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Resource management using simulation at the airport

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Abstract

To improve the airport's operation, we use Monte Carlo simulation to determine the optimal number of check-in counters required for a single flight with 200 scheduled passengers in a 2-hour check-in period. Our analysis of the passenger arrival pattern supported that the inter-arrival time can be approximated using an exponential distribution. By using the Monte Carlo Simulation model with increasing number of check-in counters, we were able to conclude that three check-in counters were optimal to satisfy the service level requirement that at least 90% of the passengers must be served within 10 minutes upon arrival at the check-in queue. In additional, we further extend our analysis to cater for different passenger loads from 50 to 550 and determine the linear relationship between the number of counters required and passenger load.

Keywords: queuing, check-in counter, resource optimization, airport operation, simulation, departure passenger

1. Introduction

The airline industry has been growing very rapidly during the past decade. An ever growing industry that needs to improve the infrastructure to meet the needs of the passengers. In the meantime, low-cost carriers are also entering into this lucrative market and capturing a lot of the market share. Modern airports need substantial infrastructure investment for their long runways, taxiways, airport operational equipment, passenger terminal areas and expensive ground handling equipment. An airport serves either as a transit point or terminal point for the passengers during a trip. Airport operation can be roughly divided into airside and landside. Most of the Asian airport are very complex and requires proper coordination and effort to facilitate the daily operations. Some of the core processes in the airport are: handling of passengers and baggage, servicing, maintenance and engineering of the aircraft, ground handling activities, leasing of rental spaces for retail shops, aviation support facility (air traffic control) and finally custom and immigration for the passengers. Airport operators do not operate alone. They normally form partnership with various partners such as ground handlers to handle the passengers and baggage, catering companies to be in-charge the meals on board, and engineering companies to take care of aircraft maintenance.

Airlines are the major customers to the airport operators and the main objectives are to ensure the on-time departure of the aircraft and improve the passengers experience and convenience at the airport. One of the criteria for judging the efficiency of an airport is the availability of operational facilities such as runways, check-in counters, people movers, baggage handling system, aerobridges, and gate-hold rooms and so on. The arrival and departure processes of aircraft at the airport are two major operations which trigger various subsequent activities at the airport. After the aircraft arrives at the airport, it will move from the runway to taxi way, and park at the designated gate. The passengers will walk to the terminals and the ground handlers will unload the baggage and cargo to the baggage claim area in the shortest possible time. As for the passengers, they will go through the immigration before they collect their luggage and custom will inspect them before they depart the terminal building. For the departing flight, the passengers will arrive at the airport approximately 2.5 hours before the departure time where most of the counters will be opened for check-in. The check-in counter will be opened for 2 hours and it will be closed 30 minutes before the scheduled departure time to ensure that the passengers have enough time to board the plane and load the baggage on board. Nowadays, there are other means to check-in including online check-in or self-service machines to minimize the waiting time of the passengers. But still, many of the passengers still need to use the check-in counters for ID verification, printing of boarding pass and weighing and checking in the baggage. After the check-in process, for the international travelers, they will need to go through the immigration before going to boarding area at the gate to be departed on-time.

In this paper, we present an analysis on check-in counters requirements at the airport. Most airlines will request the airport operators to open more counters than they require to satisfy the passengers. However, from the airport operator's perspective, opening more check-in counters require more resources (counters and staff members) and incur higher operational costs. It is not unusual for the airline to share the actual passenger load with the airport operator only until the last minutes. But, the airport operator still need to know the optimal number of check-in counters to be opened 1 day in advance based on the historical demand of passengers load to minimize the operational cost,

The remaining of the paper is organized as follows. In section 2, we summarize the check-in counter assignment challenges, its key decision variables, constraints and objective followed by a literature review in section 3. In section 4, we analyze the passenger arriving pattern and fit it to the exponential distribution and verify the goodness of fit using maximum absolute deviation (MAD) between the cumulative relative frequency and cumulative probability distribution. Section 5 presents an application of Monte Carol simulation model to analyze the check-in counter requirements. Furthermore, we have extended our analysis to various passenger loads starting from 50 to 550 and we are able to identify a linear relationship between the check-in counters and passenger loads, and the preliminary computational results are reported in section 6. Finally conclusions are given in section 7.

2. Resource challenges

There are two types of check-in counter assignment models. One model is the airline-specific check-in-counters where the check-in rows are dedicated to these airlines and the check-in counters handle all the passengers for all the flights belonging to these airlines. In another model, check-in-counters are common resources where the same spaces can be shared by different airlines at different times of the day and the check-in counters are assigned for each flight belonging to the airlines based on their schedules. In this paper, we are only looking at the latter to determine the number of check-in counters for a particular flight.

One row of check-in counters can typically consists of 12 counters/desks. If an airline requests for 8 out of 12 counters in the row, the remaining 4 counters would not be sufficient to be assigned to another airline, as it was believed that 4 counters are not enough to accommodate all the passengers for one single flight. In addition, it is also not a good practice to assign counters for the same flight across more than one row to avoid any confusion for the departing passengers.

Currently, the airport assigned the check-in counters to a flight based on the airline requests and the terminal mangers, based on the rule of thumb or experience, derive the number of counters needed. There is no proper tool for them to use to aid in their daily decision making. On several occasions, it was observed that airlines requested more check-in counters than they actually need, leaving the counters idle resulting in poor utilization of airport terminal expensive resources. Due to the gradual growth in the airline industry, the operator is faced with the issue of reaching the terminal capacity especially during the peak hours and holiday seasons. If the operator does not assign enough check-in counters, then the passengers will have to wait a long-time at a queue and in the worst scenario, they may not be able to board the plane on-time and thus delaying the departure of the aircraft. It is important for the airport operator to meet the service level arrangement (SLA) to ensure that 90% of the passengers are served within 10 minutes upon arrivals using the optimal resources. It is a difficult and challenging operational problem faced by airport operator in the attempt to decide the number of check-in counters while balancing the operational costs and the service level passengers have to be provided with, in terms of queue length and waiting times.

3. Literature review

In our literature review, we begin by looking at past works which solved the problem of assigning check-in counters. Chun and Mak (1999) developed a comprehensive intelligent resource simulation system to predict on a daily basis how many check-in counters should be allocated to each departure flight while providing passengers with sufficient quality of service. Yan et al. (2004) developed an integer programming model to assist airport authorities to assign common check-in counters on a monthly basis with the objective of minimizing passengers walking distances. The complexity of the problem required the development of a heuristic method.

Joustra and van Dijk (2001) developed a simulation toolbox to study the behavior of check-in counters and the toolbox is validated by experts of Amsterdam Airport Schiphol on the basis of a study. van Dijk and van der Sluis (2006) first used the simulation to determine minimal numbers of desks in order to meet a service level for each separate flight. Next, integer programming formulations are provided to minimize the total number of desks and the total number of desk hours under the realistic constraint that desks for the same flight should be adjacent. They also introduced some operating realistic constraints to solve the problem for real cases. However, the formulation of the resulting allocation problem turns out to be a new *NP*-hard problem, whose solutions have to be computed by using heuristic approaches. Finally preliminary results for real world shows a triple win in waiting time performance, in number of desks and in number of desk hours (staffing).

Related to check-in counter assignment, there is another group of papers which looked at performance of the airlines. The simulation model developed by Haeme et al. (1988*)* helped the airlines evaluate their on-time arrival performance. Correia and Wirashinghe (2007) developed a methodology to study the service standards at the passenger airport based on the user perceptions using the surveys. The check-in counter is identified as one of the key components of the measurement which include processing time, waiting time and space available between each passenger. The study uses data obtained from a passenger survey conducted at Sa˜o Paulo/Guarulhos International Airport, Brazil.

There are also papers which look at baggage flow problems, where one of them is Atkins et al. (2003), who combined queue theory and optimization to solve the baggage flow problem at Vancouver International Airport. The result showed that through efficient scheduling and job deployment, 90 percent of Vancouver International Airport passengers could expect to wait no longer than 10 minutes at pre-board screening security points.

Airport terminal is a complex system which involves multiple stakeholders, agents, different passengers flow, government agencies and various operational policies. In order to help the airport manager to make strategic – high level decision, Manataki and Zografos (2010) developed a generic and flexible decision-support tool to facilitate the high-level decision-making related to fundamental changes in the structure and operation of the airport terminal system. This tool has been used to access the performance of the Athens International Airport passenger terminal under different demand and resource deployment scenario.

Simulation is commonly used for planning and design of airport. Jim and Chang (1998) presented a simulation tool using SLAM II simulation language for the final design of airport passenger terminal. The tool allows the management of airport passenger terminal to plan the different design and improvements for the existing or proposed terminal before the actual construction of an airport terminal.

Ma et al. (2014) analyzed the passenger load from the past historical pattern and developed a predictive model using decision tree (DT) to forecast the passenger load based on certain criteria. The model is being tested against the actual data given for a particular month and the root mean square error of 3%-12% is observed for all the airlines at the airport.

Ma (2017) focus on the forecasting of monthly departure passenger movements for one of the busiest airport in Asia. The author forecasted the monthly airport departure passenger flows for the next 12 months for macro level planning. Next, she used SAS Forecast Studio for detailed-level planning based on airline and per airline-city combinations using hierarchical forecasting. The result shown that in most cases, the mean absolute percentage error is less than 3%, which indicates the usefulness of our model for better decision making.

From the literature review, we understand that check-in counters at the airport have been studied before. But the contribution of our paper is in the use of a simple spreadsheet model to simulate the passengers' arrival and to collect various performance statistics such as average queuing time, average system time and average queuing length at the check-in counters. Apart from the ease of use, spreadsheet model is an effective tool to display results visually. It is also very intuitive as users can change the input parameters easily to see the impact of changing number of counters on the service level.

The rest of the paper is constructed as follows. We first understand the arrival pattern of the passengers based on the data collected on the ground. We analyze the data first and fit it to the most appropriate distribution for the simulation program. We develop a simulation model using the distribution and generate the arrival of passengers to achieve a better understanding of the check-in counter utilization. This would help the airport operator to decide how many counters they actually need and thus should open in order to optimize resources while achieving the desired performance targets including average processing time, average queue length and the average queue length. There are more spreadsheet models for decision making in Leong & Cheong (2011).

4. Analysis of passengers arriving pattern

Check-in counters are usually open 2.5 hours before the scheduled time of departure (STD) of the flight and will be closed 30 minutes before STD, opening only for a period of about 2 hours. The optimal number of check-in counters to open for a particular flight will depend on the number of passengers schedule to board the flight, and the arrival pattern of the passengers to the counters.
Normally, passengers can arrive as a solo passenger, in twos, in threes, in fours, or more. We have collected the arrival times of 135 passengers for a particular flight, over a period of 2 hours, 3 minutes and 40 seconds. The inter-arrival times for different types of passenger arrivals are given in Table 1 below.

Table 1: Inter-Arrival Times of Different Types of Passenger Arrivals

No of Passengers	Inter-Arrival Time (mm:ss)
1	00:08.3
2	01:40.2
3	00:18.9
4	00:21.4
5	00:33.7

Such an arrival pattern is a compound Poisson arrival process with a discrete jump size distribution in continuous time. Assuming a stationary process within the 2-hour check-in period, we let,

- t = continuous time where $t > 0$
- λ = average arrival rate
- $1/\lambda$ = average inter-arrival time
- $N(t)$ = number of Poisson arrivals in time t
- $B(i)$ = number of passengers for the i^{th}arrival
- $X(t)$ = number of passengers to arrive by time t

Since, $P(N(t) = k) = e^{-\lambda t}\frac{(\lambda t)^k}{k!} \quad ,k \geq 0$

$X(t) = \sum_{i=1}^{N(t)} B(i)$

Using Wald's equation, $E(X(t)) = E\big(N(t)\big)E(B) = \lambda t E(B)$. If we are able to characterize the distribution for $B(i)$ we will be able simulate the compound Poisson arrival process.

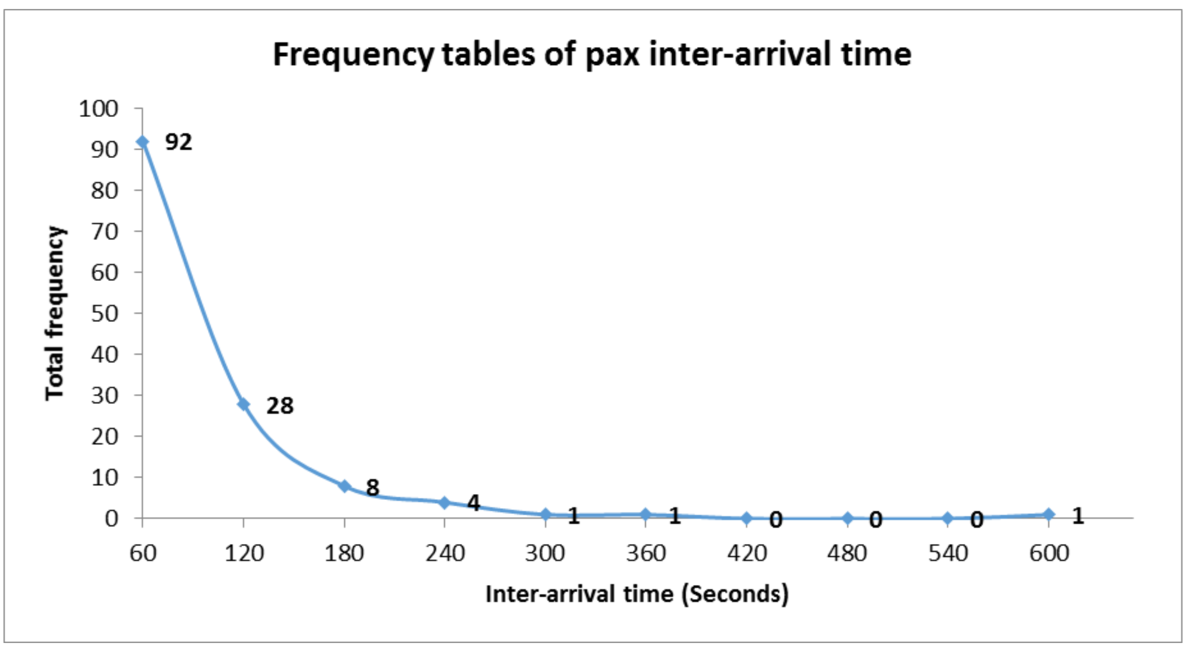
Without knowing the distribution for $B(i)$, we apply the frequency method to approximate the arrival process. From the set of sample data, we first determine the number of passengers with different inter-arrival time, using time bucket size of 60 seconds increment. For a group of passengers who arrived together, we would assume that all of them arrived individually, but their inter-arrival time would be a very small value > 0. In Table 2, we tabulated the frequency counts for 135 passengers. Among them, 92 passengers or 68.1% of the passengers have inter-arrival time of less than 60 seconds. There is only 1 passenger whose inter-arrival time is 600 seconds. We plotted the frequency count against the inter-arrival time in Figure 1. We could identify the distribution to be approximately exponential with inter-arrival time 1/λ = 55 seconds which can be obtained by using,

$$1/\lambda = \frac{total\ observed\ time}{total\ \#\ of\ pax} = \frac{02{:}03{:}40}{135} = 55(s).$$

Table 2: Frequency Count for Different Inter-Arrival Times from Sample Data

Inter-arrival Time, 1/λ (seconds)	Frequency Count	Relative Frequency (RF)	Cumulative Relative Frequency (CRF)
1/λ <= 60	92	0.681481	0.681481
60< 1/λ <= 120	28	0.207407	0.888889
120 < 1/λ <= 180	8	0.059259	0.948148
180 < 1/λ <= 240	4	0.02963	0.977778
240 < 1/λ <= 300	1	0.007407	0.985185
300 < 1/λ <= 360	1	0.007407	0.992593
360 < 1/λ <= 420	0	0	0.992593
420 < 1/λ <= 480	0	0	0.992593
480 < 1/λ <= 540	0	0	0.992593
540 < 1/λ <= 600	1	0.007407	1
Total	**135**		

Figure 1: Total Frequency Count versus Inter-Arrival Time for Sample Data



To test if the exponential distribution with inter-arrival time of 55 seconds is appropriate, we simulated 500 passengers arrival and plotted the Probability Distribution Function (PDF) and Cumulative Distribution Function (CDF) for the simulated data, and compared them with the Relative Frequency (RF) and Cumulative Relative Frequency (CRF) for the sample data set in Figure 4. In addition to visual inspection, we measure the goodness of fit using maximum absolute deviation (M.A.D) which defines the maximum difference between the cumulative relative frequency (CRF) of a given data set and its fitted distribution (CDF).

M.A.D = $\max(Abs(CRF - CDF))$

The average M.A.D for 10 iterations is 0.02, which supports the approximation of exponential distribution for inter-arrival time.

5. Simulation of queue at check-in

Given the number of passengers for a particular flight and the assumption that all the passengers will arrive within the 2-hour of check-in counter opening time, we can estimate the average inter-arrival time of the passengers using,

$$Inter - arrival\ time = \frac{Counter\ Opening\ Period}{total\ \#\ of\ passengers}$$

In addition, we also assume that the check-in process service time per passenger is 1 minute and 30 seconds and it also follows the exponential distribution. We use the template for our Monte Carlo simulation model using Excel spreadsheet, adapted from Leong and Cheong (2011).

The descriptions for the arrival time, service start time, service end time, waiting time, system time and system length are given below.

Arrival Time = Previous Arrival Time + Inter-Arrival Time
Service Start Time = If the queue length is less than number of counter, then the person will be served upon arrival (Service Start Time = Arrival Time), otherwise, the Service Start Time is the earliest Service End Time of all the counters
Service End Time = Service Start Time + Service Time
Wait Time = Waiting time from the passenger's Arrival time till he gets served = Service Start Time – Arrival Time
System Time = Total time spends in the system from the time the passenger arrives at the queue to the time the passenger leaves the counter = Service End Time – Arrival Time = Wait Time + Service Time
System Length = The number of people in front of the passenger upon his arrival at the queue
We simulated 200 passenger arrivals (from rows 7 to rows 206) and computed several performance indicators including the 90% percentile of the system time, average waiting time, average system time (average time spent in the system from joining the queue to leaving the check-in counter) and average system length (average queue length upon arrival) for a given number of check-in counter.

Figure 2 below shows a sample simulation run result for one check-in counter. The results show that with only one check-in counter, the passengers will need to wait an average of 1 hour and 28 minutes, and the average system time is also 1 hour and 29 minute with an average of 61 people queuing in front of you when you arrive. The performance target of 90 percent of the passengers served within 10 minutes is not satisfied. Thus, we need to increase the number of check-in counter to improve the service level. Table 3 below shows that the optimal number of check-in counter required is three for 200 passengers, where the 90^{th} percentile of System Time is 6 minute 16 seconds. By increasing the number of counters beyond 3 will not improve the system performance significantly. Thus, for a 200-passenger flight, three check-in counters will be needed to ensure that 90% of the passengers are served within 10 minutes according to the service level agreement.

	A	B	C	D	E	F	G	H	I
1	Total pax	200		Check-in open time	11:00:00		service time	00:01:30	
2	Duration	02:00:00		# of check in counter	1		inter-arrival	00:00:36	
3									
4				90% System time	02:30:00	Average	01:27:51	01:29:20	61.88
5		Inter-arrival	service time	Arrival time	Service start time	Service end time	Wait time	system time	system length
6				11:00:00		11:00:00			
7	1	00:00:02	00:02:19	11:00:02	11:00:02	11:02:21	00:00:00	00:02:19	0
8	2	00:01:01	00:00:24	11:01:03	11:02:21	11:02:45	00:01:17	00:01:41	1
9	3	00:00:30	00:00:47	11:01:33	11:02:45	11:03:32	00:01:12	00:01:59	2
10	4	00:00:10	00:06:36	11:01:43	11:03:32	11:10:08	00:01:49	00:08:25	3
11	5	00:01:16	00:00:21	11:02:59	11:10:08	11:10:29	00:07:09	00:07:30	2
12	6	00:00:30	00:00:27	11:03:28	11:10:29	11:10:55	00:07:00	00:07:27	3
13	7	00:00:29	00:00:09	11:03:57	11:10:55	11:11:04	00:06:58	00:07:07	3
14	8	00:01:07	00:03:08	11:05:05	11:11:04	11:14:12	00:05:59	00:09:08	4
15	9	00:02:22	00:00:14	11:07:26	11:14:12	11:14:26	00:06:46	00:07:00	5
16	10	00:00:32	00:01:46	11:07:58	11:14:26	11:16:12	00:06:28	00:08:13	6

Figure 2: Sample Simulation Run Result

Table 3: Performance Indicators for Different Number of Check-in Counters

# of Check-in Counters	90th Percentile of System Time (hh:mm:ss)	Average Waiting Time (hh:mm:ss)	Average System Time (hh:mm:ss)	Average System Length
1	02:25:15	01:19:48	01:21:13	52.51
2	00:40:01	00:18:33	00:20:12	23.65
3	00:06:16	00:02:49	00:04:30	6.96
4	00:04:05	00:00:10	00:01:35	2.65
5	00:03:44	00:00:02	00:01:22	2.15
6	00:03:23	00:00:00	00:01:19	2.12

6. Relationship between the resource and passenger load

The number of passengers per flight will vary according to the seasonal demand such as school holidays, Christmas season, route of flight and other economic factors. The airport operator is interested to find out the number of check-in counters required given the passenger load. We have run the simulation using the above model by varying the number of passengers for the flight and obtained the optimal number of counters required to meet the service level agreement. A graphical representation which shows the relationship between the number of counters and the Passenger Load is also shown in Figure 3.

The equation for a linear trendline is given as y = 0.0116x + 0.8182 and the R^2 = 0.9752 which indicates a very good approximation. We can just use the equation to determine the number of counters needed given the number of passengers. Since the number of counters is an integer value, we need to get round up to the nearest integer value. Using the linear relationship above, we can compute the number of counters required given the departure passenger load for a particular flight. We use the scheduled departure time (STD) as a reference and counters are only open two and half hours before STD and they will be opened for two hours duration for the passengers to do their check-in. We have calibrated 24 hours to 48 time-slots each 30 minutes time window. We are required to do the resource planning for a day which will give the management an overview of the resource required at thirty-minute time window. Figure 4 shows the resource requirement for a typical day at one of the terminals at the airport. From the diagram, we observe that from mid-night till 6:00am, the demand for the counter is less than 18, the peak occurs at 7:00am where there are 45 counters required. The counter requirement drops to 4 at 10:00am and remains low within the day from noon till 6:00pm. There is another peak at 8:00pm with 39 counters required and subsides slowly until mid-night. The counters requirement will also form the basis for manpower allocation to handle the departing passengers during check-in process.

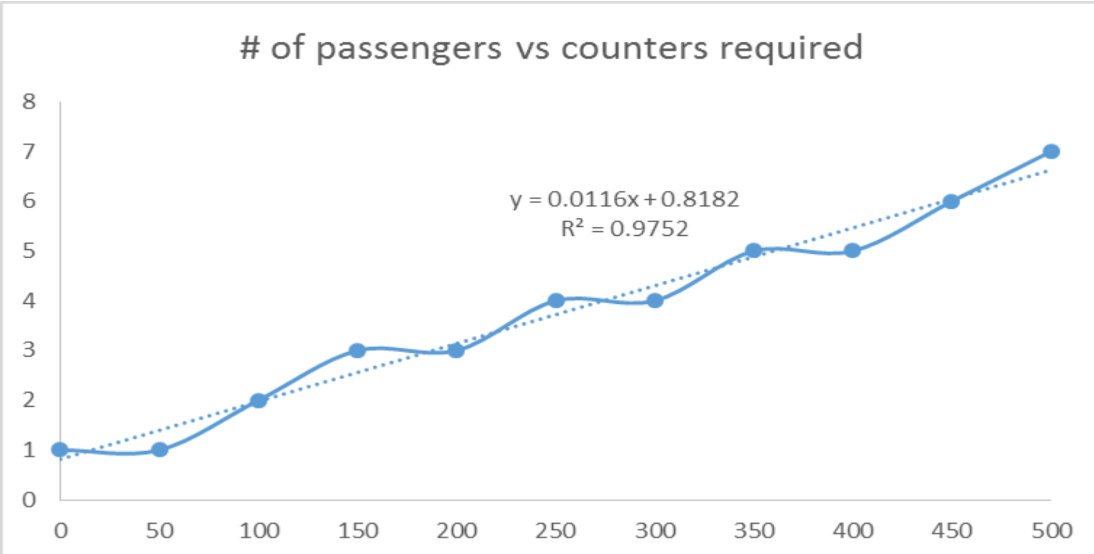


Figure 3: Graphical Representation of Number of counters and Passenger Load

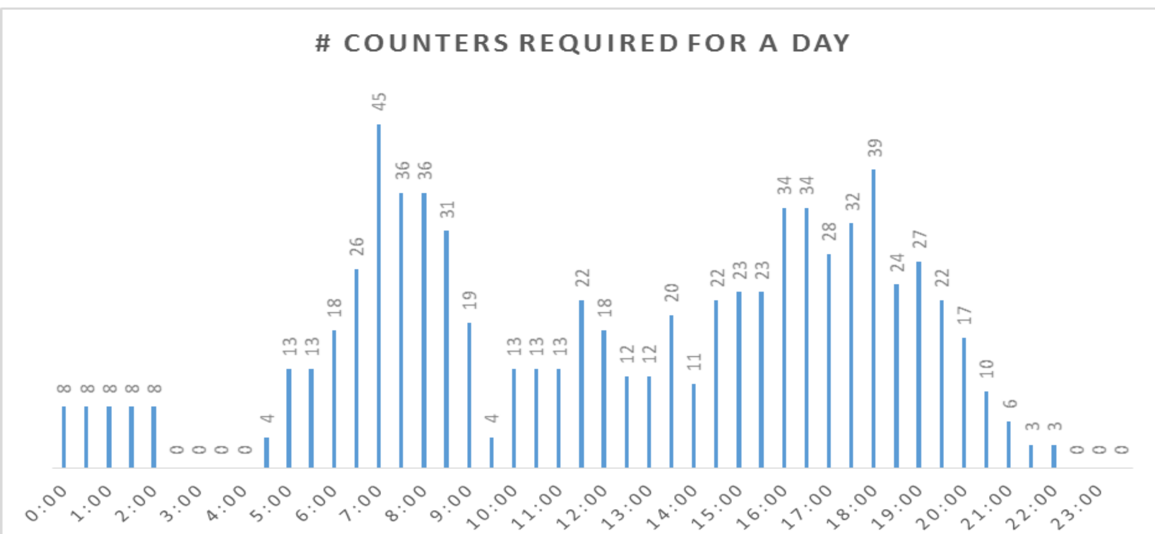


Figure 4: Counters requirement for a typical day at the airport

7. Conclusion & future work

In this paper, we are concerned with the optimal number of check-in counter required in an airport to service the passengers within 10 minutes after their arrival for a single flight. Due to the randomness of passenger arrival and service time, we have employed Monte Carlo Simulation method using Excel spreadsheet to solve the problem. Our analysis of the passenger arrival pattern supported that the inter-arrival time can be approximated to follow an exponential distribution, with the maximum absolute deviation (a measure of goodness of fit) between the Cumulative Relative Frequency of the sample data and the Cumulative Distribution Function of the fitted distribution to be 0.02. Our simulation template allowed us to perform the simulation and collect performance indicators such as average total system time, average waiting time, average queue length and the 90th percentile of the total system time. In our simulated example with 200 scheduled passengers in a 2-hour check-in period, we were able to conclude that 3 check-in counters were optimal to satisfy the service level requirement. Any increase in the number of check-in counters will not improve the service level significantly and instead it will result in wastage of check-in counters which would be under-utilized. We have also determined the linear relationship between the number of counters and passenger load to assist Terminal Managers to make quick decision**.** We have also developed the daily counter requirements for the airport looking at each individual flight, passengers load and STD.

A possible extension of this model is to explore shared check-in counters where several check-in counters are shared across several flights belonging to the same airline. This proposed extension will be useful for the airline-specific check-in-counters with the objective of reducing the total number of check-in counters assigned to a particular airline instead of to a single flight. In the most recent development, airports are also looking at self check-in kiosk to reduce the operational cost. Nevertheless, the methodology developed in this paper, can also be used with modification to estimate the number of self check-in kiosk counters requirement at the modern airport.

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Biographies

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