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Criteria selection and multi-objective optimization of aircraft landing problem

Junfeng Zhang [a,*], Pengli Zhao [a], Yu Zhang [b], Ximei Dai [a], Dong Sui [a]

[a] College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing, 210016, China
[b] Department of Civil and Environmental Engineering, University of South Florida, Tampa, FL, 33620, USA

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ABSTRACT

Inspired by the similarities of the aircraft landing problem (ALP) and the single machine scheduling problem, we propose a criteria selection method that has been used successfully in the single machine scheduling problem to determine appropriate objective functions of ALP. First, for four different types of criteria—min-max, min-sum, completion time related, and due-dates related criteria—their corresponding physical meanings in ALP are elaborated. Then, a criteria selection method is proposed to determine several appropriate criteria, which are taken as the multi-objective while modeling ALP. Different solution algorithms, including Imperialist Competitive Algorithm (ICA), are adopted to solve the multi-objective ALP. Finally, the performance of the proposed model and method are evaluated using a set of benchmark instances. The computational results demonstrate the efficiency of our approach for solving ALP, which can simultaneously improve punctual performance, enhance runway utilization, reduce air traffic controller workload, and maintain equity among airlines.

1. Introduction

The rapid growth of air traffic has led to aviation congestion problems, resulting in substantial flight delays, excessive fuel consumption, and consequential air pollutant emissions. Airports are usually the bottlenecks of the national airspace system (Zografos et al., 2017). Enhancing the utilization of runway capacity at an airport via air traffic management can improve its operational efficiency and alleviate aviation congestion. One ATM challenge is to schedule arrival aircraft efficiently, referred to as the Aircraft Landing Problem (ALP) (Bennell et al., 2013). Although ALP has been studied extensively, we propose to address it from a more holistic perspective.

To solve ALP, the sequence and time of aircraft landing on available runways should be determined by optimizing given objectives while subject to a variety of operational constraints. For environments, some studies were carried out in a static context (Bennell et al., 2013; Beasley et al., 2000) and others focused on a dynamic context (Hu and Chen, 2005; Bennell et al., 2017). Regarding solution algorithms, several methods have been used to solve ALP. CPLEX was used to solve small-scale ALP formulated as a mixed-integer linear programming (MILP) problem (Vadlamani and Hosseini, 2014). For large-scale ALP, dynamic programming (DP) (Balakrishnan and Chandran, 2010; Lieder et al., 2015) and branch and bound (BB) (Solving and Clarke, 2014) have been implemented. In addition, some studies used heuristic and meta-heuristic algorithms such as cellular automata optimization (CAO) (Yu et al., 2011), simulated annealing (SA) algorithm (Salehipour et al., 2013), particle swarm optimization (PSO) (Girish, 2016), genetic algorithm (GA) (Hu and Di Paolo, 2008; Hu and Di Paolo, 2009), and ant colony (AC) algorithm (Zhan et al., 2010; Xu, 2017).

In addition to environments and algorithms, the objectives that appeared in previous studies were not the same, including the following: (1) Minimizing the total cost (Beasley et al., 2000; Vadlamani and Hosseini, 2014; Lieder et al., 2015) (Yu et al., 2011; Salehipour et al., 2013; Girish, 2016) (Faye, 2015; Sabar and Kenall, 2015; Ji et al., 2016), i.e., the total weighted earliness plus the total weighted tardiness, in which the earliness or tardiness was the deviation of actual landing time from the target one; in addition, the cost could be a linear, piecewise linear, or non-linear function; (2) Minimizing the total or average delay (Hu and Chen, 2005) (Hu and Di Paolo, 2008; Hu and Di Paolo, 2009; Zhan et al., 2010) (Eun et al., 2010) of arrival aircraft; this criterion emphasizes on the operating cost of airlines; (3) Minimizing the scheduled time of the last aircraft (Harikiopoulo and Neogi, 2011; Ji et al., 2017) (or maximizing runway throughput); and (4) Leveling the workload of ground staff (Boysen and Fliedner, 2011; Mokhtarimousavi

* Corresponding author.
E-mail address: zhangjunfeng@nuaa.edu.cn (J. Zhang).

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et al., 2015). Some previous studies also considered two or more objectives simultaneously. Lee and Balakrishnan (Balakrishnan and Chandran, 2010) introduced a general landing cost function to encompass runway throughput maximization and average delay minimization. Tang et al. (2008) considered minimizing the total scheduled time and total cost simultaneously. Mokhtarimousavi et al. (2015) gave a new mathematical formulation of ALP that included three criteria—maximizing runway throughput, minimizing ground costs (apron and parking), and minimizing air costs (fuel consumption and carbon dioxide pollution). Hong et al. (2017) proposed a multi-objective optimization approach for ALP to minimize total flight time and the number of the sequence change. Samà et al. (2017) investigated the MILP formulations of ALP with different objective functions and examined the differences between the solutions regarding various performance indicators.

The objectives of ALP in previous studies reflect the explicit or implicit concerns of different stakeholders, such as Air Traffic Control (ATC), airlines, airports, and government. ATC aims to ensure the safety and efficiency of the national airspace system. Airlines are concerned about operating costs and on-time performance. Airports care about passenger throughput, which is the primary source of their revenue, and also hope to reduce airfield congestion. Government preference is to have air transportation help stimulate vital economic development and mitigate environmental impacts (noise and air pollution) on the local community. In summary, ALP reflects the interests of different stakeholders, and their interests may conflict with each other. Nevertheless, the selection of objective functions in previous studies is relatively straightforward without a precise mechanism.

The primary purpose of this study is to provide a theoretical background on how to choose the appropriate objective functions in multi-objective optimization for ALP. For this purpose, given that ALP is similar to the machine scheduling problem, we learn from the selection of different criteria, equivalent to objective functions, in the machine scheduling problem (Vadlamani and Hosseini, 2014; Hancerliogullari et al., 2013) by revealing the inherent link of criteria between ALP and machine scheduling and determining appropriate criteria for ALP based on existence theorems and lower bounds for scheduling to meet bi-criteria (Stein and Wein, 1997; Aslam et al., 1999; Rasala et al., 2002; Eren and Güner, 2006; Lin and Lin, 2015; Huo and Zhao, 2015; Wu et al., 2018). As elaborated later, the three criteria determined finally by learning from the machine learning problem are 1) total flight delay time, 2) total dwell time in the terminal area, and 3) maximum dwell time. It should be noted that ALP with a single runway is the focus of this study, as the Air Traffic Controller (ATCO) intends to allocate the landing runway for the aircraft based on its entry fix such that the runway allocation principle could alleviate potential conflicts in air. On the contrary, airports and airlines prefer to allocate the landing runway for aircraft based on gates. Such a principle can not only alleviate potential conflicts on the ground but also reduce taxiing time. Correspondingly, if we consider runway allocation, the model and algorithm for the multi-objective optimization of ALP will be more complicated. We will address this issue in a future study.

We propose a multi-objective optimization method to solve ALP with multiple criteria. Hoogeveen (2005) identified two methodologies—lexicographical and simultaneous optimization—and also summarized three approaches for simultaneous optimization— aggregating different criteria into one composite objective function, converting criteria into constraints, and determining Pareto optimal. In this study, we combined two approaches in simultaneous optimization—*aggregating one composite function* and *constraining one objective*—and propose a multi-objective ALP. The trade-off between the objectives, as well as the model performance of different single objectives, is discussed to obtain insights on air traffic management of arrival flights. Since the multi-objective ALP is time-consuming, an efficient meta-heuristic algorithm, Imperialist Competitive Algorithm (ICA) (Hosseinia and Khaled, 2014; Khaled and Hosseinia, 2015), is implemented to solve the ALP.

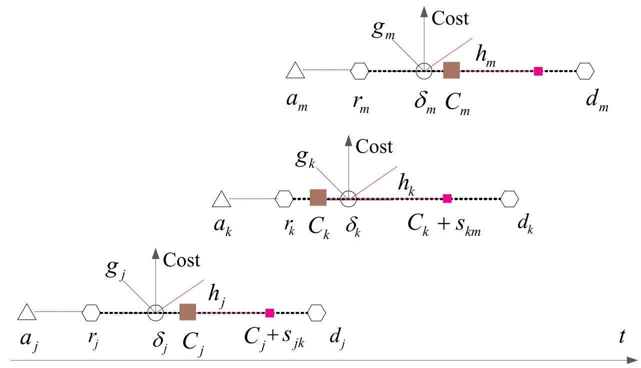

Fig. 1. Illustration of ALP

Table 1
Notation and variables.

Notation/Variables	Single Machine Scheduling	Aircraft Landing Problem
J	A set of jobs	A set of landing aircraft
a_j	Appear time	Entry time
r_j	Release date	Earliest landing time
d_j	Deadline	Latest landing time
δ_j	Due date	Target landing time
s_{jk}	Set-up time	Wake Vortex separation
C_j	Completion time	Scheduled landing time
p_j	Processing time	Runway occupied time
g_j	Earliness weight	Incurred cost for early landing
h_j	Tardiness weight	Incurred cost for late landing
$F_j = C_j - a_j$	Flow time of job	Dwell time in terminal area
$L_j = C_j - \delta_j$	Lateness of job	Lateness of aircraft
$E_j = \max(\delta_j - C_j, 0)$	Earliness of job	Earliness of aircraft
$T_j = \max(C_j - \delta_j, 0)$	Tardiness of job	Tardiness of aircraft
$q_{kj} = \{0, 1\}$	Sequence	Landing sequence
$U_j = \begin{cases} 1 & \text{if} \quad C_j > \delta_j \\ 0 & \text{otherwise} \end{cases}$	Unit penalty of job	Number of tardy aircraft

The remainder of this paper is organized as follows. The problem formulation and criteria selection for ALP are described in Section 2. Section 3 presents the proposed multi-objective optimization formulation and solution method for ALP. The computational results and discussion are summarized in Section 4, and concluding remarks are provided in Section 5.

2. Objectives for ALP

2.1. Problem description

ALP is a combinatorial optimization problem that can be defined as follows. Given a set of arrival aircraft, the goal is to assign a landing sequence and time for each aircraft by optimizing the given objectives while subject to a variety of operational constraints. In such a problem, it is usually assumed that the earliest and latest landing times of each aircraft are known. ALP with a single runway was considered in this study, which could be easily extended to multiple runway cases. Independent parallel approaches and segregated parallel operations are the most common modes for simultaneous operations on parallel runways, in which the single runway ALP could be treated separately.

Single runway ALP is similar to a single machine scheduling problem. As illustrated in Fig. 1, ALP schedules arrival aircraft (jobs) on the runway (machine), where each aircraft becomes ready to be processed

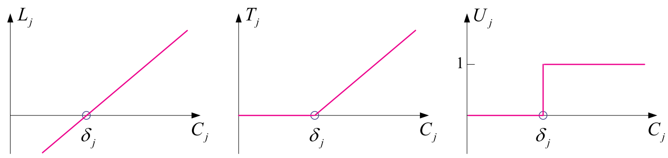

Fig. 2. Diagram of due date-related variables.

between the earliest landing time r_j (release date in machine scheduling problem), and the latest landing time d_j (deadline when the job needs to be finished) should land on the runway at the target landing time δ_j (similar to finishing a job by a due date). In the machine scheduling problem, setup times, which include, but are not limited to, adjustments, re-tooling, and fixing or removing jobs, should be taken into consideration. Such setup times are similar to wake vortex (WV) separations (time separation s_{jk}) in ALP, whose values depend on the WV categories of leading and trailing arrival aircraft.

Moreover, the Runway Occupied Time (ROT) in ALP could be considered as the processing time p_j in the machine scheduling problem. However, we did not consider ROT in this study, because in real operations, once the WV separations have been satisfied, the trailing aircraft will not need to worry about the ROT of the leading landing aircraft. Therefore, the single runway ALP could be defined as $1|r_j, s_{jk}|\gamma$ with the three-field notation scheme (Pinedo, 2015), where γ is the objective, which is described in the next subsection. Table 1 summarizes the notation and variables used in this study.

2.2. Criteria

2.2.1. Criteria in single machine scheduling

In single machine scheduling, the commonly used criteria are elaborated as follows.

(1) Maximum completion time or makespan: $\max C_j$ – Maximum completion time or makespan is equivalent to the completion time of the last job leaving the machine. A minimum makespan usually implies a high utilization of the machine.
(2) Total completion times: $\sum C_j$– Total completion times of n jobs give an indication of the total holding or inventory costs incurred by the schedule.
(3) Maximum tardiness: $\max T_j$– Maximum tardiness measures the worst violation of the due dates.
(4) Total tardiness: $\sum T_j$– Total tardiness is a measure of customer satisfaction; minimizing it represents satisfying the general requirement of on-time delivery.
(5) Maximum lateness: $\max L_j$– Maximum lateness is the maximum difference between completion time and due date$L_j = C_j - \delta_j$ and is equal to maximum tardiness, because $T_j = \max(C_j - \delta_j, 0)$.
(6) Total lateness: $\sum L_j$– Minimizing total lateness will provide the same schedule as minimizing total completion times, because $\sum L_j = \sum(C_j - \delta_j) = \sum C_j - \sum \delta_j = \sum C_j - \text{const}$.
(7) Maximum flow time: $\max F_j$ – Maximum flow time is a maximum value of flow time encountered during the processing of jobs in a machine.
(8) Total flow times: $\sum F_j$– Minimizing total flow times will provide the same schedule as minimizing total completion times, since $\sum F_j = \sum(C_j - a_j) = \sum C_j - \sum a_j = \sum C_j - \text{const}$.
(9) Total cost: $\sum(g_jE_j + h_jT_j)$– Total cost is the total weighted earliness plus the total weighted tardiness.
(10) Number of tardy jobs: $\sum U_j$– Number of tardy jobs counts the number of jobs that encountered delay.

The aforementioned criteria can be described by grouping them differently: one is an expression-related category, and the other is a criteria-related category. In the expression-related category, $\max C_j$, $\max F_j$, $\max T_j$ and $\max L_j$ are the criteria based on a *min-max* expression, while $\sum C_j$, $\sum F_j$, $\sum T_j$, $\sum L_j$, $\sum(g_jE_j + h_jT_j)$ and $\sum U_j$ are the criteria based on a *min-sum* expression. In the criteria-related category, $\max C_j$, $\sum C_j$, $\max F_j$ and $\sum F_j$ are the criteria based on *completion times*, while $\max T_j$, $\sum T_j$, $\max L_j$, $\sum L_j$, $\sum(g_jE_j + h_jT_j)$ and $\sum U_j$ are the criteria based on *due dates*. Fig. 2 presents the schematic diagram of due date-related variables.

2.2.2. Criteria in aircraft landing problem

Criteria in machine scheduling problems can find their counterparts in ALP.

First, in a single machine scheduling problem, minimizing makespan usually implies a high utilization of the machine. This objective is similar to minimizing makespan for a higher runway utilization in ALP and, thus, higher runway throughput, especially in a situation of a tight schedule (high landing demand period).

Second, flow time in a machine scheduling problem is equivalent to the time that an aircraft spent from entering the terminal area to landing on the runway in ALP, i.e., dwell time in Terminal Area (TMA). This is the duration that air traffic controllers need to pay close attention to ensure separation among aircraft to avoid potential collisions. The total dwell time is a surrogate of air traffic controller workload, and minimizing this criterion reduces air traffic controller workload. Also, minimizing maximum dwell time ensures that no flight will be kept in the air for too long. It is a way of ensuring equity among flights (and airlines that are operating the flights), which encourages airlines to accept optimized landing schedules. Furthermore, given that descending, approaching, and landing phases are when most aviation accidents occur (Kharoufah et al., 2018), taking ATC workload into consideration and preventing aircraft from staying airborne excessively will help alleviate safety concerns. Thus, both total flow time and maximum flow time should be included in the objective functions of ALP. This fills in the gap of the existing literature because such criteria have been barely considered for ALP.

Third, due date-related criteria in ALP are more complicated than those in the single machine scheduling problem because due dates (or target landing times) can be benchmarked differently. On one hand, if the target landing times are the planned landing times (published in the timetable), tardiness means schedule delay. On the other hand, if the target landing times are estimated landing times (obtained from trajectory prediction), tardiness means flight delay. The former is used more for calculating passenger delay and airline on-time performance, and the latter is used for calculating additional fuel consumption and measuring air traffic management efficiency. In this study, we considered only flight delay, as scheduled delay is the primary concern of air traffic flow management, not ALP.

Fourth, other due date-related criteria in machine scheduling problem and in ALP are the same.

2.3. Criteria selection

Although their definitions and physical meanings are different, some criteria are mathematically the same. For example, minimizing total lateness ($\sum L_j$) and minimizing total dwell times ($\sum F_j$) will produce the same landing schedule, as same as the results of minimizing total scheduled landing time ($\sum C_j$). This is also true for minimizing maximum lateness ($\max L_j$) and minimizing maximum flight delay ($\max T_j$). The number of delayed aircraft ($\sum U_j$) are not considered in this study. Furthermore, total cost ($\sum(g_jE_j + h_jT_j)$) penalizes aircraft that arrive earlier. The argument is that given gate constraints, arriving earlier could lead to waiting at the tarmac and disturb ground crew scheduling. In real operation, considering the possible propagating effect of tardiness, the cost caused by earliness is negligible. When the weight of earliness is small, it is equivalent to total lateness ($\sum L_j$). Thus in this study, total cost was not considered.

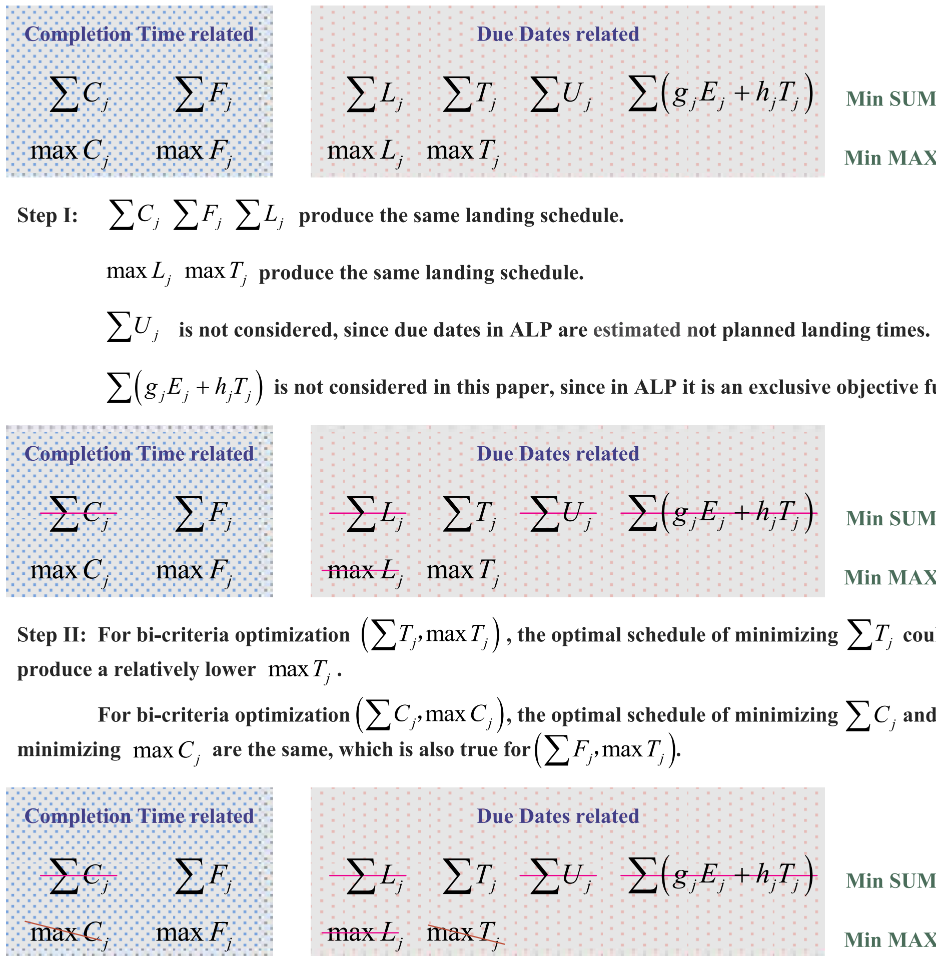

Fig. 3. Relationship between criteria for ALP

Based on these observations, when solving ALP, we need to consider only the following five criteria: $\max C_j$, $\max F_j$, $\max T_j$, $\sum F_j$ and $\sum T_j$.

Furthermore, we show that the same outcome can be obtained while optimizing two out of the five criteria. By approving it, we further cut down the number of criteria that need to be included in solving ALP.

Based on the existence theorems and bounds of bi-criteria scheduling (Stein and Wein, 1997; Aslam et al., 1999; Rasala et al., 2002), we can exclude the objective of maximum flight delay. For bi-criteria optimization ($\max T_j$,$\sum T_j$), suppose S^{bi} is an (α, β)-schedule if S^{bi} is simultaneously, at most, an α-approximation for $\max T_j$ and a β-approximation for $\sum T_j$, i.e., $T_{\max}^{S^{\mathrm{bi}}} < \alpha T_{\max}^{\mathrm{OPT}}$ and $T_{\mathrm{sum}}^{S^{\mathrm{bi}}} < \beta \sum T_j^*$, where $T_{\max}^{\mathrm{OPT}}$ and $\sum T_j^*$ are the optimum of the bi-criteria. For such bi-criterion optimization, it has been proved that there exists a ($1+\rho$, $e^{\rho}/(e^{\rho}-1)$)-schedule, where $\rho \in [0,1]$ (Rasala et al., 2002). That means when we optimize the criterion of $\sum T_j$, the criterion of $\max T_j$ will have an upper bound, i.e., the optimal schedule of minimizing total flight delays could also produce a relatively low maximum flight delay. Therefore, if we choose the criterion of $\sum T_j$, we can exclude the criterion of $\max T_j$.

Furthermore, we prove that optimizing the criteria lead to the same outcomes. To do that, we use the intermedium. According to bi-criteria optimization ($\max C_j$,$\sum C_j$) for ALP, we can put forward an important Proposition as follows:

Proposition. *The optimum schedule $S^{C^*_{\mathrm{sum}}}$ for minimizing total scheduled landing times ($\sum C_j$) is also one of the optimum schedules for minimizing the maximum scheduled landing time* ($\max C_j$), *which means* $C_{\max}^{\mathrm{OPT}} = \max(C(S^{C^*_{\mathrm{sum}}}))$.

The proof is obtained by reductio ad absurdum:

First, assume there exists $C_{\max}^{\mathrm{OPT}} > \max(C(S^{C^*_{\mathrm{sum}}}))$. Since $C_{\max}^{\mathrm{OPT}} = \min(C(S))$, where S denotes any given landing schedule, the assumption $C_{\max}^{\mathrm{OPT}} > \max(C(S^{C^*_{\mathrm{sum}}}))$ does not hold.

Second, we assume there exists $C_{\max}^{\mathrm{OPT}} < \max(C(S^{C^*_{\mathrm{sum}}}))$. In this situation, suppose the last two landing aircraft in $S^{C^*_{\mathrm{sum}}}$ is k and l, then C_l^* is either r_l or $C_k^* + s_{kl}$. It could not be more than r_l or $C_k^* + s_{kl}$ since $S^{C^*_{\mathrm{sum}}}$ is the optimum schedule for $\min \sum C_j$. Moreover, C_l^* could not equal r_l, as $C_{\max}^{\mathrm{OPT}} < \max(C(S^{C^*_{\mathrm{sum}}})) = r_l$ does not hold, which indicates that C_l^* equals to $C_k^* + s_{kl}$. Then, we can deduce that for the next-to-last landing aircraft there also exists a conclusion such as $C_{\max}^{\mathrm{OPT}} < \max(C(S^{C^*_{\mathrm{sum}}}))$, and so on. Then, there exists $\sum C(S^{C^{\mathrm{OPT}}_{\max}}) < \sum C(S^{C^*_{\mathrm{sum}}})$, which is contradicted to $S^{C^*_{\mathrm{sum}}}$ is the optimum schedule for $\min \sum C_j$. Therefore, the assumption $C_{\max}^{\mathrm{OPT}} < \max(C(S^{C^*_{\mathrm{sum}}}))$ does not hold.

Finally, we can obtain $C_{\max}^{\mathrm{OPT}} = \max(C(S^{C^*_{\mathrm{sum}}}))$.

Since minimizing $\sum C_j$ is equal to minimizing $\sum F_j$, the optimum landing schedule for minimizing ATC workload ($\sum F_j$) will be the same as the optimal from maximizing the runway throughput ($\max C_j$).

In addition, from the in-depth analysis above, we can illustrate different categories of ALP objectives and the inner relationship between them, as shown in Fig. 3.

As shown in Fig. 3, all different categories of criteria have been covered when we are developing the formulation of multi-objective ALP. For min-sum expression, we choose the total dwell time $\sum F_j$ and the total flight delays $\sum T_j$, in which the former is completion time-related and the latter due date-related. For min-max expression, we select only the maximum dwell time $\max F_j$. This is because minimizing $\sum F_j$ is equal to minimizing $\sum C_j$ whereas minimizing $\sum C_j$ could get the optimum schedule for minimizing $\max C_j$. Also, minimizing $\sum T_j$ could get the nearly-optimum schedule for minimizing $\max T_j$ and minimizing $\max T_j$ is equal to minimizing $\max L_j$.

In summary, by understanding the similarities of ALP and the machine scheduling problem, we adopt the optimization criteria used for the machine scheduling problem to be considered in ALP. Then, based on the above criteria selection analysis, we determine the suitable subset of criteria for ALP, which are total flight delays, total dwell time, and maximum dwell time, i.e., $\sum T_j$, $\sum F_j$, and $\max F_j$, respectively. These criteria are taken as the objective functions in the formulation of multi-objective ALP, which is elaborated below.

3. Multi-objective optimization for ALP

3.1. Methodology of solving multi-objective optimization problem

The objectives of ALP are to determine an optimum landing schedule to improve punctual performance, enhance runway utilization, reduce air traffic controller workload, and maintain equity among airlines. A multi-objective optimization problem can be solved by a lexicographic ordering (LO) strategy if some criteria dominate the others. LO is a hierarchical method in which the objectives are categorized into different priority levels, and a sequence of sub-optimization problems is solved in order of priority. If no criteria are dominant, simultaneous optimization will be a better alternative.

There are three different approaches of simultaneous optimization (Hoogeveen, 2005): aggregating different criteria into one composite objective function, converting criteria into constraints, and determining Pareto optimal. For ALP, we apply a hybrid simultaneous optimization, i.e., combining the first and second approaches. For the three criteria obtained from the last section, $\sum F_j$ and $\sum T_j$ are at the same magnitude, so we join them as one linear composite objective function, $\alpha\sum_{j=1}^{n} F_j + (1-\alpha)\sum_{j=1}^{n} T_j$, where $\alpha \in (0,1)$ is a weight indicating the relative importance of the criterion and determined by decision-makers. Criterion $\max F_j$ is represented by a constraint, $F_j \le F_{\max}$. This constraint requires all dwell times, including $\max F_j$, less than a given constant.

3.2. Formulation of multi-objective ALP

Thus, the formulation of multi-objective ALP is as follows:

min	$\alpha\sum_{j=1}^{n} F_j + (1-\alpha)\sum_{j=1}^{n} T_j$		(1)
s.t.	$F_j \le F_{\max}$	$\forall j \in J$	(2)
	$r_j \le C_j \le d_j$	$\forall j \in J$	(3)
	$q_{k,j} + q_{j,k} = 1$	$\forall k, j \in J; k > j$	(4)
	$C_j \ge C_k + q_{kj}s_{kj} - q_{jk}(d_k - r_j)$	$\forall k, j \in J; k \ne j$	(5)
	$E_j \ge \delta_j - C_j$	$\forall j \in J$	(6)
	$0 \le E_j \le \delta_j - r_j$	$\forall j \in J$	(7)
	$T_j \ge C_j - \delta_j$	$\forall j \in J$	(8)
	$0 \le T_j \le d_j - \delta_j$	$\forall j \in J$	(9)
	$C_j = \delta_j - E_j + T_j$	$\forall j \in J$	(10)
	$F_j = \delta_j - a_j$	$\forall j \in J$	(11)

As described earlier, Eq. (1) and Eq. (2) concern the three selected criteria. Eq. (3) specifies that each aircraft is scheduled within its time window. Eq. (4) and Eq. (5) ensure that the proper separations are assigned between the leading and trailing aircraft. Eqs. 6–10 define the earliness and tardiness of landing. Eq. (11) defines dwell time.

3.3. ICA for multi-objective ALP

The ICA (Hosseinia and Khaled, 2014) was inspired by socio-political behaviors, which was initially developed for continuous optimization problems. The ICA could also be applied to a permutation-based optimization problem such as ALP.

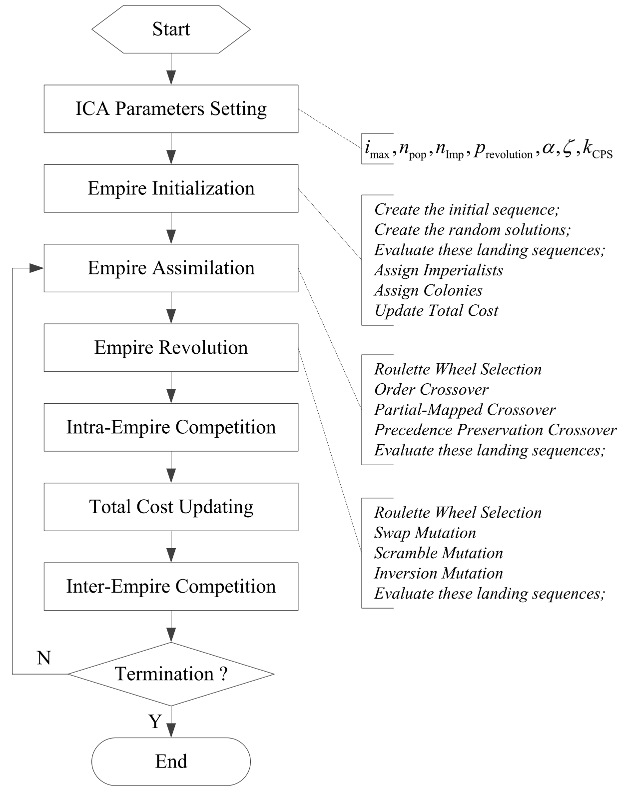

Fig. 4. Flowchart of proposed ICA

The flowchart of the proposed ICA for multi-objective ALP is shown in Fig. 4, which can be summarized as the following steps:

Step 1: Set ICA parameters. The ICA parameters include a maximum number of iteration $i_{\max}$, size of potential solutions n_{pop}, size of imperialist n_{Imp}, revolution possibility $p_{\text{revolution}}$, and a maximum number of Constrained Position Shift (CPS) k_{CPS}, which can guarantee that the potential solution is a valid one.

Step 2: Initialize the Empire. Dispatching rules (ERD and EDD) (Pinedo, 2015) are used to create the initial landing sequences. In addition, the CPS strategy is also implemented to generate n_{pop} countries (potential landing sequences). Since the landing sequence is established, the scheduled landing time can be calculated by

$$C_j = \max\{r_j, C_k + q_{kj}s_{kj}\} \tag{12}$$

where $q_{kj} = 1$. The cost of such solution is obtained based on Eq. (1). The first n_{Imp} countries are denoted as the imperialists, and the remaining countries are denoted as the colonies and assigned to any imperialist based on the power of each imperialist.

$$P_j = \frac{\exp\{-\alpha\cdot[\text{Imp}_j.\text{Cost}/\max(\text{Imp}_j.\text{Cost})]\}}{\sum_{j\in\text{Imp}} \exp\{-\alpha\cdot[\text{Imp}_j.\text{Cost}/\max(\text{Imp}_j.\text{Cost})]\}} \tag{13}$$

After initializing the imperialists and colonies, the total cost of the empire (consisting of the imperialist and its corresponding colonies) can be calculated by:

$$\text{emp}_j.\text{TotalCost} = \text{emp}_j.\text{Imp.Cost} + \zeta \times \frac{1}{n_{\text{Col}_i}} \times \sum_{i=1}^{n_{\text{Col}_i}} \text{emp}_j.\text{Col}_i.\text{Cost} \tag{14}$$

where $0 < \zeta < 1$.

Table 2
Computational scenarios.

Scale	Instances	Num. of AC	K_d	$P_{s\leq x}$		
				$x=68$ s	$x=90$ s	$x=135$ s
Small Scale	airland #13.1	49	1.382	0.388	0.449	0.612
	airland #13.2	48	1.306	0.333	0.500	0.729
	airland #13.3	57	1.218	0.491	0.579	0.684
	airland #13.4	50	1.562	0.320	0.460	0.540
	airland #13.5	45	1.062	0.489	0.622	0.800
	airland #13.6	51	0.945	0.588	0.627	0.843
	airland #13.7	49	1.345	0.429	0.571	0.776
	airland #13.8	52	1.065	0.442	0.538	0.769
	airland #13.9	50	1.128	0.560	0.640	0.700
	airland #13.10	49	1.085	0.490	0.673	0.755
Large Scale	airland #09	100	1.370	0.410	0.540	0.720
	airland #10	150	1.412	0.413	0.520	0.647
	airland #11	200	1.362	0.445	0.545	0.690
	airland #12	250	1.341	0.444	0.508	0.692

Step 3: Assimilate the Empire. In the assimilation step, crossover methods such as OX, PMX, and PPX are adopted to generate the new colonies.

Step 4: Revolutionize the Empire. In the revolution step, mutation methods such as swap, scramble, and inversion are adopted to generate the new imperialists and colonies within the revolution possibility.

It should be noted that k_{CPS} is imposed to ensure only several preceding and following aircraft participate in the assimilation and revolution process.

Step 5: Intra-Empire Competition. After assimilation and revolution, there will be a chance that some of the colonies reach better solutions than their corresponding imperialists. In such cases, the colony and its relevant imperialist exchange their positions.

Step 6: Update the Total Cost. Since the colonies and their corresponding imperialists may have been changed, the total cost should be updated according to Eq. (14).

Step 7: Inter-Empire Competition. This is the most important process in ICA, which gradually brings about a decrease in the power of weaker empires and an increase in the power of more powerful ones (Atashpaz-Gargari and Lucas, 2007). Within such competition, the weakest empire will lose its colonies, which will be seized by other stronger empires. If there are no colonies in the weakest empire, such an empire will ultimately collapse and become a colony.

Step 8: Termination. There are two termination conditions; in one there exists only one empire; in the other, the maximum number of iterations are met.

4. Numerical experiments

4.1. Instances and measurement of tightness

The performance of the selected criteria and multi-objective model is evaluated using a set of benchmark instances taken from the OR library, which can be downloaded from http://people.brunel.ac.uk/~mastjjb/jeb/orlib/airlandinfo.html. The benchmark instances (airland#1–airland#13) involve 10–500 aircraft. In this study, we focused on airland#9–airland#13 because the WV separations in these instances are similar to actual operation. The number of aircraft in airland#9–airline#12 are 100, 150, 200, and 250. Airland#13 contains 500 aircraft, which is too big to be solved by using CPLEX. Nevertheless, it is observed that there are several arrival waves of aircraft in airland#13. Thus, we partitioned the airland#13 instance into 10 small instances according to the corresponding arrival wave. Each instance contains roughly 50 aircraft (see Table 2).

The complexity of an ALP problem is reflected by the number of aircraft in a given instance, as well as the features of the arrival flight bunch, called tightness. The complexity and needed optimization computing time increase when the arrival flight bunch is tight and there is less flexibility for maneuvering the arrival flights. However, few existing studies tested and demonstrated such a hypothesis. In this study, given the 10 instances with a similar number of aircraft, we introduce two metrics to indicate the tightness of instances and test the hypothesis. We first introduce a compression index K_d, which is calculated by dividing the difference of the latest and earliest target landing time by the total WV separation.

$$K_d \quad = \quad \left(\max_{j\in J}(\delta_j) - \min_{j\in J}(\delta_j)\right)/(n\bar{s}), \tag{15}$$

where $\bar{s}$ is the average WV separation of all possible sequences of the landing aircraft. K_d is around 1. If K_d is smaller than 1, it means there is less flexibility to maneuver the flights, otherwise, more flexibility. Furthermore, we introduce an ATC-demand index $P_{s\leq x}$ to measure the percentage of leading and trailing aircraft pair with time separation less than a given separation time. The formula is as below, and larger $P_{s\leq x}$ indicates tighter target landing times.

$$P_{s\leq x} \quad = \quad \frac{1}{n}\sum_{0<j<n}\mathrm{sign}\left(\left(\delta'_{j+1} - \delta'_j\right) \leq x\right), \tag{16}$$

where δ' are ascending target landing times, and $\mathrm{sign}((\delta'_{j+1} - \delta'_j) \leq x)$ equals 1 if $(\delta'_{j+1} - \delta'_j) \leq x$ is true, otherwise 0. As shown in Table 2, three different WV separation times are chosen to measure the $P_{s\leq x}$, $x=68$ s, $x=90$ s, and $x=135$ s, which are calculated by dividing WV distance separations by aircraft ground speed.

The instances in our numerical example and their corresponding indexes are summarized in Table 2. In addition, we split the benchmark instances into small and large scales. All proposed mathematical programming models were solved using CPLEX (IBM ILOG CPLEX Optimization studio version 12.6) on a PC with 3.30 GHz Intel Core I5-4590 processor and 8 GB RAM. The stop limit of CPU computation time of the CPLEX solver is set as 600 s.

4.2. Single objective optimization of small scale instances

We first run the optimization of small-scale instances with a single objective function. Given the optimized schedule of arrival flights, we then calculate the value of other objectives. In this experiment, we consider the objectives of the total cost -$\sum \mathrm{Cost}_j(\mathrm{Cost}_j = g_jE_j + h_jT_j)$,[1] total delay -$\sum T_j$, maximum delay -$\max T_j$, total scheduled time -$\sum C_j$, maximum scheduled time -$\max C_j$, total dwell time -$\sum F_j$, and maximum dwell time -$\max F_j$. The objectives of this experiment are twofold—testing the correlation between tightness indicators and optimization computing time and exploring the impact of tightness indicators to the consistency of optimization outcomes.

4.2.1. Comparison of computational times

Table 3 compares CPU times of optimizing small-scale instances with

[1] An earlier section noted that the total cost was not an appropriate criterion and would lead to significantly different optimization outcomes from using other criteria. In this section, we list the outcomes of optimizing the total cost criterion for comparison purpose.

Table 3
CPU times for different single objective of small-scale instances.

ALP	CPU times for different single objective							Ave.(s)
	min $\sum \mathrm{Cost}_j$	min $\sum T_j$	minmaxT_j	min $\sum C_j$	minmaxC_j	min $\sum F_j$	minmaxF_j	
#13.1	25.04	0.05	0.05	24.54	0.05	23.65	0.05	***10.49***
#13.2	438.61	0.16	0.14	230.29	0.05	227.75	0.31	***128.19***
#13.3	600.01	0.23	0.28	600.09	0.05	600.01	0.61	***257.33***
#13.4	128.92	0.05	0.05	1.03	0.08	1.01	0.06	***18.75***
#13.5	600.01	122.94	0.34	600.46	4.84	600.21	0.64	***275.63***
#13.6	600.01	600.01	53.41	600.01	600.01	600.01	600.01	***521.92***
#13.7	104.97	3.17	0.95	600.15	0.06	600.12	0.3	***187.10***
#13.8	600.01	29.66	11.89	600.01	0.06	600.01	55.24	***270.98***
#13.9	600.01	2.89	24.09	600.23	0.05	600.01	80.58	***272.55***
#13.10	600.01	5.41	1.67	600.01	600.01	600.01	2.37	***344.21***
Ave.(s)	***429.76***	***76.46***	***9.29***	***445.68***	***120.53***	***445.28***	***74.02***	

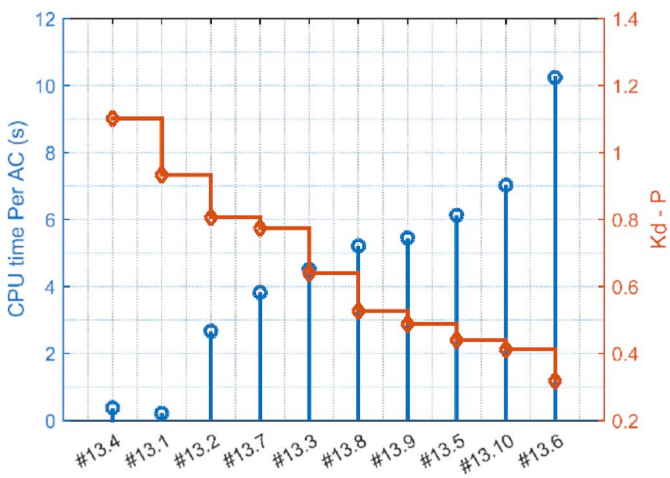

Fig. 5. Computation time and corresponding tightness of different instances.

a different single objective. It can be seen that some CPU times of CPLEX optimization are constrained by the up limit of 600 s when conducting CPLEX optimization.

It is widely known that the solving time for ALP is dependent on the number of aircraft (Beasley et al., 2000). However, as shown in Table 3, in addition to the number of aircraft, the particular instance and the distinct objective (*min-sum* objectives need more time to be solved than *min-max* objectives) also play important roles in solving the ALP.

Fig. 5 demonstrated the relationship between CUP times and instance variables, more specifically, the proposed indexes K_d and $P_{s\leq x}$. In Fig. 5, the left vertical axis shows the CPU time per aircraft, the right vertical axis shows the difference between the proposed indexes K_d and $P_{s\leq x}$, and the horizontal axis shows the different instances sorted by $K_d - P_{s\leq x}$. Fig. 5 illustrates that, in addition to the number of aircraft, instance variables also play essential roles in solving ALP. In particular, the index K_d is basically in the reverse proportion to the CUP time per aircraft, and the index $P_{s\leq x}$ is basically in the direct proportion to the CUP time per aircraft. Accordingly, $K_d - P_{s\leq x}$ is in the reverse proportion to the CUP time per aircraft.

The analysis above demonstrates the positive correlation between arrival flight tightness and computation time for obtaining optimal solutions of ALP. We also observe from Table 3 that the *min-sum* objectives need more time to be solved than the *min-max* objectives, so the selected objectives also play important roles in solving the ALP. We further explore these observations next two subsections.

4.2.2. Tightness and the consistency of objective functions

We selected instances #13.4 and #13.6 to discuss how the tightness of arrival flight bunch affects objective functions computed from

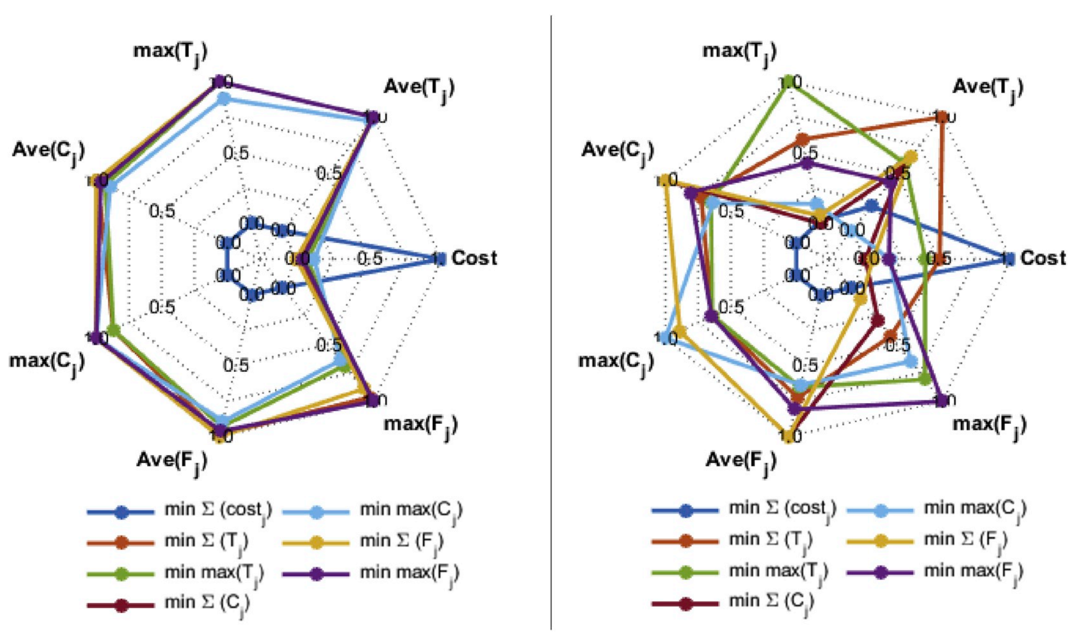

Fig. 6. Radar plots of ALP #13.4 (6a on left) and ALP #13.6 (6b on right).

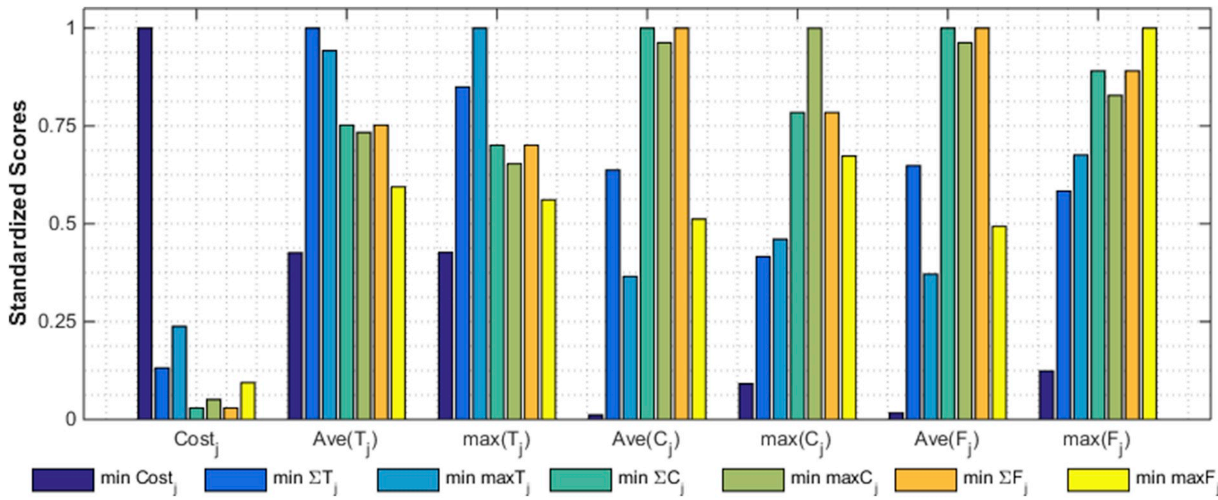

Fig. 7. Average normalized values of different criteria based on single objective optimization.

optimized landing sequences. As shown in Table 2, #13.4 has a maximum K_d and minimum $P_{s\le 135}$ while #13.6 has a minimum K_d and maximum $P_{s\le 135}$, which means that #13.4 has lower tightness, while the tightness of #13.6 is much higher.

We construct radar plots of normalized optimal objective functions of #13.4 and #13.6 (see Fig. 6), in which the normalized value is obtained by:

$$Obj_{\mathrm{Norm}} = \frac{Obj - Obj_{\min}}{Obj_{\max} - Obj_{\min}}, \tag{17}$$

where Obj is the computational outcomes in Appendix I.

From the radar plots (Fig. 6), we find that in the condition of loose target schedule time (#13.4), the objective functions computed from different optimized outcomes are consistent. To the contrary, in the condition of tight target schedule time (#13.6), the objective functions computed from different optimized outcomes are relatively independent. Note that the total cost behaves differently from other objective functions described earlier.

4.2.3. Criteria sensitivity analysis

In this subsection, a criteria sensitivity analysis is conducted. To compare the performance of different criteria about single objective optimization, we first normalize the values by Eq. (17) and then average the total 10 instances. The results are shown in Fig. 7. From Fig. 7, we can confirm several findings from subsections 2.2 and 2.3.

Again, total cost is an exclusive objective that performs significantly differently from other criteria. In addition, the optimum schedules obtained by optimizing $\sum C_j$ or $\sum F_j$ are the same. Furthermore, a positive correlation is found within due date-related criteria ($\sum T_j$ and $\max T_j$) or completion time-related criteria ($\sum C_j$, $\sum F_j$, $\max C_j$, and $\max F_j$). Finally, if we minimize the *min-sum* objectives, we can obtain the schedules that also work well for the *min-max* objectives, except $\min \sum F_j$; if we minimize the *min-max* objectives, we cannot obtain the schedules that also work well for the *min-sum* objectives.

From a CPU time perspective, we can also draw a similar conclusion that minimizing $\sum C_j$ and $\sum F_j$ are the same. The CPU times of optimizing these two objectives are nearly the same, as shown in Table 3. In addition, to minimize the *min-sum* objective is more time-consuming than to minimize the *min-max* objective, which is also presented in Table 3.

In summary, in addition to the number of aircraft and the instance variables, the distinct objective also plays an essential role in the computation time of solving the ALP.

4.3. Multi-objective optimization

4.3.1. Computational results

In this subsection, we address the multi-objective ALP defined in Eq. (1)–Eq. (11) using all instances, in which the CPU times of CPLEX optimization are constrained by 600 s.

The results for the multi-objective optimization, $\alpha = 0.5$, are given in Table 4:

Opt_S: This row presents the optimal results.
Opt_M: This row presents the optimal results when conducting multi-objective optimization.
Dev: The Dev row provides the deviation between Opt_S and Opt_M.
Opt_M_ICA: This row presents the optimal results when conducting multi-objective optimization with the proposed ICA, in which $k_{\mathrm{CPS}} = 9$, $p_{\mathrm{revolution}} = 0.5$, $\zeta = 0.2$, and $i_{\max} = 200$, $n_{\mathrm{pop}} = 75$, $n_{\mathrm{Imp}} = 5$ for large scale instances, $i_{\max} = 100$, $n_{\mathrm{pop}} = 50$, $n_{\mathrm{Imp}} = 5$ for small scale instances. The revolution rate is equal to 0.5 to increase the revolution possibility for generating a better potential solution for ALP.
Dev_ICA: The Dev row provides the deviation between Opt_S and Opt_M_ ICA.
$\boldsymbol{F_{\max}}$: The predefined dwell time constraints, which are listed in the $F_{\max}$ column. This constraint can be obtained based on controller experience, historical data analysis, or trajectory prediction (Junfeng et al., 2018). It should be noted that this value in ICA is little larger than the one by CPLEX, as we hope to generate more feasible solutions in ICA to reach the best solution.

In addition, Fig. 8 provides the average deviations between single and multi-objective optimization by CPLEX and ICA based on different criteria and instances. We find the following:

(1) The average deviations of maximum delay time and maximum dwell time are longer than the others, no matter if obtained by CPLEX or ICA, as maximum delay time is not included in the multiple objectives and maximum dwell time is only a constraint.
(2) For small-scale instances, the average deviation of #13.6 is the maximum; for #13.1 the minimum (since #13.6 is hard to be scheduled) is an easy one (as shown in Fig. 5). For large-scale instances, the average deviation of #10 is the maximum and #11 the minimum. In addition, the results obtained by ICA are worse than those by CPLEX. However, ICA is much more efficient, since the computational time of ICA is determined by the maximum number of iteration and the size of potential solutions.

Table 4
Optimization performances for multi-objective ALP.

ALP	$F_{\max}$(s)	(s)	$\sum T_j/n$	maxT_j	$\sum C_j/n$	maxC_j	$\sum F_j/n$	maxF_j
#9	1,000	Opt_S	2.02	91.00	6,070.54	12,373.00	680.53	980.00
		Opt_M	8.53	241.00	6,074.50	12,373.00	684.49	980.00
		Dev	6.51	150	3.96	0	3.96	0
	1,200	Opt_M_ICA	4.02	91.00	6074.50	12373.00	684.49	1140.00
		Dev_ICA	2.00	0	3.96	0	3.96	160.00
#10	1,200	Opt_S	9.07	189.00	9,463.94	19,086.00	697.64	1,131.00
		Opt_M	12.67	393.00	9,468.85	19,086.00	702.55	1,186.00
		Dev	3.60	204.00	4.91	0	4.91	55.00
	1,400	Opt_M_ICA	18.02	348.00	9474.28	19,097.00	707.98	1,277.00
		Dev_ICA	8.95	159.00	10.34	11.00	10.34	146.00
#11	1,100	Opt_S	0.13	15.00	12,449.75	24,007.00	672.82	993.00
		Opt_M	0.58	37.00	12,450.99	24,007.00	674.06	1,020.00
		Dev	0.45	22.00	1.24	0	1.24	27.00
	1,300	Opt_M_ICA	0.81	44.00	12,452.15	24007.00	675.22	1,043.00
		Dev_ICA	0.68	29.00	2.40	0	2.40	50.00
#12	1,200	Opt_S	2.48	175.00	14,886.04	2,8916.00	672.80	1,066.00
		Opt_M	3.71	182.00	14,888.50	28,916.00	675.26	1,173.00
		Dev	1.23	7.00	2.46	0	2.46	107.00
	1,300	Opt_M_ICA	4.71	252.00	14,890.89	28,983.00	677.65	1,107.00
		Dev_ICA	2.23	77.00	4.85	67.00	4.85	41.00
#13.1	1,000	Opt_S	0.00	0.00	3,616.65	6,191.00	644.29	805.00
		Opt_M	0.00	0.00	3,616.65	6,191.00	644.29	805.00
		Dev	0	0	0	0	0	0
		Opt_M_ICA	0.00	0.00	3,616.65	6,191.00	644.29	805.00
		Dev_ICA	0	0	0	0	0	0
#13.2	1,000	Opt_S	1.98	41.00	8,836.15	11,751.00	659.83	866.00
		Opt_M	2.83	104.00	8,837.52	11,751.00	661.21	956.00
		Dev	0.85	63.00	1.37	0	1.38	90.00
		Opt_M_ICA	2.83	104.00	8,838.54	11,751.00	662.23	956.00
		Dev_ICA	0.85	63.00	2.39	0	2.4	90.00
#13.3	1,000	Opt_S	0.40	21.00	15,038.23	18,064.00	680.30	886.00
		Opt_M	2.51	53.00	15,043.25	18,064.00	685.32	978.00
		Dev	2.11	32.00	5.02	0	5.02	92.00
		Opt_M_ICA	2.51	53.00	15,043.25	18,064.00	685.32	958.00
		Dev_ICA	2.11	32.00	5.02	0	5.02	72.00
#13.4	1,000	Opt_S	0.00	0.00	22,149.14	25,320.00	633.72	737.00
		Opt_M	0.00	0.00	22,149.14	25,320.00	633.72	796.00
		Dev	0	0	0	0	0	59.00
		Opt_M_ICA	0.00	0.00	22,149.14	25,320.00	633.72	796.00
		Dev_ICA	0	0	0	0	0	59.00
#13.5	1,200	Opt_S	1.82	68.00	27,505.89	29,346.00	746.60	964.00
		Opt_M	4.56	114.00	27,514.51	29,347.00	755.22	1,051.00
		Dev	2.74	46.00	8.62	1.00	8.62	87.00
		Opt_M_ICA	4.56	114.00	27,514.51	29,347.00	755.22	1,051.00
		Dev_ICA	2.74	46.00	8.62	1.00	8.62	87.00
#13.6	1,400	Opt_S	23.57	193.00	31,903.63	34,042.00	755.43	1,201.00
		Opt_M	24.33	434.00	31,910.71	34,086.00	762.51	1,299.00
		Dev	0.76	241.00	7.08	44.00	7.08	98.00
		Opt_M_ICA	28.47	269.00	31,913.20	34,109.00	765.00	1,292.00
		Dev_ICA	4.9	76.00	9.57	67.00	9.57	91.00
#13.7	1,100	Opt_S	4.29	115.00	37,054.43	39,533.00	681.90	913.00
		Opt_M	5.18	115.00	37,055.00	39,533.00	682.47	1,033.00
		Dev	0.89	0	0.57	0	0.57	120.00
		Opt_M_ICA	5.88	115.00	37057.73	39,533.00	685.20	1,003.00
		Dev_ICA	1.59	0	3.30	0	3.30	90.00
#13.8	1,200	Opt_S	5.44	121.00	42,234.31	44,516.00	712.77	1,051.00
		Opt_M	9.42	275.00	42,237.79	44,516.00	716.25	1,187.00
		Dev	3.98	154.00	3.48	0	3.48	136.00
		Opt_M_ICA	12.42	224.00	42,246.75	44,516.00	725.21	1,090.00
		Dev_ICA	6.98	103.00	12.44	0	12.44	39.00
#13.9	1,100	Opt_S	5.42	96.00	47,092.78	49,635.00	716.12	958.00
		Opt_M	11.24	151.00	47,096.92	49,635.00	720.26	1,081.00
		Dev	5.82	55.00	4.14	0	4.14	123.00
		Opt_M_ICA	13.50	151.00	47,099.76	49,635.00	723.10	1,061.00
		Dev_ICA	8.08	55.00	6.98	0	6.98	103.00
#13.10	1,200	Opt_S	3.12	80.00	52,478.20	54,740.00	707.96	1,101.00
		Opt_M	5.12	158.00	52,482.33	54,778.00	712.08	1,158.00
		Dev	2.00	78.00	4.13	38.00	4.12	57.00
		Opt_M_ICA	4.86	165.00	52,485.22	54,785.00	714.98	1,165.00
		Dev_ICA	1.74	85.00	7.02	45.00	7.02	64.00

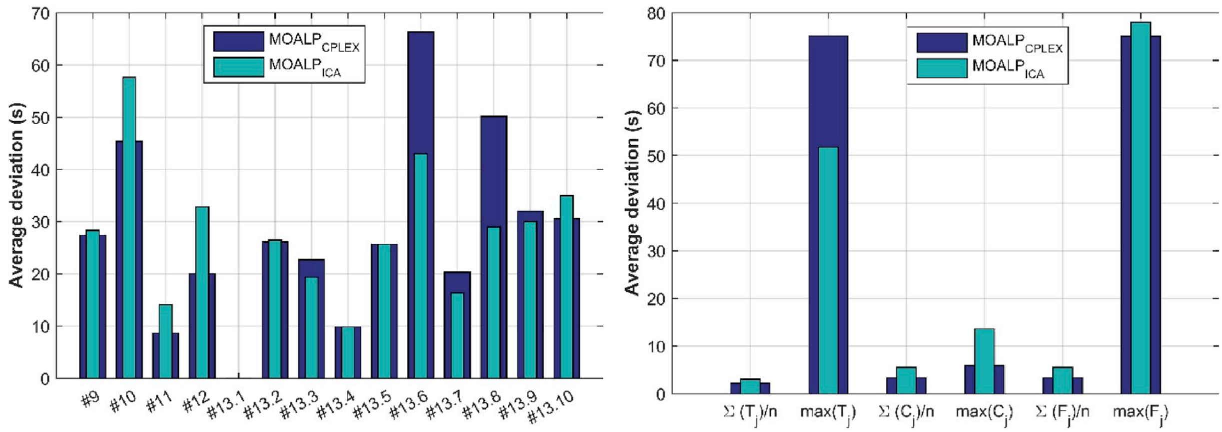

Fig. 8. Average deviations of criteria (8a on left) and instances (8b on right).

Table 5
Sensitivity analysis of different weights and maximum dwell time.

	Factors		$\sum T_j/n$	$\max T_j$	$\sum C_j/n$	$\max C_j$	$\sum F_j/n$	$\max F_j$
	α	$F_{\max}$(s)						
Opt_S	0.5	1,400	23.57	193.00	31,903.63	34,042.00	755.43	1,201.00
Opt_M	0.5	1,260	26.51	442.00	31,912.88	34,131.00	764.69	1,224.00
		1,320	24.33	434.00	31,910.71	34,109.00	762.51	1,292.00
		1,380	24.33	434.00	31,910.71	34,109.00	762.51	1,292.00
		1,440	24.33	344.00	31,909.12	34,065.00	760.92	1,348.00
	0.2	1,400	38.25	502.00	31,906.47	34,087.00	758.27	1,347.00
	0.4		26.27	524.00	31,909.39	34,109.00	761.20	1,369.00
	0.6		25.51	434.00	31,909.12	34,065.00	760.92	1,348.00
	0.8		24.33	434.00	31,910.71	34,109.00	762.51	1,382.00

(3) No matter the criteria or instances, the average deviations are generally small (no more than 80 s), which indicates that the proposed model and method, CPLEX or ICA, are effective for solving multi-objective ALPs.

4.3.2. Sensitivity analysis

The weights α in Eq. (1) indicates the tradeoff between flow time and tardiness, i.e., ATC workload (and indirectly safety) and flight delay (consequent passenger delays). It was set as 0.5 in the above subsection. We varied this value and tested how the change of the weight led to different optimization outcomes. Also, we also varied the maximum dwell time $F_{\max}$. We took ALP#13.6 as an example, and the results are shown in Table 5.

It can be seen from Table 5 that (1) when increasing $F_{\max}$ (relaxing the maximum dwell time constraint in Eq. (2)), we can easily approach the optimum of other criteria; (2) when changing the weights (varying the importance to total delay time or total dwell time in Eq. (2)), it is evident that criteria with higher weight will be reduced with the increase of weight.

5. Conclusion

In existing studies of ALP, the objectives were generally determined from the perspectives of different stakeholders for multi-objective ALP. However, those objectives might be inadequate or redundant.

In this study, we chose several appropriate objectives for multi-objective ALP based on a theoretical analysis, which was inspired mainly by the single machine scheduling field. Given the selected objective function, we proposed a multi-objective optimization to solve ALP and applied that method to a set of benchmark instances from the OR library. The results indicate that minimizing total flight delay, minimizing total dwell time, and minimizing maximum dwell time can simultaneously improve punctual performance, enhance runway utilization, reduce air traffic controller workload, and maintain equity among airlines. Most notably, this is the first study to our knowledge to carry out objectives selection for multi-objective ALP from the perspective of theoretical analysis. Moreover, in addition to the number of aircraft, instance variables and different objectives also play important roles in solving the ALP. When dealing with the multi-objective ALP, a new meta-heuristic algorithm, the imperialist competitive algorithm, was implemented to optimize the landing sequence and scheduled landing times. The simulation results indicate the promising prospects of our proposed model and algorithms.

However, some limitations are worth noting. Although there were some impressive results in this study, we addressed only the arrival sequencing and scheduling problem in the single runway scenario. Future work should, therefore, include mixed arrival and departure sequencing and scheduling in the multiple runways or metroplex scenarios.

Acknowledgments

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Appendix I. Optimization Outcomes of Different Single Objective for Small-Scale Instances

	$\sum \mathrm{Cost}_j$	$\sum T_j/n$	$\max T_j$	$\sum C_j/n$	$\max C_j$	$\sum F_j/n$	$\max F_j$
airland #13.1							
	2,523.10	17.29	305.00	3,883.02	6,414.00	910.65	1,224.00
	18,830.55	**0.00**	**0.00**	3,635.65	6,222.00	663.29	839.00
	19,954.04	**0.00**	**0.00**	3,619.96	**6,191.00**	647.59	**805.00**
	20,233.26	**0.00**	**0.00**	**3,616.65**	**6,191.00**	**644.29**	811.00
	20,348.57	4.96	243.00	3,625.51	**6,191.00**	653.14	951.00
	20,233.26	**0.00**	**0.00**	**3,616.65**	**6,191.00**	**644.29**	811.00
	19,939.57	**0.00**	**0.00**	3,619.92	**6,191.00**	647.55	**805.00**
airland #13.2							
	2,707.50	24.60	273.00	9,120.79	12,032.00	944.48	1,312.00
	10,675.35	**1.98**	55.00	8,955.63	11,777.00	779.31	1,163.00
	11,174.77	5.75	**41.00**	8,958.40	12,032.00	782.08	1,190.00
	20,344.77	9.83	175.00	**8,836.15**	**11,751.00**	**659.83**	897.00
	19,625.15	7.56	144.00	8,842.73	**11,751.00**	666.42	888.00
	20,344.77	9.83	175.00	**8,836.15**	**11,751.00**	**659.83**	897.00
	19,663.64	6.19	122.00	8,838.96	**11,751.00**	662.65	**866.00**
airland #13.3							
	3,182.05	19.74	255.00	15,256.05	18,204.00	898.12	1,336.00
	12,675.74	**0.40**	23.00	15,111.67	18,204.00	753.74	1,180.00
	10,125.62	2.40	**21.00**	15,143.98	18,225.00	786.05	1,192.00
	20,958.77	12.91	514.00	**15,038.23**	**18,064.00**	**680.30**	1,198.00
	20,086.02	12.33	195.00	15,053.23	**18,064.00**	695.30	909.00
	20,958.77	12.91	514.00	**15,038.23**	**18,064.00**	**680.30**	1,198.00
	19,801.52	23.89	212.00	15,078.07	18,350.00	720.14	**886.00**
airland #13.4							
	2,562.05	23.28	358.00	22,483.62	25,474.00	968.20	1,277.00
	24,781.66	**0.00**	**0.00**	22,153.96	25,340.00	638.54	756.00
	23,217.96	**0.00**	**0.00**	22,172.42	25,340.00	657.00	907.00
	24,990.82	**0.00**	**0.00**	**22,149.14**	**25,320.00**	**633.72**	796.00
	22,259.46	0.84	42.00	22,184.80	**25,320.00**	669.38	932.00
	24,990.82	**0.00**	**0.00**	**22,149.14**	**25,320.00**	**633.72**	796.00
	24,019.42	**0.00**	**0.00**	22,161.28	**25,320.00**	645.86	**737.00**
airland #13.5							
	3,615.25	35.71	317.00	27,706.22	29,860.00	946.93	1,274.00
	9,814.64	**1.82**	75.00	27,554.11	29,438.00	794.82	1,120.00
	9,244.49	6.33	**68.00**	27,569.36	29,438.00	810.07	1,194.00
	16,002.98	23.84	565.00	**27,505.89**	**29,346.00**	**746.60**	1,268.00
	14,107.90	23.00	260.00	27,530.51	**29,346.00**	771.22	1,204.00
	16,002.98	23.84	565.00	**27,505.89**	**29,346.00**	**746.60**	1,268.00
	12,491.24	17.04	258.00	27,545.56	29,413.00	786.27	**964.00**
airland #13.6							
	5,889.57	53.35	583.00	32,102.84	34,232.00	954.65	1,680.00
	13,462.94	**23.57**	355.00	31,958.31	34,109.00	810.12	1,474.00
	14,997.83	39.10	**193.00**	31,972.94	34,110.00	824.75	1,293.00
	21,378.90	41.20	591.00	**31,903.63**	34,063.00	**755.43**	1,541.00
	18,772.61	61.53	535.00	31,975.94	**34,042.00**	827.75	1,370.00
	20,571.86	37.00	568.00	**31,903.63**	34,063.00	**755.43**	1,631.00
	18,868.42	45.18	420.00	31,941.67	34,109.00	793.47	**1,201.00**
airland #13.7							
	2,907.34	31.90	408.00	37,305.20	40,113.00	932.67	1,259.00
	12,242.39	**4.29**	134.00	37,130.22	39,563.00	757.69	1,154.00
	11,015.86	10.86	**115.00**	37,158.67	39,563.00	786.14	1,171.00
	18,869.84	13.80	409.00	**37,054.43**	**39,533.00**	**681.90**	1,083.00
	18,327.81	20.76	209.00	37,073.06	**39,533.00**	700.53	938.00
	18,869.84	13.80	409.00	**37,054.43**	**39,533.00**	**681.90**	1,083.00
	18,019.02	19.18	231.00	37,073.37	**39,533.00**	700.84	**913.00**
airland #13.8							
	4,507.27	31.21	309.00	42,449.92	44,696.00	928.38	1,317.00
	11,001.65	**5.44**	**121.00**	42,315.35	44,632.00	793.81	1,210.00
	12,693.13	12.40	**121.00**	42,309.35	44,602.00	787.81	1,210.00
	19,908.25	23.81	500.00	**42,234.31**	**44,516.00**	**712.77**	1,412.00
	17,664.84	33.60	446.00	42,280.10	**44,516.00**	758.56	1,141.00
	19,908.25	23.81	500.00	**42,234.31**	**44,516.00**	**712.77**	1,412.00
	18,348.97	25.38	356.00	42,255.77	**44,516.00**	734.23	**1,051.00**
airland #13.9							
	5,301.21	52.64	692.00	47,282.00	49,891.00	905.34	1,673.00
	11,104.29	**5.42**	111.00	47,123.70	49,703.00	747.04	1,138.00
	10,780.14	13.88	**96.00**	47,145.04	49,703.00	768.38	1,234.00
	17,668.54	30.46	267.00	**47,092.78**	**49,635.00**	**716.12**	1,086.00
	15,158.25	30.98	253.00	47,122.38	**49,635.00**	745.72	966.00
	17,668.54	30.46	267.00	**47,092.78**	**49,635.00**	**716.12**	1,086.00
	15,134.69	35.94	287.00	47,134.50	**49,635.00**	757.84	**958.00**
airland #13.10							
	3,844.28	35.92	254.00	52,716.43	54,925.00	946.18	1,394.00
	10,896.13	**3.12**	**80.00**	52,572.55	54,800.00	802.31	1,248.00

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(*continued*)

11,844.74	12.73	**80.00**	52,576.00	54,822.00	805.76	1,248.00
20,227.12	24.76	564.00	**52,478.20**	54,789.00	**707.96**	1,678.00
22,215.68	207.49	1,086.00	52,814.53	**54,740.00**	1,044.29	2,014.00
20,227.12	24.76	564.00	**52,478.20**	54,789.00	**707.96**	1,678.00
17,363.92	16.45	300.00	52,502.04	54,784.00	731.80	**1,101.00**

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