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Optimization of Airport Field Taxi Scheduling Considering Runway Crossing

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ABSTRACT Airport congestion is a major bottleneck in the global air transportation system, and inefficient ground operations at multi-runway hub airports further intensify this challenge. The complex interactions between arriving and departing flights often lead to extended taxi times, excessive fuel burn, and increased controller workload. To systematically address these issues, this paper proposes an intelligent taxi scheduling model that dynamically optimizes both the routing sequence and timing of aircraft operations. The framework incorporates realistic operational constraints, including runway-crossing strategies and conflict-free requirements within the runway–taxiway network. A multi-objective particle swarm optimization (MOPSO) algorithm is employed to effectively solve the high-dimensional search space with competing objectives. Simulation studies at two major international hub airports in China demonstrate that dynamically selecting the optimal taxiing strategy among "direct crossing," "stop-and-wait," and "detour" options can significantly improve ground efficiency, reduce fuel consumption, and lower the frequency of controller interventions. This data-driven approach provides a scalable and practical solution to alleviate airport congestion, offering direct benefits in delay mitigation and the sustainable development of airport surface operations.

INDEX TERMS Air transportation, multi-runway airport, multi-objective particle swarm algorithm, taxiway strategy, aircraft taxiing scheduling-

I. INTRODUCTION

In recent years, the aviation industry has assumed a central role in global transportation, becoming an indispensable component of modern society [1]. As single-runway airports are unable to accommodate growing arrival and departure demands, the development of multi-runway airports is urgently needed to balance traffic demand with capacity and improve surface operational efficiency. Due to air traffic flow characteristics and runway operation procedures, multi-runway usage can generally be classified into three modes: dedicated take-off, dedicated landing, and mixed take-off and landing [2]. At congested multi-runway airports, the efficient scheduling of aircraft taxiing operations is essential for maintaining surface throughput and ensuring flight punctuality. Taxiing time and fuel consumption exert a direct impact on operating costs, schedule reliability, and environmental sustainability [3]. Therefore, optimizing aircraft taxi routes in complex multi-runway environments is critical for advancing modern airport management.

As illustrated in FIGURE 1, a comparative analysis of peak-hour runway capacity demonstrates that multi-runway configurations significantly outperform single-runway layouts in accommodating high traffic volumes [4], [5]. This underlines the urgency and necessity of advanced taxiway planning and coordination mechanisms to fully exploit the potential capacity of multi-runway systems and support the sustainable growth of air transportation.

The growing mismatch between the rapidly increasing demand for air travel and the limited capacity of airport ground resources, underscores the urgency of adopting intelligent taxiing scheduling strategies. This imbalance

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places considerable pressure on airport surface operations, particularly at congested multi-runway hubs, where inefficiencies in ground coordination can result in prolonged delays, higher fuel burn, and greater environmental impact. To overcome these challenges, advanced scheduling methods are essential for enabling real-time taxi route optimization, maximizing the use of constrained ground infrastructure, and improving the overall efficiency and sustainability of airport operations.

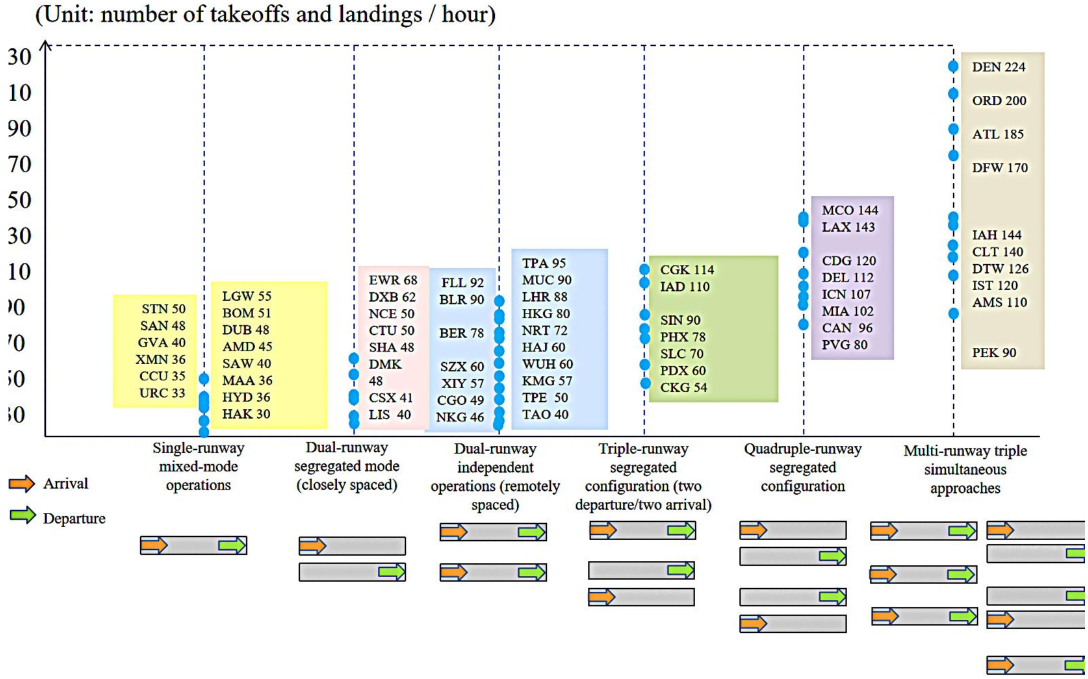

FIGURE 1. **Global representative parallel runway busy airport capacity - classified by runway operating mode.**

For the taxiing scheduling problem of aircraft at multi-runway airports, the ideal taxiing state aims to minimize taxi time and distance, reduce fuel consumption, lower environmental impact, and maximize operational safety [6]. However, in actual situations, achieving all of these objectives simultaneously is often mutually constrained by the inherent physical limitations of aircraft dynamics and airfield topology. For instance, minimizing taxi time may lead to increased fuel consumption, while pursuing the shortest taxiing path may not be the most environmentally sustainable option if it results in frequent stop-and-go maneuvers or operational conflicts [7]. These trade-offs are further complicated by heterogeneous aircraft characteristic, such as wake turbulence categories and engine types, as well as stochastic operational disruptions, including weather-driven runway configuration changes or unexpected gate unavailability. Furthermore, in multi-runway taxi scheduling, the choice of taxiing strategy for arriving and departing aircraft represents a critical factor that directly influences both airport efficiency and safety.

Traditional approaches to aircraft taxi scheduling include static routing, where fixed taxi paths are prescribed in advance and lacks adaptability to real-time variability, and dynamic routing, which selecting routes and timings based on current traffic conditions but often suffers from computational intractability i under high-density traffic scenarios [8]. Static models typically enforce predetermined paths without timing flexibility, whereas dynamic models adjust routes or speeds to accommodate evolving traffic. In all cases, the scheduler must prevent conflicts, such as head-on or crossing encounters, while simultaneously optimizing operational performance metrics. This requires solutions that can reconcile: (i) kinematic and performance constraints of heterogeneous aircraft types, (ii) temporal-spatial capacity limitations of taxiways, and (iii) regulatory requirements mandated by ICAO Annex 14 [9]. Addressing these challenges necessitates a paradigm shift toward intelligent scheduling frameworks capable of real-time, multi-criteria decision-making under uncertainty, integrating both operational realism and computational efficiency..

II. RELATED RESEARCH

Currently, scholars have conducted extensive research on airport taxiing scheduling, however, relatively few studies have specifically addressed the role of taxiing strategies. Jiang et al. [10] established a spatiotemporal coordination model for aircraft taxiing, employing bi-level programming to resolve scheduling conflicts. While effective for collision avoidance, their approach did not incorporate strategic considerations for arrival and departure taxi procedures. Zhang et al. [11] developed an optimization model utilizing remote taxiways in parallel-runway airports, demonstrating reduced total taxi time. Nonetheless, their study lacked a comparative analysis of taxiing strategy performance under heterogeneous runway configurations. Research by Li [12], and Jiang et al. [13] focused primarily on path optimization, with limited investigation into how the choice of taxiing strategy impacts overall system scheduling efficiency. Zhu et al. [14] proposed innovative metrics, including Taxiway Spatial Occupancy Index (TSOI) and Potential Conflict Index (PCI), and implemented an optimization scheme at Haikou Meilan Airport. Although effective for apron operations, their approach did not adequately account for the effects of runway crossings on overall surface efficiency. Cheng et al. [15] investigated runway exit selection algorithms, while Chen [16] analyzed fuel consumption patterns during taxiing. However, both studies underemphasized the critical role of taxiing strategies within multi-objective optimization frameworks. Yang et al. [17] integrated system-optimal traffic assignment with standardized multi-path routing, improving safety and efficiency without increasing controller workload. A notable limitation of this work is the lack of consideration for runway crossing dynamics in scheduling optimization. Deng et al. [18] formulated a mathematical taxiway planning model with a hybrid PSO-ACO (Particle Swarm Optimization-Ant Colony Optimization) algorithm coupled with velocity-priority conflict resolution. Despite these algorithmic advancements, their study provided limited actionable guidance for conflict-minimizing taxi strategies in complex multi-runway environments.

Despite this body of work, several key limitations remain:

1. Single-objective focus: Many models reduce the problem to a single criterion, such as minimizing taxiing time or distance. Aggregating multiple objectives into a single weighted metric can obscure trade-offs and only yields a single point on the Pareto frontier.

2. Limited consideration of strategic runway crossing: Runway crossings are generally treated as safety constraints rather than optimized decisions. No current framework explicitly determines the optimal timing or location for runway crossings.

3. Oversimplified kinematics modeling: Most prior approaches assume constant-speed taxiing along predefined segments, neglecting realistic aircraft behaviors such as acceleration, deceleration, turning maneuvers, and holding patterns.

To address these gaps, we propose a novel strategy-based taxi scheduling framework with the following contributions:

1. Four-phase kinematic model: Each taxiing aircraft's motion as four sequential phases: acceleration, constant-speed cruising, deceleration/turning, and holding.

2. Multi-objective optimization via hybrid MOPSO: The taxi scheduling problem is formulated as a multi-objective optimization task, solved using a hybrid, mutation-enhanced multi-objective particle swarm optimization (MOPSO) algorithm.

3. Integrated strategy optimization: The model explicitly optimizes both runway-crossing strategies and taxi trajectories, generating a Pareto front of efficient solutions that balance taxi time, fuel consumption, environmental impact, and safety.

III. PROBLEM DESCRIPTION

In this study, the airport surface infrastructure, including the runway system, taxiway network, and apron layout—is treated as an integrated optimization entity. These subsystems collectively form the spatiotemporal framework for ground operations at airports, and their coordination is essential for optimizing aircraft surface movement efficiency. To model this structure, the set of taxiway nodes N is defined to represent key locations during aircraft taxiing, such as taxiway intersections, holding points, apron entry/exit positions, and runway access thresholds. The set of edges E is defined to describe the taxiway segments connecting these nodes, each representing a feasible path segment that reflects permitted movement directions and spatial constraints [19]. Through the connection of nodes and edges, the direction of travel and path selection during taxiing are explicitly captured. In this graph-based formulation, the taxiing path of departing aircraft is defined as a sequence of nodes from the parking position to the runway entrance, Conversely, the taxiing path of arriving aircraft is defined as a sequence of nodes extending from the rapid exit taxiway or runway exit to the parking position.

Airport network connectivity encompasses both spatial topology and operational dependencies, enabling flexible route planning and traffic flow analysis [20]. A schematic representation of the constructed airport surface network is provided in FIGURE 2, illustrating the modular decomposition of the airfield layout into navigable units for scheduling and optimization purposes.

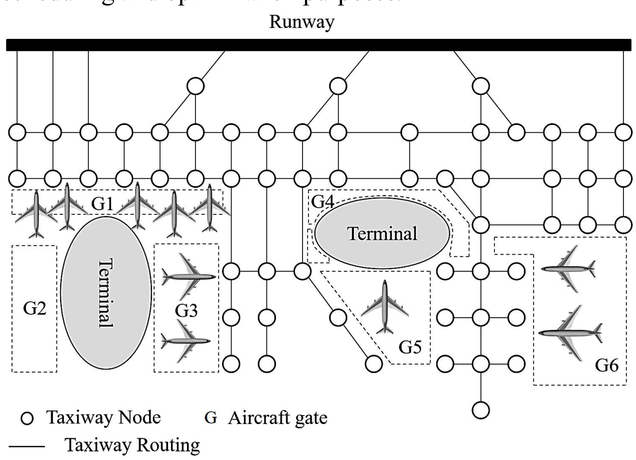

FIGURE 2. Schematic diagram of the airport ground network.

Based on the previously defined airport ground network, the aircraft taxiing process can be conceptualized as spatiotemporal resource allocation and trajectory planning within the network topology. Each aircraft departs from the starting node (e.g., runway exit/aircraft gate), moves along the edges traverses the edges (taxiway segments) of the network, passes through key nodes, such as intersections and waiting points, and ultimately arrives at the destination node (e.g. aircraft gate/runway entrance). The complex topology of this network, including highly connected intersection nodes and edges subject to capacity constraints, along with dynamically changing occupancy states gives rise to the core challenges in aircraft taxiing, which include:

1. Real-time dynamism: The occupancy states of nodes and edges (occupied or idle) evolve continuously over time, requiring adaptive routing decisions.

2. Aircraft conflicts: Conflicts primarily arise at shared resource points, particularly high-conflict nodes such as intersections and convergence points, as well as scenarios that involve crossing other taxiing paths.

3. Taxiway capacity constraints: These constraints manifest as the maximum number of aircraft permitted simultaneously on a given edge (E), as well as queue management requirements at nodes (N), including waiting areas and spaces near the parking apron.

To more accurately capture aircraft movement within this structured network and the constraints they encounter, this study proposes a refined taxiing scheduling model. The model decomposes the taxiing process into four key behavioral stages:

1. Acceleration/deceleration: Occurs primarily during transitions between edges (entering or exiting segments), when approaching or departing conflict-prone nodes (N) such as intersections, or in response to speed control directives.

2. Turning: Executed at designated turning nodes (N), typically intersections, involving specific dynamics and an increased risk of spatial conflicts with other aircraft.

3. Stopping and waiting: Enforced at predefined holding nodes (N), including runway holding points and intersection buffers, or triggered by resource contention, such as saturated edge capacity or unresolved conflicts at downstream nodes.

4. Constant-speed taxiing: Sustained primarily on conflict-free, uncongested edges (E), where continuous movement at a stable speed is feasible and operationally efficient.

This phase-based decomposition offers several advantages, It intrinsically links kinematic behaviors (acceleration, turning, waiting, cruising) to specific physical locations within network, enabling the natural incorporation of location-specific constraints, including edge capacity limits and separation minima. Furthermore, within the spatiotemporal framework of the network, the model explicitly incorporates the real-time dynamics of airport ground operations, conflicts among aircraft on nodes and edges, as well as capacity limitations of both taxiway segments (edges E) and critical nodes (N). The operational process of aircraft within the airport surface network is illustrated in FIGURE 3.

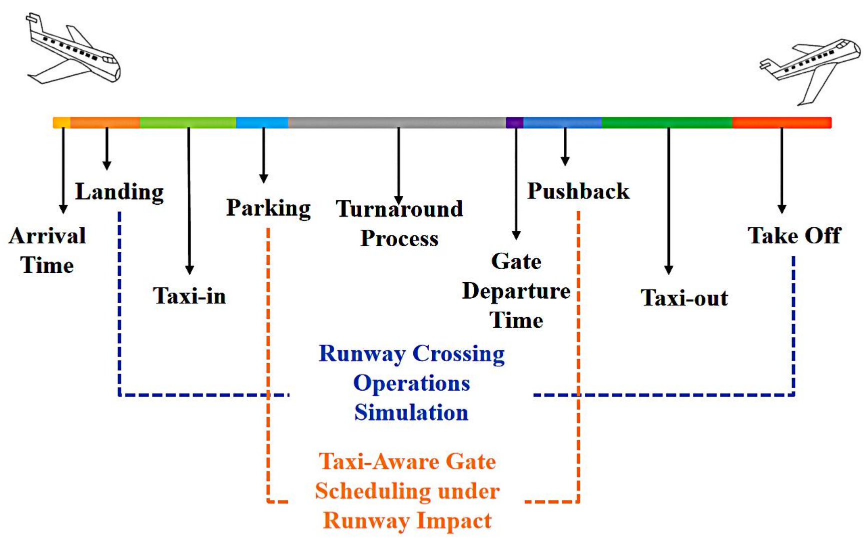

FIGURE 3. Aircraft Operations Procedures at Airport Surface Networks.

Solving this multi-objective optimization problem within the complex and constrained spatiotemporal domain of airport ground operations requires advanced algorithmic approaches. Traditional Multi-Objective Particle Swarm Optimization (MOPSO) algorithms often face challenges when navigating such intricate search landscapes. To overcome these limitations, we propose a hybrid mutation operator integrated into the MOPSO framework. This operator is specifically designed to adapt to the diverse optimization requirements encountered across different kinematic phases and network regions by intelligently combining the global exploration capabilities of Gaussian mutation with the local exploitation strengths of polynomial mutation. For example, the operator facilitates more aggressive exploration in high-decision-density areas, such as

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near conflict-prone nodes or intersections, while enabling focused exploitation during steady-state phases, such as uniform taxiing along long straight segments. A comprehensive description of this operator is provided in Section V.

The ultimate objective of this integrated approach is to develop a decision-support tool that substantially reduces aircraft ground taxiing costs, enhances overall airport operational efficiency, and provides airport management with scientifically grounded, optimal scheduling solutions. Its core contribution lies in the deep coupling and simultaneous optimization of dynamic taxiing behaviors with static network modeling, enabling a robust and practical framework for real-world multi-runway airport operations.

IV. MATHEMATICAL MODEL

A. MODEL ASSUMPTIONS

1. Let $K = \{1,2,3,\ldots,k\}$ denote the set of all aircraft considered during the study period. The flight information, aircraft type, and standard seating capacity for each aircraft are assumed to be known.

2. To ensure safety during taxiing, each aircraft must maintain a minimum wake separation of 200 m from other aircraft.

3. A constant fuel flow rate is defined for each operational phase, including acceleration, constant-speed cruising, and deceleration.

4. The time duration and required thrust for each taxiing phase of each aircraft are summarized in TABLE I.

TABLE I
TIME AND THRUST FOR EACH TAXI PHASE OF THE AIRCRAFT

Number	Taxiing Phases c (c={1,2,3,4})	Time (s)	Thrust (%)
1	Acceleration/ Deceleration	$t_1^k = 8 \cdot n_s$	9%
2	Turning	$t_2^k = 6 \cdot n_t$	7%
3	Stop-and-Wait	t_3^k	3%
4	Constant Speed	$t_4^k = T - t_1^k - t_2^k - t_3^k$	5%

Note: *The thrust settings for idle scenarios (see Table I) are based on empirical data from real-world airport operations, as documented by Nikoleris et al.* [21]

The t_c^k is the time spent by aircraft k in different taxiing phases c (c={1,2,3,4} represents acceleration/deceleration, turning, stop waiting, and constant speed taxiing, respectively), T is the total taxiing time of the aircraft, the n_s is the number of acceleration/deceleration of aircraft k during the taxiing process, and the n_t is the number of turns performed by aircraft k during the taxiing process.

Based on these definitions, an aircraft may adopt one of the following three taxiing strategies when crossing a runway:

1. The fuel consumption of an aircraft that chooses to directly cross the runway at the runway crossing point:

$$F_1^k = t_4^k \cdot f_4^k \cdot \lambda_k, \forall k \in K \tag{1}$$

2. Fuel consumption of the aircraft crossing the runway after stopping and waiting at the runway crossing point:

$$F_2^k = t_1^k \cdot f_1^k \cdot \lambda_k + t_3^k \cdot f_3^k + t_4^k \cdot \lambda_k, \forall k \in K \tag{2}$$

3. Fuel consumption of an aircraft using a taxiway to bypass a runway crossing point:

$$F_3^k = t_2^k \cdot f_2^k \cdot \lambda_k + t_3^k \cdot f_3^k \cdot \lambda_k, \forall k \in K \tag{3}$$

In the formula, F_c^k is the taxiing fuel consumption of aircraft k, the f_c^k is the fuel flow of aircraft k during taxiing phase c, and the λ_k is the number of engines of aircraft k.

According to the above three different runway crossing strategies, the strategy selection process of the aircraft when taxiing to the runway crossing point is shown in FIGURE 4.

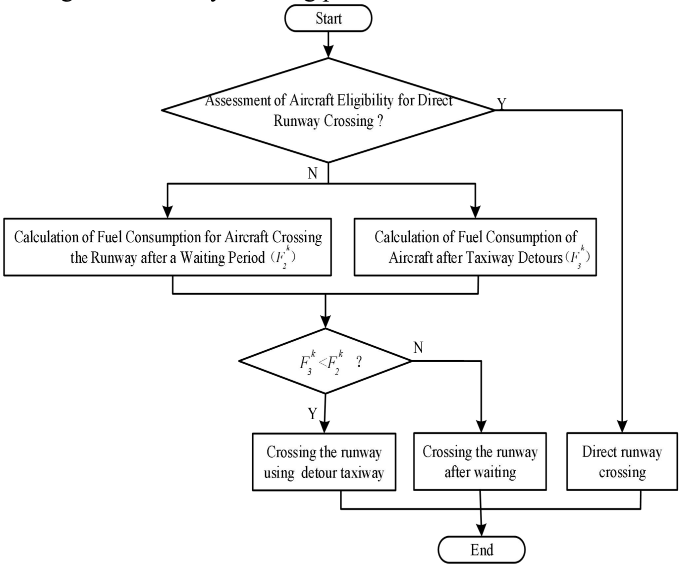

FIGURE 4. Runway crossing selection strategies for aircraft at runway crossing waiting points.

B. MODEL PARAMETER SETTINNG

In this paper, the following model parameters in TABLE II are set when constructing the model and simulation environment.

TABLE II
MODEL PARAMETERS

Parameter	Definition
K	Set of all aircraft within the study period: K={1,2,3,..., k}
P	Set of taxiway network nodes: $i, j \in P$, with P representing all navigational points on the apron/taxiway system
t_{ijc}^k	Time required for aircraft k to taxi from node i to adjacent node j in the four taxiing phases c={1,2,3,4}
x_{ijc}^k	Binary decision variable: if aircraft k taxis from node i to node j in the four taxiing phases c={1,2,3,4}, $x_{ijc}^k = 1$, otherwise 0
t_{jc}^{k-wait}	Cumulative waiting time for aircraft k during ground movement operations
μ_k	Conflict detection coefficient at node j for aircraft k

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TABLE II (Continued)

Parameter	Definition
$\omega_{k,m}$	Priority determination factor between aircraft *k* and *m*
t_s	Minimum safe separation time between consecutive aircraft at shared nodes (ICAO Annex 14 compliant)
T_{jc}^{k}	The time when aircraft *k* arrives at node *j* in four different taxiing phases *c*={1,2,3,4};
T_{jc}^{m}	The time when aircraft *m* arrives at node *j* in four different taxiing phases *c*={1,2,3,4};
η_k	Priority weighting coefficient for aircraft *k*, higher values denote elevated priority (e.g., emergency flights)
T_{in}^{k}	Taxi initiation time for arriving aircraft *k*
T_{out}^{m}	Taxi initiation time for departing aircraft *m*
ETOA	Estimated time of arrival at runway threshold
ETOD	Estimated time of departure from gate
EOBT	Ground handler-confirmed time for pushback initiation

C. OBJECTIVE FUNCTION

Considering all the inbound and outbound flights within a given time period of time at the airport as the study objects, and taking the total taxiing time and total taxiing fuel consumption of the aircraft as the optimization objectives, an airport ground taxiing scheduling optimization model is established. The model aims to determine the optimal taxiing strategy for each inbound or outbound aircraft, from the runway exit to the parking position or from the parking position to the runway entrance.

The first objective function of this study represents the total taxiing time of all aircraft. It consists of two main components: (i) the taxiing time along the taxiways during different operational phases, and (ii) the waiting time incurred to avoid conflicts. This can be formally expressed as:

$$Z_1 = \min T = \min \sum_{k\in K}\left(\sum_{c=1}^{4}\left(\sum_{i\in P}\sum_{j\in P} t_{ijc}^{k} x_{ijc}^{k}\right) + \sum_{j\in P} t_{jc}^{k-wait}\right) \tag{4}$$

$$t_{jc}^{k\text{-wait}} = \mu_k \omega_{k,m}\left(t_s + T_{jc}^{k} - T_{jc}^{m}\right), \quad \forall m\in K, \forall k\in K, m\neq k \tag{5}$$

The second objective function represents the total fuel consumption of all aircraft during taxiing. This is calculated by multiplying the duration of each taxiing phase by the corresponding fuel consumption rate. The total fuel consumption depends on the specific aircraft type as well as the runway crossing strategy adopted after reaching the runway crossing point. Formally, it can be expressed as:

$$Z_2 = \min \sum_{k\in K} F^k = \begin{cases} t_4^k f_4^k \lambda_k \\ t_1^k f_1^k \lambda_k + t_3^k f_3^k \lambda_k + t_4^k f_4^k \lambda_k \\ t_2^k f_2^k \lambda_k + t_3^k f_3^k \lambda_k \end{cases} \tag{6}$$

D. CONSTRAINTS

1. Node conflict constraints:

$$\mu_k = \begin{cases} 0, |T_{jc}^{m} - T_{jc}^{k}| \geq t_s \\ 1, \text{others} \end{cases} \tag{7}$$

Equation (7) ensures that each node (e.g., taxiway intersections or holding points) can be occupied by only one aircraft at a time. This prevents spatial conflicts and guarantees safe separation.

2. Priority constraints:

$$\omega_{k,m} = \begin{cases} 0, \eta_k < \eta_m \\ 1, \eta_k > \eta_m \end{cases} \tag{8}$$

Equation (8) enforces precedence rules for aircraft sharing critical resources, such as giving priority to landing or higher-priority departures. This maintains smooth traffic flow and operational efficiency.

3. Head-to-head conflict constraints:

$$x_{ijc}^{m} T_{jc}^{m} - x_{ijc}^{k} T_{jc}^{k} \geq 0 \tag{9}$$

Equation (9) resolves potential head-on conflicts by dynamically determining the passing sequence. The optimization algorithm ensures minimum separation while minimizing taxiing time and fuel consumption.

4. Transcend conflicting constraints:

$$(x_{ijc}^{k} T_{ic}^{k} - x_{ijc}^{m} T_{ic}^{m})(x_{ijc}^{k} T_{jc}^{k} - x_{ijc}^{m} T_{jc}^{m}) \geq 0 \tag{10}$$

Equation (10) prevents overtaking conflicts by restricting simultaneous access to overlapping taxi paths. This guarantees safe temporal and spatial separation between aircraft.

5. Cross-conflicting constraints:

$$x_{ijc}^{m} T_{jc}^{m} \geq x_{ijc}^{k}(T_{jc}^{k} + t_s) \tag{11}$$

Equation (11) avoids crossing conflicts at intersecting taxi paths by prohibiting simultaneous occupation. This reduces collision risks and unnecessary waiting times.

6. Time constraints for incoming aircraft:

$$T_{in}^{k} \geq ETOA^{k} \tag{12}$$

Equation (12) requires inbound aircraft to reach their gates within planned time windows.

7. Time constraints for departing aircraft:

$$T_{out}^{m} \leq ETOD^{m} \tag{13}$$

$$T_{out}^{m} \geq EOBT^{m} \tag{14}$$

Equations (13) and (14) ensure departing aircraft leave gates and reach runway entries within specified limits.

8. Taxiing Path Selection Constraints

(1) Start and end point constraints: The taxi path must originate from the aircraft's departure point (gate or runway exit) and terminate at the assigned destination (runway entrance or parking position);

(2) Adjacent point constraints: The distance between consecutive taxi points should be appropriate to maintain smooth, continuous motion, reducing excessive acceleration/deceleration events;

(3) Intersection constraints: The taxi path should minimize waiting at busy intersections, thereby reducing overall taxi time and potential conflict probability.

V. METHODOLOGY AND ALGORITHM DESIGN

The Multi-Objective Particle Swarm Optimization (MOPSO) algorithm [22] is a population-based metaheuristic inspired by the principles of collective animal intelligence and has been extensively applied to solve multi-objective optimization problems involving conflicting objectives under complex constraints.

In this study, MOPSO is adopted to address the aircraft taxi scheduling optimization problem, yielding a diverse set of optimal trade-off solutions that constitute the Pareto front and thereby represent the inherent conflicts among competing objectives. To enhance the conventional MOPSO framework, a hybrid mutation operator is incorporated, which adaptively adjusts particle positions and velocities in accordance with the dynamic search state and the properties of the objective functions. This mechanism significantly improves both the exploration and exploitation capabilities of the algorithm, facilitating a more efficient approximation of the Pareto-optimal solution set. In addition, all non-dominated solutions are systematically preserved within an external archive throughout the optimization process to ensure solution diversity and convergence quality.

A. EXTERNAL ARCHIVE MAINTENANCE

The iterative process of the algorithm requires the use of an external archive to systematically preserve all non-dominated solutions [23], [24]. When the MOPSO algorithm is applied to solve the proposed model, the specific procedure for external archive maintenance is as follows:

1. Initialization: An empty external archive is created to store non-dominated solutions (i.e., glide strategies). Each glide strategy is defined as a sequence of nodes that represents a feasible taxiing path from the aircraft's starting point to its designated runway threshold.

2. Updating: During each iteration, the fitness values of newly generated particles (candidate glide strategies) are evaluated with respect to the multiple objectives. These new solutions are then compared against those stored in the archive using non-dominated sorting. If a solution is neither dominated by nor dominates any existing archive member, it is added as a non-dominated solution. To control archive size and enhance exploration of the solution space, solutions with larger crowding distances are preferentially retained.

Through this dynamic updating mechanism, the external archive continuously accumulates and preserves the most competitive non-dominated solutions identified during the search process. Consequently, the archive progressively approximates the true Pareto front, providing a diverse set of optimized glide strategies for decision-makers to select from, depending on operational priorities.

B. PARTICLE VELOCITY AND POSITION UPDATE

The MOPSO algorithm effectively explores the search space and identifies optimal aircraft taxiing strategies that satisfy the defined objective functions by adaptively updating particle positions and velocities. The specific update equations for particle velocity and position are given as follows [25]:

$$\begin{aligned} v_{\mathrm{i}}(\mathrm{k}+1) &= \mathrm{w}v_{i}(k)\ldots \\ &+c_1 r_1\left(pBest_{\mathrm{i}}(\mathrm{k})-x_i(k)\right)\ldots \\ &+c_2 r_2\left(gBest_{\mathrm{i}}(k)-x_i(k)\right) \end{aligned} \tag{15}$$

$$x_{\mathrm{i}}(k+1)=x_{\mathrm{i}}(k)+v_i(k+1) \tag{16}$$

In the formula, w is the linear adjustment inertia weight factor, $v_i(k)$ is the velocity vector of particle i at the kth iteration, $x_{\mathrm{i}}(k)$ is the position vector of particle i at the kth iteration, c_1 is the individual learning factor coefficient, c_2 is the global learning factor coefficient, representing the degree to which the particle follows the individual optimal solution and the global solution respectively, r_1 and r_2 are used to generate random values to increase the randomness of the search, $pBest_i(k)$ refers to the individual optimal solution found so far, $gBest_i(k)$ is the global optimal solution selected from the external archive.

C. HYBRID MUTATION OPERATION

In conventional multi-objective particle swarm optimization (MOPSO), excessive emphasis on convergence often results in premature particle clustering around local Pareto-optimal solutions, thereby reducing the algorithm's global exploration capability. Conversely, overprioritizing diversity preservation can substantially slow convergence and degrade computational efficiency [26]. To address this inherent trade-off, we introduce a hybrid mutation operator within the MOPSO framework, designed to adaptively adjust the search dynamics according to the distinct phases of the evolutionary process. As detailed in Section III, this operator integrates Gaussian and polynomial mutation schemes in a complementary manner, thereby achieving a dynamic balance between broad global exploration and focused local exploitation. The implementation procedure of this adaptive mutation operator is described as follows:

1. During the initial phase, a random mutation mechanism is employed to facilitate broad exploration of the search space. The corresponding mathematical formulation of the random mutation operation is expressed as follows:

$$x_{i,d}^{new1}=x_{i,d}+\delta,\delta\sim N(0,\sigma^2) \tag{17}$$

In the formula, $x_{i,d}^{new1}$ is the position of particle i in dimension d after random mutation, δ is a random number drawn from a Gaussian distribution $N(0,\sigma^2)$, σ is the magnitude of variability.

2. As the number of iterations progresses, the mutation intensity is dynamically modulated to enhance the likelihood

of identifying the global optimal solution. The corresponding mathematical expression for the dynamic mutation rate is given as follows:

$$m_t = m_c - \left(\frac{m_c - m_f}{iterations_{max}} \right) * t \tag{18}$$

In the formula, m_t denotes the mutation rate at the t-th iteration. m_c denotes the initial mutation rate. m_f denotes the final mutation rate. t denotes the current iteration index.

3. During the later phase of the iteration process, a non-uniform mutation mechanism is employed to gradually reduce the mutation amplitude, allowing solutions to progressively converge toward the potential optimal region. The corresponding mathematical formulation of the non-uniform mutation operation is given as follows:

$$x_{i,d}^{new3} = x_{i,d}^{new2} + \Delta(t, y) \tag{19}$$

$$\Delta(t, y) = y * [1 - r^{(1-\frac{t}{\text{iterations}_{\max}})^b}] \tag{20}$$

In the formula, $x_{i,d}^{new3}$ is the position of particle i in dimension d after non-uniform mutation, enhanced exploration capability through dimension-wise perturbation. $x_{i,d}^{new2}$ is the position of particle i in dimension d after dynamic mutation, the time-varying mutation strength regulated by parameter b. r is a uniformly distributed random number: r~ U[0,1], its function is to determines mutation direction (expansion/contraction). y is the upper bound of mutation magnitude: if r<0.5， then， $y = 1 - x_{i,d}^{new2}$， others,. $y = x_{i,d}^{new2}$.

D. MULTI-RUNWAY TAXIING SCHEDULING OPTIMIZATION ALGORITHM

The detailed procedural steps of the proposed MOPSO-based multi-runway taxiing scheduling optimization algorithm are outlined as follows:

STEP1: Collect and analyze comprehensive flight information to provide robust data support for subsequent aircraft taxiing scheduling optimization.

STEP2: Initialize the particle population and set algorithm parameters, including swarm size, maximum number of iterations, and initial particle positions and velocities. Randomly generate the initial population, where each particle represents a candidate taxiing strategy. Integer encoding is employed to represent particle positions, converting the aircraft taxiing strategies into integer-valued position vectors.

STEP3: Evaluate the fitness of each particle. Based on the model's objective functions and constraints, calculate the particle's fitness, specifically quantifying the taxiing time and fuel consumption associated with each candidate taxiing strategy.

STEP4: Update the velocity and position of each particle according to the fitness evaluation results. The movement of particles is guided by both the individual historical best position (*pBest*) and the global historical best position (*gBest*) to iteratively seek improved taxiing strategies.

STEP5: Apply hybrid mutation operations to prevent premature convergence to local optima and maintain population diversity, thereby ensuring continued exploration of the solution space.

STEP6: Update the external archive using non-dominated sorting and crowding distance metrics. This step stores the best non-dominated solution set identified thus far, allowing the algorithm to track and preserve optimal taxiing strategies throughout the optimization process.

STEP7: Check for termination conditions. If satisfied, extract the final non-dominated solution set from the external archive and terminate the iteration. Otherwise, repeat STEP 3 until the termination criteria are met.

The detailed procedural flow of the algorithm is illustrated in FIGURE 5.

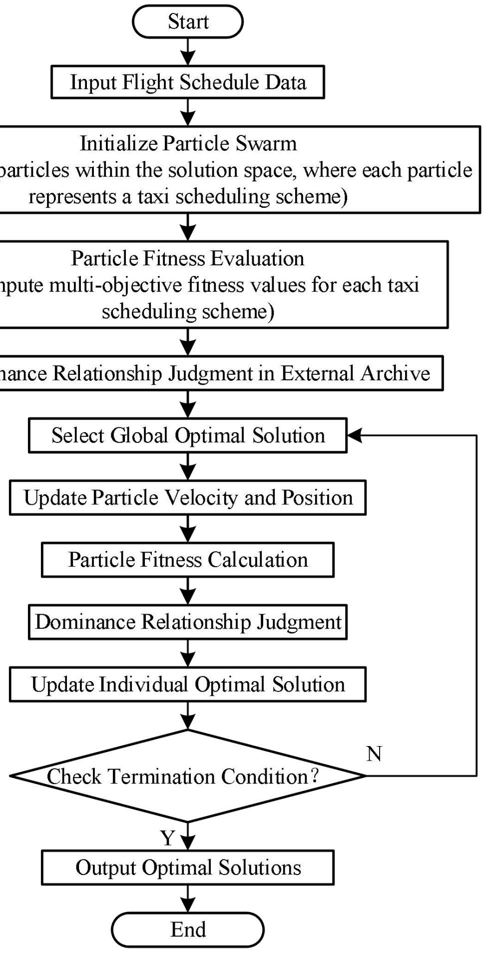

FIGURE 5. Multi-runway taxi strategy optimization algorithm

VI. SIMULATION EXPERIMENT AND ANALYSIS OF ITS RESULTS

To rigorously assess the performance and practical applicability of the proposed MOPSO-based aircraft taxiing scheduling model, a comprehensive, multi-dimensional

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simulation framework is established. This chapter details the experimental environment, scenario configurations, benchmark comparisons, performance evaluation metrics, and result analyses, aiming to provide a thorough validation of the proposed methodology's effectiveness, scalability, and real-world adaptability.

A. SIMULATION SCENARIO I

To validate the proposed methodology, a simulation was conducted using the ground taxiway network between two parallel runways at a large-scale international hub airport with multiple runways, as depicted in FIGURE 6. The runway-taxiway configuration employed in this simulation is modeled after a real-world major international airport and adheres to ICAO dimensional standards. It is assumed that all aircraft operations (landings and take-offs) are feasible within the available runway lengths, as these conditions are managed by air traffic control and flight planning procedures prior to the commencement of ground taxiing operations, which constitute the focus of this model.

Three representative runway-crossing strategies were evaluated: (①) direct runway crossing, (②) stop-and-wait runway crossing, and (③) detour taxiway crossing. To ensure a fair comparison, all three strategies share identical start and end points. Based on the airport's airfield layout and operational configuration, Runway 01/19 was designated for landing operations, whereas Runway 18L/36R was allocated for take-off operations, aiming to minimize runway crossing frequency and potential conflicts.

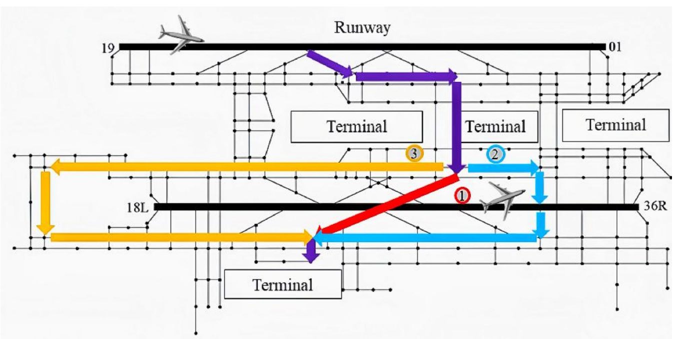


FIGURE 6. Scenario 1: Taxiway system network diagram of a large multi-runway airport.

Flight schedule data from 10:00 to 11:00 a.m. on a selected day were utilized, encompassing both arrival and departure operations. The dataset includes the origin of each aircraft (departure gate or arrival runway), the destination (arrival gate or take-off runway holding point), and timing information (earliest taxi time and scheduled runway usage time). Engine specifications for the various aircraft types are presented in TABLE III, while the detailed arrival and departure flight information is summarized in TABLE IV.

TABLE III
ENGINE FOR DIFFERENT AIRCRAFT TYPES

Type	Types of aircraft	Engine type	Number of engines
Medium-sized, Narrow-body	A319, A320, A321	CFM56-5B series, IAE V2500 series	2
	B737, B738	CFM56-7B series	2
Large-sized, Wide-body	A330	Trent700, PW4000, CF6-80E1	2
	B777	Trent 800, GE90, PW4000	2
	B787, B788	Trent 1000, GEnx	2
Very Large, Wide-body	A340	CFM56-5C4	4
	B747	B211-524 series , PW4000, CF6, GEnx(748)	4

Note: *Aircraft type designators are sourced from ICAO Doc 8643* [27]. *The operational classification herein (e.g., Medium-sized, Narrow-body) is illustrative and informed by typical seating capacity, fuselage size, and wake turbulence categories* [28]. *All technical specifications, including engine models and number of engines, are derived from the latest official documentation published by aircraft and engine manufacturers* [29-36]. *Specific engine models may vary by airline configuration and aircraft sub-type.*

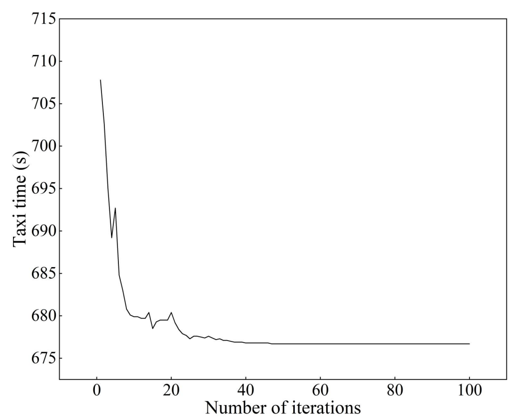
TABLE IV
PROGRAMMING INFORMATION OF APPIVAL AND DEPARTURE FLIGHTS

Flight Number	Arrival/ Departure	Terminal/ Starting point	Types of Aircraft	Time of Arrival/Take-off
1	Arrival	T2	A330	10:00:00
2	Departure	T3	B737	10:05:00
3	Departure	T3	A321	10:07:00
4	Arrival	T2	B788	10:11:00
5	Departure	T3	A320	10:12:00
6	Arrival	T2	B787	10:17:00
7	Departure	T3	B737	10:18:00
8	Departure	T3	A330	10:19:00
9	Arrival	T2	B737	10:23:00
10	Arrival	T2	B747	10:25:00
11	Departure	T3	B737	10:28:00
12	Departure	T3	B737	10:29:00
13	Departure	T3	A321	10:32:00
14	Arrival	T2	A330	10:34:00
15	Departure	T2	B737	10:34:00
16	Departure	T3	A319	10:34:00
17	Arrival	T2	A330	10:36:00
18	Arrival	T2	A321	10:39:00
19	Departure	T3	B737	10:39:00
20	Arrival	T2	B737	10:43:00
21	Departure	T3	A321	10:45:00
22	Arrival	T2	A321	10:50:00
23	Arrival	T2	A330	10:52:00
24	Departure	T3	A320	10:58:00
25	Arrival	T2	B777	11:00:00

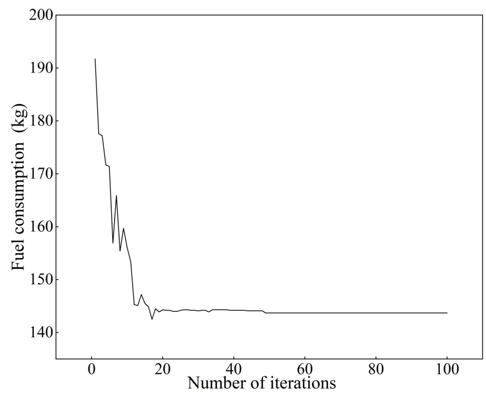
A total of 25 flights were included in the simulation, consisting of 12 arrivals and 13 departures. For arriving aircraft, the taxiing route originates from the runway exit and terminates at the apron or gate. For departing aircraft, the route begins at the apron or gate and concludes at the runway holding point. It should be noted that taxiing within the apron area was not explicitly modeled in this study. Instead, all apron zones were treated as a single integrated area, and aircraft taxiing was only simulated from or to the apron boundary.

The proposed multi-objective aircraft taxiing scheduling model was implemented and evaluated in MATLAB. The optimization algorithm employs a Multi-Objective Particle Swarm Optimization (MOPSO) framework owing to its superior global search capability and efficiency in addressing complex multi-criteria problems. The algorithm was initialized with a population size of 40 particles, acceleration coefficients set to $c1$=1.5 and $c2$=1.8, and a maximum of 100 iterations to ensure sufficient exploration of the search space and convergence of solutions.

Using the arrival and departure flight dataset provided in Tables III and IV as input, the model simultaneously optimizes two primary performance metrics: total taxiing time and total taxiing fuel consumption. These objectives capture both the operational efficiency and environmental impact of airport surface operations. The optimization explicitly accounts for aircraft-specific engine characteristics, flight schedules, and taxiing routes across three alternative runway crossing strategies. To assess optimization performance, the convergence behavior of the algorithm over successive iterations is depicted in FIGURE 7. The two objective functions improve rapidly during the initial iterations and then gradually stabilize as the algorithm progresses, ultimately converging to a set of near-optimal solutions. This convergence pattern demonstrates the robustness and effectiveness of the proposed MOPSO-based framework in addressing practical airport taxi scheduling problems.



(a)



(b)

FIGURE 7. Optimization Iteration for Taxiing time and Taxi Fuel Consumption of Aircrafts.

The trade-off between taxiing time and fuel consumption is represented by the Pareto front, as illustrated in FIGURE 8. This front consists of a set of non-dominated solutions, where improvement in one objective inevitably results in deterioration of the other. Importantly, the results indicate that minimizing taxiing time does not necessarily reduce fuel consumption. In fact, aggressively pursuing shorter taxi durations can lead to more frequent acceleration and deceleration, thereby increasing fuel usage and environmental emissions. This highlights the inherent conflict between time-efficiency and energy-efficiency objectives in aircraft taxi scheduling, which must be carefully balanced in practical airport operations. Within the Pareto front, the blue and red markers denote the extreme solutions: the shortest taxiing time and the lowest fuel consumption, respectively. The presence of a broad Pareto set enables airport controllers or decision-makers to select the most suitable strategy according to operational priorities, such as emphasizing punctuality during peak hours or minimizing environmental impact during off-peak periods.

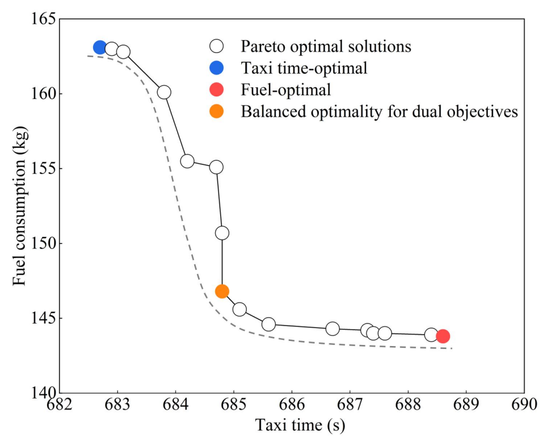


FIGURE 8. Pareto Frontier for Aircraft Taxiing Time and Taxi Fuel Consumption.

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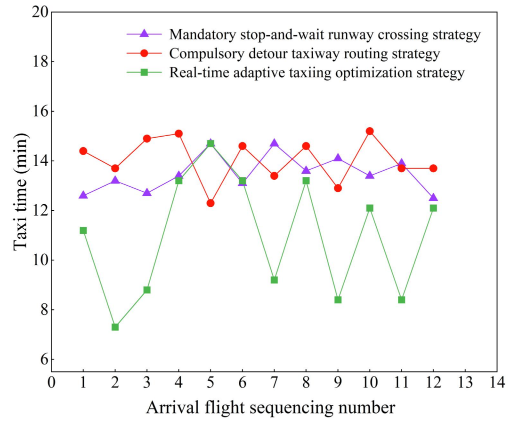
To further facilitate practical decision-making, an additional representative point depicted as an orange marker has been introduced on the Pareto diagram. This point denotes a balanced solution that achieves a reasonable compromise between taxiing time and fuel consumption. In contrast to the blue and red points, which represent the extreme cases of minimum taxiing time and minimum fuel consumption, respectively, the orange point corresponds to a solution that moderately sacrifices performance in each individual objective to attain a more operationally feasible and environmentally sustainable outcome. Such a balanced solution is particularly valuable in real-world applications, where neither the absolute minimum taxiing time nor the minimum fuel usage is ideal due to operational constraints, safety requirements, or environmental regulations. By incorporating this point into the analysis, the study demonstrates the model's capability to provide flexible, actionable recommendations that can be tailored to diverse operational priorities and policy objectives.

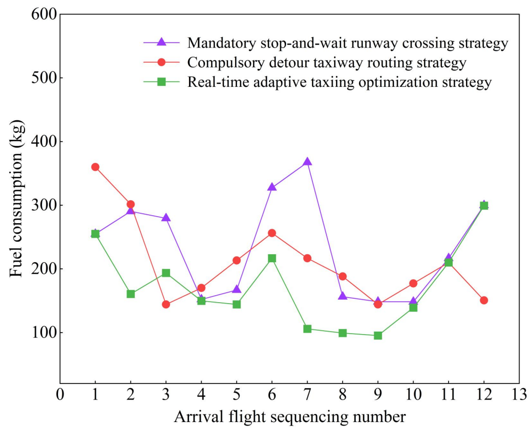
TABLE V
CALCULATION RESULTS OF AIRCRAFT TAXIING TIME AND TAXIING FUEL CONSUMPTION IN SCENARIO I

Flight Number	Runway Crossing Strategy	Taxi Time (min)	Fuel Consumption (kg)
1	Crossing the runway after stop-and-wait	11.2	255
2	No runway crossing	7.9	89.7
3	No runway crossing	6.2	71.3
4	Direct runway crossing	7.3	160.6
5	No runway crossing	8.4	96.6
6	Direct runway crossing	8.8	193.6
7	No runway crossing	7.9	83.7
8	No runway crossing	6.7	80.1
9	Crossing the runway using detour taxiway	13.2	149.8
10	Crossing the runway after stop-and-wait	14.7	176.4
11	No runway crossing	5.8	69.3
12	No runway crossing	6.2	74.4
13	No runway crossing	7.4	85.1
14	Crossing the runway using detour taxiway	13.2	216.8
15	No runway crossing	7.6	86.3
16	No runway crossing	6.9	79.4
17	Direct runway crossing	9.2	230
18	Crossing the runway using detour taxiway	13.2	151.8
19	No runway crossing	7.2	82.8
20	Direct runway crossing	8.4	95.4
21	No runway crossing	6.8	78.2
22	Crossing the runway using detour taxiway	12.1	139.2
23	Direct runway crossing	8.4	210
24	No runway crossing	6.3	72.5
25	Crossing the runway using detour taxiway	12.1	299.3

The optimal taxiing strategy under Scenario 1 was selected from the Pareto solutions using a comprehensive evaluation index that simultaneously balances both objectives. The associated results, including detailed route assignments and objective values for each aircraft, are summarized in TABLE V. These findings substantiate the model's practical applicability in real-world airport operations and demonstrate its potential to inform decision-making in intelligent surface traffic management systems.



(a)



(b)

FIGURE 9. Comparison of Taxiing Time and Taxi Fuel Consumption per Aircraft for Three Taxi Strategies.

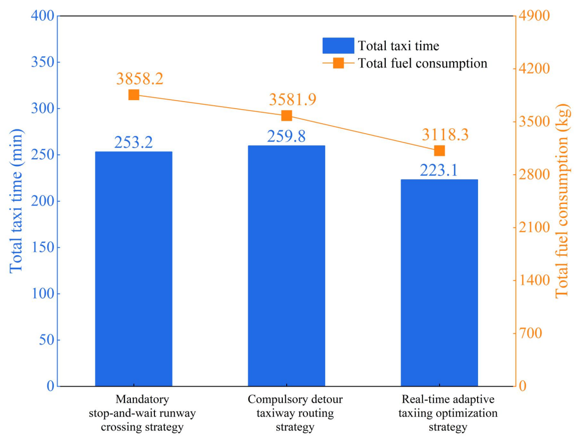


FIGURE 10. **Comparison of Taxiing Time and Taxi Fuel Consumption per Aircraft for Three Taxi Strategies.**

A comparative analysis of taxiing time and fuel consumption for arriving aircraft under three distinct taxiing strategies is presented in FIGURE 9, whereas the total taxiing time and fuel consumption across all aircraft under each scenario are summarized in FIGURE 10. The three strategies evaluated comprise: (i) a stop-and-wait runway crossing strategy, (ii) a detour taxiway strategy that entirely avoids runway crossing, and (iii) a condition-based optimized taxiing strategy derived from the proposed model.

Under the stop-and-wait strategy, aircraft are required to pause near the runway holding point until clearance is granted for crossing. This approach resulted in a total taxiing time of 253.2 minutes and a total fuel consumption of 3858.2 kg. In contrast, the unconditional detour strategy, which directs all aircraft around the runway along longer taxi paths, produced a slightly higher taxiing time of 259.8 minutes but a reduced fuel consumption of 3581.9 kg, primarily due to the elimination of stop- stop-and-go idling phases.

Notably, the proposed multi-objective optimization strategy yielded substantially superior outcomes. By dynamically assigning the most operationally suitable crossing method (direct crossing, detour, or no crossing) to each arriving aircraft based on real-time conditions, including runway occupancy status, individual aircraft positions, and prevailing queue lengths, this approach achieved a total taxiing time of only 223.1 minutes and a fuel consumption of 3118.3 kg. These results, consistently reproduced across multiple simulation runs with minimal variance (<2.5%), highlight the robustness, reliability, and practical applicability of the proposed model.

Overall, the performance of the optimized strategy demonstrates a substantial improvement over the baseline scenarios, reducing total taxiing time by 11.89% and 14.13%, and decreasing fuel consumption by 19.18% and 12.94%, respectively. The comprehensive simulation framework, grounded in empirical operational data and incorporates heterogeneous aircraft types as well as complex runway interactions, illustrates the practical robustness, scalability, and applicability of the proposed approach. Consequently, these results confirm that the model can effectively support more intelligent and adaptive surface traffic management decisions. Collectively, these findings underscore the principal contribution of this study: the development of a computationally efficient and operationally feasible multi-objective optimization framework that successfully bridges the gap between theoretical modeling and real-world airport gate and ramp operations.

B. SIMULATION SCENARIO II

To further assess the generalizability and practical applicability of the proposed optimization model, an additional case study was conducted using real operational data from a representative large-scale multi-runway hub airport. The runway–taxiway configuration employed in this simulation is based on a major international airport, with all dimensions fully compliant with ICAO standards. It is assumed that all aircraft operations, including landings and take-offs, are feasible within the available runway lengths, as these conditions are pre-managed by air traffic control and flight planning procedures prior to the commencement of ground taxiing operations, which constitute the primary focus of this study.

The layout of the taxiway network connecting the airport's two parallel runways is illustrated in FIGURE 11, highlighting three representative runway crossing strategies: (①)direct crossing, (②) stop-and-wait, and (③) detour using a perimeter taxiway. In this case study, runway 02L/20R was designated for departure, while runway 02R/20L was reserved exclusively for arrivals. This configuration reflects standard operational practice at high-density airports, aimed at streamlining traffic flow and minimizing potential conflicts. The selection of specific runway exits and terminal stands was carefully designed to ensure both operational realism and sufficient algorithmic complexity. The runway exit points correspond to the main high-speed turnoff taxiways, as specified in official airport charts and routinely utilized in practice to reduce runway occupancy time. The destination stands include a mix of remote and pier-served gates, representing a variety of realistic and challenging taxiing scenarios that fully engage the optimization algorithm across varying levels of network complexity. This setup ensures that the core taxiway structure of the major international hub is accurately modeled, providing a rigorous evaluation of the proposed model's generalizability and robustness.

Flight operation data for the time window 14:00 to 15:00 on a selected day were extracted and organized, as summarized in TABLE VI. The dataset includes aircraft types, entry and exit points, and expected pushback or landing times. These data were used as input to the simulation model to evaluate the performance of the proposed optimization framework under an alternative airport topology and traffic scenario.

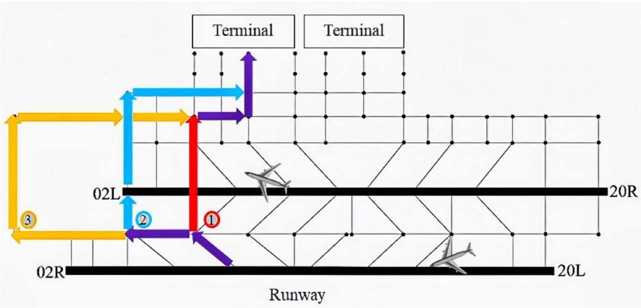


FIGURE 11. Scenario 2: Taxiway system network diagram of a multi-runway airport.

The algorithm was implemented in MATLAB, with an initial population size of 30, acceleration coefficients set to $c1$=1.5 and $c2$=1.8, and a maximum of 100 iterations. Using the provided input data and the optimization criteria, the algorithm generated the optimal taxiing strategies for all inbound and outbound flights in Scenario 2. The corresponding results, including individual taxiing strategies, total taxiing time, and total fuel consumption, are summarized in TABLE VII.

TABLE VI
PROGRAMMING INFORMATION OF APPIVAL AND DEPARTURE FLIGHTS

Flight Number	Arrival/ Departure	Terminal/ Starting point	Types of Aircraft	Time of Arrival/Take-off
1	Departure	T2	A319	14:01:00
2	Arrival	T1	A320	14:05:00
3	Departure	T1	B738	14:06:00
4	Arrival	T2	A321	14:07:00
5	Departure	T2	A320	14:09:00
6	Departure	T2	B737	14::10:00
7	Arrival	T2	A330	14:10:00
8	Departure	T1	B788	14:14:00
9	Arrival	T1	B738	14:17:00
10	Arrival	T2	A320	14:24:00
11	Departure	T2	A319	14:25:00
12	Arrival	T2	B738	14:30:00
13	Arrival	T1	A320	14:32:00
14	Departure	T1	A330	14:38:00
15	Arrival	T2	B737	14:40:00

The algorithm was implemented in MATLAB, with the initial population size set to 30, acceleration coefficients $c1$=1.5, $c2$=1.8, and a maximum of 100 iterations. Based on the input data and the optimization criteria, the optimal taxiing strategy for all inbound and outbound flights in Scenario 2 was derived. The corresponding optimization results, including individual taxiing strategies, total taxiing time, and fuel consumption, are detailed in TABLE VII.

TABLE VII
CALCULATION RESULTS OF AIRCRAFT TAXIING TIME AND TAXIING FUEL CONSUMPTION IN SCENARIO II

Flight Number	Runway Crossing Strategy	Taxi Time (min)	Fuel Consumption (kg)
1	No runway crossing	3.2	36.8
2	Crossing the runway using detour taxiway	4.3	49.5
3	No runway crossing	3.5	39.7
4	Direct runway crossing	3.3	38
5	No runway crossing	2.6	29.9
6	No runway crossing	2.9	32.9
7	Direct runway crossing	3.1	77.5
8	No runway crossing	2.7	59.4
9	Crossing the runway after stop-and-wait	3.6	40.9
10	Direct runway crossing	2.8	32.2
11	No runway crossing	3.4	39.1
12	Crossing the runway after stop-and-wait	3.9	44.3
13	Crossing the runway using detour taxiway	4.2	48.3
14	No runway crossing	3.7	92.5
15	Crossing the runway using detour taxiway	4.6	52.2

A comparative analysis of total taxiing time and fuel consumption under the three taxiing strategies is presented in FIGURE 12. When all inbound aircraft follow the stop-and-wait runway crossing strategy, the total taxiing time reaches 54.5 minutes, with an associated taxiing fuel consumption of 759.0 kg. Under the detour taxiway strategy, where aircraft bypass the runway via longer taxiing routes, the total taxiing time slightly increases to 55.3 minutes, while fuel consumption marginally decreases to 756.3 kg. In contrast, when aircraft follow the optimized taxiing strategy generated by the proposed model, which accounts for real-time operational conditions, the total taxiing time is reduced to 51.8 minutes, and fuel consumption drops significantly to 713.2 kg. Compared with the stop-and-wait strategy, the optimized approach yields a 4.95% reduction in taxiing time and a 6.03% reduction in fuel consumption. Compared with the detour strategy, improvements of 6.33% in taxiing time and 5.69% in fuel consumption are observed. These findings are consistent with the results from Scenario 1, validating the robustness and transferability of the proposed model across different airport environments.

The analysis clearly demonstrates that a static, one-size-fits-all strategy, whether prioritizing caution (stop-and-wait) or avoidance (detour), is suboptimal with respect to both operational efficiency and environmental performance. In contrast, by dynamically assigning the most appropriate taxiing strategy to each aircraft, the proposed optimization model achieves a more balanced and efficient solution. This second verification experiment confirms that the proposed model is adaptable across diverse airport configurations, exhibiting robust optimization capability under different runway usage patterns, taxiway layouts, and traffic densities. The consistent performance improvements observed across both case studies further reinforce the model's scalability and

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operational applicability, providing strong evidence for its potential deployment in real-world airport surface traffic management systems.

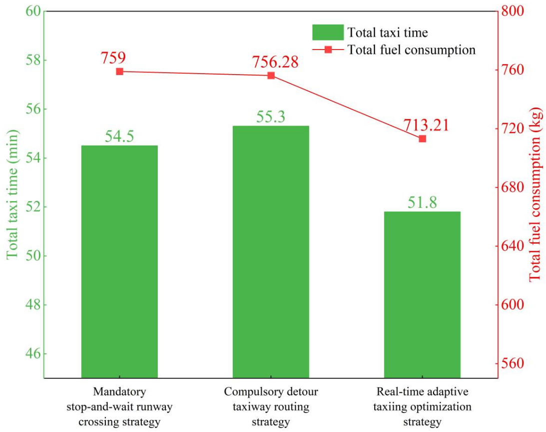

FIGURE 12. Comparison of total time and total fuel consumption under three coasting strategies

C. RESULT ANALYSIS

The comparative analysis of Scenarios 1 and 2 provides the following key insights:

1. Detour Taxiway Strategy

(1) Advantage: Routing aircraft around the runway significantly reduces the frequency of stop-and-wait maneuvers, which in turn decreases idle time and lowers fuel consumption in many instances.

(2) Limitation: The increased ground distance traveled may, under certain traffic patterns, offset these benefits, potentially resulting in a net increase in fuel consumption.

2. Stop-and-Wait Runway Crossing Strategy

(1) Advantage: Direct runway crossings minimize the total taxi distance.

(2) Limitation: Prolonged waiting periods at runway thresholds increase runway occupancy, reduce overall runway throughput, and may induce broader surface delays.

These results highlight that no single static strategy can simultaneously optimize both taxi distance and delay metrics. Instead, an effective taxi-scheduling framework must dynamically balance: (i) real-time surface traffic conditions, including queue lengths and gating constraints; (ii) runway usage configurations, distinguishing take-off and landing assignments; (iii) flight schedules, such as estimated time of arrival and departure; (iv) aircraft performance characteristics, including engine type and acceleration/deceleration profiles. By integrating these factors into a context-aware decision model, each arriving or departing flight can be evaluated individually to automatically determine the most suitable crossing method (direct, stop-and-wait, or detour). This multi-criteria, adaptive scheduling approach not only maximizes runway throughput and minimizes taxiing delays, but also achieves substantial reductions in fuel consumption and emissions, demonstrating the practical applicability and operational value of the proposed optimization framework for modern high-density airport operations.

D. ALGORITHM PERFORMANCE COMPARISON

To further validate the effectiveness and robustness of the proposed optimization framework, a comparative analysis was performed between the multi-runway taxiing scheduling algorithm based on Multi-Objective Particle Swarm Optimization (MOPSO) and the Non-dominated Sorting Genetic Algorithm II (NSGA-II). For a fair comparison, NSGA-II was configured with standard parameters. The population size was set to 40 for Scenario 1 and 30 for Scenario 2. The remaining parameters were 100 generations, a crossover rate of 0.9, and a mutation rate of 1/n , where n is the number of decision variables. The experimental results for both simulation scenarios are summarized in TABLE VIII.

In both scenarios, the MOPSO-based approach demonstrated superior performance in reducing total taxiing time and total taxiing fuel consumption. Specifically, in Scenario 1, the MOPSO-based algorithm reduced total taxiing time by 14.9 minutes and total fuel consumption by 344.6 kg compared to NSGA-II. In Scenario 2, reductions of 2.7 minutes in taxiing time and 70.5 kg in fuel consumption were observed.

These results clearly indicate the superior optimization capability of the MOPSO algorithm in the context of complex, multi-runway aircraft ground scheduling problems. The observed performance gains can be attributed to MOPSO's improved global search ability, efficient external archive maintenance mechanism, and its adaptability in handling the nonlinear, multi-constraint, and multi-objective characteristics of aircraft taxi scheduling.

While NSGA-II is a widely recognized and competitive multi-objective optimization algorithm, the findings of this study suggest that MOPSO achieves superior convergence and solution quality in the real-world multi-runway taxiing scenarios. Overall, these findings affirm the practical advantages of the proposed MOPSO-based approach in minimizing delays and reducing environmental impact, highlighting its potential for implementation in intelligent airport surface traffic management systems.

TABLE VIII
COMPARISON OF TAXIING DISPATCH OPTIMIZATION RESULTS

Simulation Scenario	Algorithm	Total Taxi Time (min)	Total Fuel Consumption (kg)
1	MOPSO	223.1	3118.3
	NSGA-II	238	3462.9
2	MOPSO	51.8	713.2
	NSGA-II	54.5	783.7

VII. CONCLUSION AND FUTURE WORK

A. CONCLUSION

As critical hubs within the air transportation system, the operating efficiency of airports is essential for ensuring flight punctuality and enhancing passenger travel experience. This paper presents a comprehensive study on runway-crossing strategy selection and ground taxi scheduling optimization at multi-runway airports, addressing the increasing demand for efficient surface operations amid growing traffic complexity.

By integrating dynamic aircraft behavior modeling, refined strategy classification, and advanced multi-objective optimization, this study achieves a robust, scalable, and practically applicable solution framework. The key conclusions and contributions of this study are summarized as follows:

1. Integrated Modeling of Multi-Runway Taxi Scheduling with Crossing Strategies. This study develops a novel multi-runway taxi scheduling model that explicitly incorporates three key runway-crossing strategies—direct crossing, detour via peripheral taxiways, and controlled waiting before crossing—within a unified optimization framework. The model captures dynamic physical behavior of aircraft, including acceleration/deceleration, turning constraints, and holding positions, providing a realistic representation of surface traffic dynamics. Unlike existing models that primarily focus on minimizing taxi time or fuel consumption, the proposed framework jointly optimizes multiple conflicting objectives, such as taxi time, fuel burn, and runway incursion risks, while ensuring conflict-free operations and adherence to capacity constraints.

2. Hybrid-Mutation-Enhanced MOPSO Algorithm Design. To effectively solve the complex multi-objective, discrete-continuous taxi scheduling problem, a customized Multi-Objective Particle Swarm Optimization (MOPSO) algorithm was proposed. The algorithm is augmented with a hybrid mutation mechanism that integrates local exploration and global perturbation strategies, improving search space coverage, convergence toward the true Pareto front. The mutation operator dynamically adjusts exploration intensity across iterations, effectively balancing solution diversity and exploitation depth, and adapting to varying traffic densities.

3. Comprehensive Simulation and Performance Evaluation. Extensive simulation experiments were conducted under various operational scenarios using a real-world multi-runway airport layout. The results demonstrate that the proposed model and algorithm significantly outperform benchmark approaches (e.g. NSGA-II) in minimizing total taxi time, reducing fuel consumption, and mitigating surface conflicts. In low-traffic conditions, direct runway crossing is most effective, whereas in congested scenarios, detour strategies reduce conflict probabilities while maintain runway throughput. The solution set exhibits superior convergence and diversity, offering high-quality decision support for dynamic ground control operations and providing actionable insights into real-time strategy selection based on prevailing surface traffic conditions.

B. CONTRIBUTIONS AND LIMITATIONS

The main contributions of this thesis are summarized as follows:

1. Model Innovation: A comprehensive, constraint-rich aircraft taxiing scheduling model is developed, accurately reflecting the operational complexity of multi-runway airports.

2. Algorithm Design: A novel hybrid mutation strategy is integrated into the MOPSO framework, enhancing global search capability, convergence, and solution robustness.

3. Simulation Validation: Realistic airport layout and operational scenarios are simulated to validate the practical effectiveness and scalability of the proposed algorithm.

4. Performance Improvement: Experimental results demonstrate notable gains over NSGA-II in key metrics, including total taxi time, fuel consumption, and conflict mitigation.

Despite the promising results, several limitations exist:

1. Fixed departure/arrival schedules: Variability in real-time pushback and arrival times is not fully addressed.

2. Controller behavior modeling: Human decision-making factors are not considered in the optimization loop.

3. Fuel estimation for detours: Fuel consumption for detours is computed using a constant-speed flow rate, neglecting acceleration/deceleration, which may slightly underestimate total fuel use for longer paths.

4. Real-time disruptions: Factors such as weather, ATC slots, and unavailable stands are not fully incorporated..

C. FUTURE WORK

Future research will focus on several directions to enhance the applicability and realism of the proposed optimization framework:

1. Dynamic Pushback Control Integration: Couple the proposed hybrid-MOPSO taxiing scheduling model with real-time pushback control strategies (e.g., DPC method), to improve system adaptability under operational uncertainty.

2. Refined Fuel Consumption Estimation: Incorporate dynamic acceleration and deceleration segments into the detour taxiway model to improve the precision of fuel consumption calculations.

3. Reinforcement Learning Integration: Investigate the use of deep reinforcement learning (DRL) techniques for adaptive taxiing decision-making in dynamic and uncertain environments.

4. Large-Scale Airport Application: Extend the framework to ultra-large international hubs with more than 100 aircraft per hour and highly complex taxiway networks.

5. Stochastic Optimization: Incorporate stochastic elements as probability distributions within the optimization model, transitioning from a purely deterministic framework to robust or stochastic optimization approaches.

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REFERENCES

[1] P. D. Mascio, M. V. Corazza, N. R. Rosa, et al., “Optimization of aircraft taxiing Strategies to reduce the impacts of landing and take-off cycle at airports,” *Sustainability*, vol. 14, no. 15, p. 9692, 2022.

[2] M. Wei, B. Sun, W. Wu, et al., “A multiple objective optimization model for aircraft arrival and departure scheduling on multiple runways,” *Mathematical Biosciences and Engineering*, vol. 17, no. 5, pp. 5545-5560, 2020.

[3] Y. L. Liu, M. H. Hu, J. N. Yin, et al., “Adaptive airport taxiing rule management: Design, assessment, and configuration,” *Transportation Research Part C: Emerging Technologies*, vol. 163, p. 104652, 2024.

[4] Airports Council International (ACI), Airport Traffic Statistics 2023 – Preliminary Results, 2024. [Online]. Available: https://aci.aero.

[5] Eurocontrol, EUROCONTROL Network Operations Report – March 2024, Brussels, Belgium, 2024. [Online]. Available: https://www.eurocontrol.int.

[6] M. Weiszer, E. K. Burke, J. Chen, “Multi-Objective Routing and Scheduling for Airport Ground Movement,” *Transportation Research Part C: Emerging Technologies*, vol. 119, p. 102734, 2020.

[7] D. K. Park, J. K. Kim, “Influential factors to aircraft taxi time in airport,” *Journal of Air Transport Management*, vol. 106, p. 102321, 2023.

[8] H. F. Fernandes, C. Müller, et al., “Optimization of the waiting time and makespan in aircraft departures: A real time non-iterative sequencing model,” *Journal of Air Transport Management*, vol. 79, p. 101686, 2019.

[9] International Civil Aviation Organization (ICAO), Annex 14 to the Convention on International Civil Aviation: Aerodromes. Volume I – Aerodrome Design and Operations, 8th ed., Montreal, QC, Canada: ICAO, 2018.

[10] Y. Jiang, H. Wang, W. G. Fan, et al., “Spatio-temporal cooperative optimization model of surface aircraft taxiing,” *Journal of Traffic and Transportation Engineering*, vol. 19, no. 1, pp. 127-135, 2019.

[11] Z. N. Zhang, T. Wang T, “Taxiing path optimization of airport at the aircraft end-around taxiway,” *Science Technology and Engineering*, vol. 19, no. 10, pp. 241-248, 2019.

[12] S. M. Li, Y. Gao, “Optimization of aircrafts taxiing Path based on improved A* algorithms,” *Computer Simulation*, vol. 37, no. 3, pp. 27-32, 2020.

[13] Y. Jiang, Z. N. Liu, Z. T. Hu, et al., “Coordinated scheduling model of arriving aircraft at large airport,” *Journal of Traffic and Transportation Engineering*, vol. 22, no. 1, pp. 205-215, 2022.

[14] X. P. Zhu, C. Xu, J. J. Qu, et al., “Design and simulation-based evaluation of taxiway operation scheme for multi-runway airport maneuvering area,” *Journal of System Simulation*, vol. 34, no. 11, pp. 2448-2457, 2022.

[15] P. Cheng, X. Zou and W. Liu, “Airport surface trajectory optimization considering runway exit selection,” *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, Qingdao, China, 2014, pp. 2656-2662.

[16] J. Chen, M. Weiszer, G. Locatelli, et al., “Toward a more realistic, cost-effective, and greener ground movement through active routing: a multiobjective shortest path approach,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 12, pp. 3524-3540, 2016.

[17] L. Yang, S. Wang, F. Liang, et al., “A Holistic Approach for Optimal Pre-Planning of Multi-Path Standardized Taxiing Routes,” *Aerospace*, vol. 8, no. 9, p. 241, 2021.

[18] W. Deng W, L. Zhang, X. Zhou, et al., “Multi-strategy particle swarm and ant colony hybrid optimization for airport taxiway planning problem,” *Information Sciences*, vol. 612, pp. 576-593,2022.

[19] H. Damgacioglu, N. Celik and A. Guller, “A route-based network simulation framework for airport ground system disruptions,” *Computers & Industrial Engineering*, vol. 124, pp. 449-461, 2018.

[20] B. Adrian, R. D. Celis and L. Cadarso, “Integration of airport terminal arrival route selection, runway assignment and aircraft trajectory optimization,” *Transportation Research Procedia*, vol. 47, pp. 299-306, 2020.

[21] T. Nikoleris, G. Gupta and M. Kistler, “Detailed estimation of fuel consumption and emissions during aircraft taxi operations at Dallas/Fort Worth International Airport,” *Transportation Research Part D Transport & Environment*, vol. 16, no. 4, pp. 302-308, 2011.

[22] X. Gang, L. Kun, X. Yu, et al., “On convergence analysis of multi-objective particle swarm optimization algorithm,” *European Journal of Operational Research*, vol. 286, pp. 32-38, 2020.

[23] Q. Lin, S. Liu, Q. Zhu, et al., “Particle Swarm Optimization With a Balanceable Fitness Estimation for Many-Objective Optimization Problems,” *IEEE Transactions on Evolutionary Computation*, vol. 22, no. 1, pp. 32-46, 2018.

[24] G. Sun, A. Zhang, Y. Yao, et al., “A novel hybrid algorithm of gravitational search algorithm with genetic algorithm for multi-level thresholding,” *Applied Soft Computing*, vol. 46, pp. 703-730, 2016.

[25] W. Hu, G. G. Yen, “Adaptive multiobjective particle swarm optimization based on parallel cell coordinate system,” *IEEE Transactions on Evolutionary Computation*, vol. 19, no. 1, pp. 1-18, 2015.

[26] H. G. Han, W. Lu and J. F. Qiao, “A multiobjective particle swarm optimization algorithm based on the diversity information and convergence degree,” *ACTA ELECTRONICA SINICA*, vol. 46, no. 2, pp. 315-324, 2018.

[27] International Civil Aviation Organization (ICAO), Doc 8643 – Aircraft Type Designators, 4th ed., Montreal, QC, Canada: ICAO, 2023.

[28] Federal Aviation Administration, Advisory Circular 90-23J: Aircraft Wake Turbulence, Washington, D.C., USA: U.S. Department of Transportation, 2020.

[29] Airbus S.A.S., Aircraft Characteristics - Airport and Maintenance Planning, Blagnac, France: Airbus, 2023.

[30] Boeing Commercial Airplanes, Airplane Characteristics for Airport Planning, Seattle, WA, USA: Boeing, 2023.

[31] CFM International, CFM56 series Engine Specifications, Cincinnati, OH, USA: CFM International, 2023.

[32] International Aero Engines, V2500 Product Information, East Hartford, CT, USA: International Aero Engines, 2023.

[33] Rolls-Royce plc, The Trent series Engine, Derby, England: Rolls-Royce plc, 2023.

[34] General Electric Aviation, GE90 Engine, Cincinnati, OH, USA: GE Aviation, 2023.

[35] General Electric Aviation, GEnx Engine, Cincinnati, OH, USA: GE Aviation, 2023.

[36] Pratt & Whitney, PW4000 Engine Series, East Hartford, CT, USA: Pratt & Whitney, 2023.

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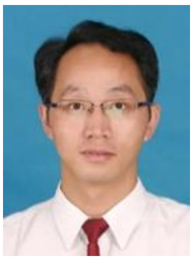

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