The impact of seasonality on efficient airport capacity utilization

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ABSTRACT

The major cause of under-capacity or overcapacity at smaller airports is seasonality. Such airports are finding it difficult to determine the capacity to meet the demand and adequately handle passengers in both high and low season. If the capacity is not optimally defined, excessive congestions and waiting times occur, resulting in lower service quality. Airports greatly benefit from capacity utilization analysis in terms of more accurate planning, designing, and adjusting capacity to the current demand in order to encourage further development as well as to reduce additional costs. Using queuing theory, this paper aims to answer the following question: is the passenger capacity at Rijeka International Airport (Croatia) optimally determined to meet the demand promptly, both in high and low season, without causing excessive congestions and waiting times. The results obtained indicate the occurrence of overcapacity since high season demand can be well served, even with reduced capacity used in the low season when demand is significantly lower.

ARTICLE INFO

1 Introduction

Peak traffic at airports has been the subject of increasing concern for airlines and airport operators around the world since it generates congestion and serious economic penalties, or delays to aircraft and passengers. Therefore, effective management of available airport capacity/demand in such an environment presents a great challenge to airport operators and airlines. Every reasonable effort should be made by airlines and airport operators to identify airport capacity limitations and potential congestion problems well before these problems occur [1]. Many analyzes show that airports need additional capacity if demand steadily reaches 80% of the capacity or acceptance rates [2]. While the main goal should be to increase airport capacity to meet increasing demand, the need to maximize the utilization of existing airport capacity and airline resources is becoming more critical than ever before [3]. Consequently, capacity should be related to design peak period processing capability, rather than annual figures [4]. This could be accomplished exclusively by an adequate coordination process involving a proper allocation of constrained airport capacity, namely by maximizing the efficient use of airport infrastructure [5]. It is often possible to increase capacities significantly through relatively inexpensive changes in procedures or personnel deployment [6]. At airports where congestion exists or is anticipated, demand/capacity and level of service examinations have to be done to [7]:

– Establish the time, degree, and cause of congestion

– Define a methodology for determining the capacity of the airport, considering the level of service to be provided, and comparing this with typical peak demand to identify capacity limitations

– Consider means of removing such limitations in the short term, at a relatively small cost, taking into account the effect of any related delay factor

– Harmonize the level of service provided with IATA recommendations for measuring individual sub-systems of the terminal.

The efficient handling of passengers is essential for reliable terminal processes [8]. In most cases, the focus

on how to adequately handle passengers and deal with capacity determination is always put on larger airports that are more competitive on the market. However, smaller airports with less passenger flow in the low season are finding it difficult to follow the step in terms of managing queuing processes to be adjusted to the various fluctuations in transport demand. While it might be considered easier to handle with fewer passengers, such airports are often faced with the great problem of defining optimal capacity due to seasonality [9]. At Rijeka International Airport, traffic intensity in the high season is almost three times higher than in the low season, presenting a great challenge for managers to adequately plan the capacity and queuing processes. Solving this problem, the aim is not to provide sufficient capacity during peak hours and to provide instant service without waiting, as this causes excess capacity that is unused in other periods when there is no traffic jam [10]. Consequently, managers have to significantly reduce the available capacity in the low season thus causing unnecessary additional costs for the equipment maintenance [11]. There is no need for so many employees in the low season as during the high season, which means a smaller number of employees can be hired throughout the year. If a solution is found in the recruitment of more employees during the high season, a problem of the provided service quality remains since those are seasonal workers which are not sufficiently familiar with the processes and need some time to adapt to the system environment. Since optimization of business processes represents the basis for improving competitiveness, it is necessary to develop a current state model of the system, supervise the processes and analyse changes in order to determine whether the reorganization is needed and where to apply corrective measures [12]. Consequently, congestion control mechanisms will ultimately reduce excessive times and associated costs [13]. Therefore, in order to assess the performance of the airport, this paper will analyze the utilization rate of terminal resources at Rijeka International Airport.

2 Methodology

Queuing theory, as one of the most commonly used operations research methods, covers a wide range of applications, such as service and manufacturing industries. This method studies the mode of serving the units that arrive in the system at irregular (random) time intervals but with a previously known probability distribution of arrival times. Queuing theory can also be very useful in predicting how some changes will affect the behaviour of a particular queuing system [14]. In determining the optimal capacity of a queuing system, there are two different types of problems that can occur: a certain number of units waiting to be served or an available server waiting for units to arrive into the system to provide the requested service [15]. Using mathematical models, the interdependence between all the processes in a certain queuing system (arrival, waiting, serving, departure) is determined to define optimal capacity. The optimal system capacity is achieved with the number of servers that will minimize waiting times, as well as associated costs. The main goal is to reduce losses caused by waiting in the queue, rather than eliminating the waiting process. This can be accomplished by speeding up the service rate or adding additional servers. The capacity of a queuing system is defined by the maximum number of units waiting and being served in a certain period [16].

The objective of this research was to examine whether the existing capacity utilization of the observed system will satisfy the theoretical stability condition. To achieve theoretical stability condition the service rate must be greater than the arrival rate. The paper aims to evaluate if the existing queuing system capacity can handle peak time demand promptly. Queuing system shown in Figure 1, where a customer must pass through several different phases in a particular order to complete the overall service process, is called a multi-phase queue and will be further analyzed in the next section. In this particular multi-phase multi-server queuing system, there is one waiting area for separate servers.
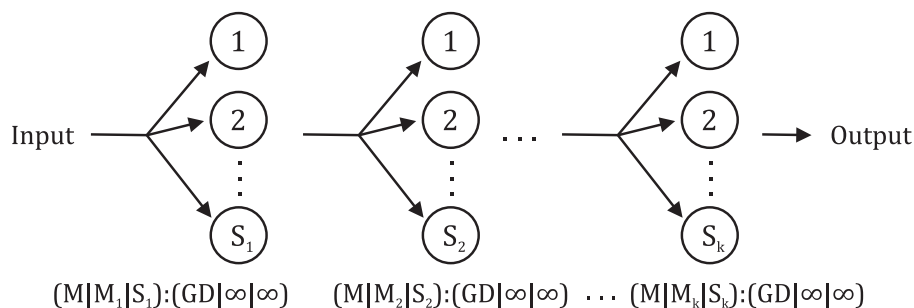

Figure 1 Multi-phase multi-server queuing system with an infinite queue length

In order to investigate whether the passenger capacity is optimally determined, basic queuing parameters are defined – average arrival rate and average service rate. The arrival rate stands for the average number of units arriving in the system in a certain period:

$$\lambda = \frac{1}{t_{arr}} \tag{1}$$

while the service rate represents the average number of units served in a period:

$$\mu = \frac{1}{t_{ser}} \tag{2}$$

In the above-given equations (1) and (2), t_{arr} denotes the average time elapsed between two consecutive arrivals and t_{ser} presents the average service time. If λ is greater than μ, units will have to wait in the queue before being served, otherwise the server will have to wait for the arrival of the unit. The most important queuing parameters that must be calculated for each phase i (i=1, 2,…, k) separately are traffic intensity:

$$\rho_i = \frac{\lambda_i}{\mu_i}; \quad i = 1, 2, \dots, k \tag{3}$$

and system utilization rate:

$$\rho_{Si} = \frac{\lambda_i}{S_i \mu_i}; \quad i = 1, 2, \dots, k \tag{4}$$

where S_i is an integer number of servers in phase i. Traffic intensity is the quotient of the arrival and service rate, representing an indicator of server utilization. The parameter ρ_i refers to the single-server system, while ρ_{Si}, defined by equation (4), is used for multi-server multi-phase queuing problems. To keep the multi-phase single-server system stable the following condition must be satisfied:

$$0 < \rho_i < 1 \tag{5}$$

meaning the arrival rate must be less than the service rate. If the system utilization rate is greater than or equal to 1, the system is unstable and congestion occurs. In that case, it is necessary to increase the number of servers until the below-mentioned criterion is met:

$$0 < \rho_{Si} < 1 \tag{6}$$

which classifies the system as a multi-phase multi-server queuing system. This condition refers only to infinite queue length systems. Based on previously defined parameters, the remaining queuing indicators can be calculated to evaluate the efficiency of a particular queuing system. Performance indicators of a multi-phase multi-server queuing system are obtained using the following expressions. First, it is necessary to calculate probabilities of zero units in each phase:

$$P_{0i} = \left[1 + \rho_i + \frac{\rho_i^2}{2!} + \dots + \frac{\rho_i^{S_i}}{S_i!} + \frac{\rho_i^{S_i+1}}{S_i!(S_i - \rho_i)}\right]^{-1} \quad i = 1, 2, \dots, k \tag{7}$$

Furthermore, the average number of units waiting in the queue is to be determined using the following equation:

$$L_Q = \sum_{i=1}^{k} \frac{\rho_i^{S_i+1}}{(S_i-1)!(S_i-\rho_i)^2} \cdot P_{0i} \tag{8}$$

This performance indicator represents the total number of units waiting in all phases of service, that is the sum of passengers waiting from the first phase to the last phase of service. By summing the average number of units in the queue with traffic intensity, the average number of units in the system is obtained:

$$L_S = \sum_{i=1}^{k} (L_{Qi} + \rho_i) \tag{9}$$

The average time a unit spends waiting in the queue can be calculated as follows:

$$W_Q = \sum_{i=1}^{k} \frac{L_{Qi}}{\lambda_i} \tag{10}$$

while the average time a unit spends in the system is determined by the following equation:

$$W_S = \sum_{i=1}^{k} \frac{L_{Si}}{\lambda_i} \tag{11}$$

The probability of n units in the system is obtained as follows:

$$P_{ni} = \begin{cases} \frac{\rho_i^n}{n!} \cdot P_{0i} & \text{for } 1 \le n \le S_i \\ \frac{\rho_i^n}{S_i! \cdot S_i^{n-S_i}} \cdot P_{0i} & \text{for } n > S_i \end{cases}; \quad i = 1, 2, \dots, k \tag{12}$$

where the first formula is used if n lies in the interval from 1 to S, and the second one is applied if n is greater than S. This performance indicator represents the probability of n units currently being in a particular phase of the service system. In other words, P_{ni} indicates that n passengers are currently being served or waiting in line to be served at each particular phase of the service. Equation (13) is used to determine the minimum number N_i of free waiting spots needed in every queue, before each phase:

$$N_i \ge \frac{\ln(1-\beta)}{\ln \rho_i} - 1; \quad i = 1, 2, \dots, k \tag{13}$$

where β represents the level of certainty that a unit will be placed in the queue. In such a way, the length of any queue can be predicted.

3 Results and discussion

With a passenger terminal capacity of 1,000,000 passengers, Rijeka International Airport tends to be an active, competitive participant in creating sustainable development and prosperity of Primorje-Gorski Kotar County [17]. Even though the overall terminal capacity utilization rate is very low, an average increase of 14% has been recorded for five years period (2015–2019). Besides that, a record number of 200,841 passengers in 2019, resulted
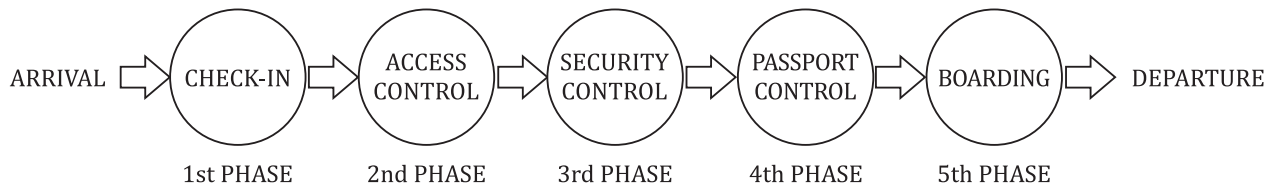
Figure 2 Queuing system at Rijeka International Airport

Source: Authors

in the highest capacity utilization so far (20%) [18]. Since passenger flow at Rijeka International Airport is highly dependent on tourism, passenger typical profile are tourists. That is one of the main reasons why a significant number of airlines are operating exclusively in peak season every year. Thus, this paper primarily deals with the impact of seasonality issues on efficient airport capacity utilization.

The research is based on the analysis of a multi-phase multi-server queuing system at Rijeka International Airport. At the airport, after the first phase, passengers automatically enter the queue for the next phase of service. As shown in Figure 2, departing passengers must pass through five different phases since they enter the airport terminal building until they board the aircraft. Since web-checked passengers are not obliged to report to the check-in counter and can proceed directly to the second phase i.e. access control point, the assumption is that the average arrival rate in the second phase will be higher than the arrival rate in the first phase.

At Rijeka International Airport, the customs control counter opens as needed, if the passenger has a connecting non-EU flight. The customs control phase is excluded from the scheme presented in Figure 2 since in this specific observed period there were no such passengers in the queuing system. Furthermore, Rijeka International Airport has only one runway. By observing take-off and landing, no potential problems were detected as a negligible number of flights take place at the same time. Therefore, runway utilization will not be discussed in this paper.

Passengers are entering the system with an infinite queue length based on the First In First Out (FIFO) queue discipline and passenger arrivals follow the Poisson distribution. In a Poisson stream, customers arrive in exponentially distributed independent intervals. The Poisson stream is important as it is a convenient mathematical model of many real-life queuing systems and is described by a single parameter – the average arrival rate. The common assumption is that the customers' service times are independent, i.e. do not depend upon the arrival process. Another assumption is that the service time is exponentially distributed. For the statistical queuing models, the most often accepted hypothesis is that the flow intensity of arrivals and service intensity follows the Poisson distribution [19]. Based on the mentioned facts, the following hypothesis is accepted: the distribution of minutes per

number of passengers at the airport behaves according to the Poisson distribution.

The queuing system has been observed in both, high season (HS) and low season (LS). In each phase, there are two servers, except in the first phase where five servers are available. Although the airport provides several servers at each phase, in the low season only one server is used in each phase to process passengers, as the number of passengers during winter is considerably smaller. However, in high season all available servers are used. The results of the multi-server queuing system analysis in high season are compared with single-server system results for the low season, obtained from previous research [20].

Based on the five-year average statistics of Rijeka International Airport (2015–2019), the highest passenger traffic in the low season has been recorded in February, while August is the busiest month in the high season [18]. According to the flight schedule, the peak period at the airport in the low season is Tuesday, while in the high season it is Thursday. Therefore, two measurements were done, the first one in low season and the second one in high season. Both measurements were performed in one hour period, at the moment when the largest number of flights overlaps, i.e. when the greatest number of flights is scheduled at a similar departure time. Furthermore, the data was collected exclusively for passengers departing from the airport, while arriving passengers were not taken into account. The collected data relating to passengers' arrival and service at the airport, both for low and high season, are listed in Table 1, for each phase separately. Using queuing theory method, the analysis is conducted on a sample of 112 passengers in low season and 306 departing passengers in high season, based on real-time data, collected by authors. The input data, both for low and high season consists of passengers' arrivals to the first phase ie. check-in counter within one hour, including the time between two consecutive individual arrivals in the range of 1 – 6 minutes (x_i) together with the associated number of passengers entering the system over the observed time (f_i). The input data also include passenger service times in the range of 10 – 80 seconds, as well as the number of passengers being served at the observed period.

The collected data shows that the greatest number of passengers arrive in the first phase within one minute. As the time interval is increasing, the number of passengers entering the first phase is decreasing. The second

Table 1 Input data: Passenger arrivals and passenger service

Phase description	High season (HS)				Low season (LS)			
	Passenger arrivals		Passenger service		Passenger arrivals		Passenger service	
	x_i [min]	f_i	x_i [sec]	f_i	x_i [min]	f_i	x_i [sec]	f_i
Check-in	1	191	30	46	1	48	30	14
	2	58	40	47	2	10	40	15
	3	24	50	43	3	15	50	11
	4	33	60	55	4	18	60	22
	5	-	70	62	5	11	70	29
	6	-	80	53	6	10	80	21
Access control	1	238	10	105	1	75	10	71
	2	50	20	49	2	24	20	17
	3	3	30	42	3	3	30	10
	4	15	40	37	4	5	40	5
	5	-	50	36	5	3	50	4
	6	-	60	37	6	2	60	5
Security control	1	238	30	65	1	75	30	33
	2	50	40	46	2	24	40	14
	3	3	50	50	3	3	50	18
	4	15	60	47	4	5	60	15
	5	-	70	49	5	3	70	16
	6	-	80	49	6	2	80	16
Passport control	1	238	30	69	1	75	30	37
	2	50	40	49	2	24	40	17
	3	3	50	47	3	3	50	15
	4	15	60	46	4	5	60	14
	5	-	70	47	5	3	70	14
	6	-	80	48	6	2	80	15
Boarding	1	252	10	123	1	86	10	89
	2	11	20	44	2	11	20	12
	3	10	30	36	3	2	30	4
	4	13	40	34	4	6	40	2
	5	11	50	35	5	5	50	3
	6	9	60	34	6	2	60	2

Source: Authors

phase data coincide with phases three and four since the servers are located physically near. Completing the second phase, passengers must automatically proceed to the third and fourth phase. Passenger service time varies from phase to phase. In the second and fifth phase, the passenger service time is relatively short, as in these phases only the following is checked: whether the name on the passenger's boarding pass matches the name in his identification document, as well as the document expiration date. In the remaining three phases, the passenger service time is slightly longer, since the passengers, their luggage, and travel documents are checked in more detail.

According to the above-mentioned input data, the average time between two consecutive arrivals and the average service time has been calculated. Based on those results, basic queuing parameters (average arrival rate, average service rate, and traffic intensity) have been calculated for each server and the system as well. As mentioned in the previous paragraph, the second phase data coincide with phases three and four. By that, the average arrival rate at the second phase is equal to phases three and four, while on the other hand, the average service rate differs for each phase due to human-controlled servers, as given in Table 2.

Table 2 Average arrival and service times

Phase description	HS		LS	
	t_{arr} [min]	t_{ser} [sec]	t_{arr} [min]	t_{ser} [sec]
Check-in	1.67	56.5	2.68	58.93
Access control	1.33	28.73	1.60	18.30
Security control	1.33	53.79	1.60	51.34
Passport control	1.33	53.17	1.60	49.64
Boarding	1.52	27.25	1.56	14.29

Source: Authors

Observing the results for the high season, the second phase has the highest average arrival rate of 1.33 minutes, while the first phase has the lowest average arrival rate of 1.67 minutes. In terms of average service time, the fifth phase provides the fastest and the first phase the slowest service with 27.25 and 56.50 seconds respectively. Regarding low season results, the passengers most often arrive in the last phase, on average every 1.56 minutes with the shortest average service time of 14.29 seconds. The first phase has the longest average time between two consecutive arrivals of 2.68 minutes, and also the longest average service time – 58.93 seconds.

Based on the data from Table 2 and according to equations (1-4), the basic parameters were obtained, as stated in Table 3. In addition to the basic queuing parameters λ, μ and ρ, the value of ρ_s is calculated for the high season since a multi-phase multi-server queuing system is analyzed. In high season, there are five servers available in the first phase, whilst all the other phases provide two servers. The parameter ρ presents the utilization rate of each server at each phase.

According to data for the high season given in the table above, the following can be concluded: the first phase has the lowest arrival rate with only 35.93 passengers per hour, unlike the second phase that has the utmost average arrival rate with 45.11 passengers per hour. Comparing the data for the low season, the lowest arrival rate in the low season is also recorded in the first phase (22.39 pass./hour), while the greater number of passengers enter the system in the fifth phase – 38.46 pass./

hour. Furthermore, the second phase and fifth phase servers can process the greatest number of passengers per hour in high season, 125.30 and 132.11 respectively, while the first phase has the lowest average service rate of 63.72 passengers per hour. It is understandable that the average service rate is the lowest in the first phase, due to differing passenger service time, since many different scenarios could occur, such as large groups with a lot of luggage wanting to sit together, passengers with reduced mobility having special requests, infants having baby equipment, unaccompanied minors, pets traveling in the cabin or in the aircraft cargo hold, etc. [20]. Results obtained for low season coincide with high season observations since the greatest number of passengers can be served in the second and fifth phase, while the first phase provides the slowest service.

Observing the obtained traffic intensity for high season, it is concluded that the servers in the third and fourth phase are the most utilized with 67%. In contrast, the level of traffic intensity is the lowest in the fifth phase with a 30% utilization rate. In low season, traffic intensity is also the highest in phases three and four. Since the value of the traffic intensity parameter is less than 1 at each phase, the theoretical condition in equation (5) has been met and the queuing system can be declared as stable. The results confirm that, even with a single server at each phase, the observed system can operate with no congestion at all. Taking into consideration the average arrival and service rates, five servers in the first phase and two servers in all the other ones are not necessary because the servers are

Table 3 Overview of fundamental queuing parameters

Phase number (i)	Phase description	λ [pass./hour]		μ [pass./hour]		ρ		ρ_s
		HS	LS	HS	LS	HS	LS	HS
1	Check-in	35.93	22.39	63.72	61.09	0.56	0.37	0.11
2	Access control	45.11	37.50	125.30	196.72	0.36	0.19	0.18
3	Security control	45.11	37.50	66.93	70.12	0.67	0.53	0.34
4	Passport control	45.11	37.50	67.71	72.52	0.67	0.52	0.33
5	Boarding	39.47	38.46	132.11	251.92	0.30	0.15	0.15

Source: Authors

Table 4 Queuing system performance indicators

Phase number (*i*)	L_Q [pass.]		L_S [pass.]		W_Q [min]		W_S [min]		P_{0i}
	HS	LS	HS	LS	HS	LS	HS	LS	
1	0.00	0.21	0.56	0.58	0.00	0.57	0.94	1.55	0.5690
2	0.01	0.04	0.37	0.24	0.02	0.07	0.49	0.38	0.6949
3	0.09	0.61	0.76	1.15	0.11	0.98	1.01	1.84	0.4959
4	0.08	0.55	0.75	1.07	0.11	0.89	1.00	1.71	0.5003
5	0.01	0.03	0.31	0.18	0.01	0.04	0.46	0.28	0.7400
Total	0.20	1.44	2.75	3.22	0.25	2.55	3.90	5.76	-

Source: Authors

Table 5 IATA Guidelines on maximum waiting times for Economy Class Passengers (in minutes)

Phase description	Over-Design	Optimum	Sub-Optimum
Check-in Desk	< 10	10 – 20	> 20
Security control	< 5	5 – 10	> 10
Outbound Passport control	< 5	5 – 10	> 10

Source: [21]

underutilized. Each server in the first phase is only 11% used, causing higher costs than needed.

Equations (7-11) are used for calculating the performance indicators of the multi-phase multi-server queuing system, as given in Table 4. The first step in determining performance indicators of a multi-server queuing system is to calculate the probability P_{0i} using equation (7). The probability P_{0i} is calculated only for the high season since the multi-server queuing system is applied exclusively in the high season.

The highest probability of a system being idle is 74%, occurring in the fifth phase, while the lowest probability of 49.59% can be found in the third phase. The third phase has the greatest number of passengers waiting in the queue both for high and low season, whereas in the first phase there are no passengers in the queue in high season. The reason is that in high season there are five available servers in the first phase, so each server manages to serve passengers promptly with no congestion. Consequently, the average waiting time in the first phase is equal to zero in the high season, but in the third phase, the average waiting time is the greatest, with a total of 0.11 and 0.98 minutes for the high and low season respectively. The third phase has the greatest, while the fifth phase has the lowest number of passengers in the system both for high and low season. Also, the average time spent in the system in high season is the greatest in the third phase, while the lowest average time can be found in the fifth phase. There is a total of 2.75 passengers in the system where on average, a total of 0.20 passengers are waiting in a queue in high season, meaning an average of 2.55 passengers are being served and that is an acceptable ratio. The total time a passenger spends in the system in high season is 3.90

minutes, which is very satisfying taking into consideration that the average waiting time is 0.25 minutes.

Regarding the low season, the third phase most adversely affects the system, providing the longest queue of 0.61 passengers. The average queuing time of 0.98 minutes is also the longest in the third phase. In the fifth phase, the number of queuing passengers is the lowest – 0.03, as well as the average waiting time of 0.04 minutes. The total number of passengers in the system is 3.22, of which the average number of passengers in the queue is 1.44, meaning that the average number of passengers being served is 1.78, representing a less acceptable ratio than in high season. The total time a passenger spends in the system is 5.76 minutes, which is a satisfactory result, considering that a passenger spends 2.55 minutes waiting in the queue.

If the data in Table 4 is compared with the International Air Transportation Association (IATA) guidelines in Table 5, it can be concluded that waiting times at Rijeka Airport are quite short and acceptable during both high and low season. All the values obtained are slightly above zero thus indicating a substantially well utilization of the system's capacity. Analyzing the results in Table 4 and comparing them with IATA guidelines in Table 5, it has been established that results obtained in the high season largely coincide with the results obtained in the low season.

The next step is to determine the probability that a certain number of passengers (0-5) will be encountered at a particular phase. Therefore, equation (7) has been used to calculate the P_{0i} value and equation (12) to obtain the remaining probabilities, as given in Table 6.

The probabilities of servers being idle at certain phases have been previously discussed after Table 4 since

Table 6 Probability P_{ni} of n ($n=0,...,5$) passengers in the i-th phase ($i=1,...,5$)

Phase	Check-in		Access control		Security control		Passport control		Boarding	
P_{ni}	HS	LS	HS	LS	HS	LS	HS	LS	HS	LS
P_{0i}	0.5690	0.6335	0.6949	0.8094	0.4959	0.4652	0.5003	0.4829	0.7400	0.8473
P_{1i}	0.3208	0.2322	0.2502	0.1543	0.3342	0.2488	0.3333	0.2497	0.2211	0.1294
P_{2i}	0.0905	0.0851	0.0450	0.0294	0.1126	0.1331	0.1110	0.1294	0.0330	0.0198
P_{3i}	0.0170	0.0312	0.0081	0.0056	0.0380	0.0712	0.0370	0.0668	0.0049	0.0030
P_{4i}	0.0024	0.0114	0.0015	0.0011	0.0128	0.0381	0.0123	0.0345	0.0007	0.0005
P_{5i}	0.0003	0.0042	0.0003	0.0002	0.0043	0.0204	0.0041	0.0179	0.0001	0.0001

Source: Authors

Table 7 Free waiting spots needed in each phase

Phase number (i)	Phase description	N_i ($\beta=0.95$)	
		HS	LS
1	Check-in	≥ 4	≥ 2
2	Access control	≥ 2	≥ 1
3	Security control	≥ 7	≥ 4
4	Passport control	≥ 6	≥ 4
5	Boarding	≥ 1	≥ 1

Source: Authors

those values are the basis for calculating the remaining performance indicators of the observed queuing system. It is evident that the probabilities P_{0i} are the greatest in comparison to the others, moreover, the last phase provides the greatest probabilities both for high and low season. There is a 74% probability that the server in the fifth phase will be idle in the high season and 84.73% in the low season. The probability that five passengers will be met in this phase both for the high and low season is equal to zero. As the number of passengers at each phase is increasing, the associated probabilities are decreasing.

In Table 7, free waiting spots that need to be available in each queue, at each phase are stated. This data have been calculated using equation (13), based on 95% certainty a passenger would be placed in a queue.

The greatest number of available waiting spots both in high and low season has to be provided in phases three and four, 7 and 6 spots respectively in high season and 4 in low season, which is significantly higher than in other phases. The cumulative sum of the probabilities at phase three, for $n=4$, is 0.9935 in high season and 0.9564 in the low season, meaning that it is possible to provide four waiting spots in the third phase, with an even higher certainty level than β (95%).

4　Conclusion

Based on the obtained results, it can be concluded that seasonality does not affect the efficient use of passenger capacity at Rijeka International Airport as significantly as expected. The present findings confirm that there is no system congestion at any phase since the system utilization rate is very low. This analysis led to the following conclusions: potential bottlenecks, in both low and high season, are identified in phases three and four – security and passport control. The average waiting times are highly acceptable, as they fall within the IATA guidelines range. If waiting times and congestions are tended to be more reduced, then additional servers and staff should be hired, which is less profitable for airport management. Since costs are the main criterion in decision making and business optimization, they should be included in the results and analysis of the solution. For further analysis, it would be necessary to consider the calculation of cost per passenger and server. Even though the results are acceptable and the system is stable, further research should be done on optimizing the usage of service facilities taking into account the criterion of minimum costs. Furthermore, that would result in greater airport competitiveness, also in higher passenger satisfaction with a direct impact on tourism and entire tertiary sector development.

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