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Applications of Queueing Models to Improve Airport Operations

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Abstract: Balancing the waiting times of passengers and the allocation of personnel and facilities among different operations in an airport is a challenging problem. Queueing models have been widely regarded as useful tools for evaluating the performance of a service system because of their ability to provide quick and reasonably accurate values for performance measures related to waiting times and queue lengths. Hence, the queueing approach is an important tool to analyze and improve airport operations. This paper reviews and categorizes the literature on the application of queueing theory to model the check-in, security screening, and baggage claim processes at passenger terminals and the runway service, taxi-out, and landing processes at aircraft terminals. In doing so, the paper also identifies potential future research opportunities, some of which are motivated by new airport technologies and processes.

Keywords: Check-in counters, departure process, landing process, queueing theory, security screening.

1. Introduction

According to the Federal Aviation Administration [24], from 2019 to 2039, the U.S. mainline carrier domestic revenue passenger miles (RPMs) and international RPMs are expected to grow at average annual rates of 1.9% and 3.0%, respectively, while the domestic and international enplanements are expected to increase at average annual rates of 1.6% and 3.1%, respectively. As more people choose to travel by air, the strain on airport facilities will grow. More passengers and flights are likely to worsen the delay and congestion at the airports (Brueckner [7]); hence, it is important to find ways to improve airport operations.

The COVID-19 global pandemic declared in March 2020 caused a sudden and dramatic decline in demand for both business and leisure air travel. With the availability of effective vaccines by the end of 2021, there was a slow but steady bounce back in especially leisure air travel, with recent reports indicating that passenger air traffic levels were back to pre-pandemic levels and projected to be around 2% higher in the first quarter of 2024 than in 2019 as per the International Civil Aviation Organization [38]. Of relevance to this article's theme are the new challenges for airport operations including screening procedures to verify passenger's vaccination or testing status before departure and upon arrival. Queueing

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models could certainly be an important tool for resource planning – e.g., the estimation of staffing levels needed to ensure the smooth flow of passengers through multiple layers of screening.

Passenger terminals and aircraft terminals are two important areas of any airport. Enplaned passengers, who arrive according to their flight schedule, must be served sequentially by check-in facilities and security screening facilities, employing airport and airline personnel and equipment. Deplaned passengers with check-in baggage must go through the baggage claim area to pick up their baggage. At the aircraft terminal, runways serve the landing and departure of airplanes. Unlike other systems, most of the procedures at an airport are time dependent. This non-stationary characteristic increases the difficulty of evaluating the performance of airport operations. Queueing models can address the time-dependent feature and provide analytical means to compute performance measures.

The main objective of this study is to summarize published research in modeling the processes in airports using queueing theory and to identify future research opportunities. To this end, this paper focuses on reviewing and categorizing the applications of queueing theory to both passenger terminal and aircraft terminal operations. The taxonomy we have developed for queueing applications in airports is shown in Figure 1. For the first group, the focus is mainly on the check-in, security screening, and baggage claim processes. In the second group, the focus is on the runway service, taxi-out, and landing processes. The many research problems and the wide variety of queueing models that were applied to study those problems in the passenger and aircraft terminals of an airport are summarized in Table 1. Besides reviewing the existing research in each focused area, we also identified limitations of current research studies in a few instances and provided suggestions for future research.

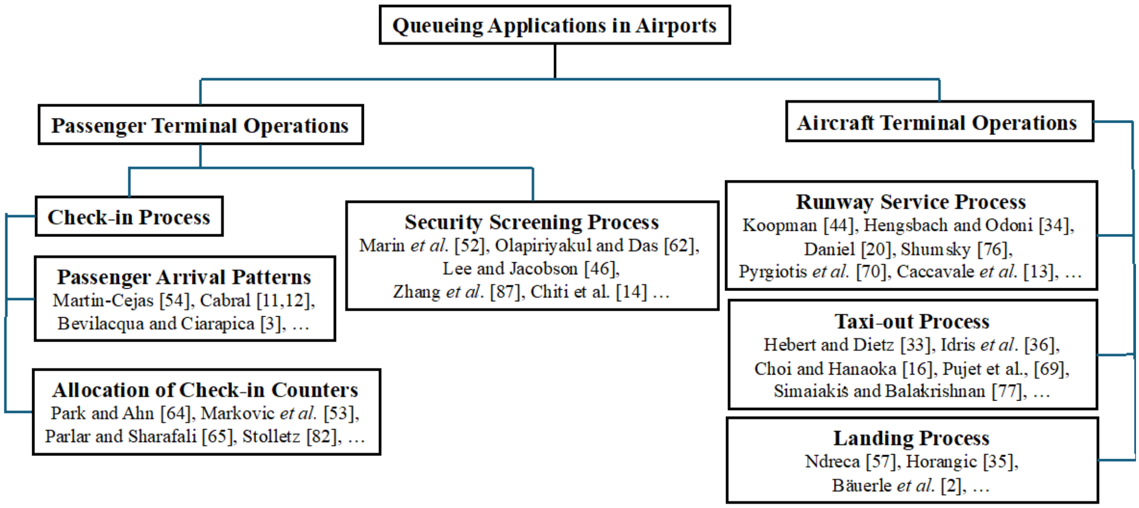

Figure 1. A Taxonomy of Literature on Applications of Queueing Models in Airports

The rest of this paper is organized according to the taxonomy as follows. Section 2 introduces the methodological approach. The queueing applications in the passenger terminal and aircraft terminal areas are reviewed in Section 3 and Section 4, respectively.

Section 5 reviews the research studies related to bus services and immigration and customs operations. Section 6 focuses on new technologies and processes being introduced at airports and the need to incorporate their influence in the models developed. Section 7 concludes by discussing the main findings and summarizing future research directions.

2. Review Methodology

We used "queueing models", "queueing theory", and related keywords as shown in Figure 1, and limited our selection to papers that discuss the problems within the two main areas, namely, passenger terminal operations and aircraft terminal operations. Within each main area, we considered key sub-areas. In passenger terminal operations, we considered check-in, security screening, and baggage claim processes. In aircraft terminal operations, we included runway service, taxi-out, and landing processes. Other operations such as airport bus operations, and immigration & custom operations are categorized as miscellaneous applications.

With the above scope in mind, we identified papers published in major journals and proceedings in transportation management and operations management, such as the ones listed below.

Transportation Science, *Transportation Research Record*, *Journal of Transportation Engineering*, *Journal of Aircraft*, *Air Traffic Control Quarterly*, *Journal of Air Transport Management*, *Transportation Research Part A: Policy and Practice*, *Transportation Research Part B: Methodological*, *Transportation Research Part C: Emerging Technologies*, *Transportation Research Part E: Logistics and Transportation Review*, *Transportation Planning and Technology*, *Research in Transportation Business & Management*, *Queueing Models and Service Management*, *Management Science*, *Operations Research*, *European Journal of Operational Research*, *Journal of the Operational Research Society*, *AIAA Guidance, Navigation, and Control Conference*, and *American Control Conference*.

From these sources, we selected articles published mainly after 1983, in which the authors applied queueing theory to address problems in the focus areas of this paper. Table 1 categorizes the problems studied in each focus area and the queueing models applied to investigate these problems.

3. Passenger Terminal Operations

At an airport passenger terminal, enplaned passengers must complete check-in and security screening before boarding. Airline companies now offer online check-in services and self-check-in kiosks at airports, which help reduce congestion and wait times. According to the 2017 Passenger IT Trend Survey, about 54% passengers used self-service check-in (SITA [79]). However, self-service has not been able to replace the counter service offered by airline staff. Many passengers still must go to the check-in counters to drop off their check-in luggage and obtain their boarding passes, especially for international travel. Besides, almost all passengers have to go through the security check point, except for those special persons who are exempt from airport security checks (O'Keefe [60]). The characteristics of the passenger arrival process and the nature of check-in, security screening, and baggage claim services will influence the capacity of the three procedures. Inadequate

Table 1. A Categorization of Problems Studied and Queueing Models Applied

Problem Area	Models	References
Passenger Arrival Patterns		
Poisson arrivals	$M/M/1$; $M/M/C$	Martín-Cejas [54]; Cabral [11, 12]
Group arrivals	$M^X/M/c$	Martín-Cejas [54]; Kabak [41]; Cromie et al. [19]; Srinivasan and Renganathan [80]
Time-dependent arrivals	$M(\mathrm{t})/M/c(t)$; $G(t)/D/c(t)$; $M(t)/G/c(t)$	Markovic et al. [53]; Park and Ahn [64]; Stolletz [82]
Allocation of Check-in Counters		
Assignment of check-in counters	$G(t)/G(t)/c(t)$; $M(t)/M/c(t)$; $G(t)/D/c(t)$	Parlar and Sharafali [65]; Markovic et al. [53]; Park and Ahn [64]
Performance of the check-in system	$M/M/1$; $M(t)/G/c(t)$	Martín-Cejas [54]; Stolletz [82]
Security Screening Process		
Two-stage inspection	$M/M/1$; $M/PH/2$; $G/M/c$	Olapiriyakul and Das [62]; Zhang et al. [87]; Chiti et al. [14]
One-stage inspection with multiple risk levels	$M/M/c$	Lee and Jacobson [46]; Lazar Babu et al. [45]
Baggage Claim Process		
Deciding the capacity		Brunetta et al. [8]; Enoma et al. [22]; Browne et al. [6]; de Barros and Wirasinghe [21]

(Continued)

Problem Area	Models	References
Runway Service Process		
Aircraft awaiting to land or takeoff in a single common queue	$M(t)/M/1/N$; $M(t)/D/1/N$; $M(t)/M(t)/c/N$; $M(t)/D/c/N$	Koopman [44]; Hengsbach and Odoni [34]; Daniel [20]
Delay estimation	$M(t)/E_r(t)/1$	Pyrgiotis et al. [70]
Multiple dependent runways	$M/G/1$	Mori and Aoyama [56]
Local runway congestion	$PSRA/D/1$; $M(t)/E_r(t)/1$	Caccavale et al. [13]; Jacquillat and Odoni [39];
Runway capacity allocation	$M(t)/E_r(t)/1$	Jacquillat et al. [40]
Taxi-out Process		
Identify factors affecting taxi-out time	$D/G(D)/1$	Idris et al. [36]
Identify the best model	$M(\mathrm{t})/M(t)/c$; $M(t)/E_r(t)/c$; $M(t)/E_r(t)/c$ with server absence	Hebert and Dietz [33]
Estimate the taxi-out time	Dynamic queueing model; Open queueing network model; $D(t)/E_r(t)/1$; $D/G(D)/1$	Pujet et al. [69]; Simaiakis and Balakrishnan [77], 2016; Idris et al. [36]; Choi and Hanaoka [16]
Landing Process		
Delay analysis	$D(t)/D(t)/1$; $M/G/1$; $M(t)/M(t)/1$; $M(t)/D(t)/1$; $M(t)/E_r(t)/1$	Horangic [35]
Predict delays under time-varying demand and capacity conditions	$M/SM/1$	Peterson et al. [66]
Arrival patterns		Ndreca [57]

terminal capacity and inappropriate utilization of terminal facilities are major factors causing congestion and delays at airport passenger terminals (Park and Ahn [64]). McKelvey [55] applied a multi-channel queueing approach to study the performance of passenger "processors" under different capacity levels. The airport terminal was modeled as a series of passenger "processors" that were linked together to form a sequenced network. The service feature of each "processor" could be easily adjusted without changing the network itself.

Tošić [84] presented a review of Operations Research models for the analysis of passenger terminal operations between the entrance/exit at the terminal building and the gates, which included demand for space and service, single service counter-type facilities, baggage processing, and gate assignment. However, Tošić's [84] review did not focus on the applications of queueing theory. Especially for the two main processes, check-in process and security screening process, only the queueing applications published before 1983 were reviewed. Thampan et al. [83] reviewed the approaches for evaluating service quality in airport passenger terminals. In contrast to the papers of Tošić' [84] and Thampan et al. [83], we mainly focus on the applications of queueing models to the check-in and security screening processes. Table 2 provides a summary of the reviewed papers' research aims and objectives, models and results, and the focus area covered in passenger terminal operations. The need for airport security increased dramatically after the September 11, 2001 terrorist attack on the US, because planes could now be weapons in the hands of terrorists who manage to take control of a flight. Extensive security screening procedures have been introduced to screen individuals for potential weapons and keep them off airplanes (Birkland [4]).

3.1. Check-in process

<u>*Passenger Arrival Patterns*</u>

The passenger arrival patterns, the number of check-in counters, and the service rate at each counter will influence the performance of the check-in process. Researchers have used simple stationary queueing models as approximations to evaluate the non-stationary check-in process. Martín-Cejas [54] applied the $M/M/1$ model to evaluate the check-in mechanism for regular flights at Gran Canaria airport; for charter flights, the arrivals were considered as groups of fixed size L, and the average waiting time at the check-in counter is $L/2\mu$, where μ is service rate. Kirby and Jones [43] demonstrated that an extension of the $M/M/1$ model can also be applied to study the scenario where passengers cut in line trying to avoid missing the flight. Typically, multiple check-in counters are used for one flight. If there is uncertainty about the service rate of each server, the check-in process can be modeled by an $M/M/c$ queue with heterogeneous servers (Cabral [11], [12]). The group arrival case is common. The group size can be deterministic or random. The research on group arrivals reported in papers by Briere and Chaudhry [5], Cromie et al. [19], and Srinivasan and Renganathan [80] has indicated that the $M^X/M/c$ queueing model with group size X is applicable for such situations, where X is a random variable with distributions such as Poisson and Geometric or sometimes a fixed value.

However, because of the high variability in the number of arrivals and departures during a typical day, it is more appropriate to assume passenger flow is time-dependent or flight-dependent. In their survey paper on time-dependent queueing systems, Schwarz et al. [74] presented several references that provided applications and solution approaches for time-dependent passenger arrivals. Kim et al. [42] focused on estimating passenger volume over a day by developing a statistical model based on the distribution of dwelling time. Accurately describing passenger arrival patterns is very important as it influences the number of check-in counters required, e.g., see Bevilacqua and Ciarapica [3] and Park and Ahn [64].

Allocation of Check-in Counters

Another important issue associated with the check-in process is the allocation of counters among different flights, which can be considered as deciding the number of servers for each flight. At least half an hour before the scheduled departure time, each flight has a dedicated number of check-in counters open. The earliest work on determining airline check-in counter capacity was conducted by Lee [47] who suggested the use of an $M/M/c$ queueing model. Later, the work of Newell [58] on diffusion approximations conducted in the late 1960s and early 1970s was applied to analyze the check-in counter operations, e.g., see Lewin [48] and Piper [67].

Researchers have begun to address the check-in process more realistically. Bevilacqua and Ciarapica [3] developed a statistical queueing model to evaluate the performance of the check-in process. To realistically capture the queueing features in the check-in process, Monte Carlo simulation was applied to achieve the steady state of the system. Park and Ahn [64] presented an assignment model to determine the most appropriate number of check-in counters and the duration for each counter based on the time-dependent passenger arrival patterns. Later, by applying the assignment model at the Seoul Gimpo International Airport in Korea, they showed that the assignment model could improve the efficiency of check-in counter operations by assigning the appropriate number of counters to meet passenger demand. Unlike Park and Ahn [64], Parlar and Sharafali [65] emphasized the finite population characteristic of check-in process in their model. They developed a multi-server, single queue model with the assumption that the finite number of arriving passengers booked a specific flight forming a "death process", and the service rate depended on the number of passengers and the number of opened counters. With this queueing model, the expected number of passengers in the system and the probability of an empty system at any time were computed. Parlar and Sharafali [65] developed a queueing optimization approach by combining a stochastic dynamic programming model with a queueing model to further capture the characteristics of time-dependent arrivals. Markovic et al. [53] studied similar problems with a computational model. They combined a non-stationary queueing model and a parallel genetic algorithm with an integrated fourth-order Runge-Kutta numerical method; this approach provided far more precise results than simulation. Stolletz [82] argued that the check-in system should be modeled as a dynamic and stochastic queueing system. Stolletz extended the stationary backlog carryover (SBC) approach (Stolletz [81) to approximate the performance measures of the $M(t)/G/c(t)$ system with a single queue.

Numerical results showed that the SBC approach overcomes the shortcomings of the stationary independent period by period approach (Green et al. [31]) and the fluid approach.

To reiterate, describing the passenger arrivals realistically is the first step to better evaluating the check-in processes. As the passenger volume is usually highly time dependent or flight dependent, it is important to capture the non-stationary characteristics of the passenger arrivals. Many of the early research studies modeled the check-in process as a single queue, multi-server system. $M/M/1$ and $M/M/c$ models were the basic models used for studying the problems related to passenger arrival patterns and allocation of check-in counters. When we consider the fact that passenger arrival rate and the number of open service counters are time-dependent, a time factor is added to the models. To capture the dynamic aspects and the fact the number of passengers arriving for a flight is finite, optimization approaches such as stochastic dynamic programming have been integrated with queueing models to optimally allocate service counters.

3.2. Security screening process

According to a survey conducted by the Bureau of Transportation Statistics (BTS) in 2004, the average time for passengers without disabilities to get through the security checkpoint was 20 minutes, and about 11 minutes for persons with disabilities (Bureau of Transportation Statistics [9]). Recently, due to the emphasis on enhanced airport security, the service rate of security checkpoints has decreased. In 2011, an average of just 149 people were cleared at airport checkpoints per hour, down from 220 people an hour five years ago. During a peak travel period like Christmas, the number is as few as 60 an hour at certain airports (Clark and Mouawad [18]). The Transportation Security Administration (TSA) tested a new screening procedure with a closer check on carry-on items at 10 airports in 2017. This new policy could mean longer waiting time at security screening points as discussed in Gillies [30]. Long waiting times are likely to cause congestion at airports and negatively impact passenger experience. At the security screening point, the service facilities must always be available, the screening procedures (service) must be correct, and all passengers must accept this service without any exception. For a queueing analysis of the security screening operation, the parameters are passenger screening (service) rate, the number of screening channels (servers), and passenger arrival rate at the security screening checkpoint as mentioned in Gilliam [29].

Some research studies have focused on the number of required screening stages and server features. Olapiriyakul and Das [62] developed a two-stage queueing inspection model with one server at each stage for a given arrival rate to minimize the total waiting time and the inspection process costs. The arriving passengers are first inspected at the first stage, and a proportion of them are cleared. The remaining passengers continue to complete the inspection at the second stage. Each inspection stage is characterized by the service rate and the inspection accuracy. The two-stage queueing model is also adopted by Zhang et al. [87] to examine the trade-off between maximizing the security screening level and minimizing the expected customer delay. In the model developed by Zhang et al. [87], the service time at the first stage is assumed to follow a two-phase Coxian distribution and exponential distribution at the second stage. To further confirm the advantage of the two-stage model, they also compared the two-stage system with a one-stage system, which is treated as $M/PH/2$ queue with 2 servers, and the passengers only need to go to one server. Marin et al. [52] focused their research on server behavior, addressing that servers may change their behavior in response to queue length. They demonstrated that servers process faster when queues are longer using empirical analysis. Chiti et al. [14] proposed a model based on the M/M/c queueing system with a focus on the operations in the second stage. The accuracy of this model was validated using data collected at Pisa airport.

Lazar Babu et al. [45] studied the benefits of classifying the passengers into different groups before the security screening process conditioned on their threat probability. They also developed a model to decide the optimal number of groups. Lee and Jacobson [46] studied the security screening as a one-stage problem with a research objective similar to Zhang et al. [87]. They considered the security screening as a multi-level security system, where passengers are assigned to different security classes (servers) according to their perceived risk level. The security class service rate follows an exponential distribution, with rates $\mu_1 > \mu_2 > \ldots > \mu_M > 0$, where M is the number of security classes. Passengers with lower (higher) level security are screened by faster (slower) security classes. With this model, they computed the results that minimized the steady state expected waiting time for a passenger in the system.

As discussed above, researchers have focused on the application of single-stage and two-stage queueing models to analyze the security screening process. The two-stage model is more traditional with all passengers placed in one security class and the second level (stage) of screening is needed only for those passengers who do not clear the first level. The single-stage model places the passengers into multiple security classes with class-specific service rates.

3.3. Baggage claim process

Baggage handling at the airport passenger terminal accounts for a large portion of the operating costs as noted in Ghobrial et al. [28], and baggage claim is the most critical step of the inbound baggage handling system. The number of passengers waiting at the baggage claim area depends on the deplaned passenger arrival rate, the baggage processing rate, and the number of aircraft arriving at that time, e.g., see Brunetta et al. [8] and Enoma et al. [22].

Research on the baggage claim process mainly focuses on deciding its capacity. Browne et al. [6] investigated the baggage claim area of the Kennedy airport in New York. They developed a model to compute the maximum expected lengths of passenger queue and baggage queue at the baggage claim area. In their model, both passengers and baggage were assumed to arrive uniformly but at different rates. The delay between the beginning of passenger arrivals and baggage arrivals was considered, but only for the situation where a passenger has only one bag. Ghobrial et al. [28] modeled the delay as a function of congestion occurring at the baggage claim area based on the principle that it is more difficult for the passengers to get their baggage on the device if the claim area is more congested. The congestion is measured by the passengers per square meter at the claim area. Then the delay is a linear function of passengers per square meter. However, the passengers traveling in clusters were ignored in the research of Browne et al. [6] and Ghobrial et al. [28]. To overcome the drawback of the aforementioned works, de Barros and Wirasinghe [21] grouped the passengers into clusters that have *i* bags in total to reach an objective similar to Brown et al. [6] by using deterministic queueing theory. In this way, their model captures the correlation between the arrival times of baggage for a cluster and the impact of clusters on the area requirements.

The queueing models used to study passenger terminal operations including check-in, security screening, and baggage claim processes are summarized in Table 1. In addition, Table 2 provides a summary of the reviewed papers' research aims and objectives and their key contributions in the focus areas.

4. Aircraft Terminal Operations

According to the Bureau of Transportation Statistics [10], the on-time arrival rate for the nation's largest carriers during 2010 was 79.8%; and in the first half of 2012, it was 83.7% for the 15 largest carriers. In addition, only 4 domestic tarmac delays longer than 3 hours between January and June in 2012 were reported, while the corresponding number for the same period in 2011 was 35 as reported by the Bureau of Transportation Statistics [10]. In 2018, the average on-time arrival rate for U.S. airlines was about 79.8% according to the Office of Aviation Enforcement and Proceedings [61]. Flight delays have significant negative effects on the performance of airline companies. Especially, the tarmac delays, where flights are delayed whilst passengers are on board, could cause significant passenger dissatisfaction and irritation. To reduce the costs of aircraft terminal operations and decrease the waiting time for aircraft landing or departing, researchers have applied queueing theory to study these operations. Table 3 provides a summary of the reviewed papers' aims and objectives, and their key contributions in modeling aircraft terminal operations. Aircraft terminal area can be considered a service facility that provides complex services depending on the availability of controllers, runways, taxiways, and gates of the area (The reader is referred to Figure 1 in Simaiakis and Balakrishnan's [77] paper for a schematic of the airport system). The aircraft, which may experience queueing while waiting for their turn to land or waiting for clearance to take off, are the users of the system. In this paper, we focus on the application of queueing models to the runway service process, taxi-out process, and landing process.

4.1. Runway service process

Both in the US and Europe, departures and landings are scheduled according to the capacity of the runways, and the assumption that each aircraft would land in a very narrow time window, e.g., see Ndreca [57]. Koopman [44] was among the first to develop queueing models for a runway under time-dependent arrivals. $M(t)/M/1/N$ and $M(t)/D/1/N$ models were adopted to study the aircraft awaiting to land or takeoff in a single common queue. The results of the two models showed that the expected number of planes in the system is greatly sensitive to the distribution of the "service" time. Later, Hengsbach and Odoni [34]

Table 2. Applications in Passenger Terminal Operations

Reference	Aims and Objectives	Models and Results	Focus Area(s)			
			Passenger Arrival	Check-in Counters	Security Screen	Baggage Claim
Browne et al. [6]	To compute the expected maximum queue length of passengers and baggage at the baggage claim area under the assumption of constant passenger arrival rate.	Mathematical models were developed to calculate the expected maximum queue length under three different scenarios - passengers and baggage arriving at the same time with one bag per passenger, passengers and baggage arriving at different times with one bag per passenger, and passengers and baggage arriving at different times with a random number of bags per passenger.				X
Kabak [41]	To investigate a queueing system with bulk arrivals under two scenarios - loss system where the blocked attempts are dismissed and delay system where all attempts are served.	The probability of blocking or not being served immediately was calculated for the two types of systems. The average delay, the variance of delay, and the delay distribution were presented as well.	X			
Cromie et al. [19]	To extend Kabak's (1970) work on bulk arrival queueing system by simplifying and correcting Kabak's (1970) results.	Fixed batch size and two random batch sizes (Poisson and Geometric distributions) were studied. The results also showed how to calculate the percentiles of the queue length and the waiting time distributions.	X			
Ghobrial et al. [28]	To investigate how the baggage claim devices perform in the presence of congestion.	A deterministic model to predict the accumulation of passengers, the average service time conditional on demand that considered aircraft size, lag between arrival of passengers and bags, and the fraction of passengers that transfer, and the characteristics of claim devices.				X

(Continued)

Reference	Aims and Objectives	Models and Results	Focus Area(s)			
			Passenger Arrival	Check-in Counters	Security Screen	Baggage Claim
Brunetta et al. [8]	To estimate the capacity and delays at the baggage claim area.	A simple landside aggregate model was proposed to estimate the facility capacity under different operating conditions and the associated level of service. The effectiveness of the model was demonstrated via applications at two airports.				X
Park and Ahn [64]	To assign the appropriate number of check-in counters and deicide the operating time duration of each counter.	An assignment model was developed and applied at the Seoul Gimpo International Airport in Korea. It showed that the assignment model supported efficient operations of time-to-time check-in counter assignments.	X	X		
de Barros and Wirasinghe [21]	To estimate the size of baggage claim device and the surrounding area.	A model was proposed to describe the correlation between the arrival times of bags within the same passenger cluster and the influence of passenger cluster on the area requirements The results suggested the use of two claim devices could potentially reduce the claim area requirements.				X
Kim et al. [42]	To estimate passenger volumes over a day with behavioral differences of individuals.	A statistical model based on the dwelling time distribution was developed to estimate the departing passenger volume in each period.	X			
Lazar Babu et al. [45]	To investigate the benefit of classifying passengers into different groups at the security screening point.	The number of groups was determined based on the objective of minimizing the number of false alarms. The passenger grouping method was effective even when the threat probability is assumed constant across all passengers.			X	

(Continued)

Reference	Aims and Objectives	Models and Results	Focus Area(s)			
			Passenger Arrival	Check-in Counters	Security Screen	Baggage Claim
Martín-Cejas [54]	To estimate the service quality of the check-in process by analyzing the average waiting time and crowding level of the check-in facilities.	The service level of check-in facilities at the Gran Canaria airport was found to be excellent for regular flights. For charter flights, the study showed that improvements were needed.	X	X		
Olapiriyakul and Das [62]	To evaluate the performance of the security screening process at US airports.	A two-stage inspection queueing model was applied to derive the optimal design of passenger security inspection operation for a given arrival rate, and to evaluate the benefits of investing in improving inspection rates.			X	
Parlar and Sharafali [65]	To determine the number of counters assigned to each scheduled flight with the lowest cost.	Time-dependent solutions were derived using a multi-server queueing model. The optimal number of counters with minimum costs was decided by applying stochastic dynamic programming.		X		
Lee and Jacobson [46]	To maximize the security level and the passenger throughput at a security screening point by assigning passengers to different security classes.	The assignment policy proposed by the authors could increase the security level and reduce the expected time a passenger spends in the security system.			X	

(Continued)

Reference	Aims and Objectives	Models and Results	Focus Area(s)			
			Passenger Arrival	Check-in Counters	Security Screen	Baggage Claim
Stolletz [82]	To analyze the passenger queueing processes at the check-in system.	A stationary backlog carryover method is developed to approximate the performance measures of a time-dependent and stochastic check-in system. Moreover, the tradeoffs between the utilization of servers and service level were analyzed.	X			
Zhang et al. [87]	To investigate a security-check system with both customer service and security goals and address the tradeoff between the service level and the expected customer delay.	A two-stage queueing model was developed with the first-stage inspection following a 2-phase Coxian distribution. Robust closed-form approximations of the performance measures were developed to achieve a balance of the security level and service quality goals.			X	
Markovic et al. [53]	To optimize the number of counters for dedicated check-in and their opening and closing times.	The check-in process was modeled as a nonstationary Markov chain and together with a parallel genetic algorithm was used to optimize the check-in service. The airline costs are minimized while providing the desired service level.	X	X		
Chiti et al. [14]	To enhance the airport management efficiency and passenger travel experience	An integrated service software platform with a focus on security screening operations was proposed based on a queueing model to predict the waiting time and the number of required security control counters.			X	

extended these single-server models to multi-server models, namely the $M(t)/M(t)/c/N$ model and the $M(t)/D/c/N$ model. Their study illustrated the usefulness of the two models in clarifying the issues related to air traffic congestion. Daniel [20] expanded the $M(t)/D/c/N$ model by integrating a bottleneck model to describe and estimate the congestion prices and capacity for large hub airports. Shumsky [76] developed a queueing model to describe the runway service process based on the assumption that aircraft are allowed to accumulate in a departure queue when the system is saturated. However, this model did not reflect the stochastic nature of the process. Pyrgiotis et al. [70] studied the system-wide effects of delay propagation in a network with major airports. They modeled the runways at each airport in the system as a server. To estimate the delay at an individual airport, $M(t)/E_r(t)/1$ model with a non-stationary Poisson arrival process and time-dependent rth-order Erlang service-time distribution was applied. They also demonstrated that the $M(t)/E_r(t)/1$ model provides a reasonably accurate estimation of local delays by applying this model to the following airports - Logan International, Newark Liberty International, and Charlotte Douglas International – in the US. The research conducted by Jacquillat and Odoni [39] and Jacquillat et al. [40] also applied $M(t)/E_r(t)/1$ model to control arrival and departure service rate to dynamically optimize runway capacity allocation. Mori and Aoyama [56] studied dependent runway operations with four runways at the Tokyo International Airport. Runway B is independent, and can be modeled as a $M/G/1$ queue; aircraft landing on runway D are affected by the departure flights on runways A and C; and departure aircraft on runways A and C take off when there is no traffic on runway D. Even though the runway operations are dependent, the expected waiting time on each runway is consistent with the $M/G/1$ model. Instead of considering the inbound air traffic as Poisson process, Caccavale et al. [13] argued that Poisson process is a poor model for arrivals at a hub airport since the actual arrivals stream is a mixing-up of the fixed schedule affected by random delays. They proposed the Pre-Scheduled Random Arrivals (PSRA) process to describe the arrival process. Besides delays, the PSRA process also considers the possibility of the flights' cancellation. Caccavale et al. [13] research provided a new direction to study the air traffic setting. The reader is also referred to the survey paper by Schwarz et al. [74], which includes a nice summary of models used for the analysis of runways considering the time-dependent nature of air traffic. Investigating delays on airport runways under heavy snowfall, staffing air traffic controllers, and congestion-based pricing for airport capacity are some of the unique applications of time-dependent queueing models reviewed in Schwarz et al. [74].

4.2. Taxi-out process

Taxi-out time of an aircraft is the time interval between leaving a terminal gate (pushback) and takeoff. The taxi-out delay is the greatest among all aviation delays and contributes significantly to fuel cost and other direct operating expenses. The average taxi-out delay is approximately twice the airborne delay in minutes-per-flight as per Atkins and Walton [1].

Hebert and Dietz [33] developed three queueing models of the airport departure process based on the data collected from La Guardia Airport located in New York City in June 1994. In their models, the departure demand was modeled as a nonhomogeneous Poisson process.

For different taxi-out times, the models were as follows - Exponential model, Erlang-k model, and Erlang-k model with server absences. Evaluation showed that the Erlang-k model performed best in terms of simplicity, accuracy, and computational efficiency. To analyze the taxi-out delay, it is important to find out the factors that cause the delay. Before building the model, Idris et al. [36] identified the main factors, such as the runway configuration, distance between gates and runway, the downstream restrictions, and the takeoff queue size, that affect the taxi-out time. A queueing model was developed to estimate the taxi-out time at the Logan International Airport based on queue size estimated. The model assumed that the number of departure aircraft (N) present at the pushback time was known and estimated the takeoff queue size (Q) given N. Then the taxi-out time (T) was modeled as a function of the take-off queue size. The queueing model reduced the mean absolute error by one minute and improved the accuracy rate by 10% compared to a fourteen-day moving average model.

Research on taxi-out is not limited to modeling the service processes and identifying the factors that may affect the taxi-out time. Researchers have also attempted to build models to predict the taxi-out time. Pujet et al. [69] proposed a dynamic queueing model of busy airport departure operations to predict the taxi-out times. They modeled the taxi-out time as the sum of runway waiting time and travel time, where travel time is the time needed to reach the runway after pushback. Gaussian-like probability density functions were used to model the travel time by considering the factors that may cause variability. Upon reaching the runways, the airplanes were served according to a probabilistic service process. Later, Simaiakis and Balakrishnan [77] presented a new queueing network model to better estimate the travel times and describe the service process at the runways. In contrast to the model proposed by Pujet et al. [69], their paper modeled the taxi-out time as the sum of the time spent in the departure process if it is the only aircraft on the ground, the time delay due to aircraft interactions on the ramp and taxiways, and the time spent in the departure queue. To decide the saturation-point of the runway, they followed the same approach as Pujet et al. [69], wherein they used the number of departing aircraft on the ground as the indicator for the loading of the departure runway. However, the runway service time was assumed to be random having three possible outcomes, which were one minute, two minutes, and the next minute increment that satisfies certain conditions. In this way, Simaiakis and Balakrishnan [77] not only simplified the model but also accounted for the probabilistic nature of the runway service process. In a recent paper, Simaiakis and Balakrishnan [78] indicated that taxi-out time is affected by the total number of aircraft pushing back when a flight pushes back, and the traffic added while it is traveling to the runway. They investigated the taxi-out process by dividing it into two modules, traveling from the gates to the departure runway and queueing process at the departure runway, with a known pushback schedule. The departure queue was modeled as a $D(t)/E_k(t)/1$. The expected travelling time calculated was used for the arrival process at the departure queue, and service time was assumed to follow an Erlang distribution.

Besides the taxi-out prediction research during normal operations, Choi and Hanaoka [16] investigated the mean taxi-out waiting time at co-operating airports in an immediate disaster response situation using the open Jackson queueing network model, where each airport (node) is modeled as an $M/M/1$ queue, and airplanes are considered as customers. The problems studied in runway service process and taxi-out process and the corresponding queueing models applied are summarized in Table 1.

4.3. Landing process

It is significantly more expensive to keep an aircraft in the air than on the ground. Since the 1970s, most researchers have considered the aircraft arrival process as a Poisson process, overlooking the uncertainty present during arrivals. Time-varying stochastic properties provide a more comprehensive description of this uncertainty according to Whitt [86]. Horangic [35] considered different implementations for the transient analysis of a conceptual single-server queueing model to analyze the delays during aircraft landing at Boston's Logan International airport. The conceptual model had time-varying demand rates, a finite FIFO queue, and time-varying service rates. The different implementations were the fluid flow model ($D(t)/D(t)/1$), steady-state approximation model ($M/G/1$), difference equation models ($M(t)/M(t)/1$, $M(t)/D(t)/1$, $M(t)/E_r(t)/1$), interpolated model ($M(t)/E_r(t)/1$) and Kivestu approximation model ($M(t)/E_r(t)/1$). The results showed that the model with time-dependent Poisson arrivals and Erlangian service time was the most useful one for investigating the landing delays on the runways. However, Horangic [35] also concluded that the Poisson arrival assumption may be questionable under certain circumstances. Peterson et al. [66] developed a Markov/semi-Markov queueing model to study the aircraft landing problem at a busy hub airport, where a set of runways were treated as a single server. The demand process in a certain time interval was assumed to be deterministic. The number of runways opened in each time interval was modeled as one of values $\mu_1, \mu_2, \ldots, \mu_S$ taken from some finite S capacity states with $\mu_1 < \mu_2 < \ldots < \mu_S$. As the weather changed, the landing capacity would switch from one state to another. Bäuerle et al. [2] applied $M/SM/1$ queues with aircraft type-dependent service times to model the landing procedure of aircraft on a single runway. The stability condition and average waiting time were derived based on this $M/SM/1$ model. Moreover, to demonstrate that the $M/SM/1$ model would provide a better approximation to the real situation, the authors also compared the results with the $M/G/1$ and $M/D/1$ models. On the other hand, in a situation when an arriving airplane finds the runway occupied and it needs to fly an extra circle around the airport before trying to land again later, retrial queueing models would seem to be the most appropriate.

Some researchers also doubt the accuracy of the Poisson assumption for the aircraft arrival process. Ndreca [57] argued that the actual flight arrivals are slightly less random than Poisson arrivals. Only when the time scales are smaller than the standard deviation of aircraft delays, the pattern of arrivals is very similar to a Poisson process. Each airport gets the daily flight schedules in advance. With this schedule information, the airport can better fit the arrival intervals to a proper distribution to describe aircraft arrival process more accurately. Table 1 includes a summary of the problems studied and queueing models applied in the landing process.

Table 3 provides a summary of the reviewed papers' research aims and objectives and their key contributions in the aircraft terminal focus areas of runway service process, taxi-out process, and landing process.

Table 3. Applications in Aircraft Terminal Operations

Reference	**Aims and Objectives**	**Models and Results**	**Focus Area(s)**		
			Runway Service	Taxi out	Landing
Koopman [44]	To quantitatively study the waiting-line situations to improve capacity and reduce delays.	The queueing behavior of an airport with k independent runways can be bounded by the characteristics of the $M(t)/M(t)/k$ and the $M(t)/D(t)/k$ queueing models, which are the "worst-case" and "best-case" estimates, respectively.	X		
Hengsbach & Odoni [34]	To estimate the delays and delay costs at major airports.	The detailed analysis of congestion at a specific airport was provided, and the total delay costs were computed. The study also illustrated the concept of marginal delay costs.	X		
Daniel [20]	To describe and estimate congestion prices and capacity for large hub airports.	The expected time in queue, early and late operating times, and total expected cost of an arrival and departure for each aircraft were determined. In addition, the possibility of internalizing the delays was also investigated.	X		
Caccavale et al. [13]	To describe and forecast the inbound air traffic over a congested hub.	The proposed queueing model with Pre-Scheduled Random Arrivals (PSRA), PSRA/D/1 was demonstrated to have a great fit with the real data from London Heathrow airport.	X		
Pyrgiotis et al. [70]	To study the propagation of delays in a large network of major airports.	Delays at each airport was captured by a stochastic and dynamic queueing model, and a delay propagation algorithm was developed to update the flight schedules and demand rates in the network.	X		
Mori & Aoyama [56]	To estimate the expected waiting time on multiple dependent runways.	The average waiting time on each runway is consistent with the M/G/1 model.	X		

(Continued)

Reference	Aims and Objectives	Models and Results	Focus Area(s)		
			Runway Service	Taxi out	Landing
Jacquillat et al. [40]	To dynamically control runway allocation under operation uncertainty.	A dynamic queuing model that captures weather conditions, runway configuration, and the stochasticity of arrival and departure queues was developed to minimize runway congestion costs.	X		
Jacquillat & Odoni [39]	To improve the prediction accuracy of runway congestion.	The proposed dynamic queueing model estimated the expected arrival and departure delays well when compared to empirical data.	X		
Idris et al. [36]	To improve the accuracy of estimating the taxi-out time.	A queueing model with the knowledge of the departure aircraft quantity during the pushback time was developed to estimate the takeoff queue size by predicting the amount of passing it may experience during its taxi out.		X	
Hebert & Dietz [33]	To model and analyze the airport departure process.	Among the three models developed, $M(t)/M(t)/c$, $M(t)/E_r(t)/c$, $M(t)/E_r(t)/c$, describing the service time as an Erlang-k random variable would yield the best estimation of runway capacity and departure delays.		X	
Pujet et al. [69]	To alleviate departure traffic congestion at the aircraft terminal.	A dynamic queueing model of the departure process is constructed and validated using real data. The study shows how active control strategies using this model could reduce congestion by using aircraft gate holding and reduce the runway queueing times as well.		X	
Simaiakis & Balakrishnan [77]	To decrease fuel burn and emissions for surface operations by reducing the taxi-out time of departing flights.	A new queueing network model of departure process at airports was developed. The model could be used to investigate queue management strategies to reduce emissions and fuel burn. Predictive models for taxi-out times and unimpeded taxi-out times were also developed.		X	

(Continued)

Reference	Aims and Objectives	Models and Results	Focus Area(s)		
			Runway Service	Taxi out	Landing
Simaiakis & Balakrishnan [78]	To analyze the aircraft departure process.	A queueing model of the departure runway system is developed using transient analysis of $D(t)/E_k(t)/1$queueing systems. Using pushback schedule as input the model can predict expected runway schedule and pushback times and expected taxi-out time and queueing delay for each flight. A case study based on Newark Liberty International Airport was presented.	X	X	
Choi & Hanaoka [16]	To estimate the mean waiting time among cooperating airports in immediate disaster response.	An open Jackson network model is developed. Numerical study results showed that by adjusting the transition probability (proportion of aircraft from one airport to another) to meet the airport's service rate is preferable to drastic role re-assignment.		X	
Horangic [35]	To analyze air traffic delays.	The assumption of Poisson arrival may be questionable under certain circumstances. Delays were found to be more sensitive to the variance of service time when the system is underutilized, but not when the system is saturated.			X
Peterson et al. [66]	To study the congestion problems of aircraft landings at a busy hub airport.	A Markov/semi-Markov queueing model was presented to estimate the queue length and waiting time. The model's estimates were shown to be reasonable by implementing the model using data for the Dallas-Fort Worth International Airport.			X
Ndreca [57]	To study the features of the arrival process of aircraft and to compare them to the Poisson process.	Only when the time scales are smaller than the standard deviation of aircraft delays, the arrival pattern is very similar to a Poisson process			X

5. Miscellaneous Applications

Clearly, the focus of almost all research studies has been operations at the passenger terminal and aircraft terminal areas. Other airport operations such as airport bus services, border crossing/immigration, and airport customs have received very little attention. We found only one paper, a study by Selvi and Rosenshine [75] that modeled bus service operations that transport travelers between terminals and gate/runway locations. Since bus travelers arrived in bulk at fixed time intervals to a service facility with multiple servers, Selvi and Rosenshine [75] applied the $D^X/M/c$ queueing model with batch size X to study this problem and presented its steady-state solution.

Delays experienced at immigration and customs operations constitute another important issue at international airports. Some researchers have investigated these operations using simulation, and a few have applied queueing models. Littler and Whitaker [51] studied the immigration staffing requirements under a guaranteed service level based on stochastic simulation of passenger arrivals. Gantt [27] considered customs as one operation of their simulation model to determine the facility changes in a hub airport. Chiu and Walton [15] studied the impact of large aircraft on passenger flow with an integrated simulation method. Immigration and customs are two stages in their simulation model, while a queueing network is used to model the passenger arrival stage. Lin et al. [50] applied $M/E_k/c$ model and a more general $BMAP/PH/c$ model with a Batch Markovian Arrival Process (BMAP) and phase type (PH) service to estimate the border crossing delay based on the data collected at the Peace Bridge, a major US-Canada border crossing. Even though Lin et al.'s [50] research did not use data from an airport, it still shows the potential of using queueing models to analyze the immigration and customs operations at an airport. Nikoue et al. [59] investigated the factors affecting passenger delay at immigration using data collected from January 2012 to May 2013 at the Sydney Airport. They modeled the immigration process as an M(t)/M(t)/c(t) queueing model. They used passengers' average walking speed to estimate arrival rates, and the observed throughput and number of active service counters to estimate the service rate. Table 4 provides a summary of the research aims and objectives of the reviewed papers, along with their key contributions to the other airport operations discussed in this section.

6. New Airport Technologies, Processes, and Data Sources

As airports continuously introduce new technologies and processes to reduce wait times and improve the passenger experience, it is important for researchers to incorporate the impact of these developments into their models and modeling approaches. Security screening and check-in processes are the two main areas in passenger terminal operations where significant wait times can occur. The introduction of online check-in has allowed domestic passengers with no check-in luggage to completely bypass the airport check-in process. This reduces the arrival rate to the check-in counters and could reduce the number of personnel needed for domestic flight check-in. Automated kiosks are available in almost all major airports to assist passengers with check-in luggage. One airline employee can typically tend to multiple self-check-in kiosks. Models for the check-in process must

Table 4. Applications in Other Airport Operations

Reference	Aims and Objectives	Models and Results	Focus Area
Selvi & Rosenshine [75]	To study airport bus operations using the $D^X/M/c$ queueing system.	The steady-state system size densities were obtained by using the steady-state equations and Neuts' method of solving $GI^X/M/c$.	Bus service
Littler & Whitaker [51]	To estimate the requirement of immigration staff at an international airport terminal to meet the given processing target.	Approximate staffing requirements were determined based on the stochastic simulation of passenger arrivals and the iterative algorithm embedded within the deterministic time-based simulation.	Immigration and customs
Gantt [27]	To determine the facility changes and operational policies to meet the required service level.	Simulation can be applied to study the existing and planned Federal Inspection Service facilities. For an existing facility, the impact of changes in staffing levels and layout/flow changes could be evaluated. For a planned facility, the size of facility, e.g., number of Immigration and Naturalization Service nspection booths, bag carousels, USCS and USDA inspection stations can also be decided.	Immigration and customs
Chiu & Walton [15]	To investigate the impact of large aircraft on passenger flow using an integrated simulation method.	Immigration and customs are two stages in the simulation model, while a queueing network is used to model the passenger arrival stage.	Immigration and customs
Lin et al. [50]	To estimate the border crossing delay based on the data collected at Peace Bridge, a major US-Canada border crossing.	$M/E_k/c$ model and a more general $BMAP/PH/c$ model with a Batch Markovian Arrival Process (BMAP) and phase type (PH) service were applied to get the estimates.	Immigration and customs

consider these newer developments while estimating the wait times for passengers who need to use the physical check-in process.

Security screening is different – all passengers must be screened, and no regular passenger can bypass the physical screening process. There is a need to develop more comprehensive models that include the different classes (regular, PreCheck, and CLEAR) of passengers and multiple stages in the screening process. TSA PreCheck (https://www.tsa.gov/precheck) reduces the physical screening time, while CLEAR (https://www.clearme.com) expedites the document/identity verification process. Given that the same number of passengers (or arrivals) must be screened, airports have begun to pilot test ways to reduce the variability in the arrival process, to reduce passenger wait times at security screening. One approach is to allow passengers to make screening appointments. In the US, Seattle's SeaTac airport had an innovative pilot program from May 4, 2021, to August 31, 2021, called the "SEA Spot Saver Program" as reported in Schlappig [72], which allowed a passenger who did not have priority screening options such as TSA PreCheck and CLEAR to reserve a time they wanted to clear security. Seattle's airport made this reservation system permanent in September 2021, and airports in Los Angeles and Dallas-Fort Worth have started piloting reservation systems according to Pohle [68]. Incorporating such newer approaches in models of the security screening process is a potential future research area.

With the development of new technologies, it is now convenient to collect data from different areas of an airport. Researchers can access airport data through sources such as Federal Aviation Administration [25], International Air Transport Association [37], OpenFlights [63], and the database maintained by United Kingdom's Civil Aviation Authority [17]. Furthermore, starting January 1, 2020, almost all the airports were reserved only for aircraft equipped with an Automatic Dependent Surveillance – Broadcast (ADS-B) system. This enables airports to use inexpensive receivers to monitor operations at the runway/taxiway system and on the apron (including parking positions) (FAA, 2023). Schultz et al. [73] applied ADS-B data to study the aircraft inbound flow into Zurich airport, clustering of ground trajectories, runway occupancy, and taxi times.

With the availability of large volumes of data, data analytics, and machine learning techniques can both supplement queueing/simulation analysis and yield alternative approaches. Descriptive and predictive analytics techniques can be used to identify distributions to fit real-world data. When these distributions are used in queueing/stochastic models, it could lead to improving their prediction fidelity. For example, Li et al. [49] used real data collected from Shenyang Taoxin International Airport to better understand the distributions of the inter-arrival and service times. Li et al. [49] studied six different queueing network structures at the security checkpoint and illustrated how the passenger data collected could be used to simulate passenger behavior.

An example of an alternative approach is presented by Scarpel and Pelicioni [71], where a Mixture-of-Experts learning model was developed to predict congested days at the São Paulo International Airport using data provided by the Brazilian National Civil Aviation Agency. Data from January 2010 to May 2014 and from August 2014 to November 2014 were used to develop the model and data from December 2014 to July 2016 were used to validate the model built. Another recent study by Guo et al. [32] used data sources available at Heathrow to forecast the connection times of passengers for international flights. The data sources available at Heathrow can be classified into two categories: flight-level data and passenger-level data. The flight-level data provides detailed information on departures, arrivals, and aircraft features (e.g., aircraft body type) for individual flights. The passenger-level data records each passenger's travel information, such as their travel class. Based on Guo et al.'s [32] prediction results, the Gamma distribution fits the passengers' connection time in more than 80% of the cases. They developed a two-phased approach, wherein the first phase predicted the connection times, and the second phase forecasted passenger arrivals to immigration and security checkpoints. Devising ways to combine the versatility of the data-centered machine learning approaches with the modeling power of physics-based queueing/simulation approaches is likely to be a fertile area for future research.

7. Conclusions and Future Research Opportunities

The applications of queueing models to operations in airport passenger and aircraft terminals were reviewed and categorized in this paper. With the increasing number of air travelers and aircraft in service, improving the performance of airports remains an important goal. Reducing the waiting time for passengers and aircraft while increasing the efficiency of facilities will not only enhance the productivity of the system but also reduce costs. With the performance measures computed using the queueing models, airports and airline companies can identify current problem areas, and find ways to improve the facilities and procedures and increase passenger satisfaction.

Tošić's [84] review was broader in scope as it covered the application of Operations Research models. However, for the two main processes, check-in, and security screening, only queueing applications published before 1983 were reviewed. Our review is narrower in scope as we focus on queueing applications. We have covered many papers that have been published since 1983 and identified several future research opportunities. We created three useful summaries of the literature reviewed – a taxonomy presented in Figure 1, a categorization of problems studied, and queueing models applied in Table 1, and a summary of the research objectives, key contributions, and focus areas of the research studies in Tables 2, 3, and 4, for passenger terminal operations, aircraft terminal operations, and other airport operations, respectively. The research opportunities in each focus area are summarized below.

Check-in Process

Check-in systems with multiple lines serving different classes of passengers have received very little attention. Considering the presence of multiple passenger types – priority and regular, and multiple counter types – regular check-in, self-service kiosks, and bag drop would more accurately model the check-in process. It is common to have a separate priority check-in line for premium class passengers. When the priority check-in queue is empty, that counter can also serve other regular passengers. Another direction for future research is incorporating the check-in for multiple flights during a certain time interval. Passengers on different flights that have close departure times usually arrive at the check-in counters at the same time. In such situations, the queueing discipline may alternate between first-come, first-served and priority for passengers on the flight with the earliest departure time. Integrating queueing models with other mathematical models should be further explored to expand the decision-making capability; an example is the work of Markovic et al. [53] combined queueing models with a parallel genetic algorithm to optimize the number of check-in counters and the workforce schedule. Another example is the work of Parlar and Sharafali [65], who adapted a stochastic dynamic programming model to their time-dependent multi-counter queueing model to decide the optimal number of counters needed over a specified time window.

<u>Security Screening Process</u>

Categorizing passengers into different classes would help improve the performance of security screening, e.g., see Lazar Babu et al. [45] and Zhang et al. [87]. The security screening is usually implemented as a 3-stage procedure, including ID verification, screening, and further inspection if needed. In addition, passengers are segregated into two classes – regular and pre-check passengers. Investigating security screening problems using open queueing network models (Whitt [85]) with multiple passenger classes (regular, pre-check, and airline crew), multiple stages/nodes with probabilistic routing (ID verification, security screening, and optional additional inspection), and class-dependent screening times could be a promising direction to explore in the future. Although limited to steady-state analysis, these models allow us to easily model variability in arrival and service processes and are excellent tools for planning resource capacities and staffing levels.

<u>Baggage Claim Process</u>

Considering the time difference between passenger arrivals and baggage arrivals is important in deciding the number of passengers waiting in the baggage claim area. Besides considering the baggage arrival as a one-step event, we can also investigate it as a multi-stage problem, since it requires four steps to move the baggage from the aircraft to the baggage claim area – unloading from the aircraft, transporting to the terminal airside, loading onto claim devices, and conveying to the claim area – the baggage arrival process could be modeled as a serial network with four stages.

<u>Runway Service and Taxi-out Processes</u>

In the departure process, an aircraft needs to leave the gate first, enter taxiways if needed, and then enter the runway for departure. The procedures at each part may affect others. Therefore, to capture the interaction among the procedures at the gates, taxiways, and runways, applying queueing network models may be a promising research direction. Furthermore, departure delays are not only caused by issues at the departure airport, such as takeoff queue length and bad weather, but also by similar issues at the destination airports. For example, if the destination airport has air traffic control or weather issues, then that airplane will most likely not take off until those issues have been resolved. The research studies reviewed earlier have mainly focused on factors at the departure airport. To capture the departure process more realistically, the influence of the destination airport should be included. This would most likely add another conditional delay at some stage of the taxi-out process and may necessitate a return to the gate.

Landing Process

The current research papers model the landing process as a service provided by a single server. Even when there are multiple landing runways, the model still treats those runways collectively as a single server. This way of modeling may provide some analysis convenience, especially when considering the influence of weather and other flights. However, at most big airports, more than one plane can land at the same time. For example, Dallas/Fort Worth International Airport (DFW) has 7 runways, without crossing each other. DFW airport can accommodate 6 landings at the same time. Under that situation, the runways are operating as multiple, parallel servers. In the multi-server system, the idle runways are the available servers, and the arriving flights are directed to the corresponding runways. Once all the runways are occupied, then a queue will be generated. Modeling landing processes using multi-server queueing models is an area for future research.

Miscellaneous Applications

There is very little research on applying queueing models to study and improve passenger experience at immigration and customs operations. Queueing models could be a great tool to evaluate the performance of service processes there. In addition, the models should consider the presence of multiple passenger types (citizens/permanent residents, visitors, etc.), self-service stations, multiple stages of service, and more importantly, bulk arrivals.

Finally, as airports introduce new technologies and processes to enhance the passenger experience and improve operational efficiency, it is important for researchers to ensure that the models incorporate these developments.

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