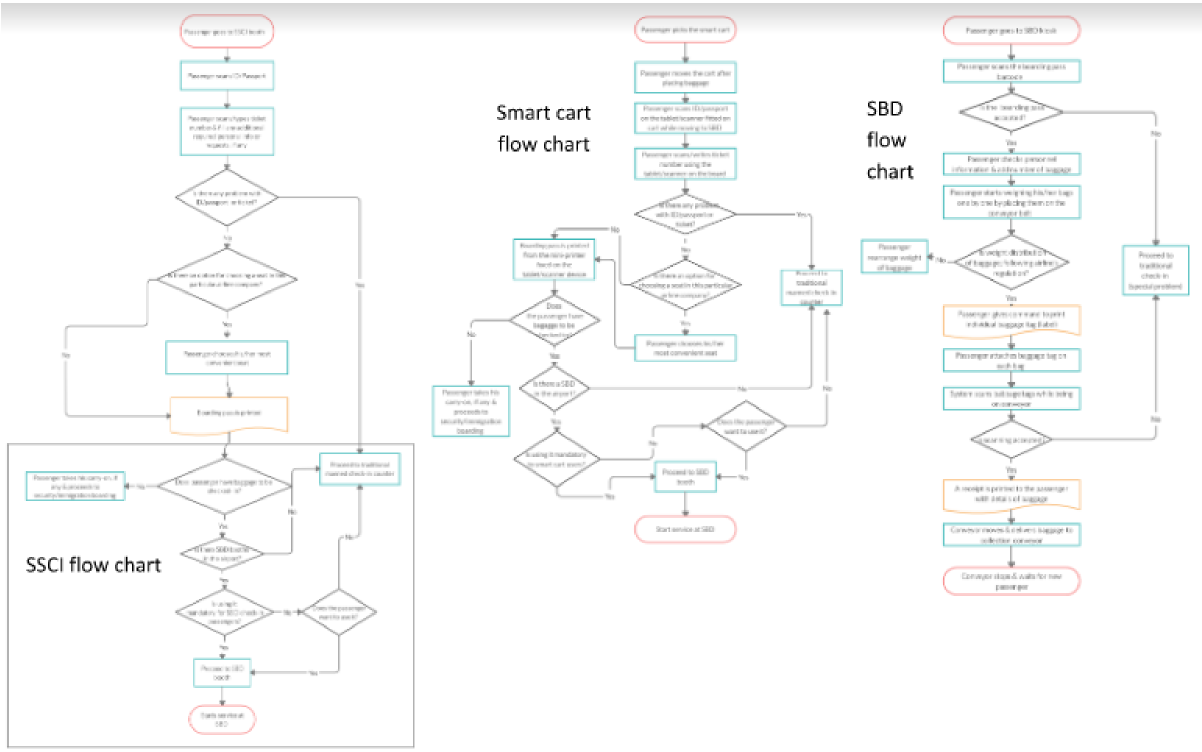
Step 3: Weighing and labeling

The common known two alternatives for this step are the traditional manned counter and SBD. Traditional counters are chosen by passengers for many reasons such as reliability and convenience. Moreover, they are sometimes chosen by a wide amount of passengers because it allows to print their boarding passes (Lee, Kim and Choi 2018) & (Nõmmik and Antov 2017). On the other hand, the passengers' adoption of another alternative for the traditional system is dependent on many factors relevant to the airline companies such as their check-in policy or passenger-related reasons such as his/her departure time, profile, or readiness to use technology (Nõmmik and Antov 2017) & (Lee, et al. 2014). In the traditional manned counter, the baggage are weighed on the check-in conveyor then labeled by the employee, and finally dispatched to the back zone conveyor named as the collection conveyor. (Kim, Kim and Chae 2017). SBD is the alternative for the use of traditional counter. Baggage was considered the biggest difficulty in accomplishing SSCI in full. Studies showed that SBD introduction led to higher passengers' satisfaction due mainly to their feeling of reduced waiting time in the check-in process (Yang and Santonino III 2016). SBD is a self-service option for checking-in baggage without a need for personal assistance, which is offered by major airlines (Lee, Kim and Choi 2018). SBD is a sort of automated drop-off area. SBD process requires passengers to approach the designated SBD booth, place bags one by one on the weighing conveyor, scan their passport and/or boarding pass, print baggage label, and attach it to the baggage (Kalakou, Psaraki-Kalouptsidi and Moura 2015).

III. METHODOLOGY

Discrete-event simulation has been widely known to be adopted in literature in queuing modeling, as it breaks down the long continuous macro processes into discrete solvable micro-steps, aiming at facilitation the study and reaching valid conclusions. Particularly, it has been vastly applied in airport terminal studies aiming at expecting and comprehending the effect of various policies and new alternatives on the flow of passengers, to help policy makers in their decisions. Moreover, simulation consumes less time and money resources to be implemented, unlike real system implementation. (Verma, Tahlyan and Bhusari 2018) & (Lee, et al. 2014).

The methodology of work in this study is based on a comparison between various currently adopted alternatives of airports' check-in methods in addition to a new suggested system, through various policies, using discrete-event simulation. Several policies of joining queues from random, JSQ, FA, and RR are applied using simulation models. The covered check-in alternatives in this study are divided into two main categories, SSCI and traditional check-in. The adopted SSCI systems will be either SSCI booths or the new suggested smart carts. Both systems are followed by SBD systems. On the other hand, Traditional manned counters are also adopted to perform both check-in and baggage drop. SSCI, the new suggested smart cart system, and SBD processes details are presented in flow charts form in Figure 1. Therefore, the simulation model will act as a virtual airport, where passengers pick one of 3 methods of check-in and join queues based on one of the 4 policies, proceeding then to the next station of SBD, if traditional counters are not used. Several runs with varying the check-in methods and policies are presented from which statistics are collected from the simulation software and analyzed. The new suggested smart check-in technology is an alternative to the current adopted systems using a smart cart with multi-functions. It is specifically a substitute to the SSCI booths in airports; where passengers don't need to move to the booth to accomplish the check-in process. Each cart will be acting as a booth on its own. Therefore, the potential savings in time, which might be wasted in case of congested queues at booths, is very obvious. It is a smart cart having a tablet installed above the fixed bar of the pushing handle, that provides the passenger with passport/ticket scanning, printing the baggage label, and information about the baggage drop locations and any other required locations in the airport. Once this process is done, the check-in procedures is accomplished and the only action left to be done by the passenger is to go to a SBD and place the baggage.



3.1 Model description

Objective function:

Minimizing passenger spent time in the system as possible, represented in the service and waiting times in queues and see whether the adoption of the new proposed smart carts will affect positively the system, are the main objectives of this study. This objective is manipulated with the different policies and chosen servers. The drawbacks from long queues are highly affecting the service level and airport quality, leading to undesired consequences on the airport/airline performance, image, competition, and worldwide rank (Kim, Kim and Chae 2017), (Lee, et al. 2014), (Wu and Xie 2017), (Roanes-Lozano, Laita and Roanes-Macias 2004)

Model components

- Entity
  - Passenger (individual passengers are only allowed in the model, groups are not).
  - Server: (traditional manned counter, SSCI booth, SBD, and smart cart).
- State
  - Server € { free, busy}
  - Number of passengers waiting in queue € N (*keep one natural number)*
- Event Queue
  - Priority queue of future events sorted by time of occurrence.
- Events (every event is represented by both time and action).
  - Every event is represented by time; in other words, time of occurrence.
  - Action: an action is responsible to change the state and the event queue and update it.

Parameters:

- Passengers parameters (Exogenous)
  - Passengers arrival using different policies (random, JSQ, RR, FA) are be drawn from an estimated exponential distribution, based on literature (Kim, Kim and Chae 2017)
- Servers parameters (Endogenous).
  - The average amount of time needed for server to go from busy to free, in other words, the amount of time server should be busy with customers. Simply, the service time (Wu and Xie 2017), (Lee, et al. 2014).
  - The average amount of time passenger need to stay on queue, referred to as queue waiting time (Wu and Xie 2017), (Kim, Kim and Chae 2017), (Savrasovs, Medvedev and Sincova 2009), (Lee, et al. 2014).

Events:

1. Passenger arrival to different check-in methods using various policies (random, JSQ, RR, FA)
2. Server event (Server goes from free to busy [Queue formation])
3. Server event (Server goes from busy to free)

Queue (algorithm):

When a passenger arrives, he/she looks for an available server:

- If found one, he/she will process his service directly and the server will be busy for a certain duration
- If didn't find one, he/she wait in queue with FCFS system (Le, Creighton and Nahavandi 2007) & (Kim, Kim and Chae 2017). When a server becomes free, he/she will go to the server; consequently, the server becomes busy

3.2 Software used in this work

Flexsim is the adopted software in this work. It is 3-D multi-purpose discrete-event simulation modeling package. It has modules in different areas of work such as material handling, warehousing, manufacturing plants, healthcare, airports, container terminals, and many others. It has been used by numerous airport related companies and authorities like US Airforce, TNT, Boeing, and others. It has many working advantages over other simulation available packages such its ease of use, superior graphical display, clear and simple statistical outputs. It could be simply used through the wide range of all selections of the drag and drop menu along with a 3-D graphical demonstration to insert the items into the model. In addition, it can run various runs with the least possible time (Flexsim 2019). It has been used by many in literature in various applications from freight terminals, flexible manufacturing systems, logistics (Chen, Hu and Xu 2013), (Kumar, Mahesh and Kumar 2015)& (Wang and Chen 2016)

3.3 Software running time:

It was found convenient in literature to run the model for a simulation time of about 24 hours for each proposed scenario, to mimic a full day of airport check-in operation. After this time, the simulation output is checked every time to see whether it is enough or not to draw valid conclusions (Johnstone, Creighton and Nahavandi 2015) & (Cavada, Cortés and Rey 2017).

IV. RESULTS AND ANALYSIS

In this study, about 65 Simulation runs were done using the Flexsim simulation package. The results were obtained and analyzed using several statistical outputs and viewgraphs. Based on the literature findings, the runs in this type of airport check-in systems simulation should be expected to last for 24 hours to mimic a full day of operation, as airports/airlines are designated to work for 24 hours a day (Johnstone, Creighton and Nahavandi 2015) & (Cavada, Cortés and Rey 2017). Therefore, accelerated runs were performed based on 24 hours' time limit for each. 4 different approaches were tested for the system: random, RR, JSQ, and FA. Based on literature, the servers were run in the system based on first come first served (FCFS) policy (Le, Creighton and Nahavandi 2007) & (Kim, Kim and Chae 2017). The inter-arrival and service times were assumed to be exponentially distributed with an average amount of inter-arrival time of 10.21 seconds and service times of 1, 2, and 7 minutes for SSCI, SBD, and traditional counters, respectively (Aguilera-Venegas, et al. 2014), (Kim, Kim and Chae 2017), (Lee, et al. 2014), (Abdelaziz, Hegazy and Elabbassy 2010). Each passenger is assumed to have 2 bags and to do his/her check-in processing individually, not in groups. The smart cart is supposed no to have processing time, as the check-in process is done while moving; however, passengers won't be moving with the same pace if they are focusing on something other than the steering. Therefore, an average allowance of 25 seconds with exponential distribution is given for each cart, as a processing time. As a start of simulation, several runs were done to get the general understanding and trend of data through following the change in the measured output variables with altering the number of servers. As the objective entitles, the main target is to minimize the passenger spent time in the system as possible, represented in the service and waiting times, and see whether the adoption of the new proposed smart carts will affect positively the system. The decision was to start with the random policy which is an unbiased policy based on random passenger behavior as it is entitled, unlike the other three targeted policies. Therefore, several runs were done using random policy were the number of servers were changed several times to get the sense of data. These runs were the pilot ones used to clarify the generic behavior of the effect in varying the number of servers used. As a starting simulation scenario, one traditional counter, 2 smart carts and 2 SSCI were used, followed by 4 downstream stations of SBD. If SSCI is preferred by passengers, they randomly pick up one of the two methods of smart carts or SSCI, as their first station to do the check-in process. There is a queue before reaching any of 2 SSCI, where the passengers randomly join it. However, passengers don't need to wait in a queue before getting a smart cart. They simply approach to the line of smart carts, get one, do the SSCI process on board while moving, and finally proceed to the SBD queue to drop the baggage. Joining any of the 4 SBD booths is done randomly after finishing the queue ahead. On the other hand, if the traditional counter is chosen, passengers will accomplish both functions of check-in and baggage drop in one stop. The counter has a queue ahead, where passengers randomly join it. The starting number was chosen based on the actual case that SSCI adopted in airports are usually more than one, therefore, a starting number with 2 is used. The same applies for the suggested new cart, where 2 carts were also applied in the model. The results of this run revealed that traditional queue reached a peak time limit relative to all runs, where the average waiting time in the traditional queue reached 61.46 minutes, which is a totally unacceptable number relative to the waiting and service times of all runs and the logical human behavior, leading to a refuse for the whole output of this run regardless the performance of SSCI and SBD queues. Therefore, the decision was made to increase the number of traditional counters to minimize its queue waiting time. A stepwise increase was performed to observed the change of the output carefully, where one traditional counter was added for each run. The next run had a total of 2 traditional, 2 smart carts, and 2 SSCI. The results revealed a decrease in the average queue waiting time of 39.47% reaching 37.2 minutes, which is a relative huge improvement; however, it is still relatively very far from the waiting and service times and the logical acceptable numbers. Therefore, adding one more station in the next run lead to an impressive enhancement of 43.5% reaching an average waiting time of 21 minutes. Moreover, improvement continued till reaching 3.34 minutes when using 9 traditional counters, which is quite logical relative to the average service time which is 6.95 minutes. Average waiting times in minutes with respective number of servers are shown in Table 1.

Table 1: Simulation runs of random policy

Run name	Traditional	Smart cart	SSCI	SBD	Trad. Av. Q (min.)	Trad. Av. Serv. (min.)
Random 11	1	2	2	4	61.46	6.34
Random 10	2	2	2	4	37.22	7.35
Random 9	3	2	2	4	21.01	6.80
Random 8	4	2	2	4	12.02	6.62
Random 7	5	2	2	4	11.60	6.82
Random 6	6	2	2	4	7.28	6.73
Random 5	7	2	2	4	4.94	6.62

Random 4	8	2	2	4	4.08	6.82
Random 3	9	2	2	4	3.34	6.95

The next step was the adoption of various policies through a careful alternation in the number of servers, to observe the effect on the queue waiting times and service times. As seen in Figure 1, the average queue waiting time in minutes is shown for the four adopted policies through the different simulation runs. A total of 31 simulation runs are shown, where the number of traditional, SBD, SSCI, and smart cart units are varied for each run. The effect of changing the number of servers is explained further in Table 2. This graph shows the effect of varying the policies on the 3 queue waiting times at the traditional counter, SBD, and SSCI booths. The trend shows that the FA policy affected negatively the average queue waiting times for the traditional and SSCI. The traditional has a minimum time of 7.88 minutes and a maximum time of 11.33 minutes, giving a range of 3.45 minutes, which is among the highest ranges among all policies. These times are way high to be considered for adoption, relative to other policies. The next maximum time in row is 8.66 minutes of random policy, which is more 0.78 minutes from the minimum of FA policy, which is considered a slight difference relative to the FA range. The same applies with FA policy and the SSCI queue. It shows the highest waiting times among all other policies, with a minimum time of 3.6 minutes and a maximum time 3.84 minutes. The next maximum time in row is 2.8 minutes of JSQ policy, which is fewer 1.04 minutes or 27.1% less from the minimum of FA policy. However, the SBD has very short average queue waiting times in the FA policy, which reached the minimum among all policies with a value of 1.6 minutes and a range of 0.1 minute. However, the FA policy is a collective system that is not divided individually among queues, where the times were highly violated in the traditional and SSCI leading to a highly undesired policy. On the other hand, the RR policy shows to be the relative minimum among all policies for the traditional and SSCI average queue waiting times, whereas the SBD has middle relative times. The traditional of RR has a minimum time of 0.33 minutes or 19.8 seconds, which is the smallest relative queue waiting time of traditional for all policies. This time increased especially in the last two runs to a maximum of 3.95 minutes when the number of servers in the traditional were minimized, leading to a congestion of passengers in the queue. These cases are observed in RR, FA, and JSQ scenarios, where the average waiting times of traditional in the last 2 runs are obviously higher, due to decreasing the number traditional counter. Table 2 will show this effect in more depth.

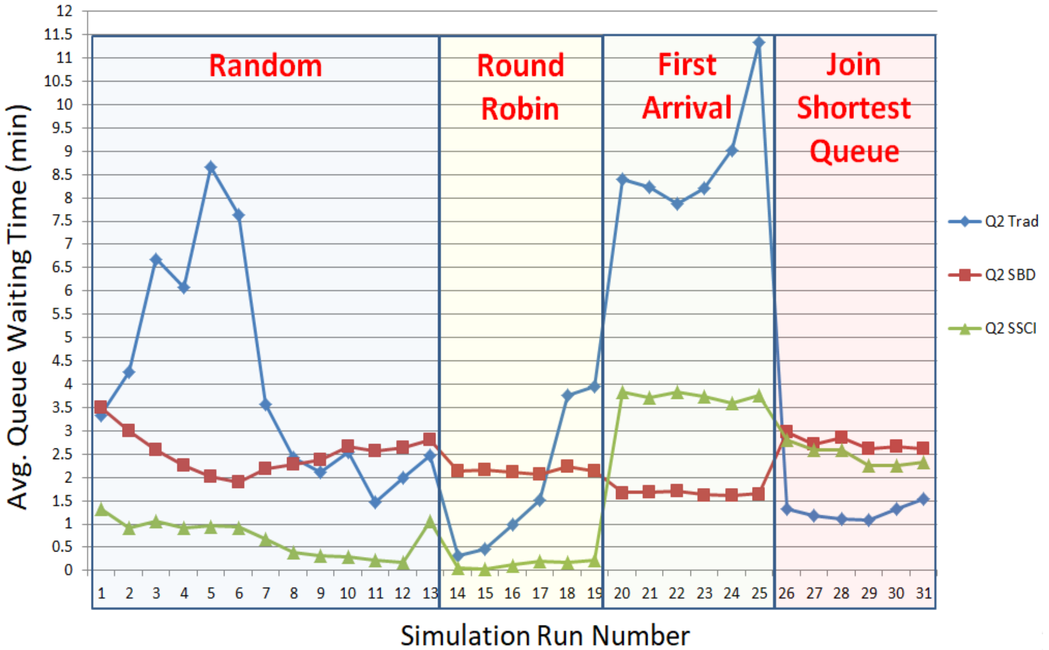


Table 2 shows the effect of changing the number of servers on the average queue waiting time and service time of different stations, through the 4 adopted policies. The percentage of increase/decrease from a simulation scenario relative to the other, within the same policy, is shown in the table. Whereas any increase in time percentage is marked in red color while the decrease in green, to show an enhancement in the system. The minimum and maximum increase/decrease percentages of each queue/service average times are marked as yellow and blue boxes, respectively. A coding system was used for the runs, which is composed of two parts. The first is the policy used and the second refers to the number of adopted servers in this run. Taking F6 as an example, it is a code used to represent a simulation run having 8 traditional counters, 6 smart carts, 2 SSCI, and

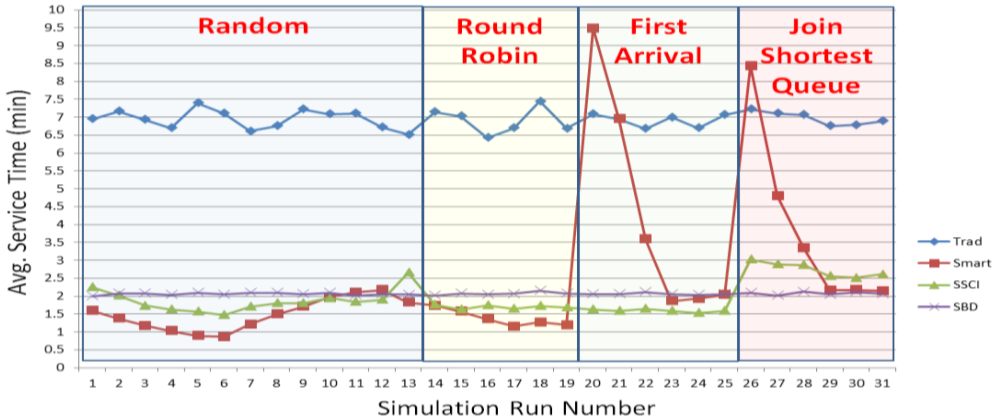
6 SBD, refer to Table 2 for other codes. A reference trial based on random policy (Ran-F6), which gave reasonable average waiting and service times relative to the initial pilot runs, was taken to be the referral run to other policies at their starting runs. As shown in table mm, it has 8 traditional counters, 6 smart carts, 2 SSCI, and 6 SBD. It resulted in average waiting times for the traditional and SBD queues of around 2 minutes and less than half a minute for the SBD. Moreover, it gave average service times at the traditional counters of less than 7 minutes and for the smart carts, SSCI, and SBD of around 2 minutes each. Referring to Table 2, the maximum % decreases in average queue waiting time of the traditional counters and SSCI were 83.51% and 70.76%, respectively, which was achieved in a RR run with 8 traditional counters, 6 smart carts, 2 SSCI, and 6 SBD. It resulted in noticeable minimized average waiting times of 0.33 minutes for the traditional, 2.14 minutes for the SBD, and 0.05 minutes for the SSCI. Moreover, the same run yielded to the maximum decrease of 33.73% in average service time for the SSCI. In addition, it is noted that decreasing the number of the smart carts, from 6 till reaching 3, lead to a noticeable increase of 38.16% (run 16), 120.38% (run 17), and 52.16% (run 18) in the in average queue waiting time of the traditional counters affecting the system negatively. Also, it is noted that when the number of traditional counters decreases, the average traditional queue waiting times percentages increased, which is quite logical. This is noticed through the 4 policies with the percentage increases at runs 12 (35.85%) and 13 (23.54%) for random, runs 18 (146.87%) and 19 (5.06%) for the RR, 24 (9.94%) and 25 (25.48%) for FA, and 30 (22.74%) and 31 (16.08%) for the JSQ.

Referring to run 2, it is noted that increasing the number of SBD from 4 (run 1) to 9 (run 6) lead to a clear % decreases in average SBD queue waiting times of 13.96%, 13.41%, 13.54%, 10.41%, and 5.66%, respectively. Moreover, % decreases in average smart carts and SSCI service times were noticed at the same runs ranging from 2.83% to 14.91% for smart carts and 3.9% to 13.66% for SSCI. Additionally, it is seen at run 7 when the number of SBD booths were minimized to 8 instead of 9 and the smart carts increased to 3, a maximum congestion was formed at the SBD downstream station leading to a maximum % increase in average queue waiting time of 15.41%. Moreover, it is noticed at the same run that the smart carts, SSCI, and SBD service times were affected negatively with the following increase percentages 40.66%, 15.55%, 2.48%, respectively. Referring to run7 till run11 , it is shown that increasing the smart carts from 3 to 6 along with the decrease in the SBD from 8 to 6 lead to less pressure on the SBD booth from passengers with % decreases in waiting times of 26.08%, 43.69%, 18.44% , 8.86%, and 22.37%, respectively. Referring to the runs based on FA policy (run 20 to 25), it is seen that the highest increase percentages and waiting times for SBD and traditional queues were reached. Particularly, run 20 with 8 traditional counters, 6 smart carts, 2 SSCI, and 6 SBD reached 312.24% and 1942.12% increases in waiting times of SBD and traditional counter, which are the highest percentages obtained of all runs. Moreover, the same run revealed the highest percentage increase in the smart cart service time with a percentage of 695.39% and a service time of 9.48 minutes. Finally, the runs based on JSQ policy (run 26 to 31), revealed intermittent average waiting times; however, average service times for the smart carts and SSCI showed very high values, especially for runs 26, 27, and 28. Particularly, run 26 with 8 traditional counters, 6 smart carts, 2 SSCI, and 6 SBD revealed the highest percentage increase in the SSCI service time with a percentage of 89.95% and a service time of 3.02 minutes. In addition, the same run showed a very high percentage increase in the smart cart service time with a percentage of 313.71% and a service time of 8.43 minutes.

Table 2: Effect of changing servers on the system among different policies

Run	Name	Policy	Trad	Smart	SSCI	SBD	Q2 Trad	% inc/dec	Q2 SBD	% inc/dec	Q2 SSCI	% inc/dec	Trad	% inc/dec	Smart	% inc/dec	SSCI	% inc/dec	SBD	% inc/dec
1	Ran-M1	Rand	9	2	2	4	3.34		3.49		1.33		6.95		1.58		2.25		2.00	
2	Ran-M2	Rand	9	2	2	5	4.25	27.25	3.00	-13.96	0.92	-30.55	7.16	2.96	1.37	-13.24	2.01	-10.82	2.08	3.86
3	Ran-M3	Rand	9	2	2	6	6.69	57.22	2.60	-13.41	1.06	15.16	6.93	-3.13	1.17	-14.91	1.74	-13.66	2.08	0.07
4	Ran-M4	Rand	9	2	2	7	6.08	-9.13	2.25	-13.54	0.91	-14.23	6.69	-3.57	1.03	-11.83	1.63	-5.89	2.04	-1.94
5	Ran-M5	Rand	9	2	2	8	8.66	42.51	2.01	-10.41	0.95	4.91	7.39	10.53	0.89	-14.10	1.57	-3.90	2.10	3.04
6	Ran-M6	Rand	9	2	2	9	7.64	-11.84	1.90	-5.66	0.93	-2.51	7.10	-3.87	0.86	-2.83	1.47	-6.34	2.04	-2.65
7	Ran-M7	Rand	9	3	2	8	3.58	-53.10	2.19	15.41	0.69	-26.08	6.61	-6.99	1.21	40.66	1.70	15.55	2.09	2.48
8	Ran-M8	Rand	9	4	2	8	2.43	-32.24	2.28	4.08	0.39	-43.69	6.75	2.22	1.49	22.93	1.80	6.10	2.09	0.03
9	Ran-M9	Rand	9	5	2	7	2.11	-12.91	2.37	3.70	0.32	-18.44	7.22	6.87	1.71	14.61	1.81	0.29	2.06	-1.69
10	Ran-M10	Rand	9	5	2	6	2.54	20.37	2.67	12.85	0.29	-8.86	7.08	-1.98	1.96	15.15	1.95	7.78	2.10	1.92
11	Ran-M11	Rand	9	6	2	6	1.47	-42.35	2.56	-4.27	0.22	-22.37	7.10	0.41	2.10	7.04	1.84	-5.39	2.01	-4.22
12	Ran-F6	Rand	8	6	2	6	1.99	35.85	2.65	3.62	0.19	-16.16	6.71	-5.52	2.17	3.16	1.90	2.99	2.05	1.96
13	Ran-M12	Rand	9	4	3	6	2.46	23.54	2.79	5.47	1.07	469.91	6.51	-3.01	1.83	-15.74	2.66	40.14	2.05	-0.20
14	RR -F6	R R	8	6	2	6	0.33	-83.51	2.14	-19.42	0.05	-70.76	7.14	9.67	1.73	-5.11	1.76	-33.73	2.01	-1.50
15	RR -F4	R R	8	5	2	6	0.45	38.16	2.17	1.51	0.03	-47.89	7.02	-1.71	1.57	-9.34	1.63	-7.47	2.07	2.57
16	RR -F2	R R	8	4	2	6	1.00	120.38	2.10	-2.91	0.12	312.54	6.42	-8.47	1.36	-13.50	1.75	7.28	2.04	-1.06
17	RR -F1	R R	8	3	2	6	1.52	52.16	2.06	-1.89	0.19	62.50	6.70	4.26	1.15	-15.30	1.64	-6.33	2.06	0.90
18	RR -T1	R R	7	3	2	6	3.76	146.87	2.24	8.41	0.17	-11.07	7.44	11.10	1.27	10.20	1.72	4.83	2.15	4.07
19	RR -T2	R R	6	3	2	6	3.95	5.06	2.13	-4.87	0.22	29.93	6.68	-10.19	1.19	-6.11	1.68	-2.00	2.07	-3.58
20	FA - F6	FA	8	6	2	6	8.39	321.24	1.67	-36.94	3.83	1942.12	7.08	5.88	9.48	695.39	1.62	-3.58	2.06	-0.66
21	FA - F4	FA	8	5	2	6	8.23	-1.92	1.68	0.69	3.72	-2.72	6.94	-1.86	6.95	-26.73	1.59	-2.12	2.06	0.11
22	FA - F2	FA	8	4	2	6	7.88	-4.29	1.70	1.19	3.84	3.16	6.68	-3.84	3.59	-48.30	1.64	3.27	2.11	2.26
23	FA - F1	FA	8	3	2	6	8.21	4.28	1.62	-4.70	3.74	-2.48	6.99	4.72	1.86	-48.23	1.58	-3.47	2.06	-2.37
24	FA - T1	FA	7	3	2	6	9.03	9.94	1.60	-1.32	3.60	-3.90	6.69	-4.31	1.93	3.73	1.53	-3.42	2.04	-0.75
25	FA - T2	FA	6	3	2	6	11.33	25.48	1.65	2.89	3.75	4.27	7.07	5.63	2.04	5.65	1.59	3.96	2.06	0.85
26	JSQ - F6	JSQ	8	6	2	6	1.33	-33.02	2.97	12.26	2.80	1392.33	7.21	2.05	8.43	313.71	3.02	89.95	2.10	2.06
27	JSQ - F4	JSQ	8	5	2	6	1.18	-11.53	2.71	-8.83	2.58	-7.72	7.10	-1.57	4.80	-43.04	2.88	-4.53	2.01	-4.14
28	JSQ - F2	JSQ	8	4	2	6	1.10	-6.80	2.85	5.24	2.60	0.60	7.06	-0.59	3.33	-30.69	2.87	-0.37	2.12	5.35
29	JSQ - F1	JSQ	8	3	2	6	1.08	-2.22	2.62	-8.28	2.25	-13.32	6.76	-4.24	2.16	-35.09	2.55	-11.12	2.04	-3.57
30	JSQ - T1	JSQ	7	3	2	6	1.32	22.74	2.66	1.51	2.26	0.34	6.78	0.35	2.17	0.27	2.51	-1.72	2.12	3.52
31	JSQ - T2	JSQ	6	3	2	6	1.53	16.08	2.62	-1.49	2.34	3.60	6.89	1.66	2.14	-1.23	2.60	3.76	2.06	-2.62

Service time is the other important indicator to be studied to understand the system behavior. As seen in Figure 2, the average service time in minutes is shown for the four adopted policies through the different simulation runs. A total of 31 simulation runs are shown, where the number of traditional, SBD, SSCI, and smart cart units are varied for each run. The effect of changing the number of servers is explained further in Table 2. This graph shows the effect of varying the policies on the 4 service times at the traditional counter, smart carts, SBD, and SSCI booths. The trend shows that the FA followed by JSQ policies affected negatively the service times for the smart carts. For FA, the smart carts have a minimum time of 1.86 minutes and a maximum time of 9.48 minutes, giving a range of 7.62 minutes, which is among the highest ranges among all policies. Moreover, JSQ led to a minimum time of 2.14 minutes and a maximum time of 8.43 minutes for the smart carts also, giving a range of 6.29 minutes. These times are way high to be considered for adoption, relative to other policies. The next maximum time in row for smart carts is 2.16 minutes of random policy, which is higher 0.3 minute from the minimum of FA, and 0.02 from the minimum of JSQ. This is considered a slight difference relative to the FA and JSQ ranges. The same applies with JSQ policy and the SSCI average service times. It shows the highest average service times among all other policies, with a minimum time of 2.51 minutes and a maximum time 3.02 minutes. The next maximum time in row is 2.66 minutes of random policy, which is more 0.15 minutes from the minimum of JSQ policy. Average service times for smart carts showed the minimum values using random and RR policies, with a minimum value of 0.86 minutes for random and 1.19 for RR. On the other hand, SBD and traditional servers showed a relative stable trend of average service time among the 4 policies, where no specific policy seems to affect the output spent time. The average time for traditional ranged from 6.42 to 7.44 minutes, whereas the SBD ranged from 2 to 2.15 minutes. Therefore, the RR and random policies shows relative minimum service times among all policies for all types of servers.



The next seen step in this analysis is to inspect the effect of a particular chosen policy on the dispatching of passengers among different servers. Due to the nature of random policy, as it is based on passengers' untraceable random behavior, only the traceable policies of JSQ, RR, and FA will be covered in this part. Referring to Figure 4, it was found out that the average dispatching of passengers to check-in methods using RR policy was divided into 17% for both traditional counters and SSCI with averages of 664 and 668 passengers, respectively, whereas smart carts represented the biggest obvious share of 66% with an average of 2521 passengers. This shows a tendency of passengers to join the new presented SSCI system, smart carts.

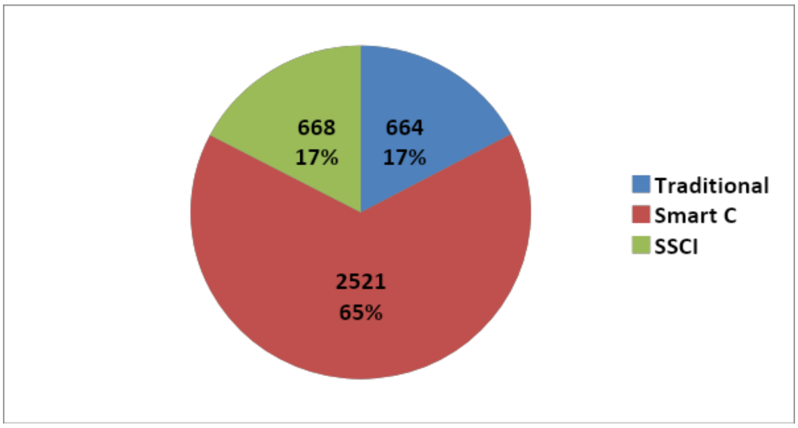


Figure 4: Average dispatching of passengers using RR policy

Referring to Figure 5, the JSQ policy revealed that an average of 25 % of passengers (844 passengers) used traditional counters, 26 % (895 passengers) SSCI and 49% (1656 passengers) smart carts. This shows an agreement with the findings in the RR policy with a tendency of passengers to join the SSCI systems from SSCI and particularly, smart carts.

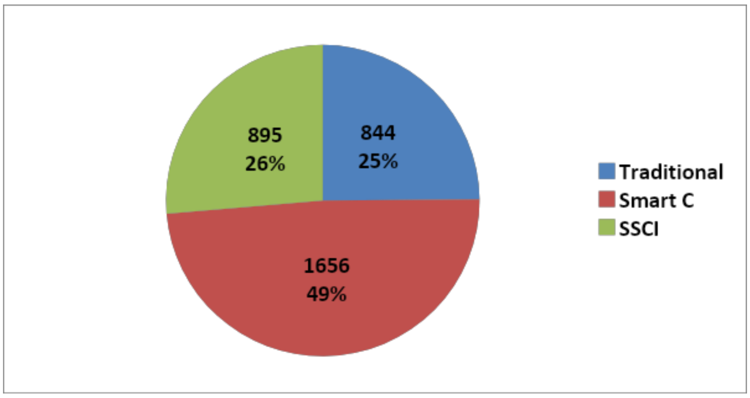


Figure 5: Average dispatching of passengers using JSQ policy

Referring to Figure 6, the FA policy revealed that an average of 27 % of passengers (1560 passengers) used traditional counters, 32% (1852 passengers) SSCI, and 41% (2336 passengers) smart carts. This shows an agreement with the findings in the RR and JSQ policy of the tendency of passengers to join the SSCI systems. However, it gave the least of smart carts among the three policies.

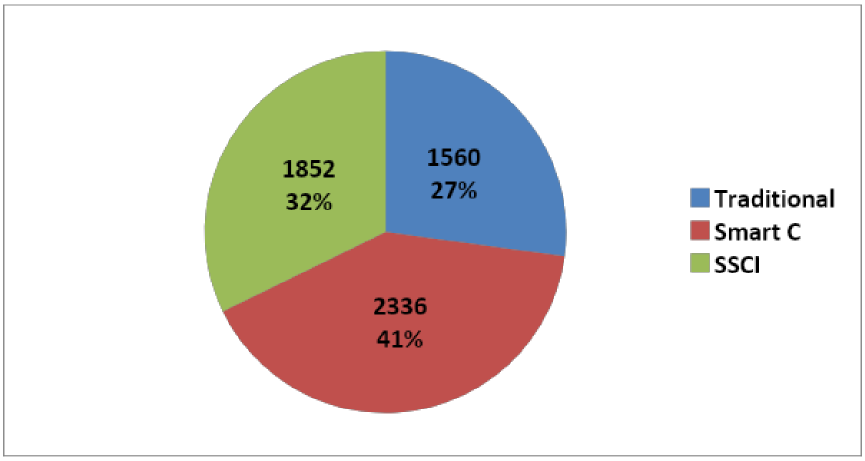


Figure 6: Average dispatching of passengers using FA policy

Figure 7 shows the effect of varying the policy on the total number of passengers served using all types of servers. It is intended to clarify the trend of total numbers of passengers relative to the run numbers (F6, F4, F2, F1, T1, and T2), which represent different simulation cases with varying the number of servers, refer to Table 2. Therefore, the same run setting (number of servers) is applied for different simulation policies to detect the change in the total number of passengers. It is obvious that the adoption of FA policy lead generally to the highest number of passengers, followed by RR, and finally JSQ. This finding should be verified with the average waiting times and service times in Table 2, to make a valid conclusion about whether the big number of passengers is being served effectively with a minimum waiting time. Taking F6 run as a trial case, it is noted referring to Table 2 that the average waiting time of FA policy for traditional and SSCI queues were 8.39 and 3.83 minutes, which are relatively very high. Moreover, service times for the smart carts reached an average of 9.48 minutes which is also very high compared to other policies. This same finding is noticed in all FA cases, leading to the conclusion that although there are a high number of passengers being served, they are not satisfied with the service. On the other hand RR showed to be second in row with high total number of passengers, showing at the same time relative minimum average queue waiting times and service times. Taking the same run case of F6, the average waiting time for traditional and SSCI queues were 0.33 and 0.05 minutes, which are relatively very low. Moreover, service times for the smart carts reached an average of 1.73 minutes which is very low compared to other policies. Therefore, a satisfaction from the service using RR is expected although it is not the policy giving the maximum number of intake passengers.

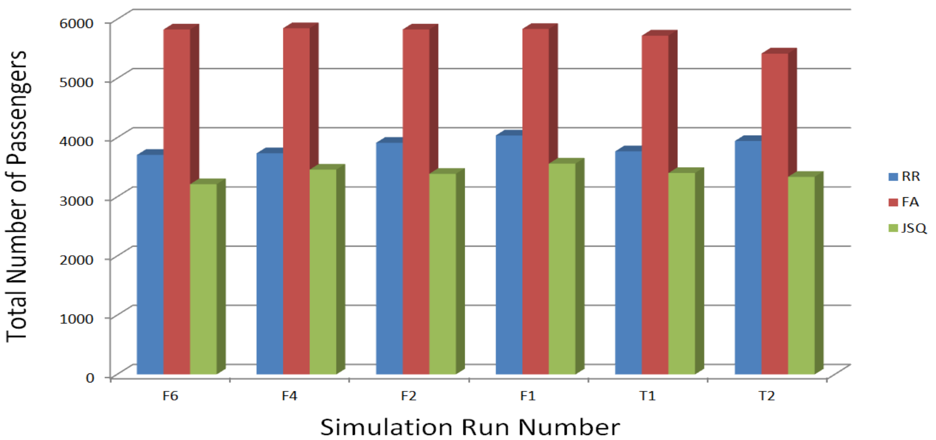


Figure 7: Different policies VS number of passengers

In Figure 8, each bar represents the average number of passengers of a particular policy calculated from all runs for the different types of services. It shows that smart carts are the favored adopted service type for the 3 policies, followed by SSCI, and finally traditional.

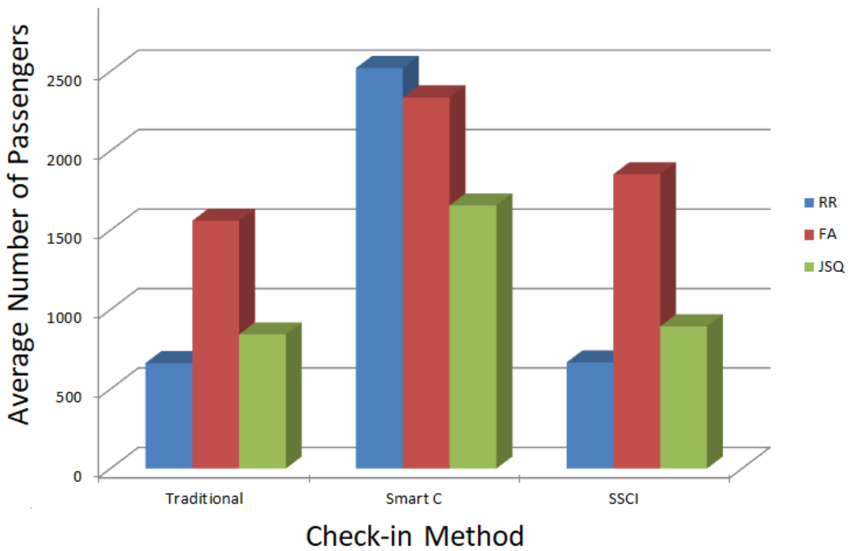


Figure 8: Dispatching of passengers on different servers through various policies

V. CONCLUSION AND RECOMMENDATION

The work presented in this paper intended to reach a valid conclusion about the usability reflected in the probable time gains, for the passengers and system, of using a new suggested type of smart carts in airports. Several simulation trials based on discrete event simulation were done, using Flexsim simulation package. Random, RR, JSQ, FA policies for dispatching passengers were tested for different complex models composed from traditional counters, smart carts, SSCI, and SBD booths. Many runs were performed with varying the conditions of the system by altering the number of servers and policies. The findings of this paper revealed that the RR policy led to the best outcomes regarding reaching the minimum queue waiting times and service times when a complex system of traditional counters, smart carts, SSCI, and SBD booths is adopted. On the other hand, FA showed the highest number of passengers' intake; however, it revealed at the same time the highest queue waiting times and service times. Therefore, FA is proven in this study to be the worst policy. Above all, the analysis showed that smart carts were the highest utilized among different check-in systems through various policies. Particularly, RR showed the highest utilization percentages among all policies, which is also the most recommended policy regarding the time spent in the system. This could lead to a conclusion that the adoption of smart carts, as a predominate check-in system, using the RR policy would lead to the best flow of passengers and minimum queue waiting times. A validation for these results using real life data in an actual airport is the next recommended step to actualize what is obtained in simulation in practice. However, it should be noted that RR policy is not easy to be adopted in practice; however, the system could be managed to ease its application through utilizing some means for monitoring and counting. Surveillance cameras connected to digital counters for times and passenger flows could be placed at each queue, with a probable help in case dispatching wasn't accomplished in the intended manner. In addition, a backup station for biased times and problematic cases could be added.

REFERENCES

[1]. Abdelaziz, Shady G., Abdelfatah A Hegazy, and Ahmed Elabbassy. "Study of airport self-service technology within experimental research of check-in techniques case study and concept." International Journal of Computer Science Issues, No 1 7, no. 3 (2010): 17-26.

[2]. Adamčík, František, Jozef Galanda, E. Jenčová, and Radoslav Šulej. "The application of online check-in in the process of passenger handling in air transportation." Magazine of Aviation Development 5, no. 4 (2017): 13-19.

[3]. Aguilera-Venegas, Gabriel, José L. Galán-García, Enrique Mérida-Casermeiro, and Pedro Rodríguez-Cielos. "An accelerated-time simulation of baggage traffic in an airport terminal." Mathematics and Computers in Simulation 104 (2014): 58-66.

[4]. Brailsford, S.C., P.R. Harper, and J. Sykes. "Incorporating human behaviour in simulation models of screening for breast cancer." European Journal of Operational Research 219 (2012): 491–507.

[5]. Cavada, Juan Pablo, Cristián E. Cortés, and Pablo A. Rey. "A simulation approach to modelling baggage handling systems at an international airport." Simulation Modelling Practice and Theory 75 (2017): 146–164.

[6]. Chalupníčková, Helena, and Helena Kejmarová. "Passenger check-in process, its future trends and human factors." eXclusive e-JOURNAL, no. 4 (2016): 1-11.

[7]. Chen, Li-Hong, Da-Wei Hu, and Ting Xu. "Highway freight terminal facilities allocation based on Flexsim." Procedia - Social and Behavioral Sciences 96 (2013): 368-381.

[8]. de Neufville, Richard. "The baggage system at Denver: prospects and lessons." Journal of Air Transport Management 1, no. 4 (1994): 229-236.

[9]. Flexsim. FlexSim Software Products, Inc. . 2019. http://www.flexsim.com (accessed September 2, 2019).

[10]. Goswami, Arkopal K., John S. Miller, and Lester A. Hoel. "Offsite passenger service facilities: A viable option for airport access?" Journal of Air Transport Management, no. 17 (2011): 263-270.

[11]. Hemdi, M.A., S.A.S. Rahman, M.H. Hanafiah, and A. Adanan. "Airport Self-Service Check-in: The Influence of Technology Readiness on Customer Satisfaction." 3rd International Hospitality and Tourism Conference. Bandung, Indonesia : Taylor & Francis Group, 2016.

[12]. Hyytiä, Esa, and Rhonda Righter. "Routing jobs with deadlines to heterogeneous parallel servers." Operations Research Letters 44 (2016): 507–513.

[13]. Hyytiä, Esa, and Rhonda Righter. "Simulation and performance evaluation of mission critical dispatching systems." Performance Evaluation 135, no. 102038 (2019): 1-22.

[14]. Hyytiä, Esa, and Samuli Aalto. "On Round-Robin routing with FCFS and LCFS scheduling." Performance Evaluation 97 (2016): 83–103.

[15]. Johnstone, Michael, Doug Creighton, and Saeid Nahavandi. "Simulation-based baggage handling system merge analysis." Simulation Modelling Practice and Theory , no. 53 (2015): 45-59.

[16]. Johri, Pravin K. "Optimality of the shortest line discipline with state-dependent service rates." European Journal of Operational Research 41 (1989): 157-161.

[17]. Kalakou, Sofia, Voula Psaraki-Kalouptsidi, and Filipe Moura. "Future airport terminals: New technologies promise capacity gains." Journal of Air Transport Management 42 (2015): 203-212.

[18]. Kim, Gukhwa, Junbeom Kim, and Junjae Chae. "Balancing the baggage handling performance of a check-in area shared by multiple airlines." Journal of Air Transport Management 58 (2017): 31-49.

[19]. Kumar, B. Santhosh, V. Mahesh, and Satish Kumar. "Modeling and analysis of flexible manufacturing system with Flexsim." International Journal of Computational Engineering Research 5, no. 10 (2015): 1-6.

[20]. Kuri, Joy, and Anurag Kumar. "On the optimal allocation of customers that must depart in sequence." Operations Research Letters , no. 15 (1994): 41-46 .

[21]. Le, Vu T., Doug Creighton, and Saeid Nahavandi. "Simulation-based Input Loading Condition Optimization of Airport Baggage Handling Systems." Intelligent Transportation Systems Conference. Seattle, WA, USA: IEEE, 2007. 574-579.

[22]. Lee, CKM, Yuankei Ng, Yaoqiong LV, and Park Taezoon. "Empirical Analysis of a Self-service Check-in Implementation in Singapore Changi Airport." International Journal of Engineering Business Management 6 (2014): 33-44.

[23]. Lee, Kang-Seok, Seung-Hun Kim, and Won-Hyuck Choi. "Self-Bag-Drop simulation development of systems for airport baggage handling system." International Journal of Advanced Science and Technology 118 (2018): 1-12.

[24]. Lin, H.-C., and C.S. Raghavendra. "An analysis of the join the shortest queue (JSQ) policy." Proceedings of the 12th International Conference on Distributed Computing Systems. Yokohama, Japan: IEEE, 1992.

[25]. Lu, Jin-Long, Jung Kyu Choi, and Wen-Chun Tseng. "Determinants of passengers' choice of airline check-in services: A case study of American, Australian, Korean, and Taiwanese passengers." Journal of Air Transport Management, no. 17 (2011): 249-252.

[26]. MathWorks. 2019. https://www.mathworks.com/help/simevents/gs/role-of-entities-in-simevents-models.html (accessed July 2, 2019).

[27]. Menich, Ronald, and Richard F. Serfozo. "Optimality of routing and servicing in dependent parallel processing systems." Queueing Systems (J.C. Baltzer A.G. Scientific Publishing Company) 9, no. 4 (1991): 403-418.

[28]. Ng, Yuankei, CKM Lee, Yaoqiong Lv, and Park Taezoon. "Empirical analysis of a self-service check-in implementation in Singapore Changi airport." International Journal of Engineering Business Management - Special Issue: The Next Generation of Aircraft Servicing and Logistics Operations ∑ Opportunities and Challenges 6, no. 6 (2014): 33-44.

[29]. Nõmmik, Allan, and Dago Antov. "Modelling Regional Airport Terminal Capacity." Procedia Engineering 178 (2017): 427-434.

[30]. Roanes-Lozano, Eugenio, Luis M. Laita, and Eugenio Roanes-Macias. "An accelerated-time simulation of departing passengers' flow in airport terminals." Mathematics and Computers in Simulation 67, no. 1-2 (2004): 163-172.

[31]. Savrasovs, Mihails, Alexander Medvedev, and Elena Sincova. "Riga Airport Baggage Handling System Simulation." 23rd European Conference on Modelling and Simulation. Madrid: European Council for Modelling and Simulation (ECMS), 2009.

[32]. Verma, Ashish, Divyakant Tahlyan, and Shubham Bhusari. "Agent based simulation model for improving passenger service time at Bangalore airport." *Case Studies on Transport Policies*, 2018: In Press, Corrected Proof.

[33]. Veronese, Fabio, Andrea Masciadri, Anna A. Trofimova, Matteo Matteucci, and Fabio Salice. "Realistic human behaviour simulation for quantitative ambient intelligence studies." Technology and Disability , 2016: 1-32.

[34]. Wang, Y. R., and A. N. Chen. "Production logistics simulation and optimization of industrial enterprise based on Flexsim." International journal of simulation modeling 15, no. 4 (2016): 732-741.

[35]. Wu, Xuepei, and Lihua Xie. "On load balancing strategies for baggage screening at airports." Journal of Air Transport Management 62 (2017): 82-89.

[36]. Yang, Changhwan, and Michael D. Santonino III. "A kano analysis on the adoption of self-service bag drops at Singapore Changi airport." International Journal of Aviation Management 3, no. 2/3 (2016): 150-171.

Abbreviations

FA	First Available
RR	Round Robin
FCFS	First Come First Served
JSQ	Join Shortest Queue
SBD	Self-Bag Drop
SSCI	Self-Service-Check-in