FOCUS

CrossMark

A decision support system to improve performances of airport check-in services

Giuseppe Bruno[1] · Antonio Diglio[1] · Andrea Genovese[2] · Carmela Piccolo[1]

Abstract

The recent remarkable increase in air passenger traffic has been fostering a considerable congestion of the airport facilities. In this context, traditional procedures employed for check-in operations have been supported by alternative methods, based on the use of self-service options (kiosks, web services, app for mobile phones, etc). However, even if such innovations are contributing to improve the service level provided to passengers, field investigations suggest that traditional procedures will be employed also in the future, especially for medium and long-haul flights, where baggage dropping is required. For this reason, the passengers allocation problem at check-in counters is attracting growing attention by the scientific community and several decision support tools, involving both optimization and simulation methods, have been proposed. Most of the available approaches aim at deciding the optimal number of check-in counters to be activated, in such a way to balance the operative costs and passengers waiting times. Such approaches assume that the service capacity (in terms of available check-in operators and counters) is given and determined on the basis of physical constraints (related to the available space in the terminal) and of staff scheduling decisions made at a tactical level. The present contribution tries to overcome this limitation, by proposing a decision support system, based on a mathematical model, capable of designing optimal check-in policies by also incorporating staff scheduling decisions. The model is tested on some real-world case studies; computational results are evaluated, along with the practical usability of the approach.

Keywords Airport check-in · Staff scheduling · Passengers' allocation · Optimization model · Decision support system

1 Introduction

With an expected annual rate of about 4.0% over the next 20 years (IATA 2017), the growth in air passengers traffic has been fostering a remarkable congestion in the use of available resources at different levels, in both airside and landside oper-

✉ Carmela Piccolo
carmela.piccolo@unina.it

Giuseppe Bruno
giuseppe.bruno@unina.it

Antonio Diglio
antonio.diglio@unina.it

Andrea Genovese
a.genovese@sheffield.ac.uk

[1] Dipartimento di Ingegneria Industriale (DII), Universita di Napoli Federico II, Piazzale Tecchio, 80, 80125 Naples, Italy

[2] Management School, University of Sheffield, Conduit Road, Sheffield S10 1FL, UK

ations. Besides investments on new airport facilities, huge interventions have been deployed in order to increase the capacity of current infrastructures and to deal with issues representing bottlenecks in air traffic logistics.

Within terminal facilities, passengers are involved in different processes. In particular, once arrived, they pass through a check-in area in order to get their boarding pass and/or to drop off their luggage. They may skip this step if they are self-checked-in and they own only a hand luggage. Then, they proceed to a security area for control operations, and they finally move toward their assigned gate. These processes require the use of several resources (equipment, personnel, etc.) and often produce significant waiting times, which can be perceived as signal of a low service quality, resulting in a negative impact on the overall image of the airport and of airlines.

Focusing on check-in operations, two types of systems can be deployed, based on common-use and exclusive-use of counters. The *common-use system* consists of a large set of counters where passengers can be accepted, regardless of their flight. Typically, it is adopted for groups of flights

Springer

operated by the same airline or by different airlines that outsource the handling operations to the same company. On the other hand, the *exclusive-use system* consists of a set of counters, dedicated to single flights. Obviously, the common-use system is more efficient as it yields higher utilization rates of available service capacity. Hence, due to above-described context of growing congestion of terminals, it has become also the most commonly adopted. Moreover, huge investments in ICTs have been deployed to support traditional check-in procedures with self-service alternatives, mainly based on the use of kiosks, web services, applications for mobile phones, etc. However, even if the introduction of these innovations certainly played and will be playing an important role, contributing to the reduction of passengers waiting times and operating costs for airlines, field investigations suggest that traditional procedures remain important and will be needed also in the future. Indeed, recent studies demonstrate that many factors affect the acceptance of self-service mode, such as passenger's age, level of education, nationality, previous experiences, flight destination, the type of journey; thus, a significant portion of the demand will continue to select the traditional check-in mode (Chang and Yang 2008; Lu et al. 2009, 2011; Wittmer 2011; Castillo-Manzano and López-Valpuesta 2013). This is particularly true for medium and long-haul flights, where baggage dropping processes involve most of the passengers (Chang and Yang 2008).

For this reason, in the recent literature, several decision support tools have been proposed to optimize check-in procedures at desks. As such process is characterized by several stochastic factors (i.e., number of passengers, passengers arrival times, check-in times, etc.), many contributions adopt simulation approaches to tackle the problem. However, if simulation may be useful for the evaluation of the system performances, the use of optimization models, separately or in combination, could be beneficial to determine the value of decision variables.

Check-in management policies can be tested against different performance functions; however, to date, the most common objectives are represented by passengers' waiting times and the number of desks activated in a given time horizon (usually a single day). This last objective is often used as a proxy of operating costs, on the assumption that the more counters are used, the more resources are needed and, therefore, more expensive will be the process. However, even if this assumption might be considered appropriate for the counter rental charge to be paid, personnel costs are also influenced by the adopted shift system.

To the best of our knowledge, no extant approach considers staff scheduling decisions in addressing the check-in management problem. For this reason, in this paper we propose a mathematical model for the optimal management of the check-in process, in which the objective function represents a measure of personnel costs associated with the delivery of the service. Available shift systems are taken into account, as a constraint for the model.

The paper is organized as follows. In Sect. 2, a survey of the scientific contributions on optimization approaches for the airport check-in problem is illustrated, highlighting literature gaps. Then, in Sect. 3, we discuss the proposed mathematical model, with a particular emphasis on the justification of the selected objective function. In Sect. 4, the procedure adopted to generate the test instances, related to real-world problems, is illustrated, while in Sect. 5 the results obtained from the application of the model to the case of two Italian airports are analyzed and discussed. Finally, some conclusions are drawn.

2 Literature review

In the literature, many contributions devoted to the optimal management of service capacity have been proposed (see, for example, Bruno et al. 2016). In particular, papers focused on the analysis of the airport check-in service traditionally adopted simulation approaches to deal with the problem (Chun and Mak 1999). Only in the last decades, researchers started to implement optimization or hybrid approaches to deal with it. One of the first works specifically devoted to check-in management optimization was the one by Park and Ahn (2003), which proposed a procedure to calculate the appropriate number of check-in counters and their operating times through a deep analysis of passengers arrival distribution and processing patterns. Yan et al. (2004, 2005) tackled the problem of assigning flights to blocks of check-in counters, considering various objective functions, such as the total passenger walking distance and a so-called inconsistency term, evaluating whether flights having some common characteristics are assigned to different counter locations. Van Dijk and Van Der Sluis (2006) highlighted the potential of combining stochastic and deterministic approaches. In particular, assuming that a peak requirement of check-in counters is estimated for each flight, they proposed an integer linear programming model aimed at determining the minimum number of desks needed for all flights. The results provided by this model were then used as inputs for a simulation model to calculate the system performance, in terms of service times. Parlar and Sharafali (2008) and Stolletz (2011) attempted to statistically analyze the queueing phenomenon at check-in counters, providing useful insights for modeling purposes.

Bruno and Genovese (2010) and Bruno et al. (2014) proposed some models (based on the mathematical structure of the lot sizing problem) for determining the optimal number of check-in counters to be activated. Considered objective functions included passenger waiting times and total opening times of counters.

Tang (2010) developed a network model for the optimization of common-use check-in counters assignments, with the goal of minimizing the number of counters required for daily operations. Stolletz (2010) addressed workforce planning problems for check-in systems, through a mathematical programming model based on a modification of the set covering model. Hsu et al. (2012) analyzed the problem of dynamic allocation of various types of check-in facilities (counters, kiosks, online check-in and barcode check-in) to minimize waiting times for passengers. They proposed a sequential stochastic assignment model to decide whether the n-th arriving passenger, requiring a certain type of check-in service, was to be assigned to a given facility or not, and then to determine the number of facilities of each type to be opened.

Araujo and Repolho (2015) proposed a modification of the model by Bruno and Genovese (2010) to optimize the Airport Check-in Counter Allocation Problem (ACCAP), introducing service level constraints. They also used a simulation approach to assess the results provided by the model. Mota (2015) studied the problem of the allocation of flights to check-in counters, considering a given layout of check-in areas, and introducing constraints related to contracts between airlines and airport operators. The problem was solved using an approach based on the combination of an evolutionary algorithm and simulation.

Parlar et al. (2018) proposed a dynamic programming model for check-in counter allocation problem, especially suitable in the case of exclusive-use systems, that was tested on real data coming from Singapore International Airport. The performance indicators adopted in the model included the expected waiting and counter activation costs; these latter were evaluated considering variable and fixed costs, also including a penalty for keeping idle counters open.

The analysis of the proposed models reveals that typical approaches aim at optimizing passengers' waiting times and/or the total number of the activated check-in counters, either using simulation or adopting mathematical models. Such approaches are characterized by an inherent multi-criteria nature, that is modeled either through explicitly multi-objective mathematical models or through the inclusion of appropriate constraints.

When effectively modeled, passengers' waiting times represent a measure of the passengers' satisfaction. In terms of efficiency, the total number of activated check-in counters may be considered a good proxy, when management costs are mainly related to counter rental charges. However, this is not appropriate when the dominant cost item is represented by the cost of staff delivering the service at counters. Indeed, in this case, as personnel is engaged according to a shift system, a more realistic objective could be represented by an estimation of the personnel cost, on the basis of feasible shifts. Typically, a shift covers consecutive time periods in which one or more break windows must be included (depending on its length). Shift works are generally regulated through work contracts in terms of length, start times and breaks (see for instance Avramidis et al. 2010; Bard et al. 2003).

In this work, we further extend the use of optimization models to solve the ACCAP. Specifically, based on the work by Bruno and Genovese (2010), we formulate a model to deal with the check-in optimization problem, in which a trade-off solution between the service level provided to passengers, in terms of waiting times, and the cost of the service is provided. In particular, the objective function is represented by the personnel cost of the staff engaged at check-in counters, according to a set of given feasible shifts, while the queue of passengers is limited by a specific set of constraints. In the following sections, the model will be introduced and some computational experiences will be shown.

3 A novel mathematical model

In order to formulate the model, the reference planning horizon (typically a single working day) has been discretized in a finite number N of periods of the same length. Each departing flight f in such time horizon is characterized by a departure time and, consequently, by a time window, in which check-in operations can be performed, whose length generally depends on various factors, such as the destination (national, international, intercontinental), the airline policies, etc. We indicate with T_f^- and T_f^+, respectively, the first and the last periods in which passengers of flight f can be accepted at check-in counters. Even if the passengers' behavior is not deterministic and it is not possible to know in advance the exact distribution of their arrivals, we assume to be able to forecast, with a significant reliability, the number of passengers of flight f arriving at desks in each period t of the time window (T_f^-, T_f^+), denoted by d_{tf}. The check-in optimization problem consists of accepting all the arriving passengers, by minimizing their waiting times and by satisfying the deadlines related to the single flights departures.

Of course, the solution of such a problem is strongly affected by the available service capacity during the planning horizon, in terms of check-in operators and desks. The higher is the service capacity, the higher is the service level that can be provided to users. In order to clarify this aspect, let indicate with UB_t the *Upper Bound* of the service capacity needed in each period t, i.e., the minimum number of desks required to accept passengers with no waiting times. As the *real service capacity* is usually lower than UB_t, due to the presence of limited resources (lack of operators or space for desks), optimization approaches are adopted in order to allocate resources with the aim of minimizing the waiting times of passengers. In Fig. 1, a typical situation is depicted in which the best policy, given by values of UB_t, cannot
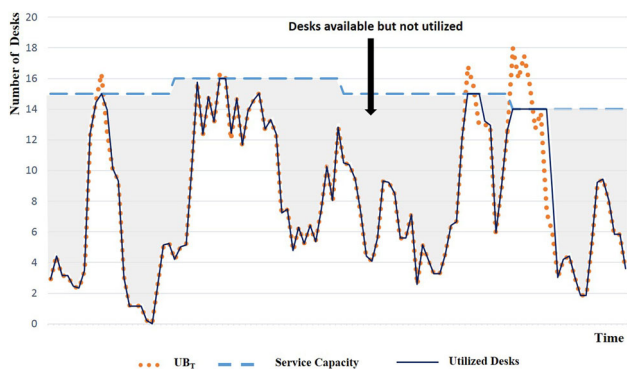
Fig. 1 Typical pattern of a check-in scheduling problem

(a)

(b)

Fig. 2 Examples of solutions based on different staff-scheduling decisions. **a** Less flexible shift schedule. **b** More flexible shift schedule

be implemented as the service capacity, in some periods, is not sufficient and an alternative feasible solution is adopted. However, such solution appears to be inefficient, as the available capacity results highly underutilized, as testified by the area between the two curves representing the available and used capacity, respectively.

As check-in activities still represent labor-intensive operations, especially for long-haul flights, it is reasonable to assume that the critical resource is represented by operators. This means that the value of the service capacity strongly depends on decisions related to staff scheduling, made at a tactical level.

As an example, in Fig. 2, two alternative solutions, obtained according to two different staff scheduling policies, are compared. In particular, the policy reported in Fig. 2b is representative of a more flexible shift schedule than the one in Fig. 2a, which allows adapting the number of available operators to the variability of the service demand over time, thanks to the use of shifts of shorter duration and/or of more shift typologies. Comparing the solutions obtained in the two cases, it is possible to notice that a higher flexibility in the number of available operators produces a more efficient solution, characterized by a lower level of underutilized desks.

In this context, operative costs could depend on the scheduling of desk operators, i.e., duration, type and/or the starting time of their working shifts.

In the light of such considerations, we propose a mathematical programming model aiming at finding a trade-off between:

– Service operating costs, by optimizing the shift-scheduling decisions of the desk operators;
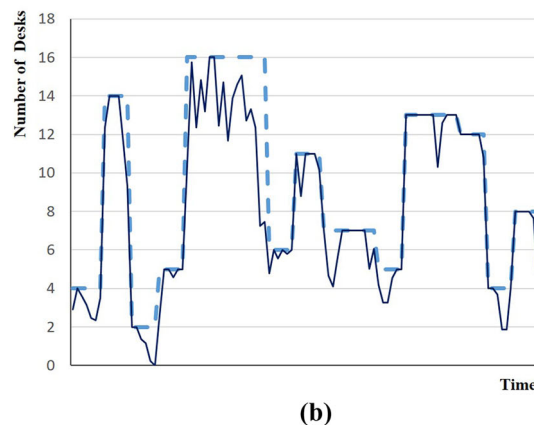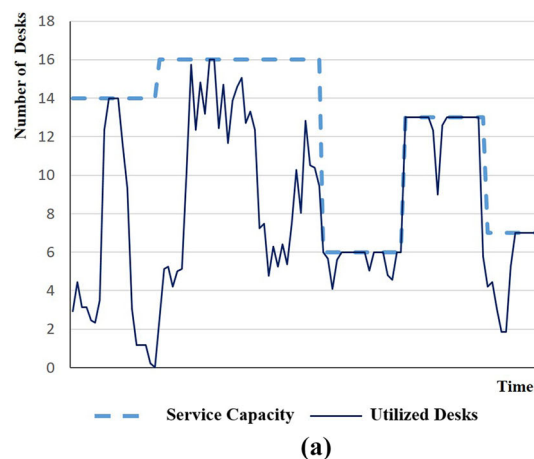– Service level, measured in terms of passengers waiting times at desks.

In order to formulate the model, the following notation is introduced:

T Planning horizon;
N Number of periods in which the planning horizon is subdivided, indexed by t;
l Length of single periods ($l = T/N$);
J Set of shift types that can be selected for desk operators;
F Set of departing flights in the considered planning horizon;
p_f Average service time to process a single passenger of flight f at check-in desks;
d_{ft} Number of arriving passengers of flight f during period t;
a_{kt}^{j} Binary parameter equal to 1 if and only if the shift j in J, activated in the period k, covers the period t (with $t > k$);

β_{ft} Binary parameter equal to 1 if and only if the check-in time window for flight f is closed in period t;

γ Service level to be guaranteed(), i.e., minimum number of passengers to be accepted expressed as percentage of arrivals;

c^j Cost for shift type j in J;

x_t^j Number of operators starting the shift type j at the beginning of period t;

q_{ft} Passengers of flight f accepted at desks in period t;

I_{ft} Passengers of flight f in queue at desks at the end of period t.

Then, the model can be formulated as follows:

$$\min z = \sum_{j \in J} \sum_{t=1}^{T} c_j x_t^j \tag{1}$$

s.t.

$$\beta_{ft} I_{ft} = 0 \quad \forall f \in F, t \in 1, \ldots, N \tag{2}$$

$$I_{ft} = I_{f(t-1)} + d_{ft} - q_{ft} \quad \forall f \in F, t \in 1, \ldots, N \tag{3}$$

$$\sum_{f \in F} I_{ft} \leq (1 - \gamma) \sum_{f \in F} d_{ft} \quad \forall t \in 1, \ldots, N \tag{4}$$

$$\sum_{f \in F} p_f q_{ft} \leq l \sum_{j \in J} \sum_{k=1}^{t} a_{kt}^j x_t^j \quad \forall t \in 1, \ldots, N \tag{5}$$

$$x_t^j \in N \quad \forall j \in J, t \in 1, \ldots, T \tag{6}$$

$$q_{ft}, I_{ft} \in \{0, 1\} \quad \forall f \in F, t \in 1, \ldots, T \tag{7}$$

The objective (1) represents the minimization of the total costs for the shift schedule. Constraints (2) impose that passengers of each flight f may be processed only within their check-in time windows; indeed, no passenger of flight f can wait at check-in desks outside the time window ($I_{ft} = 0, \beta_{ft} = 1$). Equation (3) represent passengers flow conservation constraints. Constraints (4) guarantee a minimum service level to passengers; indeed, they assure that passengers waiting in queue at the end of each period t may not exceed a given percentage $(1 - \gamma)$ of the arrivals in the same period. If γ is equal to one, a maximum service level is guaranteed to passengers, as constraints impose to have no queue in each time period; by decreasing the value of such parameter, the feasible amount of passengers in queue in each time period may increase. Coherently to the approach suggested by Araujo and Repolho (2015), constraints (5) guarantee that the service time needed to accept passengers in each time period t ($\sum_{f \in F} p_f q_{ft}$) does not exceed the service capacity, defined as the product between the total number of available operators in period t ($\sum_{j \in J} \sum_{k=1}^{t} a_{kt}^j x_t^j$) and the duration l of the period itself. Finally, constraints (6) and (7) define the nature of the introduced decision variables.

In the next sections, the results deriving from the application of the above model to real case studies related to two Italian airports will be introduced and discussed.

4 Methodology for instances generation

In this section, the steps followed to generate test instances of the problem are illustrated. It is worth to highlight that the main aim here is to characterize the crucial parameters to be considered in real-world situations, in order to effectively use the proposed model as decision support system and to verify its performances in a set of possible scenarios. Therefore, the reproduction of realistic values of considered parameters is out of the scope of the paper and it should be performed on the basis of specific field investigations.

We used, as reference planning horizon (T), the single working day, defined as the time span between the 4:30 am and the 10:30 pm, that was subdivided in a finite number N of time periods of 15 min ($N = 72$).

A single case study is characterized by a set F of departing flights, with the corresponding departure times t_f and destinations, distinguished between national and international. Along with this information, retrieved by the official websites of the selected airports, a set of further data are needed; in particular:

- *Check-in time windows*;
- *Passengers requiring the check-in service at desks*;
- *Passengers arrival distribution at desks*;
- *Service characteristics*.

4.1 Check-in time windows

For each flight $f \in F$, the completion time t_f^+ of check-in operations was fixed equal to $t_f - D_f$, where D_f represents the time span between the end of check-in operations and the departure time. Subsequently, the starting time t_f^- of check-in operations was fixed equal to $t_f^+ - L_f$, where L_f represents the duration of check-in operations. In the test instances, we considered D_f equal to 30 and 60 min and L_f equal to 60 and 90 min, for national and international flights, respectively.

4.2 Passengers requiring traditional check-in service mode

For each flight $f \in F$, the total number of passengers on board n_f was firstly estimated. At this end, information about the airplane model utilized for each flight f and the associated passengers' capacity C_f, were collected (www.flightradar24.com) and a parameter δ_f, representing the aircraft utilization rate, was introduced ($n_f = \delta_f C_f$). For each instance, the utilization rates δ_f were randomly generated from a uniform distribution in the range $(\delta - r, \delta + r)$, whose parameters (δ, r) are fixed as described in the next section. Finally, a further coefficient ω_f was introduced to estimate the portion of passengers requiring check-in ser-

vices at desks (and, hence, do not use self-service modes). It assumed different values, according to the length of flight f; in particular, it was set equal to 0.2 for short-haul flights (national), 0.5 for medium-haul flights (international with a duration under 6 h) and 0.9 for long and ultralong-haul flights (over 6 h).

4.3 Passengers' arrival distribution at desks

We assume that passengers arrive at check-in desks according to a given distribution, that varies, in dependence of flight destination, national or international. The percentages σ_{ft} of arriving passengers of flight f during the single periods within the associated check-in windows are reported in Fig. 3 and were derived from a survey conducted at Naples International Airport in the time span April–May 2016, that involved more than 150 flights (equally distributed between national and international) and more than 5000 passengers. From these values, the number of arriving passengers at desks, for each flight f and each period t, were calculated ($d_{ft} = \sigma_{ft}\omega_f n_f$).

4.4 Service characteristics

We considered the most adopted work shifts for desk operators, that can be 4 (part time) or 6 h and half long (full time). According to the Italian regulations, shifts lasting 4 h need to include a break window of 15 min (1 period), positioned in a way that avoids that more than two consecutive hours of work are performed; in the case of longer durations, shifts have to include an additional break for the meal, lasting 30 min (2 periods). By combining these aspects, we adopted six shift configurations, whose structure is shown in Fig. 4. The cost for each shift is considered proportional to the length of the shift itself.

Moreover, the unit service time p_f, i.e., the time needed to process a single passenger of flight f at check-in desks, was assumed constant for each flight f ($p_f = p$) and equal to 90 s.

Figure 5 summarizes the information needed for the instances generation.

5 Model results

The proposed model was tested on case studies, obtained by considering daily timetables of typical working days of some Italian airports. Italy accounts for 41 civil airports, with different characteristics in terms of passenger traffic and number of flights (ENAC 2017). Only five of them can be classified as hubs (FCO, MXP, LIN, BGY, VCE), being characterized by more than 40.000 flights per year (i.e., more than 100 per day), while most of them are micro-airports, with less
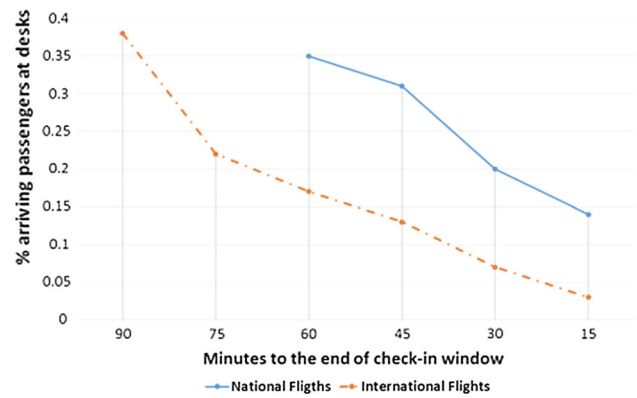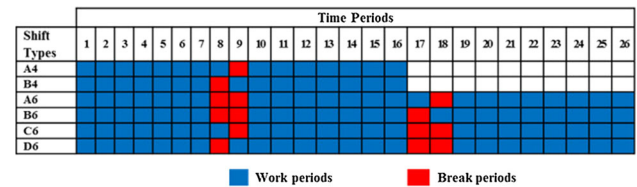

Fig. 3 Passengers' arrival profiles

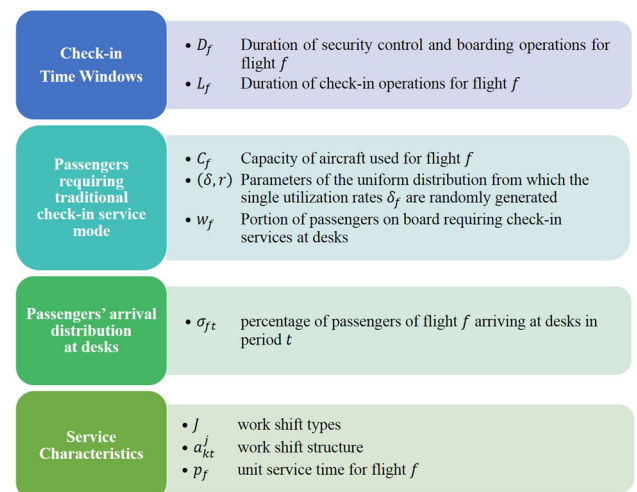**Fig. 4** Characteristics of work shift types

Fig. 5 Information needed for the instances generation

than 10.000 departing flights per year (i.e., 30 per day), and medium-size airports, with a range of 10.000–40.000 flights per year, as reported in Fig. 6. In order to test the proposed model, we focused on the class of medium-size airports, as they are those that most likely adopt a management strategy based on the common-use of check-in counters. Within such class, two airports of different size were selected: Napoli Capodichino (NAP) and Firenze Peretola (FLR). The number of departing flights from the two airports is significantly different (on average 45 from FRP and 120 from NAP), but in both cases most of them are short- and medium-haul flights, as shown in Fig. 7.
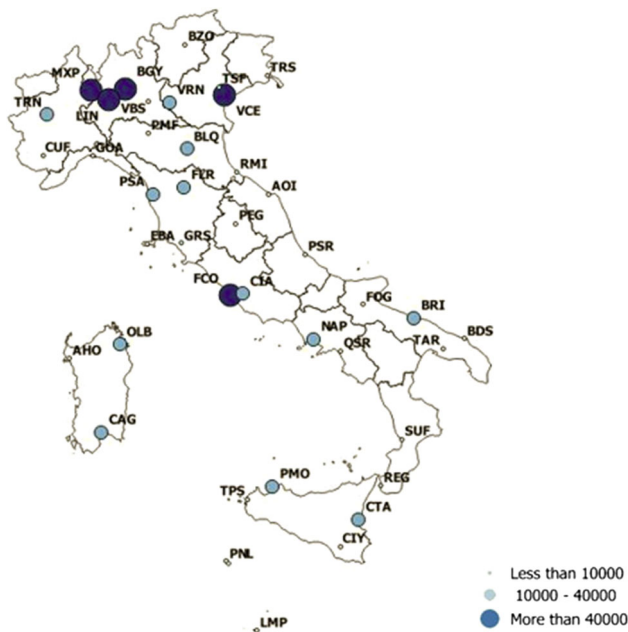
Fig. 6 Italian airports per number of departing flights per year. *Source*: ENAC (2017)

In order to analyze the variation of the total cost according to different service levels, the model was solved with different values of parameter γ ($\gamma = 0.2, 0.4, 0.6, 0.8, 1.0$). Moreover, also the expected utilization rate δ was varied, with the aim of simulating different congestion levels of the terminal ($\delta = 0.4, 0.6, 0.8, 1.0$). Then, parameter r was fixed equal to 0.2 in order to assure a significant variability around the central value δ but avoiding the overlapping of generated demand profiles. Hence, for each case study, a set of 20 scenarios was produced (one for each combination of the parameters α and δ).

Each instance was optimally solved in limited computational times, i.e., within 3600 s, using Cplex 12.4 on an Intel Core i7 with 1.86 GHz and 4 GB of RAM. Tables 1 and 2 show results obtained for the two case studies, in terms of values of the objective function. It is possible to notice that, by fixing the parameter δ, the value of the objective function decreases when a higher service level is guaranteed to passengers (i.e., when the value of parameter decreases); indeed, the model is constrained to activate more shifts in order to have more available service capacity and minimize the passengers in queue. Moreover, for each given value of the service level α, the objective function increases when the congestion level of the terminal increase (i.e., when the value of parameter δ decreases), as the number to be accepted at check-in counters increase and more operators will be needed in each time period.

In the following, some solutions obtained for the case of FLR are analyzed, in order to show the capability of the model to support the decision maker.
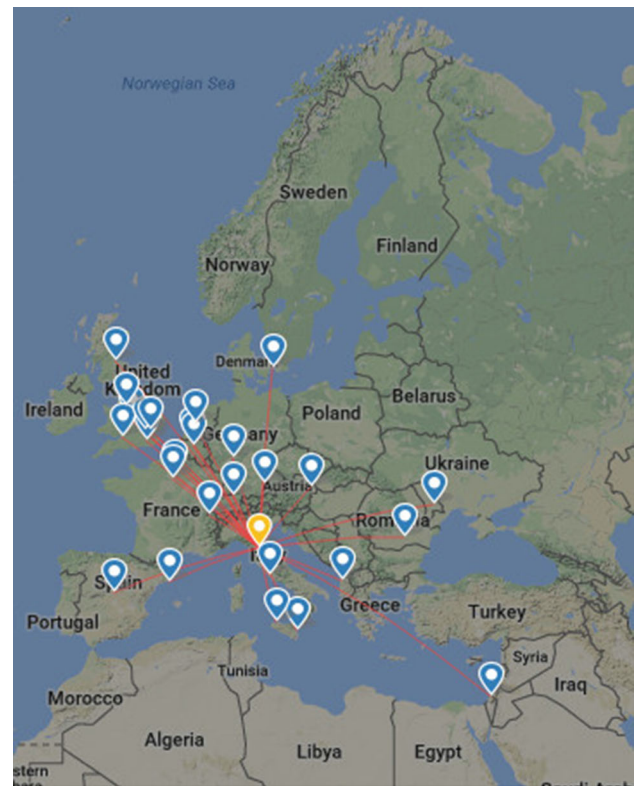
(a)
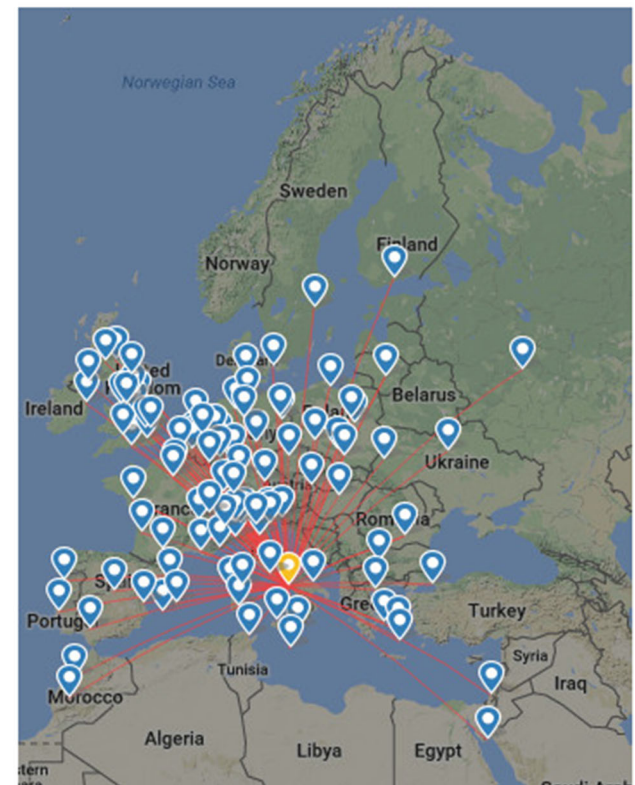
(b)

Fig. 7 Map of departing flights from FLR (**a**) and NAP (**b**) airports during a typical week. *Source*: www.flightradar24.com

Table 1 Computational results: FLR airport

δ	γ				
	1.0	0.8	0.6	0.4	0.2
0.4	365	304	281	273	273
0.6	546	463	402	387	387
0.8	637	538	508	500	500
1.0	864	720	652	652	652

Table 2 Computational results: NAP airport

δ	γ				
	1.0	0.8	0.6	0.4	0.2
0.4	736	624	593	562	562
0.6	906	791	732	700	692
0.8	1225	1050	981	957	943
1.0	1465	1249	1180	1140	1125
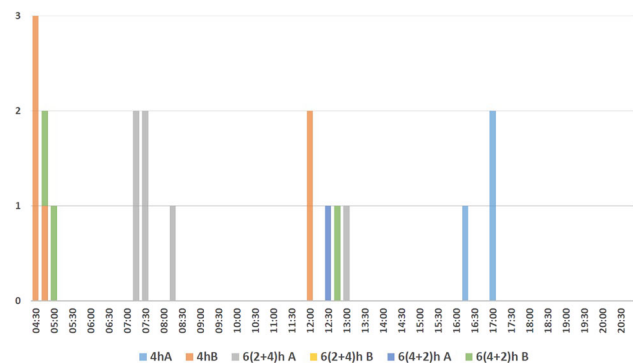
Fig. 8 Number of activated shifts (distinguished per typology) in each time period ($\gamma = 1$, $\delta = 0.4$)
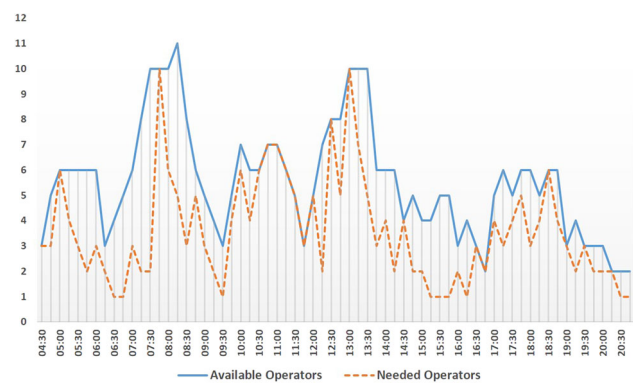

Fig. 9 Allocation of available operators ($\gamma = 1$, $\delta = 0.4$)

Figures 8 and 9 show the solution obtained by imposing the maximum service level ($\gamma = 1$) and an expected aircraft utilization rate δ equal to 0.4. In particular, Fig. 8 indicates
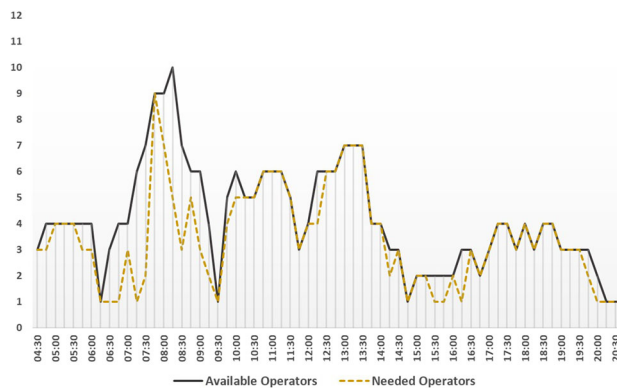
Fig. 10 Allocation of available operators ($\gamma = 0.4$, $\delta = 0.4$)
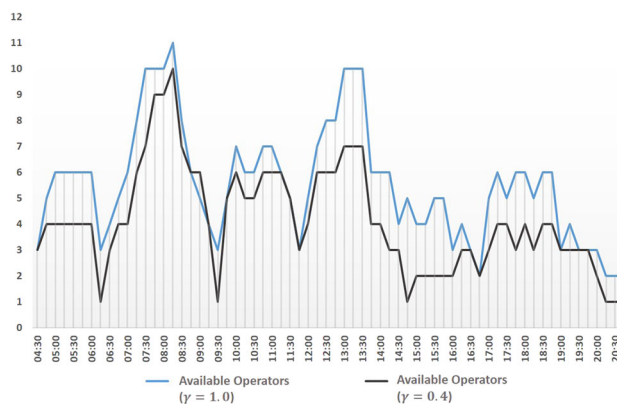

Fig. 11 Available service capacity profile by varying service level γ from 1 to 0.4

the number of operators that, in each time period, starts their work shift, classified according to the six considered shift types, while Fig. 9 reports the number of available operators over time, and the number of needed operators to process passengers, determined on the basis of the allocation decisions made by the model. In this case, the desk operators are scheduled in such a way to have no any passenger waiting in queue; then, the solution represent an upper bound in terms of objective function, i.e., shift costs to be activated in terms of working hours. Indeed, if, in a given period, the passengers arrivals require more operators than the available ones, the model activates new shifts, that last for a certain number of successive periods; then, such operators remain active even if they are not needed later. This circumstance may lead to an underutilization of the available capacity. Obviously, by decreasing the service level provided to users, it is possible to have more flexibility in the use of resources; indeed, if passengers can wait in queue, a lower number of operators is required in each time period. Figure 10 shows the results provided by the model by fixing $\gamma = 0.4$. As expected, the underutilization rate decreases as the gap between needed

and available operators is generally lower over the whole time horizon if compared with the one in Fig. 9. Finally, in Fig. 11 we compared the number of needed operators in the two scenarios; of course, the line corresponding to the number of needed operators for $\gamma = 0.4$ is dominated by the one corresponding to $\gamma = 1.0$. This testifies that higher costs would be required to guarantee higher service levels to passengers (conflicting objectives).

6 Conclusions

Historically, passengers check-in operations have represented a very resource-intensive process taking place in airports, being recently supported by technological advances. Notwithstanding, field investigations suggest that traditional check-in procedures will continue to be needed also in the future, especially for long-haul flights, where baggage dropping processes are involved.

For this reason, the check-in problem has been gaining popularity in the recent operational research literature, with the development of both optimization and simulation methods.

The contribution presented in this study has extended the current state of the art by proposing a mathematical model capable of performing check-in decisions by also incorporating staff scheduling considerations, in order to deliver more realistic and accurate planning decisions. Specifically, the model is capable of finding trade-off solutions between the cost of the personnel employed in the check-in operations and the service level provided to passengers, expressed in terms of waiting times. These two criteria have been included in the model as an objective function to be optimized and as constraints to be satisfied, respectively.

The proposed model was tested on case studies, obtained by considering daily timetables of typical working days of some Italian airports; tests were performed considering two midsized airports, likely to adopt management strategies based on the common-use of check-in counters.

Results show that the model is capable of identifying the most appropriate staff configuration (in terms of number of operators, shift start time and shift type) in order to optimize the mentioned trade-off.

Future researches might involve the adoption of stochastic version of the model, in order to better represent the variability in passengers arrivals, along with the integration with simulation tools, in order to improve the capability of the model of dealing with real-world scenarios. Also, additional case studies might be gathered, to explore to a wider extent the applicability of the model and gain new insights about further practical constraints to be added to the mathematical formulation.

Compliance with ethical standards

References

Araujo GE, Repolho HM (2015) Optimizing the airport check-in counter allocation problem. J Transp Lit 9(4):15–19

Avramidis AN, Chan W, Gendreau M, Lecuyer P, Pisacane O (2010) Optimizing daily agent scheduling in a multiskill call center. Eur J Oper Res 200(3):822–832

Bard JF, Binici C et al (2003) Staff scheduling at the united states postal service. Comput Oper Res 30(5):745–771

Bruno G, Genovese A (2010) A mathematical model for the optimization of the airport check-in service problem. Electron Notes Discrete Math 36:703–710

Bruno G, Genovese A, Piccolo C (2014) The capacitated lot sizing model: a powerful tool for logistics decision making. Int J Prod Econ 155:380–390

Bruno G, Genovese A, Piccolo C (2016) Capacity management in public service facility networks: a model, computational tests and a case study. Optim Lett 10(5):975–995

Castillo-Manzano JI, López-Valpuesta L (2013) Check-in services and passenger behaviour: self service technologies in airport systems. Comput Hum Behav 29(6):2431–2437

Chang HL, Yang CH (2008) Do airline self-service check-in kiosks meet the needs of passengers? Tour Manag 29(5):980–993

Chun HW, Mak RWT (1999) Intelligent resource simulation for an airport check-in counter allocation system. IEEE Trans Syst Man Cybernet Part C (Appl Rev) 29(3):325–335

ENAC (2017) Dati di traffico 2017. URL: https://www.enac.gov.it. Accessed in May 2018

Hsu CI, Chao CC, Shih KY (2012) Dynamic allocation of check-in facilities and dynamic assignment of passengers at air terminals. Comput Ind Eng 63(2):410–417

IATA (2017) Annual review 2017. URL: www.iata.org/publications/pages/annual-review.aspx. Accessed in May 2018

Lu JL, Chou HY, Diglio A (2009) Investigating passengers intentions to use technology-based self check-in services. Transp Res Part E: Logist Transp Rev 45(2):345–356

Lu J, Chou HY, Tseng WC (2011) Determinants of passengers choice of airline check-in services: a case study of American, Australian, Korean, and Taiwanese passengers. J Air Transp Manag 17(4):249–252

Mota MM (2015) Check-in allocation improvements through the use of a simulation-optimization approach. Transp Res Part A: Policy Pract 77:320–335

Park Y, Ahn SB (2003) Optimal assignment for check-in counters based on passenger arrival behaviour at an airport. Transp Plan Technol 26(5):397–416

Parlar M, Sharafali M (2008) Dynamic allocation of airline check-in counters: a queueing optimization approach. Manag Sci 54(8):1410–1424

Parlar M, Rodrigues B, Sharafali M (2018) Event-based allocation of airline check-in counters: a simple dynamic optimization method supported by empirical data. Int Trans Oper Res 25(5):1553–1582

Stolletz R (2010) Operational workforce planning for check-in counters at airports. Transp Res Part E: Logist Transp Rev 46(3):414–425

Stolletz R (2011) Analysis of passenger queues at airport terminals. Res Transp Bus Manag 1(1):144–149

Tang CH (2010) A network model for airport common use check-in counter assignments. J Oper Res Soc 61(11):1607–1618

Van Dijk NM, Van Der Sluis E (2006) Check-in computation and optimization by simulation and IP in combination. Eur J Oper Res 171(3):1152–1168

Wittmer A (2011) Acceptance of self-service check-in at Zurich airport. Res Transp Bus Manag 1(1):136–143

Yan S, Tang CH, Chen M (2004) A model and a solution algorithm for airport common use check-in counter assignments. Transp Res Part A: Policy Pract 38(2):101–125

Yan S, Chang KC, Tang CH (2005) Minimizing inconsistencies in airport common-use checking counter assignments with a variable number of counters. J Air Transp Manag 11(2):107–116