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Impact of Passenger-Arrival Patterns in Outbound Processes of Airports

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Abstract

This paper considers how the arrival pattern of passengers affects international terminal operations, including major outbound processes such as check-in, security screening, and immigration. The pattern of passenger arrivals is considered an important factor in planning airport-terminal facilities, such as the number of check-in counters and service agents, along with the operation times of passenger check-in and queue length. A Discrete-Event Simulation (DES) model was used to address this problem. It was built using ExtendSim V9.2 simulator software. The DES model can also be used to identify the system's bottlenecks. Numerical testing shows that different arrival patterns have a significant impact on the performance of operational processes to determine the best policy for passenger arrival time.

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Keywords: arrival patterns; simulation; passenger flow; airport; modelling; Discrete-Event Simulation.

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1. Introduction

In recent years, airports have played a significant role in driving the economy and connecting cities and countries around the world. Numerous travellers prefer to travel by airline rather than other transportation modes, such as trains, buses, and private cars. Based on the International Air Transport Association (IATA, 2014) report, in 2013, the number of airline travellers exceeded 3 billion passengers, a growth of about 5.1% compared with the previous year [1]. The pattern of passenger arrivals is considered an important factor in planning airport-terminal facilities, such as the number of check-in counters and service agents, along with the operation times of passenger check-in and queue length [2, 3]. The arrival pattern of passengers and the rate of passenger arrivals are affected by many factors, including flight-departure times, type of traveller (business/leisure), and flight destination. According to [4], passengers with early flights generally arrive later than the statistical average. The airport check-in rules are considered significant factors influencing passenger-arrival patterns at the airport [5]. Most airports share some common arrival behaviours for passengers in international terminals. These behaviours are as follows:

- 90% of passengers arrive at the airport 60 minutes before departure time;
- Business passengers arrive later than leisure passengers;
- The peak hours of check-in are 100–120 minutes before the departure time; and
- In the morning, the peak hours are shorter but busier than in the evening [6, 7].

A simulation model has been developed to analyse the effect of passenger arrival variation. This model also investigates the influence of arrival patterns on the efficiency of airport-terminal processing and focuses on mandatory processes, including check-in, security checkpoints, and immigration. The outcome of this analysis could help in setting the time-of-arrival policy for international airports. To determine the most suitable arrival policy for an airport, two basic parameters are critical: the mean value of time before flight and the arrival time before flight. Two experiments were conducted to investigate the influence of these parameters on arrival patterns and airport terminals at check-in points. Finally, we present the strategy for determining the optimum policy for the airport.

2. Literature Review

This section discusses different types of models used in the study of current problems occurring in airport-terminal systems. These models focus particularly on departure systems to measure the performance of workstations and to understand significant factors affecting system performance. Wu and Mengersen [8] point out that existing airport models can be categorised into four types: ‘capacity planning, operational planning and design, security policy and planning, and airport performance review’. These models can be based on analytic, simulation, or hybrid approaches. They require different levels of detail (e.g. macroscopic, microscopic, and mesoscopic) and have deterministic and stochastic characteristics [8, 9]. The models capture different performance metrics for ‘operational efficiency’, including service time, queue length, and congestion. Several models have been developed. The methods can be separated into four categories – analytical, simulation, optimisation, and integrated models [8, 10–13]. Takakuwa and Oyama [14] developed a microscopic simulation model of an airport terminal in order to assess passenger flow, with a primary focus on international departures. Their model considers the influence of such variables as flight schedules, passenger nationality, walking speed, volumes of bags, and passenger group size to analyse the facilitation process capacity. Recent research conducted by Alodhaibi, Burdett [1] employed Discrete-Event Simulation (DES) models to identify potential bottlenecks occurring between kerbside and boarding procedures. The key input of the model is the flight schedule, which describes flight size, scheduled departure time, and the airline. The simulation results show that the flight schedule influences passenger flow and suggest that integrated flight-schedule creation and passenger-flow modelling can help address the issues of passenger flow within an international terminal.

3. ExtendSim Simulation Models

In this paper, a DES of passenger flow and queuing through different airport facilities has been implemented using the simulation software package, ExtendSim. This enables developers to connect blocks together in order to

move items through the system from the beginning of processes until the item exits the system [15]. This software package facilitates the simulation of passenger flow in the context of processes within the airport. This will assist in identifying any existing or expected bottlenecks and passenger-processing times. It also can be a supportive tool to provide the optimisation of operational capabilities and the personnel resources required to minimise processing times. In addition, this simulation package has the capability to program the assumptions of a system via a variety of blocks and connections. The simulated arrivals at the airport terminal can be generated according to a prescribed statistical distribution that mimics the behaviour of passengers in real life. The blocks are activated when entities pass through them, demonstrating the operations that are performed in the system [16]. The input for the outbound simulation model consists of the following: flight attributes, outbound passenger attributes, passenger-processing facility requirements, the service characteristics of individual facilities, and the arrival characteristics of the system [17].

3.1. Development of the passenger-arrival process model

Passenger-arrival time is treated as a random variable. The distribution of passengers arriving at the check-in counters varies by time of day, day of week, airport, season, type of passenger, etc. Other factors, such as the mode of transportation and the security requirements, are not considered. Furthermore, this model explains the behaviours of any passenger (business or leisure). The flight schedule was obtained from an international airport and used as input for the model to estimate the volume of passengers showing up at the terminal and the passenger-arrival pattern during the day (24 h).

Several different statistical distributions can describe the arrival profile based on the given flight schedule. These distributions include the exponential distribution, uniform distribution, empirical distribution, and normal distribution [18–20]. From these, the normal distribution was selected to characterise the passenger-arrival pattern. Figure 1 depicts the flow chart used to obtain the arrival pattern under normal distribution from the flight-schedule data.

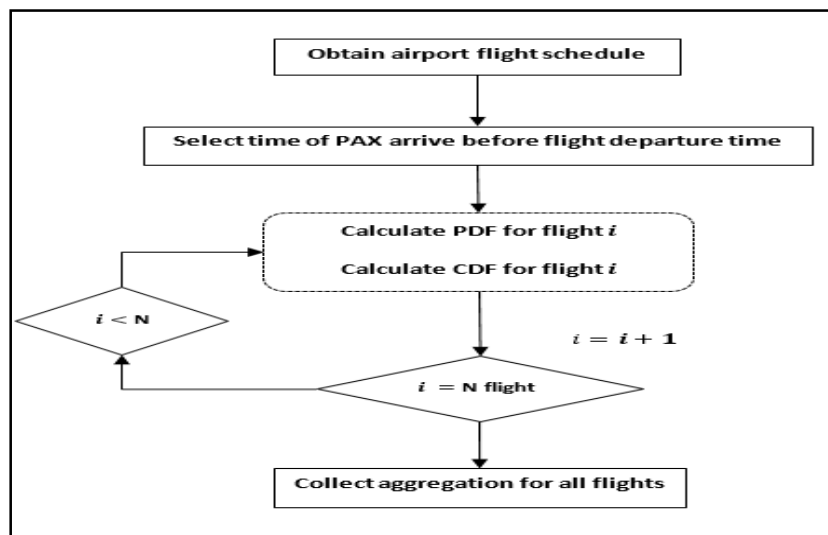


Fig. 1. Flowchart for modelling passenger arrivals at the international terminal

The modelling procedure for estimating the volume of passengers arriving at the airport over time is based on the following algorithm:

- Obtain flight schedule of the airport, including the related flight information that contains the airline, scheduled time of departure, and number of passengers on each flight.
- Select the policy for passenger-arrival time at the international airport. For example, 2 hours, 3 hours, or 4 hours beforehand (scheduled departure time).
- Determine the relevant distribution, along with critical parameters such as mean and standard deviation.

- Calculate the probability distribution function (PDF) and the cumulative distribution function for each flight (i) to determine the number of passengers arriving per time interval before the departure time.
- Add the number of passengers arriving at each time interval for each flight to estimate the incremental total number of passengers arriving for all flights. Thereby, the aggregate numbers of passengers arriving per time interval can be obtained for the entire flight timetable[5].

3.1.1. Generation departing passengers

Generated departing passengers can be represented by objects or items in structure of the simulation. The departing-passenger generation model is based on basic flight-schedule information, such as departure time, the time the departure gate opens and closes, and the flight code. The first step is to generate a flight-attributes table, which is a vital component of the DES. Flight attribute refers to the necessary information for the establishment of the outbound system. There are three types of flight attributes: flight schedules, passenger characteristics, and boarding characteristics. The next step is to generate the attributes of outbound passengers. Each passenger should have unique attributes, characterising the exact nature of the arriving passengers. An algorithm is developed and implemented in VBA within Excel. To understand these characteristics greater, passengers' attributes were divided into five main phases as shown in Figure 2. The third step is to link the outbound passenger-attributes table with ExtendSim through the global-array database. The global array is a two-dimensional (row and column) selection of data accessible by any block in the model. The role of the global array is to move information between blocks when a direct connection is either impossible or inconvenient and to exchange data or store information that can be accessed by a row and column index.

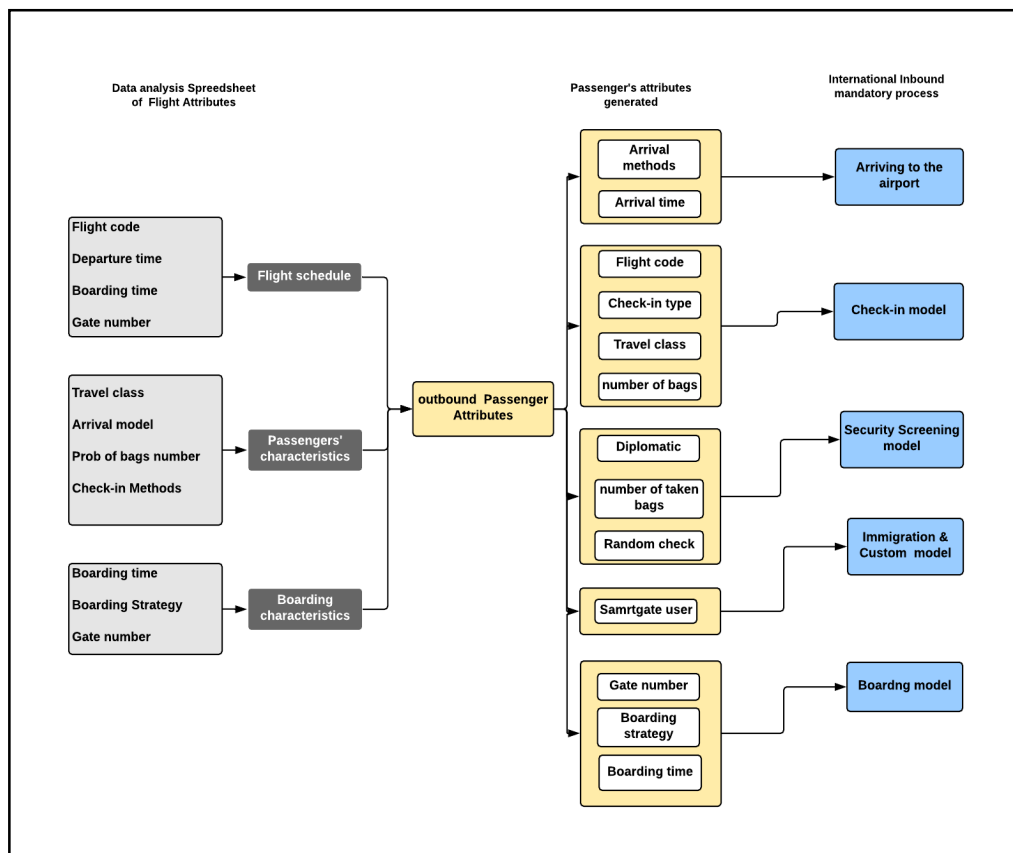


Fig. 2. The input modelling of outbound simulation model

4. Model demonstration

The developed model has been applied to the Brisbane International Airport (BNE). The model describes the main characteristics of BNE in terms of flight schedule, passenger-flow processes, and a variety of functional areas and facilities. Hence, the aim of the model is to provide insight into the impact of the variability of arrival patterns at the international terminal processing points. The first set is conducted to study the impact of different arrival times at the airport given fixed μ (see Table 1). The second set investigates the impact of a variable mean value given a fixed arrival time (such as 3 hours before departure time) as shown in Table 2.

Table 1. Selection of Ω values under a fixed μ values.

μ (min)	Sets of time before departure Ω (in min)				
60	120	150	180	210	240
90	120	150	180	210	240
120	120	150	180	210	240
150	150	180	210	240	
180	180	210	240		
210	210	240			

Table 2. Selection of Ω values under different μ values.

Ω (min)	Mean value μ (min)							
120	60	90	120					
150	60	90	120	150				
180	60	90	120	150	180			
210	60	90	120	150	180	210		
240	60	90	120	150	180	210	240	

A combination of 26 arrival time policies at an international airport were simulated. These policies involved passengers arriving at the airport 2 hours, 2.5 hours, 3 hours, 3.5 hours, and 4 hours before departure. The simulation model was conducted a number of times to investigate the effect of many different arrival patterns, and especially the possible effect on passenger flow at terminal processing points.

4.1. Behaviour of departing-passenger arrival profile

For a given μ value, the arrivals patterns were calculated using the approach proposed in Section 1. This procedure was followed for every μ value where: $\mu = \{60, 90, 120, 150, 180, 210\}$. Figure 3 illustrates arrival profiles of departing passengers for different times before flight Ω under a given mean μ . For any given μ , the arrival pattern is similar for any Ω value that has the condition $\Omega > \mu$. Despite the slight differences for this situation, the figure shows that the arrival pattern with different Ω values is similar, irrespective of the μ value. However, for the graphs $\Omega \leq \mu$, the arrival pattern shows variation from other graphs in certain regions as follows:

- For $\mu \leq 120$, a considerable increase of PAX of can be seen in the $\Omega=120$ curve in the time interval around 12:00 h to 20:00 h.
- For $\mu=150$, considerable increase of PAX can be seen in the $\Omega=150$ curve in the time interval around 07:00 h to 22:00 h.
- For $\mu \geq 180$, slight decrease of PAX of can be seen in the $\Omega=180$ and 210 curves in Graphs (e) and (f) respectively in the time interval around 14:00 h to 22:00 h.

On the other hand, the behaviour of arrival patterns for a given time before the scheduled departure time under different values of mean μ has similar trends for every mean value. Figure 4 illustrates the arrival profile of the departing passengers for a given time before the scheduled departure time under different value of mean μ . For each plot, the peak value is the same for any mean values. All plots reach their peak in the time interval around 05:00 h to 10:00 h and in the time interval 20:00 h to 24:00 h. In this case, for any graphs where $\Omega \leq \mu$, arrival patterns show little variation compared with what we have seen in the case study.

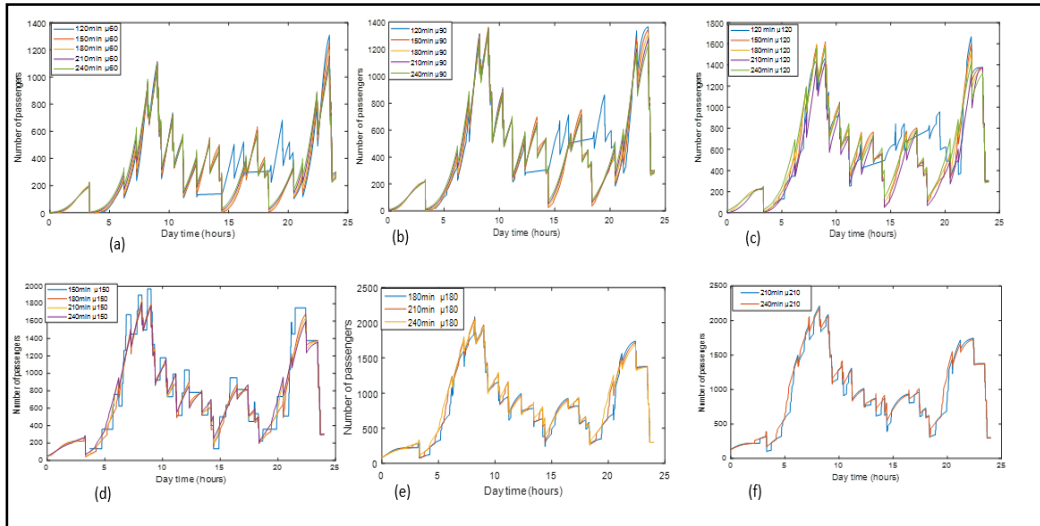


Fig 3. Departing of passenger arrival profiles at airport terminal for different (Ω) under given (μ): (a) $\mu = 60$ min; (b) $\mu = 90$ min; (c) $\mu = 120$ min; (d) $\mu = 150$ min; (e) $\mu = 180$ min (f) $\mu = 210$ min.

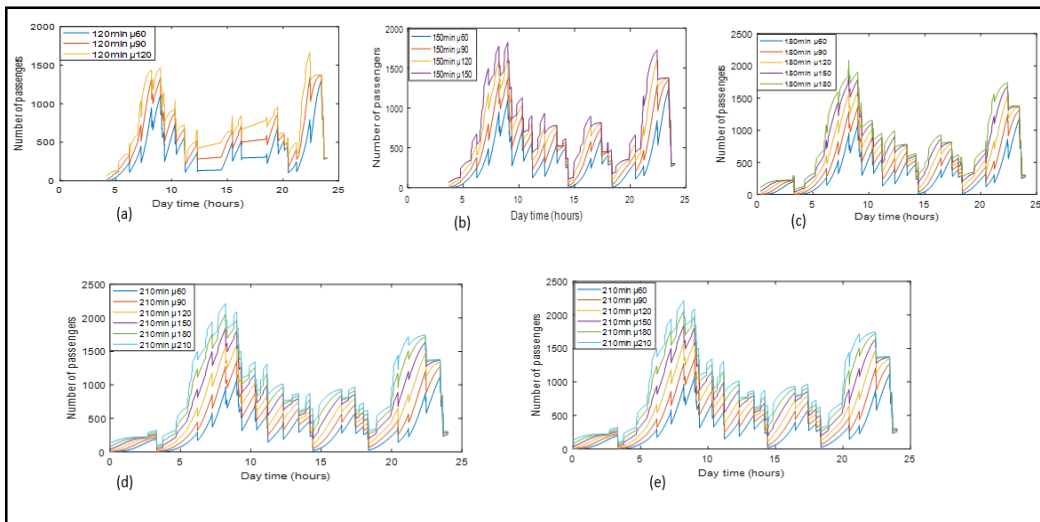


Fig. 4. Departing passenger arrival profiles at airport terminal for different (μ) given (Ω): (a) $\Omega = 120$ min; (b) $\Omega = 150$ min; (c) $\Omega = 180$ min; (d) $\Omega = 210$ min; (e) $\Omega = 240$ min

5. Simulation results

This section discusses the effect of different arrival patterns on the airport-terminal processing points, including check-in, security screening, and immigration. The key performance metrics, such as waiting time, average waiting time, queue length, and average queue length, have been considered in this analysis. In the first experiment, the queue lengths and waiting time decrease when required arrival time before a flight is increased, as shown in Table 3, The minimum queue length of immigration processes was found at $\Omega = 240$ with $\mu = 60$ min. In the check-in process, the maximum queue length occurs at $\Omega = 240$ min with $\mu = 60$ min and $\mu = 90$ min. In contrast, in the second experiment, the queue lengths increase from check-in processes to immigration.

Table 3. The summary of simulation results

Scenarios				Check-in				Security				Immigration			
				Queue length		waiting time (min)		Queue length		waiting time (min)		Queue length		waiting time (min)	
Case #	Time before flight (min)	mean	STD	Max	Average	Max	Average	Max	Average	Max	Average	Max	Average	Max	Average
1	120	60	26.4134	46	2.06	23.58	3.38	111	7.68	12.45	1.87	413	61.48	82.33	20.37
2	150	60	35.0737	40	1.04	17.85	1.7	105	4.33	11.14	1.06	321	43.38	64.06	14.42
3	180	60	43.734	40	1.14	15.29	1.9	126	7.07	13.04	1.73	344	47.66	68.66	15.91
4	210	60	52.3943	59	2.02	27.54	3.33	103	5.46	10.85	1.33	237	34.51	47.51	11.43
5	240	60	61.0546	84	2.95	37.61	4.87	54	1.76	5.36	0.43	220	20.85	43.93	6.86
6	90	90	17.8	98	5.63	38.47	9.33	174	13.11	19.33	3.21	406	69.7	81.38	23.07
7	120	90	26.4134	22	0.81	10.67	1.33	210	18.71	21.86	4.57	431	72.58	86.15	23.8
8	150	90	35.0737	16	0.288	3.25	0.25	187	16.29	20.19	3.99	376	55.47	75.13	18.32
9	180	90	43.734	14	0.31	6.16	0.51	138	9.95	15.11	2.27	353	54.84	70.51	18.34
10	210	90	52.3943	19	0.42	9.53	0.71	109	5.76	12	1.41	366	60.36	73.09	20.01
11	240	90	61.0546	34	0.56	14.03	0.92	49	2.88	5.26	0.71	295	47.22	58.88	15.58
12	120	120	26.4134	37	1.12	14.82	1.86	163	13.44	16.9	3.29	443	80.74	88.57	26.61
13	150	120	35.0737	11	0.2	4.28	0.33	178	15.38	18.64	3.75	413	68.45	82.47	22.45
14	180	120	43.734	7	0.08	3.92	0.124	181	13.34	19.86	3.25	408	70.36	81.69	23.19
15	210	120	52.3943	27	1.01	12.21	1.7	95	3.93	9.93	0.96	306	46.01	61.2	15.05
16	240	120	61.0546	16	0.12	6.21	0.2	125	8.3	13.28	2.03	330	49.12	65.77	16.33
17	150	150	35.0737	11	0.11	4.03	0.19	140	9.85	15.28	2.41	389	65.82	77.69	21.89
18	180	150	43.734	12	0.11	4.68	0.18	137	10.29	15.16	2.51	407	72.59	81.33	24.16
19	210	150	52.3943	4	0.03	1.48	0.04	127	9.63	13.13	2.36	371	62.97	74.22	20.68
20	240	150	61.0546	8	0.07	3.14	0.11	116	6.13	12.2	1.51	379	66.76	75.96	21.87
21	180	180	43.734	8	0.04	3.24	0.07	163	11.31	18.19	2.77	359	58.21	71.68	19.63
22	210	180	52.3943	7	0.07	2.87	0.011	128	9.84	14.06	2.41	393	66.74	78.26	22.22
23	240	180	61.0546	31	0.7	14.2	1.16	121	7.59	13.06	1.86	382	64.3	76.22	21.21
24	210	210	52.3943	42	2.19	19.98	3.61	151	11.94	15.84	2.91	396	67.79	79.13	22.56
25	240	210	61.0546	69	3.21	27.59	5.27	78	3.56	8.94	0.087	294	46.93	58.49	15.61
26	240	240	61.0546	92	6.38	42.42	10.52	207	19.25	22.75	4.7	393	62.09	78.59	20.66

Moreover, the corresponding μ value for check-in remains at 60 min until Ω increases to 210 min. Afterwards, the corresponding maximum queue length occurs at $\mu=240$ min for $\Omega=240$ min. The minimum queue length for check-in starts at 90 min with $\Omega=120$ min. As Ω increases, this value reaches 150 min. The variation of queue length with changing μ is not always the same for any Ω . In order to understand the best policy that satisfies check-in, security screening, and immigration in terms of minimum waiting time and length of queue, we assumed that all three processes have the same priority with equal factor 33.3%. This factor is multiplied by the KPIs values of each process. Then, for each scenario, we compute the sum of the particular KPI value to get the total value for all three processes.

According to the graph below, the minimum queue length occurred at scenario number 5, while the policy of $\Omega = 150$ under $\mu = 120$ min gives minimum value for both queue length and waiting time. This scenario was selected as the best policy.

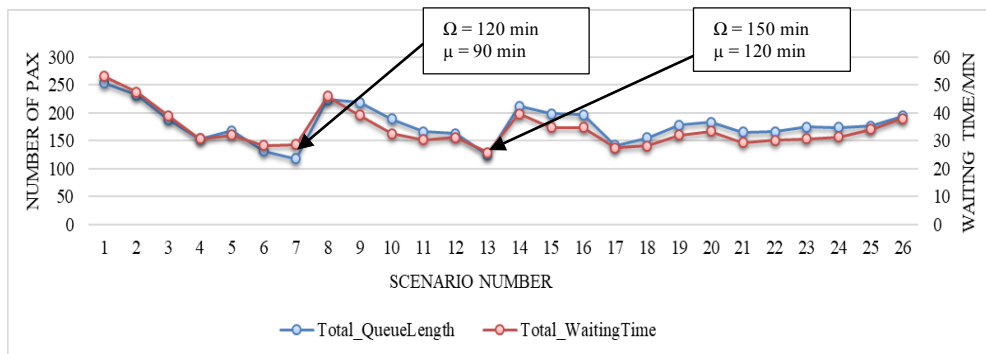


Fig 5. The aggregation of selecting arrival time policy

6. Conclusion

This paper analyses the influence of different arrival patterns on passenger-processing activities (check-in, security and immigration) using DES. These results provide important insight into the two important parameters, namely time

before flight Ω and mean μ before the flight and how they impact the performance of an international terminal system. Observations of the first experiment show that for a given μ under different Ω values there is a significant influence on the departing passengers' profiles, especially during time before flight $\Omega \leq \mu$. However, in the second set of experiments, the behaviour of arrival patterns is similar for all scenarios. Furthermore, the simulation results demonstrate how much congestion the airport will incur.

Taken together, the numerical explorations of this article suggest that the best policy is arrival at the airport $\Omega = 2.5$ hours beforehand under mean time before flight $\mu = 120$ min.

Future research will focus on the following fields of modelling:

- Investigating the impact of arrival patterns with respect to different distribution functions.
- Extending the simulation model to inbound passenger processes within an international terminal.
- Investigating the impact of arrival patterns on the resource-allocation management, including both systems of an international terminal outbound/inbound.

7. References

- [1] Alodhaibi, S., R.L. Burdett, and P.K.D.V. Yarlagadda, *Framework for Airport Outbound Passenger Flow Modelling*. Procedia Engineering, 2017. **174**: p. 1100-1109.
- [2] Park, Y. and S.B. Ahn, *Optimal assignment for check-in counters based on passenger arrival behaviour at an airport*. Transportation Planning and Technology, 2003. **26**(5): p. 397-416.
- [3] Fayez, M.S., et al., *Managing airport operations using simulation*. Journal of Simulation, 2008. **2**(1): p. 41-52.
- [4] Rauch, R. and M. Kljajić, *Discrete event passenger flow simulation model for an airport terminal capacity analysis*. Organizacija, 2006. **39**(10).
- [5] Manataki, I.E. and K.G. Zografos, *A generic system dynamics based tool for airport terminal performance analysis*. Transportation Research Part C: Emerging Technologies, 2009. **17**(4): p. 428-443.
- [6] Ashford, N., S.A. Mumayiz, and P.H. Wright, *Airport engineering: planning, design, and development of 21st century airports*. 4th/4; ed. 2011, Hoboken, N.J: Wiley.
- [7] Cheng, L., *Modelling airport passenger group dynamics using an agent-based method*. 2014, Queensland University of Technology
- [8] Wu, P.P.-Y. and K. Mengersen, *A review of models and model usage scenarios for an airport complex system*. Transportation Research Part A: Policy and Practice, 2013. **47**: p. 124-140.
- [9] Zografos, K.G. and M.A. Madas, *Development and demonstration of an integrated decision support system for airport performance analysis*. Transportation Research Part C: Emerging Technologies, 2006. **14**(1): p. 1-17.
- [10] Law, A.M. and W.D. Kelton, *Simulation modeling and analysis*. Vol. 2nd. 1991, New York: McGraw-Hill.
- [11] Tošić, V., *A review of airport passenger terminal operations analysis and modelling*. Transportation Research Part A: Policy and Practice, 1992. **26**(1): p. 3-26.
- [12] Zidarova, E.D. and K.G. Zografos, *Measuring quality of service in airport passenger terminals*. Transportation Research Record: Journal of the Transportation Research Board, 2011. **2214**(1): p. 69-76.
- [13] Cheng, L., et al., *A review of pedestrian group dynamics and methodologies in modelling pedestrian group behaviours*. World, 2014. **1**(1): p. 002-013.
- [14] Takakuwa, S. and T. Oyama, *Modeling people flow: simulation analysis of international-departure passenger flows in an airport terminal*, in *Proceedings of the 35th Conference on Winter Simulation: Driving Innovation*. 2003, Winter Simulation Conference: New Orleans, Louisiana. p. 1627-1634.
- [15] Diefenbach, M.L., *Application of operations research techniques to improve efficiency in the emergency department*. 2010, Queensland University of Technology.
- [16] Wang, W.-X., H.-Y. Wang, and F.-X. Lu, *Simulation of effectiveness evaluation of warship multi-layer air defense system with extendsim*, in *Material Engineering and Mechanical Engineering*. 2016, WORLD SCIENTIFIC. p. 375-385.
- [17] Chiu, C.-Y., *Impacts of new large aircraft on passenger flows at international airport terminals*. 2002, The University of Texas at Austin: Ann Arbor. p. 209.
- [18] Olaru, D. and S. Emery, *Simulation and GA-optimisation for modeling the operation of airport passenger terminals*. in *Proceedings of the 29th conference of Australian institutes of transport research (CAITR)*. Adelaide, Australia. 2007.
- [19] Schultz, M. and H. Fricke, *Managing passenger handling at airport terminals*. in *9th Air Traffic Management Research and Development Seminars*. 2011.
- [20] Fonzone, A., J.-D. Schmöcker, and R. Liu, *A Model of Bus Bunching under Reliability-based Passenger Arrival Patterns*. Transportation Research Procedia, 2015. **7**: p. 276-299.