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Impact Analysis of Demand Management on Runway Configuration in Metroplex Airports

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ABSTRACT Congestion in airports and metroplexes is increasingly becoming a key bottleneck in the global air transport system. It is largely due to inefficient utilization of runway resources and its consequences of imbalance between demand and capacity. Existing studies mainly focus on runway configuration in a single airport system, and little consideration is given to the impact of demand management on runway configuration in metroplexes. Therefore, this paper proposes a methodology and assessment framework for runway configuration with a focus on the exploitation of multiple active runways in metroplex airports. The primary innovation is an integrated runway configuration management formulation with air traffic demand management options. The first is static and dynamic runway configuration management models featuring three optimization objectives, four cases of demand-capacity imbalance, three air traffic demand management options and three assessment scenarios, for eleven priority settings. The second is an efficient multi-objective evolutionary algorithm with a mechanism of objective-guided individual selection, which can obtain close-to optimal solutions with a very low computational cost within 6 seconds. Computational experiments for the real-world case of the Shanghai metroplex airports show that, the inducing strategy of minimizing the total number of adjusted flights is the best mechanism for making satisfactory tradeoffs among multiple objectives in dynamic runway configuration. The proposed model reduces the total number of adjusted flights by an average of 36% compared with the baseline static runway configuration management. Furthermore, unlike the conventional approach of giving priority to arriving aircraft, a higher priority for departures is more effective in enhancing the performance of runway systems and reducing the number of adjusted flights. The proposed framework can be applied at pre-tactical (e.g., one-day planning) as well as tactical (e.g., several-hours rolling horizon) levels.

INDEX TERMS Runway configuration, demand management, metroplex system, airports, performance tradeoff, optimization.

I. INTRODUCTION

A. PROBLEM DESCRIPTION

Growing air traffic congestion in airports and metroplexes is a major concern in the global air transport system due to the imbalance between increasing demand and insufficient capacity. The resulting low-performance, such as conflict, queue and delay, experienced at high density traffic airports, poses significant costs to relevant stakeholders including air navigation service providers, airports, airlines and passengers. In particular, runway performance is crucial to the system-wide efficiency of airport movements, and its inefficient operation is generally believed to be the critical bottleneck in airports and metroplexes. Therefore, enhancing the runway performance has the potential to increase capacity enabling a higher level of traffic demand to be accommodated.

There has been some effort devoted to addressing the imbalance of demand and capacity at busy airport systems. The first is delivering enhanced capacity through the

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construction of new runways and new airports. However, such measures mainly focus on increasing capacity through investment in either building or maintaining infrastructure. This is costly, time consuming, and sometimes impractical because of political, economic, social and environmental constraints. The second is controlling traffic demand given a level of capacity in a specified period of time. For example, (i) optimizing landings and take-offs by runway sequencing and scheduling [1], [2] (ii) planning spatial-temporal movements in a taxi network system by the management of taxi movements [3], [4], and (iii) optimizing the gate assignment for arrival movements [5], [6]. However, most of these studies are conducted based on a fixed runway configuration without considering flexible use of existing runway resources. In fact, Runway Configuration Management (RCM) in practice is dynamic, due to the influence of weather conditions and runway status. The runway status for either arrivals or departures has a significant influence on runway configuration and in turn airport capacity. If the runway configuration changes between any two successive time intervals, the planning traffic management initiatives have to be re-optimized to satisfy runway constraints. Therefore, an effective alternative is to firstly enhance runway performance through dynamic RCM and secondly, make it a key input to the other studies referred to above.

The purpose of RCM is to generate a combination of runways that are active at any particular time in an airport system. Inefficient runway configurations cause an imbalance between demand and capacity leading to airport congestion and flight delays on a network scale. Taking, China, the world's second largest aviation market, as an example, many airports such as Shanghai Pudong (ZSPD), Shanghai Hongqiao (ZSSS), Shenzhen Baoan (ZGSZ), Hangzhou Xiaoshan (ZSHC) and Nanjing Lukou (ZSNJ) are generally characterized by segregated parallel operations as the main mode or sub-mode for a long period of time after the completion of multi-runway construction [7]. This makes a two-runway system approximately equals to a single runway (except for saving on runway occupancy time) resulting in low capacity serving high traffic demand.

In the case of a metroplex where a group of airports are in close geographical proximity, the runway configuration of one airport has some effect on other airports simultaneously used for landings and takeoffs [8], [9]. This is because different patterns of arrival and departure at one airport lead to different resource (airport and airspace) usage in the whole terminal area with multiple airports. In practice at these airports, the selection of runway configuration is a major task faced by Air Traffic Controller Officers (ATCOs) primarily based on their experience. Therefore, a more efficient use of available runway resources has the potential to improve the integrated efficiency (e.g., maximum ultilization of capacity) in metroplex airports.

In this paper, we propose a methodology and assessment framework for RCM research in metroplex airports. We use it to analyze the impact of multiple Air Traffic Demand Management (ATDM) options on RCM performance compared to a baseline static case.

B. LITERATURE REVIEW

The core of RCM is related to the integration of air traffic flow management (i.e., controlling demand based on capacity) and runway capacity management (i.e., controlling capacity based on demand). It started to receive appreciable attention in the past few years. In this section, we conduct a literature review of the existing RCM studies, including their strengths and limitations.

The existing RCM studies focus on strategic configuration [10] and tactical configuration [11]–[13], to satisfy the decision-making needs at different operational phases. When selecting the runway configuration in a particular time horizon, the key factors considered by ATCOs include weather conditions, runway status, traffic demand and environmental considerations [14]. In particular, when the wind speed and direction exceed the maximum allowable levels (defined by the airport operational procedures), ATCOs are required to change to a new runway configuration [15]. Most of the RCM studies are based on the Runway Configuration Capacity Envelope (RCCE), defined by the axes of acceptance rate and capacity curve [16]. The capacity curve is a piecewise linear function representing a set of capacity values that reflect the operational capabilities of an airport under certain conditions. The RCCE has been applied to make tradeoffs between arrivals and departures, which can be served to a maximum extent during a period of time (e.g., 15 minutes, 30 minutes or 1 hour).

The RCM models can be either optimized or analytical. In the former, almost all the models minimize the cost of flight adjustment due to the imbalance between demand and capacity, subject to a variety of constraints. Bertsimas *et al.* [8] propose a mixed integer programming model to select the optimal sequence of runway configurations and determine the optimal balance of arrivals and departures. By considering the uncertainty factors of airport operations, a robust RCM optimization model is proposed to minimize the average delay cost [17]. Through the course of a day of operations as a function of observed congestion on the ground and in the air, and meteorological and wind conditions, Jacquillat *et al.* [12] minimize congestion costs by jointly controlling runway configurations and arrival and departure acceptance rates. Ng *et al.* [13] established a formulation for robust runway scheduling with RCM considerations, and adopted the min-max regret approach to solve the proposed model.

Analytical RCM primarily focuses on data-driven approaches. Ramanujam and Balakrishnan [14] formulate a statistical model to characterize the selection process of runway configuration and propose a framework of discrete-choice modeling to identify the influence of some factors using a utility function. Avery and Balakrishnan [18] present a probabilistic RCM model to predict the configuration of runway resources at 15-minute intervals, extendable to 3 hours. Altinok *et al.* [19] use machine learning techniques on historical data in airport systems, such as weather and runway status, to determine the key features of weather conditions that are significantly correlated with RCM selections.

Corresponding to the RCM models, the algorithms mainly include heuristic and meta-heuristic algorithms [7], [8], [10], [13], exact algorithms [12] and data mining algorithms [19], [20]. Besides the influencing factors such as weather and runway status referred to above, others are also considered. Roach [21] determines that reducing the number of runways is the primary factor in causing flight delays, with the secondary factors being reduced approach precision and high workload arising from uncommon runway configuration. In order to closely represent the real world conditions, some research effort is devoted to the transition cost (e.g., capacity loss) of configuration change. For example, considering the capacity decrease incurred by configuration switching, Weld *et al.* [22] introduce a transition penalty matrix to specify the relative transition costs, which benefits from allowing customizable transition penalties.

However, research to date firstly, mainly focuses on the runway configuration in a single airport system, and the RCM formulation is commonly a single-objective model minimizing the cost of flight adjustment, while ignoring the RCM in metroplex systems. Secondly, the minimum cost configuration, commonly used by most of existing optimized models, is not the best choice for RCM. Finally, the impact of demand-capacity imbalance patterns on RCM is still not clear in the existing studies. Therefore, in this paper, we formulate two RCM models for metroplex operations with multiple optimization objectives. We classify the imbalance cases and ATDM options in detail, and design multiple assessment scenarios and a set of priority settings to assess the impact of ATDM options on runway configuration. Accounting for the three weaknesses, this paper optimizes the selection of runway configurations in metroplex airports under multiple ATDM options, using flexible tradeoffs of priorities between arrivals and departures.

C. CONTRIBUTION OF THE RESEARCH

This paper proposes a novel framework to optimize the dynamic runway configuration in metroplex airports and assess the impact of ATDM options on runway configuration. The methodology improves the flexibility of ATDM and RCM, and performance of runway operations in different assessment scenarios. The proposed framework allows for the application of a set of priority coefficients for arrival and departure movements to obtain expected computational results of flight adjustments. The contributions of the research are summarized as follows.

a) This paper focuses on dynamic and integrated runway configuration in the Shanghai metroplex system with 2 high-density traffic airports ZSPD and ZSSS, and analyzes the impact of ATDM options on runway configuration by establishing in detail 4 cases / 6 subcases of demand-capacity imbalance and 3 options of RCCE-based ATDM.

b) The formulated dynamic RCM (DRCM) and static RCM (SRCM) models optimize 3 objectives of cost, total number and maximum number of flight adjustment, subject to a variety of constraints. We design 3 assessment scenarios with 11 priority settings for arrival and departure movements and establish the relationship between assessment scenarios and ATDM options.

c) We present an improved Efficient Multi-Objective Evolutionary (EMOE) algorithm with an Objective-Guided Individual Selection (OGIS) mechanism, which can obtain close-to optimal solutions with a very low computational cost within 6 seconds and satisfy operation needs on pre-tactical and tactical levels. The designed 3 inducing evolution strategies can be applied to make reliable tradeoffs among different objectives.

d) Computational results show that the DRCM model has a significant advantage over the baseline SRCM, and the minimum total number configuration is the best choice to make satisfactory tradeoffs among cost, total number and maximum number. A higher priority for departures is suggested to reduce the number of adjusted flights.

D. ORGANISATION OF THE PAPER

The rest of this paper is structured as follows. In Section II, we present the methodology. First, we analyze the Demand-Capacity Balancing (DCB) patterns of RCCE and establish a set of ATDM options. Second, two RCM models are formulated to optimize the runway configuration in metroplex airports. Third, we establish 3 assessment scenarios and propose a framework to analyze the impact of ATDM options on runway configuration. Section III presents our EMOE algorithm with the OGIS mechanism. Section IV presents the EMOE performance, and computational results from a real-world case study for Shanghai metroplex airports. Findings and insights are presented by analyzing the numerical results for multiple scenarios and models. Finally, Section V discusses the results and concludes the paper.

II. METHODOLOGY

In this paper, a multi-objective runway configuration model is formulated to enhance the performance of integrated runway operations in metroplex airports, considering a series of RCCE-based ATDM options. The ATDM options reflect the priority settings for arrivals and departures based on different cases of demand and capacity imbalance. In other words, for a certain runway configuration with a known RCCE, the selection of ATDM options defines the nature of flight adjustment which in turn has a significant impact on runway configuration. Compared with the existing studies, our model is applied to not only manage runway configuration, but also evaluate the impact of ATDM options on runway configuration.

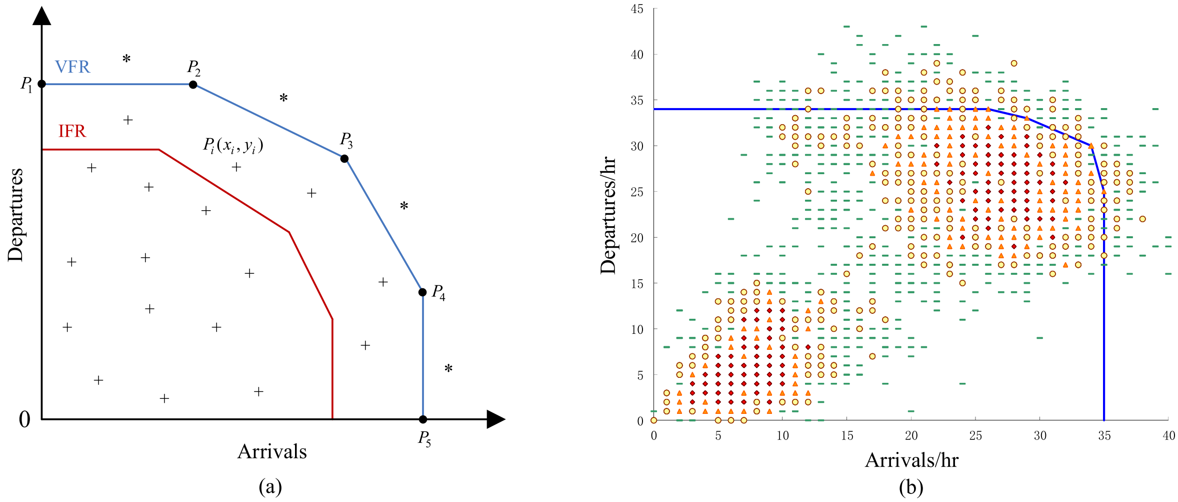

FIGURE 1. Illustration of RCCE and DCB patterns of operating points. (a) RCCE under different meteorological conditions; (b) Distribution of operating points in a particular RCCE.

A. RCCE-BASED ATDM

The runway capacity under different configurations can be represented by the RCCE [8], [12], [23], [24], which captures the tradeoffs between arrival rate and departure rate. In this section, we analyze 4 cases / 6 subcases of demand-capacity imbalance, and then propose 3 options for RCCE-based ATDM to design a flight adjustment mechanism with 11 priority settings.

1) DCB PATTERNS

Fig. 1(a) illustrates the general RCCEs for an airport for two different meteorological conditions of Visual Flight Rules (VFR) and Instrument Flight Rules (IFR). Each operating point inside the RCCE corresponds to a feasible combination of arrivals and departures, while any point outside the RCCE is infeasible [7], [8]. Taking the RCCE-VFR in Fig. 1(a) as an example, the points '+' inside the RCCE-VFR and ' ·' on the RCCE-VFR are feasible, which means that no ATDM options will be applied to these points in our RCM model. However, the points '∗' outside the RCCE-VFR represent where the runway system does not have a sufficient capacity to accommodate simultaneously the number of arrivals and departures, which means that some flight adjustments should be made to keep the DCB. In Fig. 1(b), we present the historical statistics of observed air traffic data in Shanghai Pudong airport, and depict the distribution of all the feasible and infeasible operating points in a particular RCCE. It can be seen that some points are located outside the RCCE. This is due to the existing runway configuration in ZSPD not being dynamically optimized but statically selected as a long-period configuration. This results in a low efficiency of runway operations and motivates us to conduct dynamic optimization of runway configuration.

We can formulate the equations for all the RCCE segments P_1P_2, P_2P_3, P_3P_4 and P_4P_5, if the coordinates of any two adjacent points are known [25]. For example, let x_2 and y_2 be the arrival and departure values for point P_2, and x_3 and y_3 the corresponding values for point P_3, then the mathematical expression of the RCCE-VFR segment P_2P_3 is

$$(y_2 - y_3)x + (x_3 - x_2)y + (x_2y_3 - x_3y_2) = 0 \tag{1}$$

Then, any feasible point $P_i(x_i, y_i)$ of RCCE in Fig. 1(a) must satisfy

$$(y_2 - y_3)x_i + (x_3 - x_2)y_i \leq x_3y_2 - x_2y_3 \tag{2}$$

For any infeasible point which does not satisfy the inequality (2), the extra arrivals or departures corresponding to this point will be adjusted to the next time interval, to keep the DCB in RCCE. Fig. 2 shows that several flight adjustment

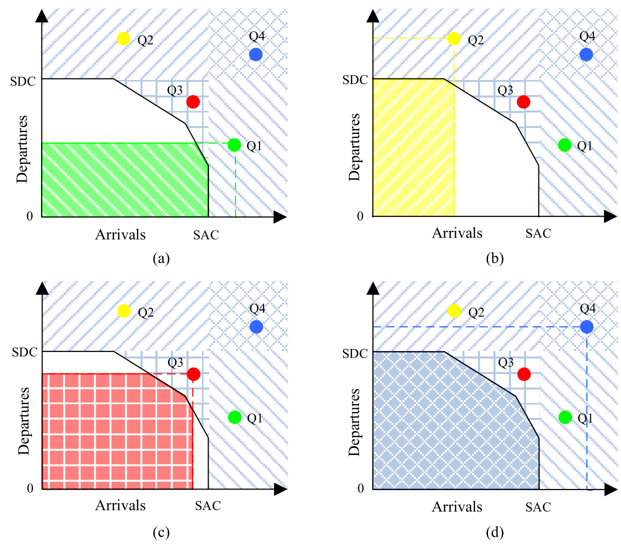

FIGURE 2. Feasible space to keep the DCB in different cases of demand-capacity imbalance. (a) Case a-AODI; (b) Case b-AIDO; (c) Case c-AIDI; (d) Case d-AODO.

strategies are available for consideration to keep the DCB, in different imbalance cases of demand and capacity.

Note that the 'imbalance' referred to here and the rest of the paper indicates the infeasible points outside RCCE. We define the maximum arrival rate as Saturated Arrival Capacity (SAC) and the maximum departure rate as Saturated Departure Capacity (SDC) for the convenience of analysis. Then, all the infeasible points in Fig. 2 can be classified into the following 4 cases:

- ***Case a: Arrival Outside and Departure Inside*** **(AODI)**

The area containing point Q1 in Fig. 2(a) is where while the arrival demand exceeds SAC, the departure demand does not exceed the SDC. Hence, only arrival capacity is insufficient to accommodate air traffic demand and point Q1 will be adjusted to the green-hatched area.

- ***Case b: Arrival Inside and Departure Outside (AIDO)***

The area containing point Q2 in Fig. 2(b) is where while the departure demand exceeds SDC, the arrival demand does not exceed the SAC. Hence, only departure capacity is insufficient to accommodate air traffic demand and point Q2 will be adjusted to the yellow-hatched area.

- ***Case c: Arrival Inside and Departure Inside (AIDI)***

The area containing point Q3 in Fig. 2(c) is where while the arrival (departure) demand does not exceed SAC (SDC), the sum of arrival and departure demands exceeds the RCCE constraint. Hence, RCCE is insufficient to simultaneously accommodate air traffic demand, and point Q3 will be adjusted to the red-hatched area.

- ***Case d: Arrival Outside and Departure Outside (AODO)***

The area containing point Q4 in Fig. 2(d) means that arrival (departure) demand does exceed SAC (SDC), and the total demand exceeds the RCCE constraint. Hence, RCCE is not sufficient to separately accommodate air traffic demand and point Q4 will be adjusted to the blue-hatched area.

2) ATDM OPTIONS

In view of the analysis of feasible space for *Case a* $\sim$ *Case d*, ATCOs can formulate corresponding ATDM options to adjust queuing flights, and then ensure that all the infeasible points in Fig. 2 can be relocated in the RCCE feasible space. Fig. 3 illustrates the multiple ATDM options for different imbalance cases. Similar to the SAC and SDC, we define Restricted Arrival Capacity (RAC) as the maximum arrival rate under SDC, and Restricted Departure Capacity (RDC) as the maximum departure rate under SAC.

Obviously, each of *Case a* and *Case b* in Fig. 3 has 2 subcases. The flight adjustment strategy for each subcase should be selected, according to the priority settings for arrival and departure operations. Let p_a and p_d be the weight coefficients of priority for arrivals and departures in runway operations, and satisfy

$$p_a, p_d \in [0, 1] \tag{3}$$

$$p_a + p_d = 1 \tag{4}$$

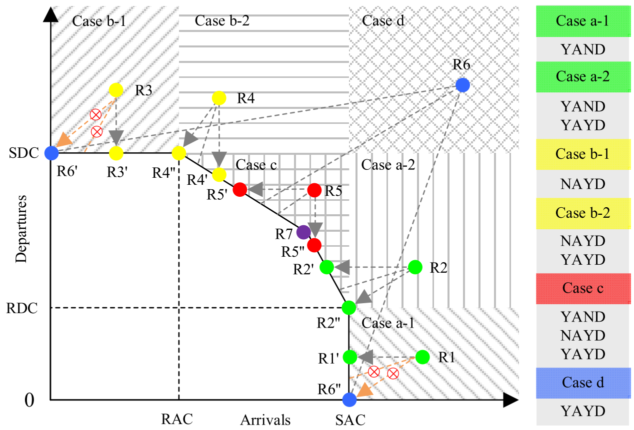

FIGURE 3. **ATDM options for different imbalance cases of demand and capacity.**

Therefore, we design 11 arrival / departure priority settings, which includes:

- **Prior arrival adjustment:** {(0,1)};
- **Prior departure adjustment:** {(1,0)};
- **Tradeoffs between arrival and departure adjustments:** {(0.1,0.9), (0.2,0.8), (0.3,0.7), (0.4,0.6), (0.5,0.5), (0.6,0.4), (0.7,0.3), (0.8,0.2), (0.9,0.1)}.

Definition 1 (Flight Adjustment Coefficients): The arrival (departure) adjustment coefficient $\wp_a$ ($\wp_d$) is defined as the proportion of the number of adjusted arrivals (departures) during the DCB. Ideally, the priority coefficients and adjustment coefficients hold:

$$\wp_a = 1 - p_a \tag{5}$$

$$\wp_d = 1 - p_d \tag{6}$$

Table 1 illustrates the ATDM options selection strategy for *Case a* $\sim$ *Case d*.

Note that more than one ATDM option may exist and can be applied to keep the DCB in each imbalance case. For example, the candidate set of ATDM options for *Case a* includes: (a) adjusting only arrivals and (b) adjusting both arrivals and departures. From the perspective of global optimization for all the time intervals in the planning horizon, the solution (b) should also be considered in runway configuration, even though the departure demand satisfies the RCCE constraint. Therefore, optimizing the selection of multiple ATDM options for different imbalance cases is one of our main concerns in this research, which is also the basis for assessing the impact of ATDM options on runway configuration in metroplex airports. As illustrated in Fig. 3 and Table 1, the ATDM strategy for each imbalance case can be classified into the following 3 options:

- ***Option a: adjusting arrivals and not adjusting departures*** **(YAND)**

The priority setting for arrival and departure operations is $p_a = 0$, $p_d = 1$. The YAND adjustment strategy for all the

TABLE 1. ATDM options selection strategy for different imbalance cases.

ATDM options	Priority settings	*Case a*		*Case b*		*Case c*	*Case d*
		Case a-1	*Case a-2*	*Case b-1*	*Case b-2*		
YAND	$p_a = 0,\ p_d = 1$	√	√	×	×	√	×
NAYD	$p_a = 1,\ p_d = 0$	×	×	√	√	√	×
YAYD	$0 < p_a, p_d < 1$	×	√	×	√	√	√

imbalance cases is as follows.

$$Adj\ (YAND) = \begin{cases} R_1 \to R_1', & Case\ a\text{-}1 \\ R_2 \to R_2', & Case\ a\text{-}2 \\ R_5 \to R_5', & Case\ c \\ \emptyset, & Case\ b\text{-}1,\ b\text{-}2,\ d \end{cases} \tag{7}$$

Definition 2 (Inactive ATDM Option): An ATDM option $\zeta \in \Theta$ is declared to be inactive in the imbalance case $l \in \Phi$ for a certain RCCE $X \in \Gamma$, if the imbalance case l cannot be adjusted (i.e., $Adj\ (\zeta)_{Xl} = \emptyset$, or '×' in Table 1) to keep the DCB in RCCE X by the ATDM option $\zeta \in \Theta$.

$$F(X, \zeta) = \{l | Adj\ (\zeta)_{Xl} = \emptyset\} \tag{8}$$

According to Definition 2, $F(X, 1) = \{3, 4, 6\}$. The ∅ in Eq. (7) corresponds to the '×' in the first row of Table 1 and means that the infeasible points cannot be adjusted within RCCE using the YAND option. In other words, we have to adjust departures to keep the DCB. Note that the ∅ under the YAND option can be further transformed as:

$$Adj\ (YAND|\emptyset) = \begin{cases} R_3 \to R_3', & Case\ b\text{-}1 \\ R_4 \to \overline{R_4' R_4''}, & Case\ b\text{-}2 \\ R_6 \to \overline{R_6' R_4'' R_7 R_2'' R_6''}, & Case\ d \end{cases} \tag{9}$$

- ***Option b: not adjusting arrivals and adjusting departures* (NAYD)**

The priority setting for arrival and departure operations is $p_a = 1, p_d = 0$. The NAYD adjustment strategy for all the imbalance cases is as follows.

$$Adj\ (NAYD) = \begin{cases} R_3 \to R_3', & Case\ b\text{-}1 \\ R_4 \to R_4', & Case\ b\text{-}2 \\ R_5 \to R_5'', & Case\ c \\ \emptyset, & Case\ a\text{-}1,\ a\text{-}2,\ d \end{cases} \tag{10}$$

According to Definition 2, $F(X, 2) = \{1, 2, 6\}$. The ∅ in Eq. (10) corresponds to the '×' in second row of Table 1 and means that the infeasible points cannot be adjusted within the RCCE using the NAYD option. In other words, we have to adjust arrivals to keep the DCB. The ∅ under the NAYD option can be further transformed as:

$$Adj\ (NAYD|\emptyset) = \begin{cases} R_1 \to R_1', & Case\ a\text{-}1 \\ R_2 \to \overline{R_2' R_2''}, & Case\ a\text{-}2 \\ R_6 \to \overline{R_6' R_4'' R_7 R_2'' R_6''}, & Case\ d \end{cases} \tag{11}$$

- ***Option c: adjusting both arrivals and departures* (YAYD)**

The priority setting for arrival and departure operations is $0 < p_a, p_d < 1$. The YAYD adjustment strategy for all the imbalance cases is as follows.

$$Adj\ (YAYD) = \begin{cases} R_2 \to \overline{R_2' R_2''}, & Case\ a\text{-}2 \\ R_4 \to \overline{R_4' R_4''}, & Case\ b\text{-}2 \\ R_5 \to \overline{R_5' R_5''}, & Case\ c \\ R_6 \to \overline{R_6' R_4'' R_7 R_2'' R_6''}, & Case\ d \\ \emptyset, & Case\ a\text{-}1,\ b\text{-}1 \end{cases} \tag{12}$$

According to Definition 2, $F(X, 3) = \{1, 3\}$. The ∅ in Eq. (12) corresponds to the '×' in the third row of Table 1 and means that we do not simultaneously, but separately, adjust the arrivals and departures. The ∅ under the YAYD option can be further transformed as:

$$Adj\ (YAYD|\emptyset) = \begin{cases} R_1 \to R_1', & Case\ a\text{-}1 \\ R_3 \to R_3', & Case\ b\text{-}1 \end{cases} \tag{13}$$

Remark 1 (Reset Flexibility of ATDM Options With ∅ Outputs in non-Extreme Conditions): The ATDM options will be converted into the YAYD option if one of the following conditions exists with ∅. First, the NAYD option with ∅ for *Case a-2*. Second, the YAND option with ∅ for *Case b-2*. Third, the YAND and NAYD options with ∅ for *Case d*.

$$Adj\ (YAND, NAYD, YAYD|\emptyset)_{Non\text{-}extreme} = \begin{cases} R_4 \to \overline{R_4' R_4''}, & Case\ b\text{-}2 \\ R_2 \to \overline{R_2' R_2''}, & Case\ a\text{-}2 \\ R_6 \to \overline{R_6' R_4'' R_7 R_2'' R_6''}, & Case\ d \end{cases} \tag{14}$$

That is to say, regarding the ∅ for *Case b-2* and *Case d* in Eq. (9), and the ∅ for *Case a-2* and *Case d* in Eq. (11), we do not separately, but simultaneously, adjust the arrivals and departures.

Remark 2 (Reset Restriction of ATDM Options With ∅ Outputs in Extreme Conditions): The NAYD and YAYD options with ∅ for *Case a-1* are converted into the YAND option. Similarly, the YAND and YAYD options for *Case b-1* are converted into the NAYD option.

$$Adj\ (YAND, NAYD, YAYD|\emptyset)_{Extreme} = \begin{cases} R_1 \rightarrow R_1' \\ R_3 \rightarrow R_3' \end{cases} \neq \begin{cases} R_1 \rightarrow \overline{R_1' R_6''}, & Case\ a\text{-}1 \\ R_3 \rightarrow \overline{R_3' R_6'}, & Case\ b\text{-}1 \end{cases} \quad (15)$$

That is to say, regarding the $\emptyset$ for *Case b-1* in Eq. (9), *Case a-1* in Eq. (11), and *Case a-1* and *Case b-1* in Eq. (13), we do not simultaneously, but separately, adjust the arrivals and departures. Remark 2 can be validated by Definition 3 and Proposition 1.

Definition 3 (Equivalent ATDM Options): For any two ATDM options $\zeta, \vartheta \in \Theta$, ζ is declared to be equivalent to ϑ if the number of adjusted flights $\Delta(\zeta)$ for ζ equals $\Delta(\vartheta)$ for ϑ.

$$\Delta(\zeta) = p(\zeta) + q(\zeta) \quad (16)$$

$$\Delta(\vartheta) = p(\vartheta) + q(\vartheta) \quad (17)$$

where $p(\cdot)$ and $q(\cdot)$ denote the number of adjusted arrivals and departures, respectively. If $\Delta(\zeta) = \Delta(\vartheta)$, then ζ is equivalent to ϑ. If $\Delta(\zeta) < \Delta(\vartheta)$, then ζ is better than ϑ, i.e., ϑ is worse than ζ.

Proposition 1 (The Optimal DCB on RCCE With the YAND and NAYD Options for Case a-1 and Case b-1): For any initial arrival-departure operating point for *Case a-1* and *Case b-1* in Remark 2, the YAYD option is not equivalent to, but worse than, the YAND and NAYD options.

Proof: Let $R_1 = (x_1, y_1)$, $R_1' = (SAC, y_1)$. For any point $R_i = (SAC, y_i)$ in segment $\overline{R_1' R_6''}$, the number of adjusted flights using the YAND and YAYD options for *Case a-1* satisfy

$$\Delta(YAND)_{Case\ a\text{-}1} = x_1 - SAC \quad (18)$$

$$\Delta(YAYD)_{Case\ a\text{-}1} = (x_1 - SAC) + (y_1 - y_i) \quad (19)$$

Obviously, $\Delta(YAND)_{Case\ a-1} < \Delta(YAYD)_{Case\ a-1}$. Then, the YAND option is better than YAYD option for *Case a-1*.

Similarly, Let $R_3 = (x_3, y_3)$, $R_3' = (x_3, SDC)$. For any point $R_j = (x_j, SDC)$ in segment $\overline{R_3' R_6'}$, the number of adjusted flights using NAYD and YAYD for *Case b-1* satisfy

$$\Delta(NAYD)_{Case\ b\text{-}1} = y_3 - SDC \quad (20)$$

$$\Delta(YAYD)_{Case\ b\text{-}1} = (y_3 - SDC) + (x_3 - x_j) \quad (21)$$

Obviously, $\Delta(NAYD)_{Case\ b-1} < \Delta(YAYD)_{Case\ b-1}$. Then, the NAYD option is better than YAYD option for *Case b-1*.

Therefore, Eq. (15) holds. □

Remark 3 (The Scalability and Versatility of ATDM Options in any RCCE): The ATDM options can be flexibly recombined and applied to any runway configurations (e.g., the RCCE_I ∼ RCCE_VI in Fig. 4) in an airport system, according to the structure of RCCE.

The RCCE provides a complete description of runway capacity under any specific set of conditions. Through the RCCE-based ATDM method, we formulate two multi-objective RCM models in the following section, aiming to keep the DBC and maximize the utilization of runway resources in metroplex airports.

B. RCM OPTIMIZATION MODELS

Most of the existing studies of RCM optimization mainly focus on a single-objective optimization in a single airport system [10], [12], [13]. The RCM problem in metroplex airports involves different concerns from air transport stakeholders such as minimizing flight delay, maximizing the rate of flight punctuality, and maximizing airport slot utilization in multiple airports. However, there is very little published research on multi-objective optimization of RCM in metroplex system [8]. In real practice at hub airports, the tradeoffs among multiple objectives may lead to a set of options for scheduling aircraft to meet different needs of several stakeholders. Hence, in this paper we seek to minimize the cost (economic view), total number and single maximum number (punctuality view) of flight adjustment due to the DCB, by formulating two multi-objective RCM optimization models in metroplex airports:

(I) Dynamic RCM (DRCM) model, and
(II) Static RCM (SRCM) model.

1) NOTATIONS

Consider a set of airports A in a metroplex system, indexed by i. Let S be the set of intervals in the planning horizon for runway configuration management, indexed by t. Each airport i has an available runway configuration set denoted as M_i. In our runway configuration model, we assume the influencing factors of M_i, such as wind, visibility, runway status and environment, to be known in the planning horizon. Let $M_{it} \subseteq M_i$ be the set of available configurations in interval t at airport i, indexed by k. Let Φ be the set of imbalance cases in Fig. 3 and Fig. 4, indexed by l. The parameters and variables of our models are shown in Table 2.

2) DRCM MODEL

DRCM encapsulates multiple flexible configurations used in the planning horizon. Hence, the configurations between any two intervals can be different from each other, which is the main focus of our RCM optimization problem.

The objective function (22) focuses on the system delay in the whole planning horizon and aims to minimize the total cost of adjusted arrivals and departures. The objective function (23) focuses on the adjusted flights in the whole planning horizon and aims to minimize the total number of adjusted arrivals and departures. The objective function (24) focuses on the adjusted flights in a single time interval and aims to improve the adherence rate of each interval. From the literature the objective functions (23) and (24) are usually ignored in the existing studies. However, they are important issues of concern to the air transport stakeholders due to a reflection of flight punctuality. Actually, we find that the objective function (22), used by most of the research papers, is not the best choice to solve the RCM problem when making tradoffs among the three objectives Eqs. (22)∼(24). This is

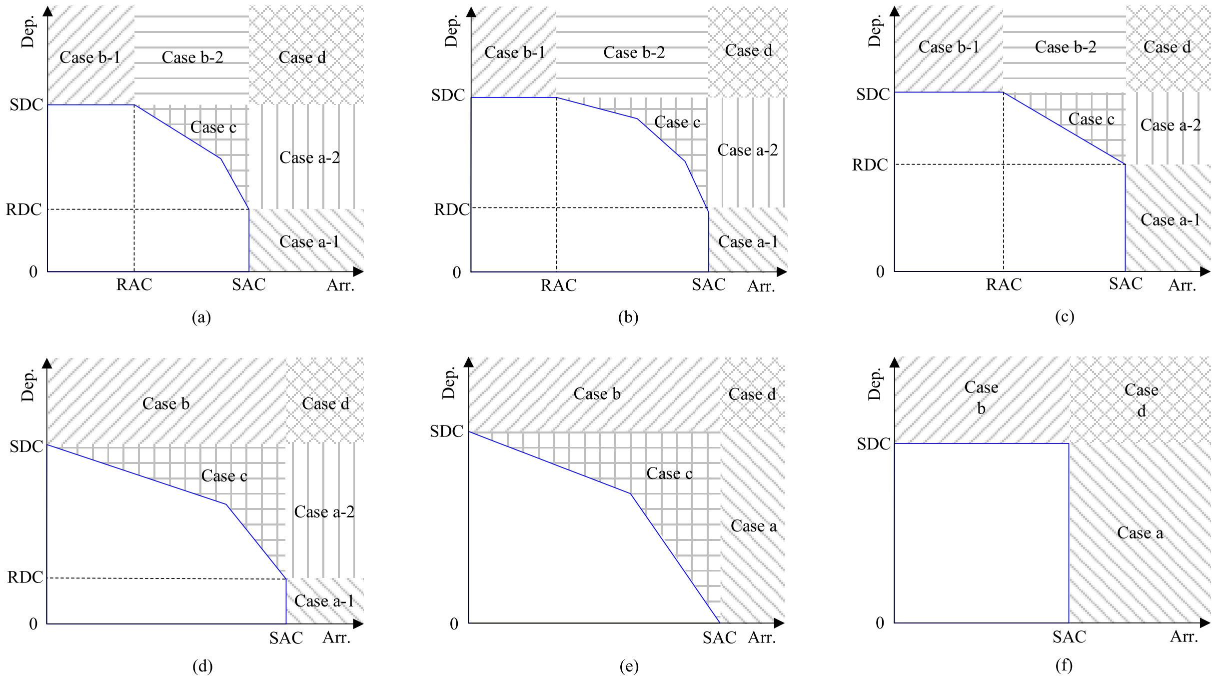

FIGURE 4. ATDM options in different types of RCCE. (a) RCCE_I; (b) RCCE_II; (c) RCCE_III; (d) RCCE_IV; (e) RCCE_V; (f) RCCE_VI.

TABLE 2. Parameters and variables of the DRCM and SRCM models

Parameters	Explanation
a_{it}, d_{it}	The number of scheduled arrivals (departures) in interval t at airport i
φ_{it}, ϕ_{it}	The cost of adjusting a single arrival (departure) for one interval in interval t at airport i
Λ_{itk}	The set of linear segments defining the RCCE for configuration k in interval t at airport i, indexed by j for each segment
$\alpha_{ikj}, \beta_{ikj}$	The linear coefficient for arrivals (departures) of segment j for configuration k at airport i
γ_{ikj}	The constant coefficient of segment j for configuration k at airport i
Z	A large number for constraint analysis to keep the feasible region of RCCE
C_t	The maximum acceptance rate in interval t in metroplex system
ω_{it}	The capacity loss coefficient during configuration transition at the start of interval t at airport i
Variables	**Explanation**
ξ_{itk}	1, if configuration k is selected in interval t at airport i; 0, otherwise
τ_{itl}	1, if case l is the imbalance case for identifying the ATDM option in interval t at airport i; 0 otherwise
σ_{it}	1, if configuration k in interval t at airport i does not equal the configuration k' ($k' \neq k$) in interval t-1 at airport i, which means there is a transition of configuration at the start of interval t; 0, otherwise
x_{it}, y_{it}	The number of served arrivals (departures) in interval t at airport i
p_{it}, q_{it}	The number of adjusted arrivals (departures) in interval t at airport i

discussed in detail in Section IV.

$$\min \sum_{i\in A}\sum_{t\in S}\sum_{k\in M_{it}}\sum_{l\in\Phi} \xi_{itk}\tau_{itl}(\varphi_{it}p_{it}+\phi_{it}q_{it}) \tag{22}$$

$$\min \sum_{i\in A}\sum_{t\in S}\sum_{k\in M_{it}}\sum_{l\in\Phi} \xi_{itk}\tau_{itl}(p_{it}+q_{it}) \tag{23}$$

$$\min \left\{\max_{t\in S}\sum_{i\in A}\sum_{k\in M_{it}}\sum_{l\in\Phi} \xi_{itk}\tau_{itl}(p_{it}+q_{it})\right\} \tag{24}$$

These objective functions (22) $\sim$ (24) are achieved while operating within the following constraints. Constraint (25) ensures that only one of the eligible runway configurations is selected in any airport i and any interval t. Constraint (26) ensures that only one of the ATDM cases is identified for a certain RCCE in any airport i and any interval t. Constraint (27) ensures that any feasible operating point must fall into the RCCE, where Z is a large enough constant such that, when $\xi_{itk} = 0$, the constraint cannot reduce the RCCE feasible region under the condition $\xi_{itk'} = 1(k' \neq k)$. When a transition of runway configuration is made, Constraint (28) will set a value of capacity loss coefficient $\omega_{it} \in [0, 1]$ [17] to decrease the frontier represented by constraint (27). Constraints (29) and (30) ensure the conservation of air traffic demand between any two consecutive intervals. That is to say, the demand in interval t, plus the adjusted (i.e., remaining or carryover) demand from interval $t-1$, and minus the served demand in interval t, does not exceed the adjusted demand in interval t. Constraint (31) ensures that the sum of served arrivals and departures at all the airports in interval t should not be larger than the maximum acceptance rate C_t in the metroplex system. Note that C_t is a value issued by the air navigation service provider, considering the conditions of airport ground and terminal areas in a metroplex system. Constraint (32) ensures that the queue length of arrivals and departures at the start of the planning horizon at an airport is equal to 0. Non-zero initial queues can be modelled by increasing the values of p_{i0} and q_{i0}. In addition, for all the infeasible operating points outside each selected RCCE, Eqs. (7) and (9)~(13) must hold to maximize the DCB.

$$\sum_{k \in M_{it}} \xi_{itk} = 1 \quad \forall i \in A,\ \forall t \in S \tag{25}$$

$$\sum_{l \in \Phi} \tau_{itl} = 1 \quad \forall i \in A,\ \forall t \in S \tag{26}$$

$$\begin{aligned} &\alpha_{ikj} x_{it} + \beta_{ikj} y_{it} \quad \forall i \in A,\ \forall t \in S, \\ &\leq \gamma_{ikj}(1 - \sigma_{it}\omega_{it}) + Z(1 - \xi_{itk}) \quad \forall k \in M_{it}, \\ &\forall j \in \Lambda_{itk} \end{aligned} \tag{27}$$

$$\omega_{it} \leq \sigma_{it} \quad \forall i \in A,\ \forall t \in S \tag{28}$$

$$a_{it} + p_{i,t-1} - x_{it} \leq p_{it} \quad \forall i \in A,\ \forall t \in S \tag{29}$$

$$d_{it} + q_{i,t-1} - y_{it} \leq q_{it} \quad \forall i \in A,\ \forall t \in S \tag{30}$$

$$\sum_{i \in A} (x_{it} + y_{it}) \leq C_t \quad \forall t \in S \tag{31}$$

$$p_{i0} = q_{i0} = 0 \quad \forall i \in A \tag{32}$$

and

(7), (9)~(13)

3) SRCM MODEL

SRCM requires that only one fixed configuration and RCCE is used in the planning horizon, which is a common strategy used in Chinese airports in a single day. Hence, the SRCM model is used as a baseline model for comparison with our DRCM model. Hence, for any airport i and any interval t, there will be no notations ω_{it} and σ_{it} to reflect capacity loss during a transition of configuration. According to the objectives and constraints of the DRCM model, the SRCM model can be formulated as follows:

Eqs. (22)~(24)

$$\text{s.t.} \sum_{t \in S} \xi_{itk_0} = |S| \quad \forall i \in A,\ \exists k_0 \in M_{it} \tag{33}$$

$$\begin{aligned} &\alpha_{ikj} x_{it} + \beta_{ikj} y_{it} \quad \forall i \in A,\ \forall t \in S, \\ &\leq \gamma_{ikj} + Z(1 - \xi_{itk}) \quad \forall k \in M_{it},\ \forall j \in \Lambda_{itk} \\ &\text{and} \\ &(7), (9)\sim(13), (26), (29)\sim(32) \end{aligned} \tag{34}$$

Note that k_0 in Eq. (33) is set based on the operational experience of air traffic controllers and the most frequently used historical configuration in each airport. Through the RCCE-based ATDM method, and the DRCM and SRCM models, three assessment scenarios are designed to investigate the impact of ATDM options on runway configuration in metroplex airports.

C. ASSESSMENT OF ATDM IMPACTS

As discussed in Section II, we use 3 ATDM options, YAND, NAYD and YAYD, to optimize the runway configuration in the 4 cases / 6 subcases of demand-capacity imbalance. It can be seen from Table 1 that there is only one ATDM option to select when the imbalance between demand and capacity arises in the form of *Case a-1*, *Case b-1* and *Case d*. However, for *Case a-2*, *Case b-2* and *Case c*, multiple options make the problem complicated. For these cases, we further design 3 assessment scenarios to analyze the impact of ATDM options on runway configuration.

(I) Priority for Arrival Adjustment (PAA),
(II) Priority for Departure Adjustment (PDA), and
(II) Tradeoffs for Flight Adjustment (TFA).

1) ASSESSMENT SCENARIOS

In this section, *Scenario PAA*, *Scenario PDA* and *Scenario TFA* are designed, aiming to ensure only one ATDM option is selected for each imbalance case, not only *Case a-1*, *Case b-1* and *Case d*, but also *Case a-2*, *Case b-2* and *Case c*, for any airport in metroplex system. The strategy for selecting an ATDM option for each scenario is as follows.

- ***Scenario PAA***

PAA represents the scenario that a departure aircraft has an absolute priority to operate in the metroplex system, while the arrival aircraft has no priority when an imbalance between demand and capacity arises. Table 3 illustrates the basic rule to select a unique ATDM option for each imbalance case in *Scenario PAA*.

- ***Scenario PDA***

PDA represents the scenario that an arrival aircraft has an absolute priority to operate in the metroplex system, while the departure aircraft has no priority when an imbalance between demand and capacity arises. Table 4 illustrates the basic rule to select a unique ATDM option for each imbalance case in *Scenario PDA*.

TABLE 3. ATDM option selection for different imbalance cases in *Scenario PAA*.

ATDM	*Case a*		*Case b*		*Case*	*Case*
options	*a-1*	*a-2*	*b-1*	*b-2*	*c*	*d*
YAND	√	√	×	×	√	×
NAYD	×	×	√	×	×	×
YAYD	×	×	×	√	×	√

TABLE 4. ATDM option selection for different imbalance cases in *Scenario PDA*.

ATDM	*Case a*		*Case b*		*Case*	*Case*
options	*a-1*	*a-2*	*b-1*	*b-2*	*c*	*d*
YAND	√	×	×	×	×	×
NAYD	×	×	√	√	√	×
YAYD	×	√	×	×	×	√

TABLE 5. ATDM option selection for different imbalance cases in *Scenario TFA*.

ATDM	*Case a*		*Case b*		*Case*	*Case*
options	*a-1*	*a-2*	*b-1*	*b-2*	*c*	*d*
YAND	√	×	×	×	×	×
NAYD	×	×	√	×	×	×
YAYD	×	√	×	√	√	√

- ***Scenario TFA***

TFA represents the scenario that there is no absolute priority for arrivals and departures, but that a tradeoff of ATDM should be made when the imbalance between demand and capacity arises. The adjustment of arrivals and departures depends on the weight coefficients of priority p_a and p_d described in Section II. Table 5 illustrates the basic rule to select a unique ATDM option for each imbalance case in *Scenario TFA*.

2) ASSESSMENT FRAMEWORK

According to the ATDM option selection rules discussed in Table 3∼Table 5 and the DRCM and SRCM models, we establish a framework for assessing the impacts of ATDM options on runway configuration for multiple scenarios of *PAA*, *PDA* and *TFA*.

Section II has presented the RCCE-based ATDM method, the RCM models and assessment method of ATDM impacts. Accordingly, we propose an efficient evolutionary algorithm in Section III to solve the RCM models, and make tradeoffs among three objectives Eqs. (22)∼(24).

III. EVOLUTIONARY ALGORITHM

Different from the single-objective RCM optimization, there are some tradeoffs among the three optimization objectives Eqs. (22)∼(24). Hence, we propose an improved Efficient Multi-Objective Evolutionary (EMOE) algorithm to solve the multi-objective RCM models in metroplex airports, based on the nondominated sorting genetic algorithm [26]. The EMOE algorithm is featured with an Objective-Guided Individual Selection (OGIS) mechanism which is different from a traditionally weighted objective function adopted by most studies when dealing with multiple objectives [1], [27]. In addition, the solutions searched by our EMOE algorithm for different scenarios of *PAA*, *PDA* and *TFA* are used to assess the impacts of ATDM options.

A. IMPLEMENTATION FRAMEWORK

Our EMOE algorithm employs techniques inspired by evolutionary biology such as inheritance, mutation, natural selection, and recombination to find satisfactory Pareto solutions for RCM problem. Before the start of computation, an initial set of candidate solutions is generated based on the RCCE No. coding in each interval. The problem to be solved, is represented by a list of variables, called individual. Each individual is evaluated, and the values of fitness are returned by three functions designed by Eqs. (22)∼(24). By removing less desired solutions from the current generation with the OGIS mechanism, and producing the new generation, the population gradually evolves to increase in fitness until the process of iteration ends on the pre-set termination condition. The pseudocode of the EMOE algorithm will be presented in the following.

B. ALGORITHM DESIGN

The constructive metaheuristic provides initial solutions which are generated in the range of RCCE sets and maintains the population diversity. Then, the EMOE seeks nondominated Pareto solutions based on the assessment and evolution in each iteration. In this section, we discuss the EMOE details as follows.

1) SOLUTION REPRESENTATION

The variables τ_{itl}, σ_{it}, x_{it}, y_{it}, p_{it} and q_{it} in Table 2 can be calculated according to the selected assessment scenario and ATDM options, if the values of ξ_{itk} are known. Hence, we design ξ_{itk} in the form of RCCE No. coding, and generate an initial configuration number k as a gene for each interval at each airport, to represent the binary variable ξ_{itk}. The phenotype of each gene in the chromosome is randomly created in the range of M_{it}. For example, $\xi_{123} = 1$ means that the runway configuration $3 \in M_{12}$ is used in interval 2 at airport 1. If $\xi_{123} = 1$ and $\xi_{132} = 1$, then there is a transition of configuration at the start of interval 3 and $\sigma_{13} = 1$. Fig. 5 illustrates the solution representation rule of EMOE algorithm in RCM problem.

Obviously, the number of genes in each chromosome equals to $|A| \cdot |S|$, which is the product of the number of airports in the metroplex system and number

Implementation Procedure of the Assessment Framework

Input: Airport set in metroplex system, planning horizon, length of single interval, RCCE sets in each airport, initial air traffic demand, cost of adjusting flights, maximum acceptance rate, capacity loss coefficient, etc.
Output: The cost and number of flight adjustment in metroplex airports.
Main Loop:
Initialization:
(I) **LOAD** the assessment scenario of ATDM impacts:
Scenario PAA: Selection ATDM options in Table 3.
Scenario PDA: Selection ATDM options in Table 4.
Scenario TFA: Selection ATDM options in Table 5.
(II) Set the initial time interval $t = 0$.
WHILE $t < |S|$ **DO**
(I) Generate the runway configurations in interval t for each airport:
Apply the ATDM method and RCM models presented in Section II.
Apply the evolutionary algorithm presented later in Section III.
(II) Identify the imbalance case in interval t for each airport.
(III) Calculate the DCB results in interval t for each airport:
IF *Scenario PAA*
IF *Case a-1, Case a-2, Case c*
Only adjust the remaining arrivals p_{it} from t to $t + 1$ to keep DCB.
ELSE IF *Case b-1*
Only adjust the remaining departures q_{it} from t to $t + 1$ to keep DCB.
ELSE *Case b-2, Case d*
Simultaneously adjust the remaining arrivals p_{it} and departures q_{it} from t to $t + 1$ to keep DCB.
END
ELSE IF *Scenario PDA*
IF*Case a-1*
Only adjust the remaining arrivals p_{it} from t to $t + 1$ to keep DCB.
ELSE IF *Case b-1, Case b-2, Case c*
Only adjust the remaining departures q_{it} from t to $t + 1$ to keep DCB.
ELSE *Case a-2, Case d*
Simultaneously adjust the remaining arrivals p_{it} and departures q_{it} from t to $t + 1$ to keep DCB.
END
ELSE *Scenario TFA*
IF *Case a-1*
Only adjust the remaining arrivals p_{it} from t to $t + 1$ to keep DCB.
ELSE IF *Case b-1*
Only adjust the remaining departures q_{it} from t to $t + 1$ to keep DCB.
ELSE *Case a-2, Case b-2, Case c, Case d*
Simultaneously adjust the remaining arrivals p_{it} and departures q_{it} from t to $t + 1$ to keep DCB.
END
END
(IV) Iteration continues:
SAVE Results of $x_{it}, y_{it}, p_{it}, q_{it}$.
$t = t + 1$
END WHILE
Assessment:
Multi-objective analysis; *PAA*, *PDA* and *TFA* analysis; comparison between DRCM and SRCM.
RETURN Results of impact analysis of ATDM options on runway configuration.

of intervals in the planning horizon. The computational cost is independent of the specific information of each flight.

2) ASSESSMENT WITH THE OGIS MECHANISM

According to the three objectives Eqs. (22)∼(24) in the formulated RCM models, the fitness functions of EMOE

Iteration Procedure and Pseudocode of EMOE Algorithm:

Input: Airport set in metroplex system, planning horizon, length of single interval, RCCE sets in each airport, initial air traffic demand, cost of adjusting flights, maximum acceptance rate, capacity loss coefficient, etc.
Output: The optimized runway configuration in each interval of metroplex airports.
Main Loop:
Initialization:
(I) Set the population size $NIND$, maximum generation $MAXGEN$, evaluation generation No. $g = 0$, algorithm performance matrix $OBJ\ [NIND, 3] = size(OBJ)$ returns the sizes of each dimension of OBJ.
(II) Generate the initial population I_g, to represent the solutions. $|I_g| = NIND$.
WHILE $g < MAXGEN$ **DO**
(I) Update OBJ of I_g using the three optimization objectives Eqs. (22)~(24).
(II) Generate the parent population P_{g+1} using the OGIS mechanism:
Set the strategy for inducing evolution in the OGIS mechanism for minimum scenarios
Inducing evolution strategy I: Minimum cost configuration
Inducing evolution strategy II: Minimum total num. configuration
Inducing evolution strategy III: Minimum max. num. configuration
Apply the strategy of preferred level identification in the OGIS mechanism
Divide all nondominated Pareto fronts of I_g: $F = Sort\_1(I_g)$, $F = (F_1, F_2, \cdots)$.
Set $P_{g+1} = \emptyset$ and $i = 1$
WHILE $|P_{g+1}| + |F_i| \leq NIND/2$ **DO**
Apply the strategy of single-level assessment in the OGIS mechanism
Calculate Euclidian distances of all the individuals in F_i
$P_{g+1} = P_{g+1} \cup F_i$
$i = i + 1$
END WHILE
Apply the strategy of cross-level assessment in the OGIS mechanism
Sort the solutions in F_i using the partial order operator $\prec_n$: $F_i = Sort\_2(F_i, \prec_n)$
$P_{g+1} = P_{g+1} \cup F_i[1 : ((NIND/2) - |P_{g+1}|)]$
(III) Generate the offspring population Q_{g+1} based on P_{g+1}:
Crossover operator: $\{x, y\} \Rightarrow \{x', y'\}$, $\mu, \nu \in [0, 1]$

$$x' = INT\{\mu x + (1 - \mu)y\} \tag{35}$$

$$y' = INT\{\nu y + (1 - \nu)x\} \tag{36}$$

Mutation operator: Rand mutation model
$Q_{g+1} = NewPop(P_{g+1})$, and $|Q_{g+1}| = |P_{g+1}|$.
(IV) Combine the new P_{g+1} and Q_{g+1}, let $R = P_{g+1} \cup Q_{g+1}$.
(V) Set $g = g + 1$, $I_g = R$
END WHILE
RETURN the set of nondominated solutions in F_1
Tradeoff:
Set the benefit needs from different stakeholders, and assess the single and multiple objective-guided inducing strategies
RETRUN The minimum cost, total num. and single max. num. of flight adjustment for different tradeoff scenarios.

algorithm are formulated in Eqs. (37)~(39).

$$f_1 = \left\{\sum_{i\in A}\sum_{t\in S}\sum_{k\in M_{it}}\sum_{l\in\Phi}\xi_{itk}\tau_{itl}(\varphi_{it}p_{it} + \phi_{it}q_{it}) + \varepsilon\right\}^{-1} \tag{37}$$

$$f_2 = N - \sum_{i\in A}\sum_{t\in S}\sum_{k\in M_{it}}\sum_{l\in\Phi}\xi_{itk}\tau_{itl}(p_{it} + q_{it}) \tag{38}$$

$$f_3 = N - \max_{t\in S}\sum_{i\in A}\sum_{k\in M_{it}}\sum_{l\in\Phi}\xi_{itk}\tau_{itl}(p_{it} + q_{it}) \tag{39}$$

where $\varepsilon \in (0, 1)$ denotes any real number, and N the total number of arrivals and departures in the planning horizon.

The OGIS mechanism in EMOE considers the Eqs. (22)~(24) to measure the individual performance during the evolution iteration. We can then produce the top $NIND/2$ best solutions from generation g as the parent population P_{g+1} in the next evolution. The OGIS mechanism can be divided into the following four perspectives.

a: PREFERRED LEVEL IDENTIFICATION

The preferred level identification focuses on all the individuals in each population. According to the performance matrix OBJ, the evolutionary individuals in each iteration can be divided into different levels with priority. Then we can

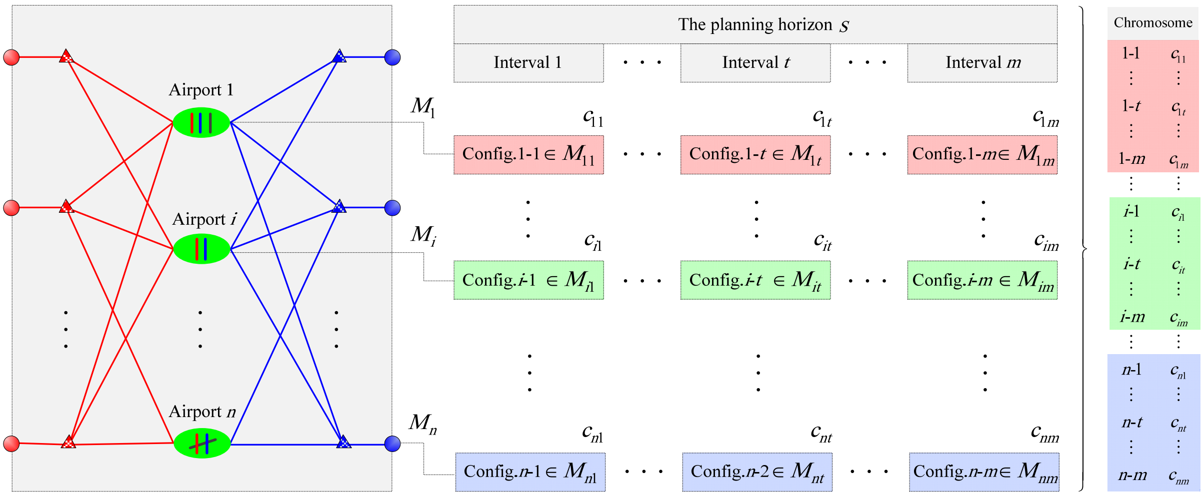

FIGURE 5. EMOE solution representation in RCM problem.

obtain the preferred individuals at each level and the dominant relationships among different levels. First, we calculate all the performance indicators $OBJ(1:NIND, 1:3)$ corresponding to the cost, and total and single maximum numbers of flight adjustments. For any individual p in the population I_g, we compare its performance indicators with those of all the other individuals q $(q \in I_g, q \neq p)$. Then we analyze the dominance relationship between p and q, and get the dominated set S_p and parameter n_p [26]. Finally, The solutions with $n_p = 0$ are selected into the first level F_1, and similarly for the other solutions in the levels F_2, F_3, ...based on the dominated sets of all the individuals.

b: SINGLE-LEVEL ASSESSMENT

The single-level assessment focuses on all the individuals with the same n_p in each level. According to the individuals in level $F = (F_1, F_2, \cdots)$, we can analyze the density of solution distribution around each individual and assess the preferred sequence in level F_i. First, we sort all the individuals in level F_i in ascending order based on the cost, and total and single maximum numbers of flight adjustments. Then the Euclidian distance for each individual in level F_i can be calculated based on the three objectives. During each evolution, the Euclidian distances are mainly decided by OBJ. In addition, for each iteration, the single-level assessment will focus on $OBJ(:,1)$ for Eq. (22) condition, $OBJ(:,2)$ for Eq. (23) condition, and $OBJ(:,3)$ for Eq. (24) condition. Finally, we can get the preferred No. of each individual in level F_i.

c: CROSS-LEVEL ASSESSMENT

The cross-level assessment focuses on the individuals with the top $NIND/2$ best performance in each population. Based on the partial order operator $\prec_n$, we can get the preferred No. of all individuals in the population I_g. The guiding rule is: for the same level, we select the solutions with the larger Euclidian distances; but for different levels, the lower levels will be selected.

d: INDUCING EVOLUTION STRATEGY

Based on the preferred level identification, single-level assessment and cross-level assessment, we adopt different inducing evolution strategies from the single-objective-guided and multiple-objective-guided perspectives. We comprehensively compare the evolutionary direction and assess the optimization results. We then make tradeoffs among multiple performance indicators under different inducing evolution strategies presented in Section IV.

3) EVOLUTION WITH GENETIC OPERATORS

For the top $NIND/2$ best individuals from the OGIS mechanism, we use the genetic operators of linear recombination crossover and rand mutation to produce the other $NIND/2$ high quality offspring. Note that the initial phenotypes of some new genes in the offspring will be non-integer values. Hence, the new offspring will be further converted into an integer by the round down function $INT(\cdot)$. Let the gene codes on the same position in the old two chromosomes be x and y, then the gene codes in the new chromosomes x' and y' can be represented as the Eqs. (35) $\sim$ (36). The rand mutation operator changes the value of chosen gene in the range of M_{it}. Finally, the next evolution population is fully formulated, and the next iteration begins.

IV. NUMERICAL RESULTS AND ANALYSIS

In this section, DRCM / SRCM models and EMOE algorithm are applied to optimize the runway configuration problem in the Shanghai metroplex system, including Shanghai Pudong airport (ZSPD) and Shanghai Hongqiao airport (ZSSS). We report the performance of the EMOE algorithm, and present results calculated by using the DRCM and SRCM

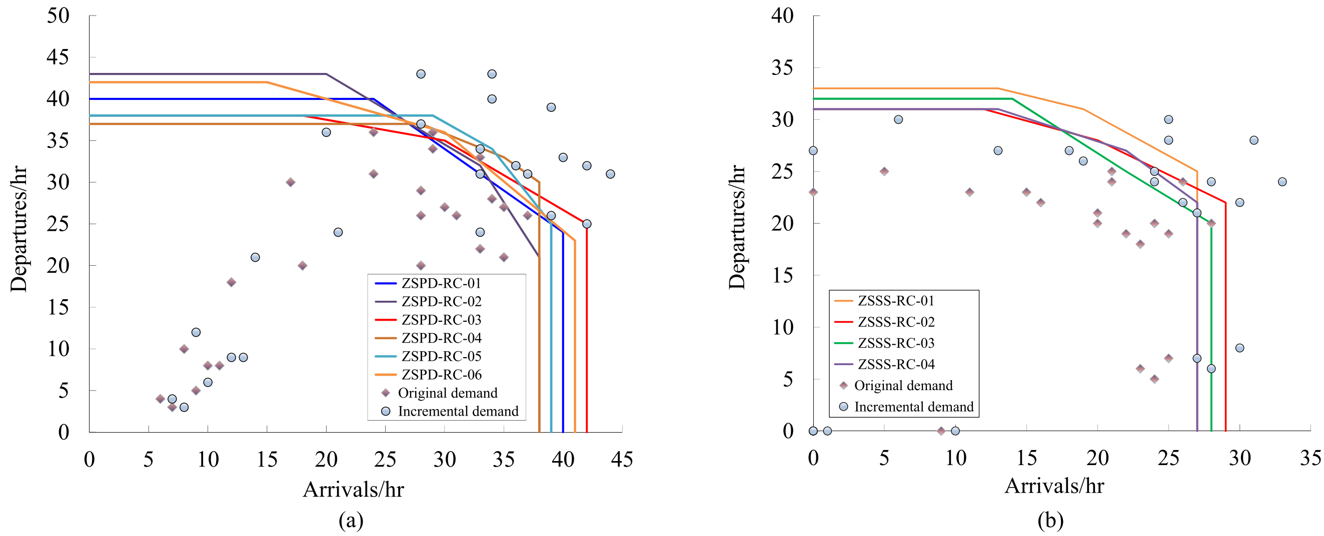

FIGURE 6. The RCCEs in Shanghai metroplex airports. (a) ZSPD; (b) ZSSS.

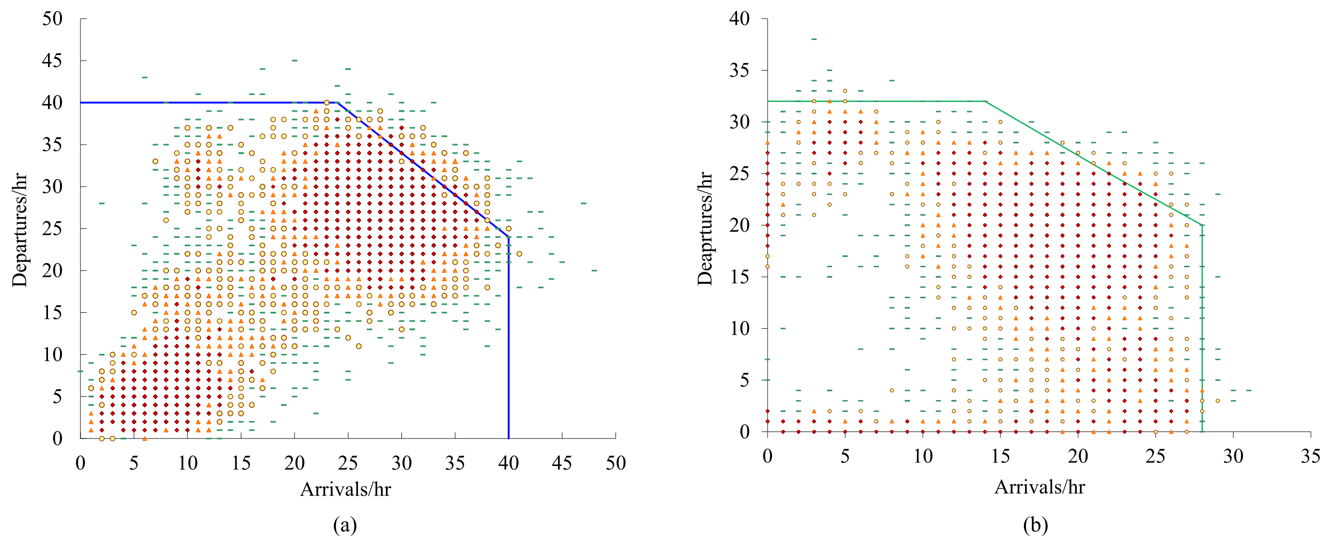

FIGURE 7. Baseline RCCEs and DCB results in Shanghai metroplex airports. (a) ZSPD; (b) ZSSS.

models for *Scenarios PAA*, *PDA* and *TFA*. Finally, we analyze the impacts of ATDM options on runway configuration in the Shanghai metroplex system and conduct a comprehensive analysis and comparison.

A. EXPERIMENTAL ENVIRONMENT

In the Shanghai metroplex system, all the preset runway configurations and daily operating points are illustrated in Fig. 6. The RCM horizon is set to 10 hours. Based on the decision-making needs in practice at the ZSPD and ZSSS airports, the single interval of dynamic configuration is assumed as 1 hour, with 10 intervals in the planning horizon. The available runway configuration sets for ZSPD and ZSSS are {ZSPD-RC-01, ZSPD-RC-04, ZSPD-RC-05, ZSSS-RC-03, ZSSS-RC-04}. In order to assess the runway performance under saturated conditions, we apply an incremental coefficient of 20% to the original demand. The air traffic demand in the Shanghai metroplex system is 1225, the total number of ZSPD / ZSSS and arrivals / departures are 708 / 517 and 634 / 591 respectively.

Note that the existing runway configurations in the Shanghai metroplex airports are usually static, mainly considering the prevailing wind conditions. However, dynamic configurations are still rarely used in practice. Based on historical operations data for a single static configuration frequently used in each airport, Fig. 7 shows the baseline RCCEs and DCB results in the Shanghai metroplex airports. We can see that many operating points in the ZSPD and ZSSS airports are

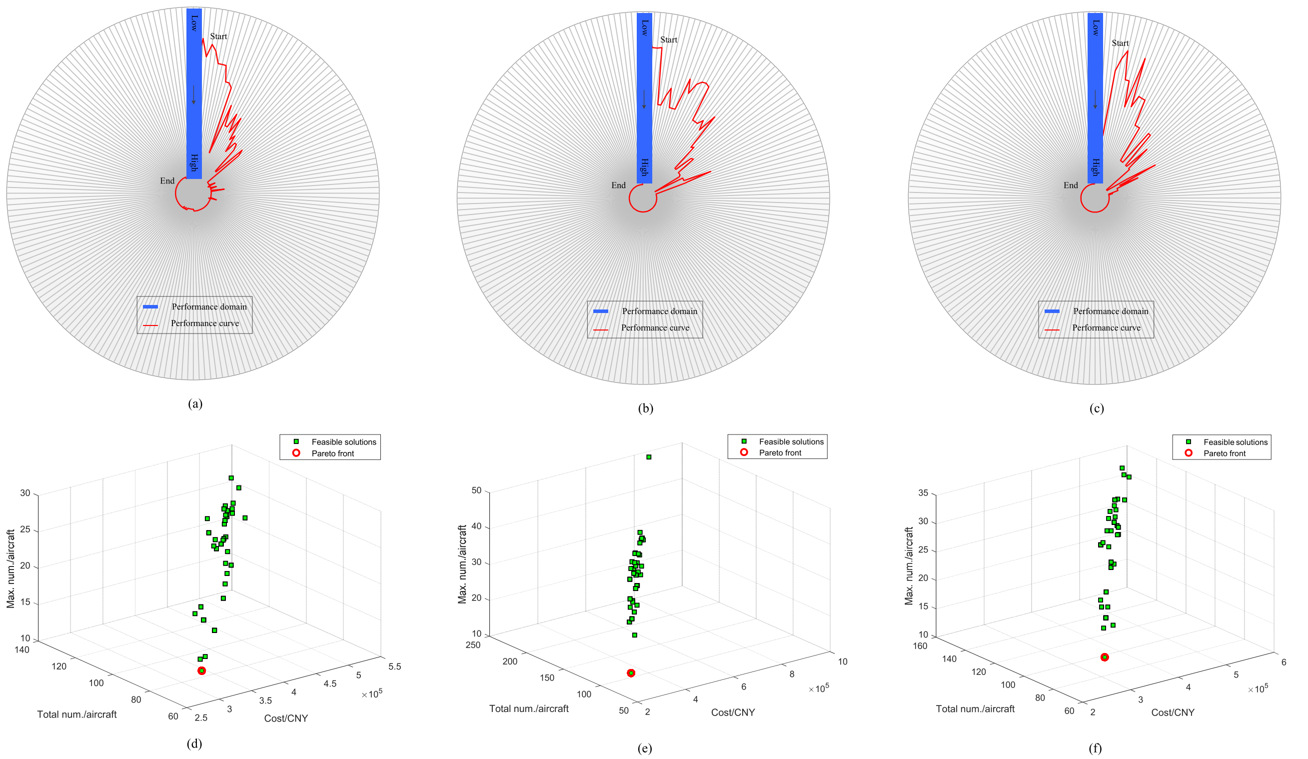

FIGURE 8. **Performance of the EMOE algorithm for different assessment scenarios. (a) EMOE algorithm performance for *Scenario PAA*; (b) EMOE algorithm performance for *Scenario PDA*; (c) EMOE algorithm performance for *Scenario TFA*; (d) Solution distribution for *Scenario PAA*; (e) Solution distribution for *Scenario PDA*; (f) Solution distribution for *Scenario TFA*.**

located in the infeasible area of RCCEs, and results in some inevitable congestion and delay. In this paper, the frequently used RCCEs in Fig. 7 are selected as baselines for SRCM model to compare with the optimization effect of the DRCM model.

In our EMOE algorithm, the size of the RCM population in each generation is 100, the maximum number of EMOE evolution iterations is 200, and the coding length (i.e., sum of ZSPD and ZSSS intervals) of each chromosome is 20. The crossover and mutation probability are 0.9 and 0.15 respectively. Additionally, we also conduct a further analysis on the sensitivity of the EMOE parameters to the computational results.

B. COMPUTATIONAL PERFORMANCE

The proposed EMOE algorithm is coded in Matlab 2016 and run on a PC with a 8-core, 3.60 gigahertz and 3 gigabytes RAM. Without loss of generality, we set the priority coefficients of arrival and departure for *Scenario TFA* as $p_a = 0.3$ and $p_d = 0.7$ for analysis.

The computational performance and solution distribution of the proposed EMOE algorithm for *Scenarios PAA*, *PDA* and *TFA* are shown in Fig. 8. It can be seen that the EMOE algorithm has a significantly good performance and approaches the optimum direction as the evolution iteration increases in Fig. 8(a) $\sim$ Fig. 8(c). Based on the OGIS mechanism designed in Section III, there are more than 50% Pareto front solutions in Fig. 8(d) $\sim$ Fig. 8(f) among the whole evolution population for *Scenarios PAA*, *PDA* and *TFA*, respectively. In Fig. 8(d) $\sim$ Fig. 8(f), the green squares are feasible solutions, and the red circles are non-dominated solutions on the first-level Pareto front. It can be seen that the algorithm searches the Pareto front solutions under the premise of keeping the diversity of the population, which prevents a premature convergence of the EMOE algorithm. For a sample with 1225 aircraft, the running time of the EMOE algorithm can be controlled within 6 seconds, which can satisfy the decision-making needs in metroplex airports on the pre-tactical or tactical levels. The EMOE algorithm has a very low computational complexity, because we control the air traffic demand at the aggregate level in which runway assignments and flight sequences are not important for RCM problem.

We design three strategies of minimum cost, minimum total num., and minimum max. num. to analyze the computational results of RCM studies. In this section, we take the minimum cost strategy for an instance to illustrate the performance changes during the EMOE iteration. Note that the performance changes for the other two strategies are similar to that for the minimum cost strategy. Fig. 9 shows the changes of cost, total num. and max. num. during the evolution of the EMOE algorithm. Fig. 9(a), Fig. 9(d) and Fig. 9(g)

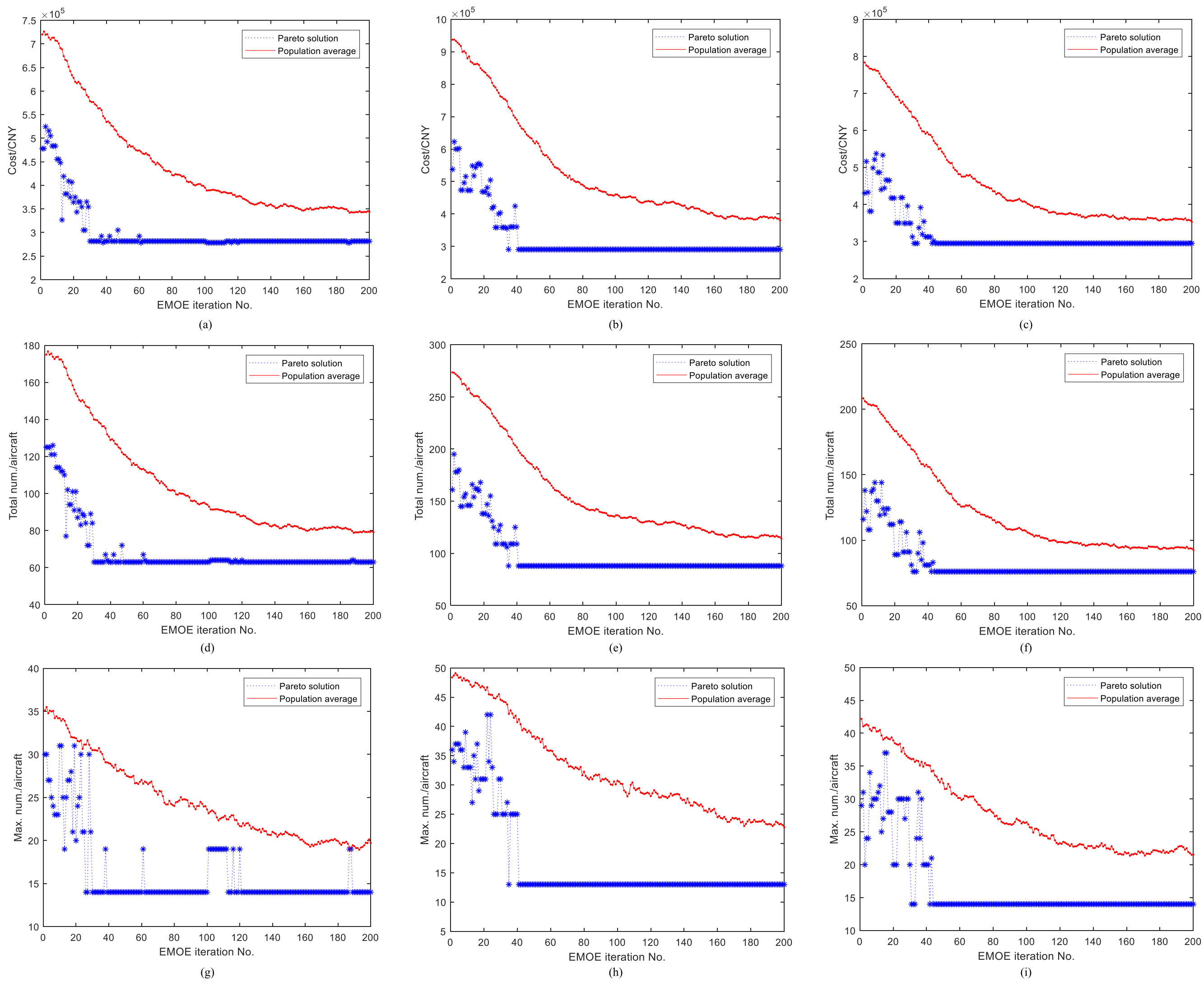

FIGURE 9. Changes of cost, total num. and max. num. for a minimum cost strategy during the evolution of EMOE algorithm. (a) Cost-*PAA*; (b) Cost-*PDA*; (c) Cost-*TFA*; (d) Total num.-*PAA*; (e) Total num.-*PDA*; (f) Total num.-*TFA*; (g) Max. num.-*PAA*; (h) Max. num.-*PDA*; (i) Max. num.-*TFA*.

illustrate the performance changes for *Scenario PAA*. With the EMOE iteration increasing, the cost of adjusted flights decreases from 477,993 CNY in the first evolution generation to 281,599 CNY in the last evolution generation, the total num. of adjusted arrivals and departures decreases from 125 aircraft in the first evolution generation to 63 aircraft in the last evolution generation, and the EMOE algorithm tends to be close to the optimal performance after generation No.61. However, the max. num. of adjusted flights in a single interval fluctuates during iteration, which reveals the fact that when the cost / total num. approaches the minimum value, the max. num. can be larger than the minimum max. num.

Similarly, the performance changes for *Scenario PDA* are illustrated in Fig. 9(b), Fig. 9(e) and Fig. 9(h). With the EMOE iteration increasing, the cost of adjusted flights decreases from 537,627 CNY in the first evolution generation to 290,794 CNY in the last evolution generation. The total num. of adjusted arrivals and departures decreases from 161 aircraft in the first evolution generation to 88 aircraft in the last evolution generation, and the EMOE algorithm tends to be close to the optimal performance after generation No.41. Different from the *Scenario PAA*, the changes of max. num. of adjusted flights for *Scenario PDA* are similar to those of cost and total num. In addition, Fig. 9(c), Fig. 9(f) and Fig. 9(i) present the performance changes for *Scenario TFA*. With the EMOE iteration increasing, the cost of adjusted flights decreases from 430,621 CNY in the first evolution generation to 295,115 CNY in the last evolution generation. The total num. of adjusted arrivals and departures decreases from 116 aircraft in the first evolution generation to 76 aircraft in the last evolution generation, and the EMOE algorithm tends to be close to the optimal performance after

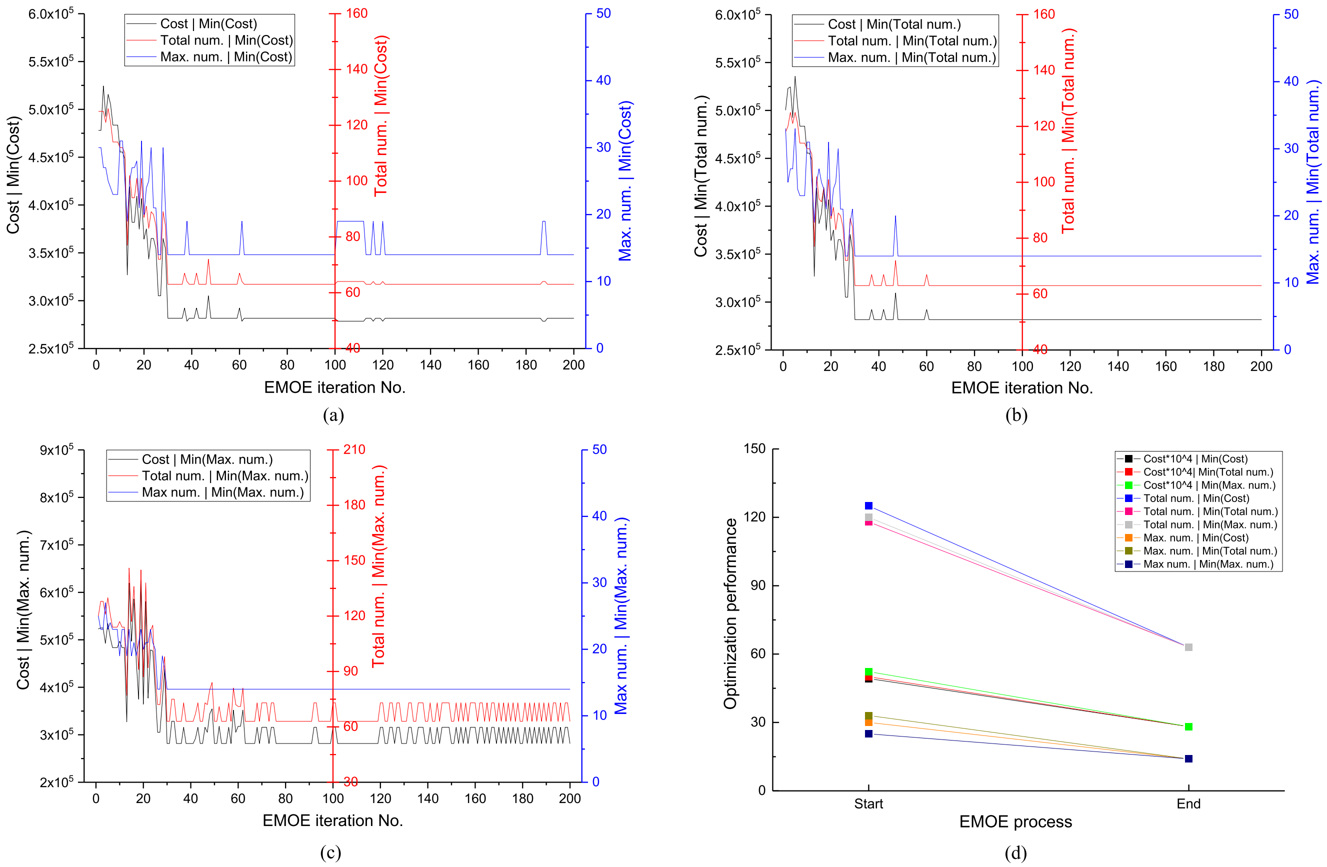

FIGURE 10. Tradeoffs among cost, total num. and max. num. for multiple minimum configurations during the evolution of the EMOE algorithm. (a) Minimum cost configuration; (b) Minimum total num. configuration; (c) Minimum Max. num. configuration; (d) Optimization performance under multiple minimum configurations.

generation No.42. There are no fluctuations in the change of max. num. of adjusted flights as the EMOE iteration continues.

C. COMPUTATIONAL RESULTS

In this section, we conduct a comprehensive comparison of the results from the DRCM and SRCM models, from the perspectives of multiple objectives (cost, total num. and max. num.) and multiple scenarios (*PAA*, *PDA* and *TFA*). Then we present a comprehensive discussion of the impact of ATDM options on runway configuration in the Shanghai metroplex airports. Finally, the sensitivity of model and algorithm inputs to RCM results is investigated.

1) MULTI-OBJECTIVE TRADEOFFS

For the fixed configuration in the SRCM model, there is only one solution in the whole planning horizon, which is different from the DRCM model characterized by tradeoffs among multiple optimization objectives Eqs. (22)∼(24). Actually the EMOE algorithm might search a set of nondominated Pareto solutions from the different perspectives of cost, total num. and max. num. Hence, it is necessary to investigate the tradeoffs among these objectives. According to the three inducing evolution strategies presented in Section III, we select the minimum cost / total num. / max. num configuration, respectively, to investigate the tradeoffs among cost, total num. and max. num. Taking *Scenario PAA* as an example, the results of these three inducing strategies based on the DRCM model on 1000 iterations, an extension of 200 iterations in Fig. 9, are summarized in Table 6. Obviously, we can get the same final results for different minimum configurations.

However, the evolution processes of the EMOE algorithm for the three inducing strategies are significantly different. Fig. 10 illustrates the tradeoff results for multiple minimum configurations during the evolution of the EMOE algorithm. For the minimum cost configuration, Fig. 10(a) shows that the step-by-step changes of total num. differ little from those of cost, but are similar to those of max. num., after No.100 evolution of the EMOE algorithm. Some fluctuations exist during the whole evolution of the EMOE algorithm. However, for the minimum total num. configuration, Fig. 10(b) shows that there is no fluctuation after generation No.61, and both cost and max. num. can also reach the minimum when the total num. reaches the minimum. In addition, we can see from Fig. 10(c) that the changes of cost and total num. differ a lot from those of max. num. That is to say, a nondominated solution with a minimum max. num. is not a good choice to optimizing the DRCM problem, because it can also result in

TABLE 6. Comparison of optimization performance for different inducing strategies.

EMOE	Minimum cost		Minimum total num.		Minimum Max. num.	
performance	Start	End	Start	End	Start	End
Cost (CNY)	477993	281599	500302	281599	522943	281599
Total num. (a/c)	125	63	118	63	120	63
Max. num. (a/c)	30	14	33	14	25	14

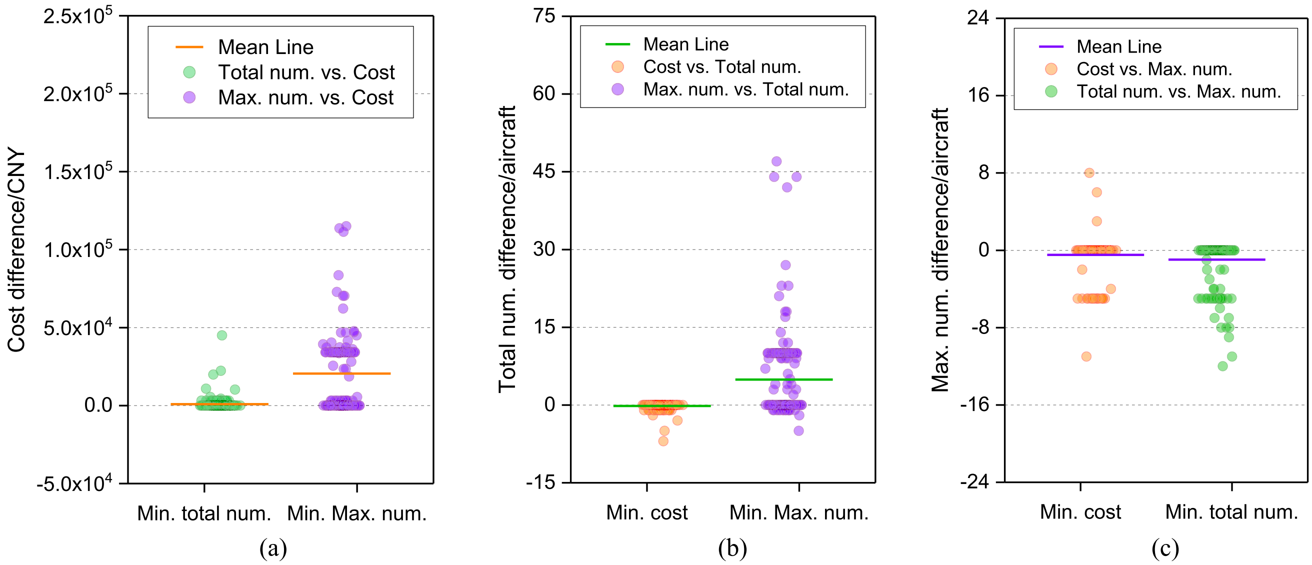

FIGURE 11. Comparisons of cost, total num. and max. num. differences for multiple minimum configurations during the evolution of EMOE algorithm. (a) Cost differences for the minimum cost, total num. and max. num. configurations; (b) Total num. differences for the minimum cost, total num. and max. num. configurations; (c) Max. num. differences for the minimum cost, total num. and max. num. configurations.

a large cost and total num. As presented in Table 6, Fig. 10(d) shows that the three inducing strategies can achieve the same performance at the end of the EMOE algorithm.

To summarize the above results illustrated in Fig. 10, we can conclude that the inducing evolution strategy of minimum total num. in Section III can be selected as an optimal OGIS mechanism when optimizing the DRCM problem. However, the inducing strategy of minimum max. num. is not a good choice for the DRCM model. Note that most of the RCM optimization studies focus on minimizing the cost, while ignoring the performance indicator of total num. during flight adjustment. Actually, the total num. is a key metric to assess ATDM options and measure flight punctuality, and therefore, can be considered to be a significant reference for RCM studies.

In order to investigate the difference among the three inducing strategies, we analyze the comparisons of cost, total num. and max. num. differences for multiple minimum strategies. Fig. 11(a) shows that the mean cost difference between minimum total num. / max. num. configuration and minimum cost configuration is 872 / 20565 CNY, and the corresponding standard deviations are 4006 / 34715 CNY. For the cost optimization, the minimum total num. configuration has a significant advantage over the minimum max. num. configuration. Fig. 11(b) shows that the mean total num. difference between the minimum cost / max. num. configuration and the minimum total num. configuration is approximately equal to 0 / 5 aircraft, and the corresponding standard deviation is 1 / 8 aircraft. For the total num. optimization, the minimum cost configuration has a significant advantage over minimum max. num. configuration. Additionally, Fig. 11(c) shows that the mean max. num. difference between minimum cost / total num. configuration and minimum max. num. configuration is approximately equal to 0 / -1 aircraft, and the corresponding standard deviation is 2 / 2 aircraft. For the max. num. optimization, there is no significant difference between the minimum cost configuration and minimum total num. configuration. We can see from Fig. 10(c), Fig. 11(a) and Fig. 11(b) that the minimum max. num. configuration is an unsatisfactory strategy which can be ignored in the real practice of RCM in metroplex airports.

In summary, the minimum max. num. configuration is the worst inducing strategy in the proposed OGIS mechanism of our EMOE algorithm. However, the minimum total num. configuration is the best choice to make satisfactory trade-offs among cost, total num. and max. num. concerned with multiple stakeholders. In fact, the cost and max. num. can also approach the minimum when minimizing the total num.

TABLE 7. Comparisons of total num. for different assessment scenarios and RCM models.

Flight adjustment	RCM models	Movement type	*Scenario PAA*	*Scenario PDA*	*Scenario TFA*
Metro.	DRCM	Arr.	49	27	45
		Dep.	14	61	31
		Total	63	88	76
	SRCM	Arr.	103	16	78
		Dep.	6	108	43
		Total	109	124	121
ZSPD	DRCM	Arr.	25	13	23
		Dep.	14	33	25
		Total	39	46	48
	SRCM	Arr.	54	6	36
		Dep.	6	66	32
		Total	60	72	68
ZSSS	DRCM	Arr.	24	14	22
		Dep.	0	28	6
		Total	24	42	28
	SRCM	Arr.	49	10	42
		Dep.	0	42	11
		Total	49	52	53

Therefore, the minimum cost configuration, which is frequently used by existing studies, is not the most sensible choice for the RCM problem. The minimum max. num. configuration can be ignored in the real practice of airport operations, that is because it causes significant disturbances to the cost and total num. Actually, the solution got from optimizing the total num. is exactly that got from optimizing the max. num.

2) *PAA/PDA/TFA* AND DRCM/SRCM COMPARISONS

Based on the results of multi-objective tradeoff, especially for Fig. 10(b), we select the total num. as a key performance indicator to assess the impact of ATDM options on the RCM problem in the Shanghai metroplex airports. We also set the priority coefficients for *Scenario TFA* as $p_a = 0.3$ and $p_d = 0.7$ for analysis. The comparison results of adjusted flights for different assessment scenarios (i.e., *PAA*, *PDA* and *TFA*) and RCM models (i.e., DRCM, SRCM) are summarized in Table 7. The computational results for each combination of assessment scenarios and RCM models are significantly different because of the selection of runway configurations and ATDM options.

For *Scenario PAA* and the DRCM model, the number of adjusted arrivals / departures in ZSPD, ZSSS and metroplex systems are 49/14, 25/14 and 24/0 aircraft, respectively. For the SRCM model, the corresponding performance indicators are 103/6, 54/6 and 49/0 aircraft, respectively. Compared with the SRCM model, the DRCM model has a significant effect with a 42.2% reduction in the total num. of adjusted flights in the metroplex system for *Scenario PAA*. Similarly, for *Scenario PDA* and the DRCM model, the number of adjusted arrivals / departures in ZSPD, ZSSS and metroplex systems are 27/61, 13/33 and 14/28 aircraft, respectively. For the SRCM model, the corresponding performance indicators are 16/108, 6/66 and 10/42 aircraft, respectively. Compared with the SRCM model, the DRCM model has a significant effect with a 29.0% reduction in the total num. of adjusted flights in the metroplex system for *Scenario PDA*. In addition, for *Scenario TFA* and the DRCM model, the number of adjusted arrivals / departures in ZSPD, ZSSS and metroplex systems are 45/31, 23/25 and 22/6 aircraft, respectively. For the SRCM model, the corresponding performance indicators are 78/43, 36/32 and 42/11 aircraft, respectively. Compared with the SRCM model, the DRCM model has a significant effect with a 37.2% reduction in the total num. of adjusted flights in the metroplex system for *Scenario TFA*. Based on the results presented in Table 7, a comparison of the total num. of adjusted flights for multiple assessment scenarios and RCM models is shown in Fig. 12. The comparisons are discussed from four perspectives:

- **Assessment scenarios:** *PAA*, *PDA* and *TFA*;
- **RCM models:** DRCM and SRCM;
- **Airport systems:** Metroplex, ZSPD and ZSSS;
- **Movement types:** Arrival and Departure.

a: PAA/PDA/TFA COMPARISONS

For any airport systems (Metroplex, ZSPD or ZSSS) and any RCM models (DRCM or SRCM), the total num. of adjusted flights in *Scenario PAA* is smaller than that for *Scenarios PDA* and *TFA*. Compared with *Scenario PDA* using the DRCM model, *Scenario PAA* further reduces the total num. of adjusted flights in the Metroplex, ZSPD and ZSSS by 28.4%, 15.2% and 42.9%, respectively. This reflects the practice in Shanghai metroplex system in which a higher priority for departure movements can gain an advantage of reducing the total num. of adjusted flights over the current

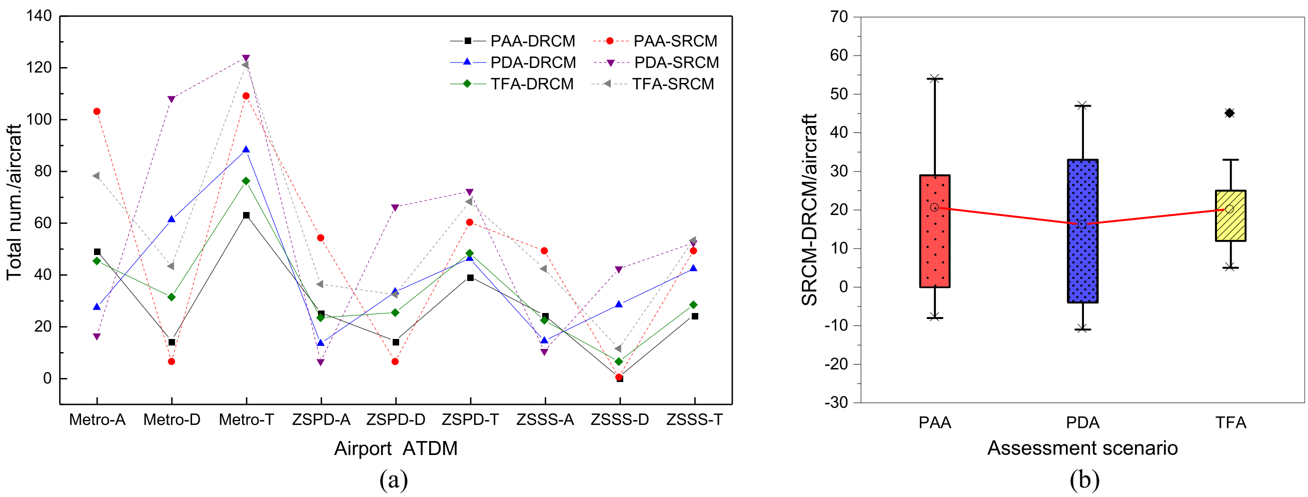

FIGURE 12. Comparison of total num. for multiple assessment scenarios and RCM models. (a) Total num. under multiple *Scenarios PAA, PDA, TFA* and DRCM, SRCM models; (b) Difference between DRCM and SRCM models.

way of setting a higher priority to arrivals. For *Scenario TFA*, as the priority coefficients change, the number of adjusted arrivals/departures is between *Scenario PAA* and *Scenario PDA*. However, for the total num. of adjusted flights, no obvious rules can be followed.

b: DRCM/SRCM COMPARISONS

For any airport systems (Metroplex, ZSPD or ZSSS), the total num. of adjusted flights using the SRCM model is much larger than the DRCM model. Taking the SRCM as the baseline model, the DRCM model further reduces the total num. of adjusted flights in Metropex, ZSPD and ZSSS by 42.2% / 35.0% / 51.0%, 29.0% / 36.1% / 19.2% and 37.2% / 29.4% / 47.2% for *Scenarios PAA*, *PDA* and *TFA*, respectively. In practice in the Shanghai metroplex, a single and fixed configuration, which is generally used for a long period of time, has the effect of increasing airport congestion and flight delay. The advantages of the DRCM model is very important in reducing the impact of demand and capacity imbalance through efficient utilization of existing runway systems.

c: METROPLEX/ZSPD/ZSSS COMPARISONS

For any airport systems (Metroplex, ZSPD or ZSSS) and any RCM models (DRCM or SRCM), the total num. of adjusted flights in the Metroplex is the sum of those at the ZSPD and ZSSS airports. In particular, the total num. of adjusted flights in ZSPD is larger than that in ZSSS because the air traffic flow in the former is denser. Taking the DRCM model as an example, the proportion of flight adjustment in ZSPD/ZSSS are 61.9%/38.1%, 52.3%/47.7% and 63.2%/36.8% for *Scenarios PAA*, *PDA* and *TFA*, respectively. Actually, the flight schedule in the ZSPD and ZSSS airports can be further optimized at the strategic level to distribute air traffic in each airport and enhance the integrated performance of the DCB.

d: ARRIVAL/DEPARTURE COMPARISONS

For any airport system (Metroplex, ZSPD or ZSSS) and any RCM model (DRCM or SRCM), the number of adjusted arrivals for *Scenario PAA* is larger than the number of adjusted departures, while the result for *Scenario PDA* is the exact opposite of that for *Scenario PAA*. Taking the DRCM model as an example, the proportions of flight adjustment for arrivals/departures in the Metroplex are 77.8%/22.2%, 30.7%/69.3% and 59.2%/40.8% for *Scenario PAA*, *PDA* and *TFA*, respectively. In addition, the tradeoffs between arrivals and departures in *Scenario TFA* having a varied relationship with *Scenarios PAA* and *PDA*.

In addition, the differences between the SRCM and DRCM results are shown in Fig. 12(b). The mean value/standard deviation of the SRCM-DRCM differences for the *Scenarios PAA*, *PDA* and *TFA* are 20/21, 16/20, and 20/12 aircraft, respectively. We also investigate the correlations among cost, total num. and max. num. for different inducing evolution strategies in Fig. 13.

Here we use the label *i-j* to indicate the subgraph located in row *i* and column *j* in Fig. 13. The histograms in subgraphs 1-1, 2-2 and 3-3 show that under the premise of ensuring the diversity of the evolution population, the OGIS mechanism in the EMOE algorithm can keep most of the values of cost, total num. and max. num. close to the minimum, which also can be validated by Fig. 8. The subgraphs 1-2 and 2-1 prove that the linear correlation between cost and total num. is strong, with the reason that the total num. has a key contribution in the calculation of cost. In addition, the subgraphs 1-3, 2-3, 3-1 and 3-2 in Fig. 13 show that the correlations between cost / total num. and max. num. are not significant, as seen in Fig. 10.

In summary, different ATDM options have significantly different impacts on runway configuration in the Shanghai

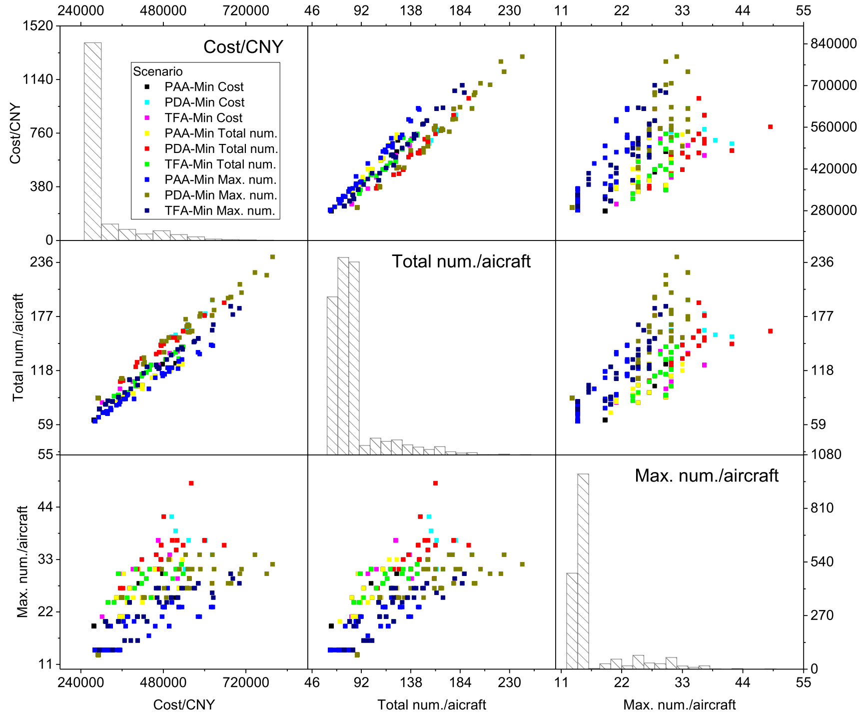

FIGURE 13. Correlations among cost, total num. and max. num. for multiple minimum configurations.

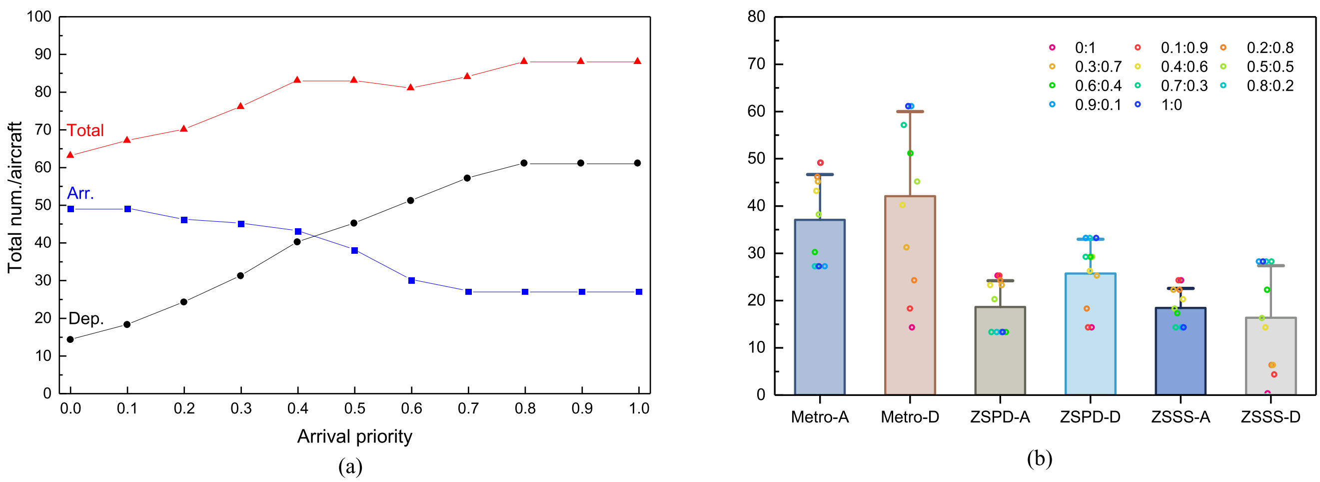

FIGURE 14. Comparison of total num. for multiple parameter settings of priority. (a) Total num. distribution of adjusted arrivals and departures in metroplex system; (b) Total num. distribution of adjusted arrivals and departures in each airport system and metroplex system.

metroplex system. The proposed DRCM model with *Scenarios PAA*, *PDA* and *TFA* can improve the flexibility of selecting runway configuration rules and ATDM options and keep the DCB in a single airport and metroplex airports.

3) PARAMETER SENSITIVITY ANALYSIS

For any mathematical model or system, the output uncertainty can be apportioned to different sources of input uncertainty [28], [29]. Hence, parameter sensitivity analysis can be useful to increase the understanding of relationships between inputs and outputs. In this section, we investigate the sensitivity of inputs (e.g., priority coefficients, capacity loss coefficient and algorithm parameters) to the DRCM model and EMOE algorithm to the outputs, to further validate the reliability of the proposed DRCM model.

a: SENSITIVITY OF PRIORITY COEFFICIENTS

Note that the results for *Scenario TFA* in Fig. 8, Fig. 9, Fig. 12, Fig. 13 and Table 7 are all based on the priority setting $p_a = 0.3$ and $p_d = 0.7$. Here the impact of other priority coefficients (0.1:0.9, 0.2:0.8, 0.4:0.6, 0.5:0.5, 0.6:0.4, 0.7:0.3, 0.8:0.2, 0.9:0.1) for arrivals and departures on runway configuration is also studied. Fig. 14 illustrates the computational results of the total num. for multiple priority settings.

It can be seen from Fig. 14 that the flight adjustment for *Scenario TFA* depends on the priority coefficients for arrivals and departures. The number of adjusted arrivals decreases and the number of adjusted departures increases, as the arrival priority increases. Similarly, the number of adjusted departures decreases and the number of adjusted arrivals increases, as the departure priority coefficients increase. Additionally, the total num. of adjusted flights has an overall increasing trend as the arrival priority increases, which reflects the fact that the existing initiative with a higher priority for arrival movements is not a good measure to improve flight punctuality in the Shanghai metroplex system. Actually, according to the decision needs in practice, multiple priority options can be set to get the corresponding results of flight adjustments.

b: SENSITIVITY OF CAPACITY LOSS COEFFICIENT

In the DRCM model, the capacity loss coefficient ω_{it} in Constraints (27) $\sim$ (28) determines the decrease of RCCE frontier during configuration transitions. We set $\omega_{it} = 0.3$ based on the requirements from ATCOs. We also test the results for *Scenario PAA* with other settings of capacity loss coefficient. For example, the total num. of adjusted flights with $\omega_{it} = 0/\omega_{it} = 0.5$ is 52/71 aircraft. Through a comprehensive analysis of *Scenarios PAA*, *PDA* and *TFA*, we can conclude that the runway configuration tends to be more dynamic between successive intervals with a lower value of ω_{it}, and more static with a higher value of ω_{it}. Therefore, capacity loss during configuration transition can be reduced by improving the response capability of ATCOs to changes of runway operations.

c: SENSITIVITY OF ALGORITHM PARAMETERS

According to the parameter settings of the EMOE algorithm, the coding length of each chromosome is fixed and depends on the number of intervals in the planning horizon. In addition, Fig. 8 $\sim$ Fig. 10 prove that the EMOE algorithm tends to be close to the optimal performance after generations No.61, No.41, No.42 for *Scenarios PAA*, *PDA* and *TFA*, respectively. Hence, no further study is needed for the sensitivity analysis of the maximum number of EMOE evolution iterations. Instead, we investigate other settings of the size of the RCM population in each generation (e.g., 60, 80, 120, 200), crossover probability (e.g., 0.6, 0.7, 0.8) and mutation probability (e.g., 0.05, 0.1, 0.2). The computational results show that the EMOE algorithm can approach the optimal performance before generation No.120, and the running time can be controlled within 10 seconds.

In summary, from the results in Sections IV, some important conclusion can be drawn. Firstly, the minimum total num. configuration is the best choice to make satisfactory tradeoffs among cost, total num. and max. num. concerned with multiple stakeholders. Secondly, a higher priority to departure movements is suggested when selecting runway configuration in the Shanghai metroplex airports. Thirdly, we can apply the DRCM model with *Scenarios PAA*, *PDA* and *TFA* to flexibly select the runway configuration in metroplex airports, and to maximally realize the DCB for arrivals and departures.

V. DISCUSSIONS AND CONCLUSION

In this paper, we propose a methodology to assess the impact of ATDM options on runway configuration in metroplex airports. Our RCM research simultaneously focuses on the perspectives of (i) 2 airports in a metroplex system: ZSPD and ZSSS, (ii) 4 cases / 6 subcases of demand-capacity imbalance: AODI (*Case a-1*, *Case a-2*), AIDO (*Case b-1*, *Case b-2*), AIDI (*Case c*) and AODO (*Case d*), (iii) 3 options of RCCE-based ATDM: YAND, NAYD and YAYD, (iv) 2 configuration models: DRCM and SRCM, (v) 3 optimization objectives: cost, total num. and max. num., (vi) 3 assessment scenarios: *PAA*, *PDA* and *TFA*, (vii) 11 priority settings for arrivals and departures: {0:1, 0.1:0.9, 0.2:0.8, 0.3:0.7, 0.4:0.6, 0.5:0.5, 0.6:0.4, 0.7:0.3, 0.8:0.2, 0.9:0.1, 1:0}. The SRCM model, commonly used in Chinese airports in a single day, is used as a baseline model for comparison with our DRCM model. From the results our DRCM model can reduce the total num. of adjusted flights in metroplex airports by 42.2%, 29.0% and 37.2% for *Scenarios PAA*, *PDA* and *TFA*, respectively. The advantage of our DRCM model is more pronounced for runway configuration in metroplex airports, which can be applied to keep the DCB of runway operations through a set of flexible ATDM options.

Considering the multi-objective tradeoffs in the DRCM and SRCM models, we have proposed an improved evolutionary algorithm EMOE, with the mechanisms of objective-guided individual selection (OGIS) to solve the formulated RCM models. The OGIS mechanism involves four perspectives of preferred level identification, single-level assessment, cross-level assessment and inducing evolution strategy. The EMOE algorithm allows us to flexibly make tradeoffs among cost, total num. and max. num. of flight adjustment. Computational results show that the EMOE algorithm has a very low computational complexity with a running time within 6 seconds. The close-to optimal solutions can be obtained for tradeoffs among multiple objectives and satisfy the decision-making needs in metroplex airports. Taking the minimum cost configuration for *Scenario PAA* as an example, the performance in terms of cost decreases from 477,993 CNY (No.1 iteration) to 281,599 CNY (No.200 iteration), and the total num. decreases from 125 aircraft (No.1 iteration) to 63 aircraft (No.200 iteration). The max. num. in a single interval can be controlled within 15 aircraft.

A comprehensive analysis and comparison of computational results is conducted for different assessment scenarios, RCM models and inducing evolution strategies. There are some tradeoffs among cost, total num. and max. num. for the minimum cost/ max. num. configurations. The minimum total num. configuration is the best choice to make satisfactory tradeoffs among cost, total num. and max. num. However, the minimum max. num. configuration is the worst inducing strategy in the proposed OGIS mechanism of our EMOE algorithm. The *PAA*/*PDA*/*TFA* comparisons show that different ATDM options have significantly different impacts on runway configuration in the Shanghai metroplex system. The proposed DRCM model with *Scenarios PAA*, *PDA* and *TFA* can improve the flexibility of selecting runway configuration rules and ATDM options and keep the DCB in a single airport system and a metroplex system.

Parameter sensitivity analysis shows that the existing initiative with a higher priority for arrival movements is not an effective measure to improve the flight punctuality in the Shanghai metroplex system. That is to say, a higher priority for departure movements is more useful to keep the DCB and reduce the number of adjusted flights.

The significance of this paper is a framework for characterization of DCB patterns, ATDM options and integrated optimization of runway configurations in metroplex airports. The proposed DRCM model can be applied to different assessment scenarios (i.e., *PAA*, *PDA*, *TFA*) for runway configuration problems, to solve different demand-capacity imbalances (i.e., AODI, AIDO, AIDI, AODO) with a flexible setting of priority coefficients for arrivals and departures. The DRCM model and EMOE algorithm presented in this paper are expected to be particularly beneficial in these cases. The findings can provide some significant references about multi-runway operations (configuration, sequencing and scheduling) in a metroplex system or a single airport system, which brings significant benefits to air traffic demand management and runway capacity utilization in hub airports and metroplex systems at the pre-tactical (i.e. one-day planning) and tactical (i.e. several-hour rolling horizon) levels.

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