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A review on airport gate assignment problems: Single versus multi objective approaches☆

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ABSTRACT

Assigning aircraft to gates is an important decision problem that airport professionals face every day. The solution of this problem has raised a significant research effort and many variants of this problem have been studied. In this paper, we review past work with a focus on identifying types of formulations, classifying objectives, and categorising solution methods. The review indicates that there is no standard formulation, that passenger oriented objectives are most common, and that more recent work are multi-objective. In terms of solution methods, heuristic and metaheuristic approaches are dominant which provides an opportunity to develop exact and approximate approaches both for the single and multi-objective problems.

1. Introduction

The world-wide growing air traffic and the strongly competitive airline industry require an ever more efficient use of airport and airline resources. According to European Commission's report on Air Transport Market, the number of flights performed worldwide showed a great increase from 27.8 million in 2010 to 36.8 million in 2016. Meanwhile, the number of air passengers carried worldwide grew by 6.3 percent to a record 3.7 billion in 2016 and the total revenue reached 709 billion dollars [1]. Due to the high demand for air transport many large airports today must handle hundreds or even thousands of flights per day. Airports Council International (ACI) [2] announced the top 10 busiest airports in the world as presented in Table 1. For example, Hartsfield Jackson Atlanta International Airport welcomes on average 2700 arrivals and departures daily at 192 gates [3]. The International Air Transport Association (IATA) expects 7.2 billion passengers to travel in 2035, a near doubling of the 3.8 billion air travelers in 2016 [4]. Passenger expectations coupled with increasing air travel demand and the competitive environment in which airline companies and airports operate, require an efficient usage of the available resources. This translates into a large range of relevant and important optimization problems with high economic impact that these entities face.

The task of assigning aircraft/flights to gates is known as the gate assignment problem (GAP). In its basic form, GAP finds a minimum cost assignment such that only one aircraft may occupy a gate at a time. In some cases, this assignment could be done by the airline depending on the assignment strategy. At an airport, two main strategies are common use of gates and exclusive use of gates. Common use of gates means the airport controls gate use and ensures gates are used most efficiently [5]. On the other hand, certain gates could be leased to an airline for the specific use of that airline. The airline may use leased gates for its flights only or may even rent the gates to other airlines. In contrast to the general situation in Europe, gates are leased for long periods of time to airlines in US airports [6].

Depending on the strategy that is applied, assigning an aircraft to a gate impacts three main stakeholders at varying degrees, namely the airport operator, the airline and the passengers. Airline operators are concerned with easy access to terminals and short ground times. Passengers look for convenience in terms of quick and smooth boarding, short walking distances and access to airport amenities like restaurants, rest and entertainment areas, and shopping. Finally, airport operators want to increase their revenues by providing a good airline and passenger experience while maximizing efficiency of airport resources and minimizing congestion, required resources, interruptions and delays, etc. This difference in stakeholder perspectives results in a wide range of objectives. The different and mostly conflicting objectives, as well as frequent

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Table 1
Top 10 busiest airports in the world.

Rank 2017	Airport city/Country/Code	Passengers: Departing and Arriving	Passengers: Percent change
1	ATLANTA GA, US (ATL)	103 902 992	−0.3
2	BEIJING, CN (PEK)	95 786 442	1.5
3	DUBAI, AE (DXB)	88 242 099	5.5
4	TOKYO, JP (HND)	85 408 975	6.5
5	LOS ANGELES CA, US (LAX)	84 557 968	4.5
6	CHICAGO IL, US (ORD)	79 828 183	2.4
7	LONDON, GB (LHR)	78 014 598	3
8	HONG KONG, HK (HKG)	72 664 075	3.4
9	SHANGHAI, CN (PVG)	70 001 237	6.1
10	PARIS, FR (CDG)	69 471 442	5.4

changes to the underlying flight schedule on the day of operation make the problem even more complicated.

Unlike other airline planning operations, gate assignment is multi-objective in nature because of the multiple stakeholders involved as well as the multiple and conflicting objectives for the same stakeholder. This defining characteristic of gate assignment together with the fact that gates are expensive and scarce resources in an airport explain the multitude of objectives studied in the literature, both in single and multi-objective frameworks, and motivates the current review of the literature.

Early research contributions treat this problem from a passenger perspective and try to solve the problem by defining various objective functions targeted at minimizing the total passenger walking distance in airports. Following contributions also consider airport-oriented objective functions such as minimizing the number of un-gated flights or minimizing the number of towing activities. Dorndorf et al. [7] state that the research on the GAP may be classified with respect to the main objectives considered in various formulations. They distinguish two classes: passenger-oriented and airport-oriented objectives. We extend this classification by explicitly considering a third class of objectives related to robustness. Robustness is viewed as an important property of gate schedules since the arriving and departing time of flights are mostly uncertain. Although robustness is another airport-oriented objective, the growing number of articles only considering robustness related objectives shows how important this objective is for managing daily operations at airports. Owing to this situation, we discuss robustness-oriented objectives, under a new class, independent of other airport-oriented objectives.

In our review we not only focus on the objectives considered in earlier studies, but we also highlight those that make use of a multi-objective framework and the methods used to solve the resulting models. Given that there is no uniform solution approach that can been used for all multi-objective problems, we discuss the potential advantages and disadvantages of the adopted approaches.

The article is structured as follows. We define the basic GAP in Section 2 and provide two types of constraints that model feasible gate assignments. The first uses assignment-type variables and constraints. The second is modelled on a graph and uses flow-type variables and constraints. We detail how some of the more common gate feasibility requirements may be incorporated in each. In Section 3, we classify the literature based on the objective functions studied into three categories; namely, passenger, airport/airline, and robustness oriented. We then analyze the objectives used simultaneously in a multi-objective framework. In Section 4 we review solution methods focusing on three main features: exact versus heuristic, single objective versus multi-objective, and deterministic versus stochastic. For metaheuristics, we detail most common neighborhood structures. Finally, we present conclusions together with recommendations for future work in Section 5.

2. The gate assignment problem

The gate assignment problem is defined on a set of m gates, an apron denoted as gate 0 and a set of n aircraft. Each aircraft $i = 1, \ldots, n$ has an arrival time a_i and a departure time d_i. An aircraft usually serves two consecutive flights: an arriving flight and a departing flight. So the arrival and departure times of the aircraft correspond to those of the arriving and departing flights. As such, it is possible to model GAP based on either aircraft or flights. We use aircraft in this section. Minor modifications are needed to write similar models using flights instead of aircraft. The main decision is to assign each aircraft to a gate or to the apron. While only one aircraft may use a gate at a time, the apron has unlimited capacity. In other words, there is no limit on the number of aircraft that use the apron simultaneously. Let x_{ik} be a binary assignment variable having a value 1 if aircraft i is assigned to gate k; 0, otherwise. A feasible gate assignment must satisfy the following constraints.

$$\sum_{k=0}^{m} x_{ik} = 1, \quad i = 1, \ldots, n \tag{1}$$

$$x_{ik} x_{jk} (d_j - a_i)(d_i - a_j) \leq 0, \quad i, j = 1, \ldots, n, k = 1, \ldots, m \tag{2}$$

$$x_{ik} \in \{0, 1\}, \quad i = 1, \ldots, n, k = 0, \ldots, m. \tag{3}$$

Constraint (1) ensures that each aircraft is either assigned to a gate or to the apron. Constraint (2) guarantees that aircraft assigned to the same gate do not overlap, i.e., for aircraft i and j to be both assigned to gate k, the departure time of aircraft i must be after the arrival time of aircraft j or vice versa. That is, if there is overlap between the ground times of aircraft i and j, these flights cannot be assigned to the same gate. Nonlinear constraint (2) may be linearised in several ways. For example, Mangoubi and Mathaisel [8] use the concept of conflict set. They define the conflict set $L(i)$ as the set of all aircraft j that land before aircraft i and are still on the ground at the time aircraft i arrives.

$$L(i) = \{j \mid d_j \geq a_i, j = 1, \ldots, i-1\} \tag{4}$$

Then constraint (5) is used to avoid the assignment of aircraft with conflicting ground times to the same gate.

$$\sum_{j \in L(i)} x_{jk} + x_{ik} \leq 1 \quad i = 1, \ldots, n, k = 1, \ldots, m \tag{5}$$

In addition to the above feasibility constraints, requirements related to space restrictions and gate compatibility have been added. A large gate is flexible to accommodate various sizes of aircraft whereas a small gate may only accommodate aircraft with certain sizes. Due to this physical restriction, aircraft and gate size compatibility needs to be taken into account during the assignment process. On the other hand, a small aircraft is compatible with any

gate and a large aircraft may use more than one small gate. A large gate may serve more than one aircraft at a time, hence it may be modelled as a single gate or as multiple gates. For example, a large gate is split into two smaller gates. To model this situation, a shadow constraint (6) is used. Let gates k and l correspond to a split gate, if aircraft i is of large size and is assigned to gate k then gate l cannot be used. This constraint ensures that only one gate is used if a large aircraft is assigned [9–12]. While this is observed in EU airports, in the US, large aircraft do not occupy more than one gate. Typically, each gate is designated for a size of aircraft. Smaller aircraft may occupy the gate, but larger aircraft may not occupy multiple gates.

$$x_{ik} + x_{il} \leq 1 \quad \text{for large aircraft } i \text{ and split gates } k \text{ and } l \tag{6}$$

Ground movement of aircraft may lead to conflicts in the ramp area. When an aircraft lands, it taxies and then parks at a gate or at a parking position in an apron area to disembark passengers and to load and unload baggages. Before the aircraft takes off, it pushes back (towes) and taxies to a runway. Modelling physical conflicts is most often reflected in the form of an objective function. Inevitably, the use of complex objective functions to model these conflicts increases the number of constraints. These physical conflicts and objectives used to model them are described in detail in Section 3.2.

An alternative way to model GAP is using flow variable. Define network $G = (N, A)$ where the set of nodes N correspond to aircraft $i = 1, \ldots, n$, a dummy starting node s and a dummy ending node e. An arc $(i, j) \in A$ exits if aircraft j may follow aircraft i on the same gate. Arc y_{sjk} defines the first aircraft j in gate k, arc y_{ijk} defines that aircraft i is followed by aircraft j on gate k and finally, arc y_{iek} defines that aircraft i is the last aircraft assigned to gate k. Then, a feasible gate assignment satisfies the following constraints;

$$\sum_{i \in \{1,\ldots,n\} \cup \{s\}} y_{ijk} - \sum_{i \in \{1,\ldots,n\} \cup \{e\}} y_{jik} = 0, \quad j = 1, \ldots, n, k = 1, \ldots, m, \tag{7}$$

$$\sum_{j=1}^{n} y_{sjk} = 1, \quad k = 1, \ldots, m \tag{8}$$

$$\sum_{i=1}^{n} y_{iek} = 1, \quad k = 1, \ldots, m \tag{9}$$

$$\sum_{k=1}^{m} \sum_{i \in \{1,\ldots,n\} \cup \{e\}} y_{ijk} \leq 1, \quad i = 1, \ldots, n \tag{10}$$

$$y_{ijk} \in \{0, 1\}, \quad i, j = 1, \ldots, n, k = 1, \ldots, m. \tag{11}$$

Constraint (7) ensures flow conservation at aircraft nodes, Constraints (8,9) ensure the flow out of the starting node s and into the ending node e. Together constraints (7,8,9) form m paths, one for each gate. Constraint (10) assigns an aircraft to at most one gate.

The network G and constraints (7,8,9,10) may be modified to model identical or multiple gate types, to include an apron, and to model other requirements of space, compatibility, etc. As such, several variants of the flow formulation are suggested [13–18].

While a feasible gate assignment may be modelled using mixed integer constraints, determining an optimal gate assignment is a more challenging task mainly due to the multi-objective nature of the problem. In addition, often times the objectives are nonlinear. These two features of gate assignment drive the research models and solution methods. We next discuss the types of objective functions used in the literature and then we discuss the solution methods.

3. Classification of objectives used in GAP

In this section we present a classification of objectives under three main classes, namely passenger-oriented, robustness-oriented and airport/airline-oriented. We then discuss how the objectives are used in multi-objective models.

3.1. Passenger-oriented objective functions

Gate assignment affects the quality of the service an airline or an airport provides to its passengers [19]. Hence, passenger-oriented objectives have been used by researchers since the 1970s. Braaksma and Shortreed [20] make one of the first attempts to use quantitative measures to minimize intra-terminal travel. Following this work, various objectives accounting for passenger walking distance, passenger waiting or transit time, and baggage transport distance have been proposed. One dimension of high-quality service is passenger comfort which is affected by passenger walking distance in the airport. For departing passengers, it is the distance between the check-in desk and the gate with air bridges; for arriving passengers, it is the distance between the gate and the baggage claim area; and for transfer passengers, it is the distance between the gates of consecutive flights. The objective of minimizing total passenger walking distance is expressed as:

$$min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{m+1} \sum_{l=1}^{m+1} p_{ij} d_{kl} x_{ik} x_{jl} + \sum_{i=1}^{n} p_{0i} d_{0k} x_{ik} + \sum_{j=1}^{n} p_{j0} d_{l0} x_{jl} \tag{12}$$

where x_{ik} is a binary assignment variable having a value 1 if aircraft i is assigned to gate k; p_{ij} is the number of transfer passengers from flight i to flight j, d_{kl} is the walking distance between gates k and l for connecting flights i and j, d_{0k} is the walking distance between the check-in desks and gate k and d_{l0} is the walking distance between gate l and the baggage handling area or exit. Due to the first term that represents the walking distance of transfer passengers, this objective function (12) is quadratic.

Among the passenger-oriented objectives, minimizing passenger walking distance is the most used [8,13,18,21–33]. A few papers [15,23,24] suggest linearizing the quadratic term and solving the linearized model exactly. The remaining papers apply heuristics as the solution technique. Moreover, several variants are used. For example, Babic et al. [34] minimize the average passenger walking distance of arriving and departing passengers. Yan and Tang [14] minimize the total passenger waiting time defined as the time an aircraft waits on the apron to enter a gate multiplied by the number of passengers. Kim et al. [35] minimize passenger transfer time calculated as the ratio of the distance between gates and an average passenger walking speed.

Several definitions of the parameter multiplying the quadratic term in (12) are suggested. For example, Xu and Bailey [24] consider the connection time between flights instead of distance between the gates. Maharjan and Matis [15] define a cost coefficient, which accounts for both the distance between connecting flights and the connection time. Similarly, Benlic et al. [36] define a parameter as a function of the number of transfer passengers and the time it takes to go from arriving gate to the departing gate to ultimately reduce possible passengers missing a connecting flight.

Finally, baggage transport distance related objectives are considered as another factor affecting passenger service as it impacts the time passengers wait for their luggage [37]. However, this objective has not received as much attention [22]. We note here that the solution approaches addressing the objective of minimizing passenger walking distance may be easily extended to the objective of baggage transport distance [38]. A detailed list of the passenger-oriented objective functions is presented in Table 2.

Table 2
Passenger oriented objective functions.

Objective	References	Number of objectives single (S)/Multiple (M)
Minimize total walking distance of all passengers or transfer passengers	Braksma and Shortreed (1971)[20]	S
	Mangoubi and Mathaisel (1985)[8]	S
	Bihr (1990)[21]	S
	Cheng (1997)[22]	M
	Haghani and Chen (1998)[23]	S
	Xu and Bailey (2001)[24]	S
	Yan and Huo (2001)[13]	M
	Ding et al. (2005)[25]	M
	Lim et al. (2005)[19]	M
	Hu and Paolo (2009)[46]	M
	Drexl and Nikulin (2008)[27]	M
	Pintea et al. (2008)[28]	M
	Cheng et al. (2012)[29]	S
	Yu et al. (2016, 2017)[18,41]	M
	Deng et al. (2017)[30]	M
	Dell'orco et al. (2017)[31]	M
	Daş (2017)[32]	M
	Mokhtarimousavi et al. (2018)[33]	M
	Dijk et al. (2018)[49]	S
Minimize average passenger walking distance	Babic et al. (1984)[34]	S
Minimize expected passenger discomfort	Maharjan and Matis (2012)[15]	M
Passenger waiting time/Transit time		
Minimize total passenger waiting time	Yan and Huo (2001)[13]	M
	Yan and Tang (2007)[14]	S
Minimize passenger transit time	Kim et al. (2013, 2017)[35,51]	M
Minimize estimated transfer time for passengers	Benlic et al. (2017)[36]	M
Baggage distance		
Minimize baggage transferring distance	Cheng (1997)[22]	M
	Hu and Paolo (2009)[46]	M

3.2. Airport/airline-oriented objective functions

Flight operations at an airport may lead to congestion on the ground mainly at the gates, apron area, taxiways, and runways. The last two are often referred to as the airport movement areas. Since congestion causes delays both in flight and departure times as well as inconvenience to passengers, efficient use of these bottleneck resources has been a focus in the gate assignment literature.

When a flight could not be assigned to a gate, it is assigned to a parking position or to a so called remote gate at the apron. Since passengers have to be transferred from and to the aircraft stationed at the apron by buses, this practice increases passenger waiting time and affects passenger satisfaction negatively, especially in extreme cold or hot weather. So to avoid low value ground operations at the apron and to make efficient use of the gates, the objective of minimizing the number of flights/aircraft assigned to the apron (13) is very common in GAP literature [11,25,27,28,30,39,40]. The objective may be expressed using the gate assignment variables as

$$\min \sum_{i=1}^{n} x_{i0} \tag{13}$$

where gate 0 represents the apron. This objective is equivalent to maximizing the number of flights/aircraft assigned to gates since the rest are assigned to the apron which usually has an unlimited capacity. It is critical when the number of gates available at an airport cannot serve all scheduled flights, which is the case in most airports. A variant of this objective models the apron as a fixed number of remote gates that are then treated similar to the rest of the gates.

When its assigned gate is busy, an aircraft has to wait for it to become available which may result in a delay in landing or take off. Hence the objective of minimizing aircraft waiting time is studied. In [22] the objective is to minimize the total passenger waiting time calculated as the product of the aircraft waiting time and the number of passengers. Another stream of research defines a time window $[begin_i, end_i]$ during which aircraft/flight j may start using the gate at time $enter_i$ as shown in Fig. 1. Aircraft/flight delay is the time between $begin_i$ and $enter_i$. In [19] the objective is to minimize total delay calculated as the number of passengers multiplied by the delay.

Apart from efficient use of gates and the apron, the cost of ground operations is also relevant to gate assignment. The procedure of moving an aircraft from one location to another using tow tractor is called towing. If the arrival and departure gates of an aircraft are different or if the gate is needed for an arriving aircraft, towing is used to move the aircraft between gates. Since these are expensive operations, minimizing the cost of towing activities is necessary. Kumar and Bierleire [10] use a linear objective function that computes the towing cost of gate assignments by multiplying the cost of towing an aircraft c_{tow} by the variable indicating that a towing is realized. On the other hand, Yu et al. [41] minimize a quadratic objective function (14) representing towing cost of assignments by assuming aircraft arrival and parking as separate activities. If an aircraft assigned to a gate k for an arrival activity i is also assigned to the same gate k for a parking activity, then a towing cost is not incurred. Otherwise a towing cost of c_{tow} is accounted for as

$$\min \sum_{i=R\cup P} c_{tow}\left(1-\sum_{k=1}^{m} x_{ik}x_{\sigma(i)k}\right) \tag{14}$$

where x_{ik} represents activity i assigned to gate k, R represents the set of arrival activities, and P represents the set of parking activities. $\sigma(i)$ represents activity succeeding activity i. The objective of minimizing the number of tow moves to minimize the towing cost is also considered in [12,36,39].

Taxiing is another type of surface movement which occurs after landing or before take-off and refers to aircraft movement from

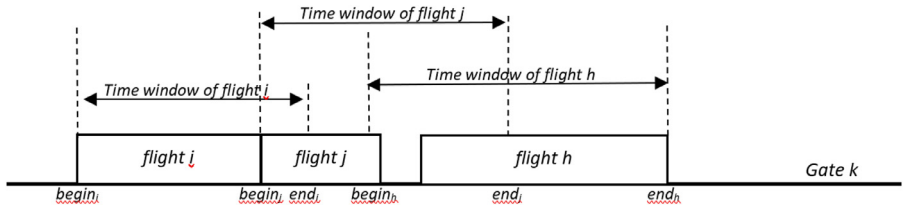

Fig. 1. Use of time windows in a gate schedule.

the runway to the gate and vice versa. Taxiing may result in physical conflicts between aircraft trajectories namely: taxi blockage and push-back blockage. Taxi blockage occurs when two aircraft move in opposite directions along a straight taxiway. Push-back blockage occurs when a departing aircraft cannot leave the gate because another aircraft is blocking its push back trajectory.

Kim et al. [35] minimize the total taxiing time using an objective function that includes linear and quadratic terms arising because of taxi time with and without taxi delays. The linear term computes taxi time without delays which is defined as the time an aircraft i requires taxiing from a spot to gate k considering aircraft taxi speed. On the other hand, the quadratic term computes taxi time with taxi delays because of blockage.

Unlike other objectives related to taxiing, Maharjan and Matis [15] consider the objective of minimizing the fuel consumption of taxiing operations, which depends on the fuel burn rate, average runway speed of an aircraft, fuel cost, and distance from an arrival runway to the gate.

Finally, objectives reflecting the preference of gate planners or airlines aim to maximize preferences (scores) of a specific airline for a specific gate [7,9–12,36,40]. The only single objective model among these studies is offered by Jaehn [42] to maximize flight/gate preference score (15) as presented below:

$$\max \sum_{k=1}^{m} \sum_{i=1}^{n} \rho_{ik} x_{ik} \tag{15}$$

where ρ_{ik} denotes the preference value of assigning flight i to gate k. The preference value is an integer valued priority determined by airport operators.

Aircraft gate size compatibility is modeled in the objective function in [11,36], and is otherwise modelled using constraints as discussed in Section 2. Research contributions having airport/airline-oriented objective(s) are presented in Table 3.

3.3. Robustness-oriented objective functions

Like other airline operations, planned gate assignments are affected by changes in the real time operation. For example a delay in an aircraft arrival is bound to cause a delay in all subsequent flights assigned to the same gate and may require a real time update of the assignments. Hence gate assignments that are robust to delays are very important for gate planners. This quality is usually captured in the objective. Researchers use either idle-time based objectives or gate conflict based objectives to obtain robust schedules. These objectives are summarized in Table 4.

The first studies on robustness use idle time based objectives. The time between two successive utilizations of a gate is called idle or slack time [43]. When the idle time is sufficiently large, the schedule is less likely to be affected by delays. Consequently, airports may require a minimum buffer time between consecutive flights/aircraft, both to guarantee safety and to absorb delays. Idle time is the slack time that occurs in a gate between a departing and an arriving aircraft; while buffer time is a standard slack time between two consecutive flights enforced at the time of planning. Long buffer times decrease gate utilization and the number of flights/aircraft assigned to the gates. The difference between idle time and buffer time is shown in Fig. 2.

To make better use of gates, several idle time oriented objectives are studied. Cost functions that penalize small and large idle times are used in [11,36,44]. Kumar and Bierlaire [10] penalize idle time that exceeds a predetermined value that corresponds to flight delay estimated using past data. While most models are deterministic, Şeker and Noyan [45] propose scenario based stochastic models where uncertainty in flight arrival and departure times causes gate conflicts between flights. The main objective of their models is to minimize gate conflict. In addition, they suggest other objectives to penalize the deviation of idle time and buffer time, namely, minimizing the expected variance of idle times. As a second objective they choose to minimize the expected variance of idle times, to minimize the expected total semi-deviation (where idle time smaller than a predefined buffer time is called a semi-deviation), and to minimize the expected number of positive semi deviation.

Unlike idle time based models which are mostly deterministic, models with gate conflict based objectives are mostly stochastic. A gate conflict (blockage) occurs when an aircraft requests a gate that is occupied by another aircraft. In other words, a gate conflict is observed when the ground times of flights assigned to the same gate coincide. In this case, the latter should wait for this or other available gate. Gate conflicts negatively impact passenger delays, connections, and fuel consumption [17]. To reduce gate conflicts, objectives such as minimizing the expected number of gate conflicts, expected duration of gate conflicts and expected gate conflict cost are suggested. Recently, Castaing et al. [17] compare different robustness measures, namely, the expected number of gate conflicts, the expected duration of gate conflict, the expected connecting passenger blockage time, and the worst case of expected gate conflict. They conclude that the objective of expected connecting passenger blockage time generates better schedules compared to the FIFO rule. Dorndorf et al.[9] study the use of strategies to recover the original plan as soon as possible after a disruption. For this purpose they minimize the absolute deviation of a new gate assignment from a reference schedule.

In addition to mathematical models, simulation models and expert systems are used to obtain robust gate assignments. These studies mainly investigate the effect of buffer time on gate schedules. They are reviewed in Section 4.3.

3.4. Multi-objective models

Given the multitude of objectives that are relevant to gate assignment, it is no surprise that most of the research addresses multiple objectives usually using a combination of objectives from the three categories: passenger-oriented, aircraft/airport-oriented, and robustness-oriented. Passenger-oriented objectives are frequently coupled with airport/airline-oriented objectives [15,19,25,27,28,31,35]. Among these, two categories are most popular: minimizing passenger walking distance and minimizing the number of flights assigned to the apron [22,25,27,28,31]. On the other hand, only Daş [32] consider passenger and robustness-oriented objectives simultaneously. Daş [32] couple the objective

Table 3
Airline/Airport oriented objective functions.

Objective	References	Number of objectives Single (S)/Multiple (M)
Objectives related to un-gated flights		
Minimize number of un-gated flights	Ding et al.(2005)[25]	M
	Dorndorf et al. (2008, 2012, 2017)[39,40,50]	M
	Drexl and Nikulin (2008)[27]	M
	Pintea et al. (2008)[28]	M
	Neuman and Atkin (2013)[11]	M
	Deng et al. (2017)[30]	M
	Kaliszewski et al.(2017)[47]	M
Minimize number of flights assigned to remote gates	Cheng (1997)[22]	M
	Tang and Wang (2013)[16]	M
	Dell'orco et al. (2017)[31]	M
Maximize total duration of flights assigned to gates	Genç et al. (2012)[74]	S
Minimize cost of not assigning a flight to a gate	Kumar and Beirlaire (2014)[10]	M
Objectives related to towing operations		
Minimize number of towing moves	Dorndorf et al. (2007b, 2008, 2012, 2017)[9,39,40,50]	M
	Nikulin and Drexl (2010)[12]	M
	Benlic et al. (2017)[36]	M
	Dijk et al. (2018)[49]	S
Minimize towing cost	Kumar and Beirlaire (2014)[10]	M
	Yu et al. (2016, 2017)[18,41]	M
	Mokhtarimousavi et al. (2018)[33]	M
Maximize number of arriving flights and the subsequent departing flights assigned to the same gate, if served by the same aircraft	Tang and Wang (2013)[16]	M
Objectives related to taxiing operations		
Minimize fuel consumption of taxiing operations	Maharjan and Matis (2012)[15]	M
Minimize taxi time	Kim et al. (2013, 2017)[35, 51]	M
	Ding and Zhang (2013)[80]	M
Objectives related to gate/ delay costs		
Minimize aircraft waiting time for a gate (waiting delay)	Cheng (1997)[22]	M
	Hu and Paolo (2009)[46}	M
Minimize total delay penalties	Lim et al. (2005)[19]	M
Minimize sum of waiting times for an aircraft for a gate	Kaliszewski et al.(2017)[47]	M
Minimize cost of assigning an aircraft to a gate	van Schaijk and Visser (2017)[52]	S
Objectives related to gates/ airline preferences		
Maximize total flight-gate preferences	Dorndorf et al. (2007b,2008,2012,2017)[9,39,40,50]	M
	Drexl and Nikulin (2008)[27]	M
	Nikulin and Drexl (2010)[12]	M
	Jaehn (2010)[42]	S
	Kumar and Beirlaire (2014)[10]	M
	Neuman and Atkin (2013)[11]	M
	Benlic et al. (2017)[36]	M
Maximize aircraft-gate size compatability	Neuman and Atkin (2013)[11]	M
	Benlic et al. (2017)[36]	M
Objectives related to airline/ airport specific goals		
Maximize number of departing flights assigned to short distances to target airline VIP lounges	Tang and Wang (2013)[16]	M
Maximize number of flights assigned to gates with short distance to customs		
Maximize number of passengers at gates close to shopping facilities to increase potential revenues	Daş (2017)[32]	M
Maximize potential airport commercial revenues	Dijk et al. (2018)[49]	S
Maximize number of passengers at gates	Daş (2017)[32]	M
	Dijk et al.(2018)[49]	S

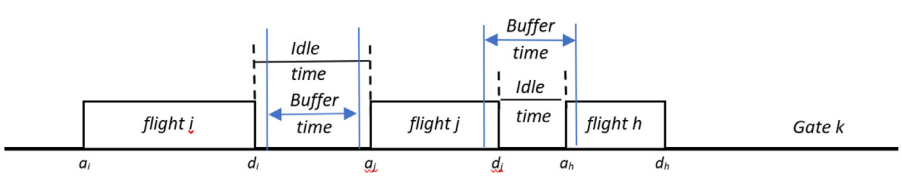

Fig. 2. Idle time and buffer time in a gate schedule.

of minimizing passenger walking distance with three other objectives and offer three models. The aim of these models is to analyze which objective enables the assignment of more passengers to gates close to shopping facilities. For this purpose the objectives of minimizing the variance of idle time at specific gates, maximizing the number of passengers at gates close to shopping facilities, and maximizing the number of passengers in all gates are considered and the corresponding models are compared. The ultimate goal is to assign more passengers to specific gates which could possibly increase an airport's shopping revenues.

Other models consider multiple objective functions from only one category. For example, Hu and Paolo [46] and Yan and Huo

Table 4
Robustness oriented objective functions.

Objective	References	Number of objectives single (S)/Multiple (M)
Idle time based objectives		
Minimize range of idle times	Bolat (1999)[43]	S
Minimize idle times at the gates at peak times	Genç (2010)[75]	S
Minimize variance of idle times	Bolat (2000,2001)[76,77]	S
	Liu et al. (2016)[78]	M
	Deng et al. (2017)[30]	M
	Daş (2017)[32]	M
Maximize robustness by avoiding assignment of two flights with low buffer times to same gate	Dorndorf et al. (2008)[39]	M
Maximize idle time between consecutive flight pairs by penalyzing idle times with cost function	Diepen et al. (2012)[44]	S
	Neuman and Atkin (2013)[11]	M
	Benlic et al. (2017)[36]	M
	Kumar and Beirlaire (2014)[10]	M
Minimize expected variance of idle times	Şeker and Noyan (2012)[45]	M
Minimize expected total semi-deviation of idle time from buffer time		
Minimize expected number of positive semi-deviations of idle time from buffer time		
Gate conflict (blockage) based objectives:		
Minimize expected number of gate conflicts	Lim and Wang (2005)[26]	S
	Şeker and Noyan (2012)[45]	M
	Castaing et al., (2016)[17]	S
	Dorndorf et al., (2017)[50]	M
Minimize the number of conflicts of any two adjacent aircraft assigned to the same gate	Mokhtarimousavi et al. (2018)[33]	M
Minimize the expected gate conflict duration	Kim et al. (2017)[51]	M
	Castaing et al. (2016)[17]	M
	Yu et al. (2017)[41]	S
Minimize expected gate conflict cost	Yu et al. (2016)[18]	M
Minimize expected connecting passenger bloackage minute	Castaing et al. (2016)[17]	S
Minimize worst case expected gate conflict		
Deviation from a reference schedule:		
Minimize absolute deviation of new gate assignment from a reference schedule	Cheng (1997)[22]	M
	Dorndorf et al. (2007b, 2012)[9, 40]	M
	Nikulin and Drexl (2010)[12]	M

[13] couple the objective of minimizing passenger walking distance with the objective of minimizing passenger waiting time. Similarly, Şeker and Noyan [45] use multiple robustness-oriented objectives as discussed in Section 3.3. Tang and Wang [16] and Kaliszewski et al.[47] consider only airport/airline-oriented objective functions. Tang and Wang [16] offer a model, including the objectives of maximizing the number of departing flights assigned to gates with short distances to the target airlines VIP lounge and maximizing the number of arriving flights assigned to gates with short distances to customs. Kaliszewski et al. [47] suggest a queuing system where the gates and the apron act as servers and aircraft are jobs. They model the objectives of minimizing the total waiting time of flights assigned to the gates and minimizing the total number of flights assigned to the apron where flights that wait in the queue more than a threshold time are assigned to the apron.

A few studies use objectives from all three classes, usually transforming three to four objective functions into a single one using the weighted-sum method [18,22,30]. Finally, Benlic et al. [36] formulate a weighted sum model by considering nine objective functions such as minimizing average passenger walking distance, minimizing the number of towing moves, maximizing total gate preferences, etc. All of these contributions are summarized in Table 5.

4. Solution methods

A wide range of solution approaches is developed to solve variants of GAP with varying objectives and practical constraints. Early researchers proposed single objective models that they solved with branch and bound [34] and Simplex Algorithm [21]. Later, with the increasing size and complexity of models, simple heuristics were combined with exact approaches to generate feasible solutions quickly. These heuristics mainly sort flights with respect to a criterion such as arrival time or number of passengers, then assign the highest ranked flight in the sorted list to the first available gate. Hamzawi [48] assign the first arriving flight first by giving priority to large aircraft, airline gate preferences and flight sector (either domestic or international). The heuristic by Mangoubi and Mathaisel [8] assigns the flight with the highest number of passengers to the gate with the shortest distance to the exit. This algorithm heuristically aims to generate a good solution for the gate assignment problem with the objective of minimizing total passenger walking distance. Similarly, Haghani and Chen [23] propose a heuristic to minimize passenger walking distances by assigning successive flights to the same gate, if the schedules of these flights are not overlapping. In case of a coincidence between flight schedules, the conflicting flight pairs with the smallest passenger walking distance is assigned first. Ding et al. [25] develop a greedy algorithm to obtain an initial solution for their hybrid algorithms based on Tabu Search and Simulated Annealing. This heuristic assigns a flight with the latest departure time to an available gate, otherwise to the apron. Similar, Xu and Bailey [24] assign the first flight with latest departure time to the earliest available gate.

Column generation [44], dynamic programming [42] and network flow models [13,14,16,17] are more recent approaches to single objective GAP. Meta-heuristics and local search approaches are also employed to solve both single and multi-objective GAPs. In the next section a discussion on how these methods have been applied to GAP is presented.

While the solution approaches discussed so far handle the problem deterministically, stochastic approaches are used to deal

Table 5
Classification of multi objective models.

References	Year	Passenger	Airline/Airport	Robustness
Yan and Huo[13]	2001	x		
Hu and Paolo[46,79]	2009, 2009	x		
Tang and Wang[16]	2013		x	
Kaliszweski et al.[47]	2017		x	
Şeker and Noyan[45]	2012			x
Ding et al.[25]	2005	x	x	
Lim et al.[19]	2005	x	x	
Drexl and Nikulin[27]	2008	x	x	
Pintea et al.[28]	2008	x	x	
Maharjan and Matis[15]	2012	x	x	
Kim et al.[35]	2013b	x	x	
Dell'orco et al.[31]	2017	x	x	
Dorndorf et al.[9,39,40,50]	2007b, 2008, 2012, 2017		x	x
Nikulin and Drexl[12]	2010		x	x
Neuman and Atkin[11]	2013		x	x
Kumar and Beirlaire[10]	2014		x	x
Liu et al.[78]	2016		x	x
Daş[32]	2017	x		x
Cheng[22]	1997	x	x	x
Benlic et al.[36]	2017	x	x	x
Kim et al.[51]	2017	x	x	x
Yu et al.[18,41]	2016, 2017	x	x	x
Deng et al.[30]	2017	x	x	x
Mokhtarimousavi et al.[33]	2018	x	x	x

with the problem under uncertainty. These approaches consider arrival and departure times of flights as stochastic parameters. Among the methods to handle stochastic models, scenario based stochastic programming [14,45,49] are mostly used.

Yan and Tang [14] formulate an integer multicommodity network flow problem to minimize total passenger waiting time. They add a penalty value to each connecting flight arc for each delay scenario. Then, a heuristic approach is used to solve the model which aims to minimize total passenger waiting time, the expected penalty value, and the expected semideviation risk measure. Şeker and Noyan [45] offer stochastic models to model gate conflicts due to uncertain arrival and departure times of flights. Dorndorf et al. [50] consider a set of objectives including the objective of minimizing expected gate conflict. More, they offer recovery strategies if conflicts can not be prevented. Recently, Dijk et al. [49] obtain robust schedules considering uncertain arrival times of an aircraft using the concept of recoverable robustness. Taking into account historical data on flight delays, they generate scenarios representing early or late arrival of aircraft. In case of gate conflict, they offer three recovery actions: (1) waiting for a gate till a maximum waiting time, if conflict time is greater than maximum waiting time; (2) assignment to a gate; and (3) assignment to the apron. They suggest that these policies that lead to recoverable robustness provide better solutions compared to strict robustness where no recovery is allowed.

In some stochastic models, assumptions about distribution of arrival times, departure times and delays are made. Lim and Wang [26] use unsupervised estimated functions to estimate the probability of gate conflict between flights i and j when assigned to the same gate. Castaing et al. [17] use historical data on delays to predict the distribution of gate conflict. Kim et al. [51] define the expected conflict duration between an arrival and departure as an exponential function of slack time $\triangle_{i,j}$ where $f(\triangle_{i,j}) = ab^{\triangle_{i,j}}$ and a, b are determined using historical flight delays. Later, Yu et al. [41] also use this objective function. Recently, van Schaijk et al. [52] propose an IP model with a stochastic constraint and the objective of minimizing the cost of assigning an aircraft to a gate within a given time window. The proposed constraint calculates the expected gate conflict probability of two flights using flight presence probabilities which are obtained by combining the arrival and departure delay cumulative probability distributions with the planned arrival and departure times.

Only Nikulin and Drexl [12] define arrival and departure data using fuzzy numbers as a way of treating uncertainty. Fuzzy numbers are fuzzy sets defined on an interval with a specific membership function that can take values in [0,1]. In an optimization problem either the objective and constraint coefficients or the right hand side values could be fuzzy. Although there are various ways of solving fuzzy models, two popular approaches are either transforming the fuzzy numbers to crisp values using defuzzification methods or comparing the fuzzy numbers with ranking functions. Nikulin and Drexl [12] consider the flight earliness and tardiness as a fuzzy parameter and they handle the objectives of maximizing the total gate preferences and minimizing the total number of towing activities and the absolute deviation of the new gate assignment from a reference schedule.

4.1. Multi-objective solution methods

Solution methods of multi-objective optimization problems are classified based on when the preferences of the decision maker for the objectives is articulated, namely, a priori, a posteriori, and no articulation. Methods using an a priori articulation of preferences mostly aggregate objectives into a single one with the help of weights. These weights represent the decision maker's preferences provided prior to the optimization process and reflect the relative importance of objectives. It is the most common approach to multi-objective optimization [53]. When it is difficult for the decision maker to express preferences, a posteriori approach can be used to generate a representation of the Pareto optimal set. In this case, the decision maker may select a single solution from the generated solutions. Methods with no articulation of preferences are mostly simplified versions of methods using a priori articulation of preferences. For other methods with no articulation of preferences interested readers may refer to Marler and Arora's review [53]. Different from the above mentioned approaches, interactive methods require preferences from users during the solution process.

When solving a multi-objective problem, the goal is to return a set of mutually non-dominated solutions [54]. These solutions are called Pareto optimal or efficient solutions of a multi-objective optimization problem. The solutions in this set are said to be non-

Table 6
Research using the weighted sum approaches.

References	Solution method
Cheng (1997)[22]	GA, TS, SA
Yan and Huo (2001)[13]	Column Generation+ Branch and Bound Alg.
Ding et al. (2005)[25]	TS+ SA
Lim et al. (2005)[19]	Memetic Algorithm
Hu and Paolo (2009)[46]	GA
Dorndorf et al. (2008)[39]	Ejection Chain Alg.
Pintea et al. (2008)[28]	AS
Şeker and Noyan (2012)[45]	Stochastic Programming, TS
Kim et al. (2013)[35]	Branch and Bound Alg., TS, GA
Maharjan and Matis (2012)[15]	IP
Tang and Wang (2013)[16]	IP
Neuman and Atkin (2013)[11]	MIP
Kumar and Beirlaire(2014)[10]	IP
Benlic et al. (2017)[36]	Breakout Local Search
Yu et al.(2016)[18]	MIP based heuristics
Kim et al. (2017)[51]	TS
Yu et al. (2017)[41]	Large Neighborhood Search
Deng et al. (2017)[30]	Adaptive PSO
Dell'orco et al. (2017)[31]	BCA

dominated; that is, each solution in this set has an improved value in one objective without worsening the performance in any other objective.

The widely used weighted sum (weighting) method is one of the scalarization methods in the literature. Scalarization methods most often applied in multi-objective combinatorial optimization are the weighted sum method, e-constraint method and the weighted Chebychev method [55]. The weighted sum method combines all objectives into a single weighted sum function which then may be dealt with using single objective solution methods. When using the e-constraint method, the most important objective function is optimized, while the others are written as constraints bounded with an ϵ value. In Chebychev scalarization, there are also bounds on objective function values. The distance to an ideal point, which is composed of the optimal value of each objective function, is also considered. Interested reader may refer to Ehrgott et al. [55] for a general formulation representing all these scalarizations.

These scalarizations lead to linear single objective formulations that need to be solved repeatedly to generate Pareto-optimal solutions. Only e-constraint and Chebychev methods are able to generate all efficient solutions. Even though weighted sum approaches cannot compute any non-supported efficient solutions [55], some (supported) efficient solutions may be found this way [56]. In spite of this, weighted sum is often used due to its simplicity and ease of implementation. Further, Das and Dennis [57] discuss two difficulties with this approach. The weighted sum approach succeeds in generating points from all parts of the Pareto set only if the Pareto front is convex. In addition, even for a convex Pareto front, an evenly distributed set of weights, fails to produce an even distribution of Pareto-optimal points. As a result, solutions often appear only in some parts of the Pareto front, while other parts are not covered [58]. Finally, Messac and Mattson [59] discuss that the spacing of the points is largely dependent on the relative scaling of the objectives. Methods that overcome these difficulties such as compromise programming, the exponential weighted criteria method, the normal boundary intersection method, and homotopy based techniques are developed [59]. However, these methods are not utilized in the GAP literature. In fact, the most common method is the weighted sum approach, as shown in Table 6.

To solve weighted sum models, mostly Genetic Algorithms (GAs) [22,35,46], Tabu Search (TS) [25,35,45,51] and Simulated Annealing (SA) [22,25] are used. Other than classical metaheuristics, population based metaheuristics such as Particle Swarm Optimizaton (PSO) [30], Ant System (AS) [28] and Bee Colony Algorithms (BCA) [31] are also adopted. Meta-heuristic algorithms are preferred due to their ability to adopt to different combinatorial problems and their ability to explore the solution space relatively fast. Local search algorithms such as Ejection chain [39] and Breakout local search [36] are also applied.

Our review indicates that approaches other than the weighted sum did not receive much attention from the researchers dealing with GAP. These approaches are listed in Table 7. According to Emmerich and Deutz [60] there are three main paradigms for multi-objective evolutionary algorithm (MOEA) designs: Pareto-based, Indicator based and Decomposition based. Most of the reviewed work in Table 7 are Pareto-based algorithms. The aim of these algorithms is to reach a representation of the Pareto front by comparing the objective vectors using the concept of dominance while considering contributions of points to diversity. The most popular of these algorithms are NSGA-II proposed by Deb et al.[61] and SPEA2 proposed by Ziztler and Thiele [62]. Usually, Pareto based algorithms require only a few parameters so they can handle a large number of objective functions but they do not guarantee a regular spacing of solutions [60]. Drexl and Nikulin [27] and Nikulin and Drexl [12] use Pareto SA for models with objective of different types. Daş [32] use a hybrid local search algorithm called Two Phased Local Search. In the first phase the weighted sum problem is solved whereas in the second phase other non-dominated solutions are searched using Pareto Local Search. Recently, Mokhtarimousavi et al.[33] use the well known NSGA-II algorithm.

4.2. Neighbourhood moves in metaheuristics

Metaheuristics are high-level strategies which guide an underlying, more problem specific heuristic, to increase their performance [63]. In combinatorial optimization they are preffered when the aim is to find a good solution in a relatively short time instead of a guaranteed optimum which is difficult to obtain in most cases. Metaheuristics applied to GAP are used mainly to handle quadratic objective functions or multiple objectives. Researchers use various algorithms and design neighborhood moves which are well suited to the problem. Some of these neighbourhood moves are discussed next.

Xu and Bailey [24] design three neighbourhood moves to solve GAP using TS. In Insert Move, a flight, previously assigned to a gate, is reassigned to another gate. In Exchange 1 type move, two flights exchange gates. Similarly, in Exchange 2 type move, the gate of a flight pair is exchanged with the gate of another pair.

Table 7
Other multi objective approaches.

References	Multi-objective approach	Solution method
Drexl and Nikulin (2008)[27]	Pareto based	Pareto SA
Nikulin and Drexl (2010)[12]	Pareto based	Pareto SA
Kaliszewski et al.(2017)[47]	Scalarization by Achievement Function Method	IP, Evolutionary Algorithm
Daş (2017)[32]	Pareto based	Two Phase Local Search
Mokhtarimousavi et al. (2018)[33]	Pareto based	NSGA-II

Ding et al.[25] observe that Exchange 1 and 2 do not always produce feasible solutions. Instead, they design a move called Interval Exchange where all the flights in gate k whose arrival and departure times are between flights i and j are exchanged with the flights in gate l whose arrival and departure times are between flights g and h. That is, a set of flights scheduled to gate k exchange gates with another set of flights at gate l.

Lim et al.[19] propose Memetic algorithms and use modified Insert Move and Interval Exchange move. As discussed in Section 3.2, their goal is to minimize the waiting delay of the aircraft by considering time windows for each flight. To enable the use of Insert Move and Interval Exchange move for time windows, they develop two subroutines, ShiftLeft and ShiftRight, that shift the ground time of an aircraft in the time window left and right. Drexl and Nikulin [27] introduce an improved version of Apron Move which assigns a flight at the apron to a gate until the objective of minimizing the minimum number of flights assigned to the apron could not improve any further. After this point, they only use Exchange 1 and Exchange 2 moves in the developed Pareto SA.

Daş [32] use Two Phase Local Search algorithm combined with Pareto Local Search, and define two neighborhood moves: a new exchange move and a greedy move. In the exchange move, the assigned positions (whether the flight is assigned to a gate or apron) of two flights are exchanged. That is, if both flights are assigned to a gate, the gates are exchanged. If flight i is assigned to gate k and flight j to the apron, then flight i is assigned to the apron and flight j to gate k. If both flights i and j are already at apron, then the latter flight is assigned to a random gate. On the other hand, in a greedy move, selected flights are first assigned to the apron, then they are reassigned to the gates with the shortest walking distance when possible, with the goal of minimizing total passenger walking distance.

Yu et al.[41] propose an Adaptive Large Neighborhood Search for GAP. They propose different methods to destruct the current solution by removing some assignments from the schedule. Then they use various repair moves to fix these schedules. Contributions offering GAs use crossover and mutation which are well-known GA operators. For GAP, a mutation operator may make a change in the gate of a flight or may assign a flight from gate to apron or vice versa. It should be noted that in most cases a feasibility check is needed after applying crossover and mutation operators. Hu and Paolo [46] offer the use of new encoding schemes for GAP, namely absolute position based and relative position based. Using these two representations, they apply various mutation operators. They show that problem specific encoding schemes improve performance.

4.3. Other approaches for GAP

The complex and uncertain nature of airline operations lead to the use of methods like simulation and expert systems. Simulation models enable researchers to observe the dynamic behavior of the complex operation in airports. Baron [64] analyzes the effect of different gate usage policies on passenger walking distance for typical terminal designs. Hamzawi [48] offers a simulation model for efficient handling of the day-to-day assignments. Yan et al.[14] analyse the relationship between static gate assignments and real-time gate assignments as affected by stochastic flight delays. To observe the effects of flight delays on gate assignments, they design flexible buffer times. Their experiments show that flight delays do negatively affect the performance of static gate assignments as expected.

Expert systems utilize domain-specific expertise and support real time operations. They have been used for gate assignment in Gosling [65], Srihari and Muthukrishnan [37] and Su and Srihari [66]. However, these approaches have several shortcomings compared to exact optimization approaches. Observing this deficiency, Cheng [22] proposes a knowledge-based airport gate assignment system integrated with mathematical programming to treat both static and dynamic situations. The author applies the knowledge-based approach to take advantage of human expertise and the integer programming model to obtain an exact solution for easily modeled aspects of the problem. Unlike other approaches in the literature, the author assigns a group of aircraft that may be located to gates at sub-areas of airport. First, integer programming is used to assign aircraft to gates; then the obtained solution is evaluated by experts in terms of special requirements and a feasible solution is reached. In a similar manner, Lam et al. [67] offer a hybrid approach that combines a knowledge-based expert system in the form of an intelligent agent and an optimization model while considering real-time changes in the gates and flights.

5. Conclusions and futurework

In this paper, an overview of research contributions to modeling and solving gate assignment in airports is presented. Our review indicates that there is not a standard problem formulation for GAP due to the multitude of stakeholders, feasibility requirements, and objectives. Two main types of formulations are common based on assignment and flow variables, respectively. The feasibility requirements and objectives determine the type of modelling and solution method in most cases.

The classification of objectives reveals a number of interesting observations. Objectives related to passenger walking distance have been popular since the 1990s. The importance of robust gate schedules to airport and airline operators motivated the use of robustness-oriented objectives in recent years. Airline/airport oriented objectives, employed to improve the efficiency of taxi and tow operations, are mostly used in conjunction with passenger or robustness oriented objectives. Finally among airline/airport oriented objectives, only a few reflect an airport operator's perspective.

When it comes to solution methods, a variety of heuristic and meta-heuristic algorithms are developed mostly to solve multi-objective models. Very little, if any, multi-objective exact methods have been suggested. It is known that the task of finding the complete Pareto set is computationally very demanding even when metaheuristics are used. In spite of this, the idea of using exact approaches to obtain an approximation of the Pareto front triggered research on the field. Recently, column generation based approaches [68–70] for various bi-objective optimization problems

are reported. These recent advances offer an opportunity for research to develop such methods for multi-objective GAP.

Among the solution methods for multi-objective models, only a few studies use approaches other than the weighted sum method. In the light of the discussion on the drawbacks of this method, there is a need to develop new solution algorithms to generate the complete set of Pareto solutions or a tight approximation of it.

One issue we identify is the lack of standard test cases. Some research [25,39,45] generate test cases and provide distribution properties instead of the data itself, whereas others use real data that is not made available to the research community. This situation hinders a systematic comparison of the available models and solution methods. Introducing such testing instances would help bring the research on this problem together.

Only a few studies handle GAP along with other related problems in airport operations. Diepen et al. [71] study the integrated gate and bus assignment problem at Amsterdam Schiphol airport, Yu et al. [72] study the gate reassignment and taxiway scheduling problem, and Behrends and Usher [73] integrate aircraft taxi problem with GAP. We believe that future research on integrating GAP with other airport planning and scheduling problems is important for a better utilization of airport resources and an efficient operation of the air transportation system as a whole.

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Appendix A

The following notations are used in the manuscript.

Sets

$L(i)$	set of all aircraft j that land before aircraft i and are still on the ground at the time aircraft i arrives
R	set of arrival activities
P	set of parking activities
Parameters	
n	number of aircraft
m	number of gates
a_i	arrival time for aircraft i
d_i	departure time for aircraft i
p_{ij}	number of transfer passengers from flight i to flight j
p_{j0}	number of passengers walking to exit from flight j
p_{0i}	number of passengers walking to flight i from check-in desks
d_{kl}	walking distance between gates k and l for connecting flights i and j
d_{0k}	the walking distance between the check-in desks and gate k
d_{0k}	walking distance between the check-in desks and gate k
d_{l0}	walking distance between gate l and the baggage handling area or exit
Decision Variables	
x_{ik}	binary variable showing whether aircraft i is assigned to gate k or not
y_{ijk}	binary variable showing aircraft i followed by aircraft j on gate k
c_{tow}	towing cost
σ_k	activity succeeding activity i
ρ_{ik}	preference value of assigning flight i to gate k

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