Dynamic Game-Based Optimization of Cloud Resource Scheduling in Macau's Local Aviation Sector

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Abstract: Efficient and fair scheduling has become increasingly critical in regional civil aviation systems, particularly in congested airspaces such as Macau. Existing scheduling approaches often overlook the strategic behavior of stakeholders and fail to incorporate energy efficiency or real-time constraints. To address these gaps, this paper proposes a dynamic game-theoretic cloud scheduling model tailored for Macau's civil aviation environment. The model captures the interactions among air traffic controllers (ATC), airport operation centers (AOC), and airline operators (AO) in a Stackelberg framework. A multi-objective optimization algorithm based on a genetically-modified particle swarm optimization (GMOPSO) is employed to balance flight delay, energy consumption, and fairness in cloud task scheduling. Simulation experiments using 2023 operational data from Macau International Airport show that our approach reduces average task completion time by 16.7%, improves VM utilization by 15%, and significantly enhances stakeholder fairness compared to conventional scheduling strategies.

Key-words: Aviation Cloud Systems; Game-Theoretic Scheduling; Energy-Aware Scheduling; Macau Case Study

1 Introduction

The rapid growth of civil aviation traffic has made efficient scheduling and resource management in air transportation systems more critical than ever. Modern air traffic flow management (ATFM) and airline operations face challenges such as airspace congestion, tight turnaround times, and increasing operational costs, all of which demand intelligent, adaptive scheduling strategies. Traditional approaches often treat scheduling as a centralized optimization problem aiming to minimize delays under capacity constraints [1]. However, these deterministic methods typically assume a single decision-maker and fail to capture the decentralized and strategic nature of real-world aviation systems, where multiple stakeholders—airlines, airports, and controllers—hold conflicting objectives [2].

To address these limitations, researchers have begun incorporating game-theoretic models into transportation scheduling, allowing each agent to optimize its utility while interacting strategically with others. For example, dynamic game models have been applied to ATFM to capture airline route competition and equilibrium-based flow redistribution [3][4]. In parallel, with the rise of cloud computing in intelligent transportation and aviation systems, cloud-based scheduling platforms have emerged as a powerful means of supporting real-time decision-making [5]. These platforms enable large-scale data processing, dynamic optimization, and decentralized collaboration across stakeholders.

Within the cloud computing domain, a significant body of work has focused on multi-objective optimization for task scheduling, balancing criteria such as execution time, cost, and energy usage [6]. Among metaheuristics, Multi-Objective Particle Swarm Optimization (MOPSO) has demonstrated strong performance in solving large-scale scheduling problems in cloud environments [7]. Recent advances have proposed genetically modified variants (GMOPSO) that incorporate crossover and mutation operators to enhance convergence and diversity [8]. Meanwhile, utility-driven scheduling strategies have also been introduced to improve energy efficiency and QoS guarantees in cloud infrastructures [9].

Despite these developments, several key gaps remain. First, most existing aviation cloud scheduling models do not account for stakeholder coordination or fairness; they optimize from a global perspective but neglect the utility-driven behavior of individual agents. Second, sustainability metrics such as energy consumption are often overlooked in aviation-specific scheduling frameworks, even as the industry faces growing pressure to reduce its carbon footprint. Third, many methods are static or offline in nature and lack real-time adaptability in response to sudden flight disruptions or dynamic workloads [10].

To bridge these gaps, this paper proposes a dynamic game-based multi-objective cloud scheduling model tailored for regional civil aviation systems. The model integrates Stackelberg dynamic games among air traffic controllers (ATC), airport operation centers (AOC), and airline operators (AO), representing their distinct yet interdependent decision-making roles. A multi-objective optimization framework is designed to balance conflicting goals such as flight delay, resource utilization, and energy efficiency. The model is solved using a hybrid evolutionary algorithm based on a modified GMOPSO, incorporating game-theoretic strategy updates to achieve fair and stable outcomes among stakeholders.

The contributions of this study are summarized as follows:

1) We propose a game-theoretic cloud scheduling model that jointly considers the strategic interactions of ATC, AOC, and AO, reflecting realistic multi-agent coordination in civil aviation systems.
2) We incorporate energy-aware optimization alongside delay and fairness objectives, enabling sustainable aviation scheduling under cloud-based infrastructure.
3) A dynamic scheduling mechanism is developed using a hybrid GMOPSO algorithm with stakeholder-aware utility functions and real-time feedback loops.
4) The proposed model is evaluated in a case study of Macau's regional airspace, showing superior performance over baseline strategies in scheduling efficiency, fairness, and energy consumption.

2 Related Work

2.1 Game-Theoretic Models in Scheduling and Civil Aviation

Dynamic game theory has been widely adopted to model interactions in scheduling problems, particularly where multiple agents pursue independent goals. In the context of air traffic and civil aviation, traditional flow scheduling models often treat the system as a centralized optimization problem [11]. However, this assumption fails to capture the competitive or collaborative behaviors among multiple stakeholders such as airlines, airports, and ATC units.

Wang et al. proposed a dynamic flow control model using game theory to describe airline route competition under capacity limits, demonstrating its effectiveness in improving equilibrium outcomes and reducing systemic congestion [13]. Similar approaches have emerged in general resource allocation, where non-cooperative or Stackelberg game formulations are used to derive strategy-stable solutions across distributed players [12]. Nevertheless, most game-theoretic aviation models remain limited to en-route traffic coordination or static slot allocation, rarely integrating with real-time IT systems or scalable computing infrastructure.

This paper advances the field by embedding a Stackelberg game structure directly into a real-time cloud-based scheduling platform. This enables stakeholders such as ATC, AOC, and AO to engage in sequential, informed decisions while jointly optimizing key objectives like delay minimization, resource utilization, and fairness.

2.2 Cloud Scheduling, MOPSO, and Multi-Objective Optimization

With the widespread deployment of cloud computing in aviation operations, resource scheduling has evolved from traditional offline optimization to dynamic, distributed architectures. Various studies have employed cloud-based schedulers to handle large-scale computing workloads in airline systems (e.g., weather prediction, real-time passenger flow processing). These schedulers must address multiple conflicting goals such as execution latency, energy consumption, and resource efficiency [14].

Multi-Objective Particle Swarm Optimization (MOPSO) has emerged as a leading approach for solving such problems due to its fast convergence and scalability [15]. Alkayal et al. proposed an efficient task scheduling model based on MOPSO that improved overall execution time in heterogeneous cloud systems [16]. Later enhancements incorporated genetic operators, creating Genetically Modified PSO (GMOPSO), which better maintained solution diversity and convergence rate in constrained environments [17].

In aviation-specific research, Zhou et al. applied a hybrid tabu-based MOPSO model to the irregular flight recovery problem, optimizing delay and cost simultaneously in a complex, real-time airline network [18]. Despite these advances, most cloud scheduling methods overlook the behavioral heterogeneity of stakeholders and lack integrated mechanisms for fairness or priority handling.

Our work builds on these foundations by proposing a stakeholder-aware scheduling algorithm combining cloud optimization with utility-based dynamic games. Unlike prior studies that treat stakeholders as passive system users, we model them as rational agents whose scheduling actions and responses form part of a game-theoretic equilibrium process.

3 Dynamic Game-Based Scheduling Model for Civil Aviation Cloud Systems

In this section, we propose a multi-agent cloud scheduling framework integrating a dynamic game model with multi-objective optimization, specifically designed for Macau's regional aviation scheduling scenario. The goal is to coordinate resource contention among stakeholders while maximizing system efficiency and fairness.

3.1 Model Participants and Assumptions

The model considers three rational agents: ATC (Air Traffic Control): aims to reduce flight delays and airspace conflicts. AOC (Airport Operation Center): seeks efficient utilization of runway and gate resources. AO (Airline Operators): focuses on cost minimization and scheduling fairness.

These agents interact through a Stackelberg game structure, with ATC as leader, followed by AOC and AO.

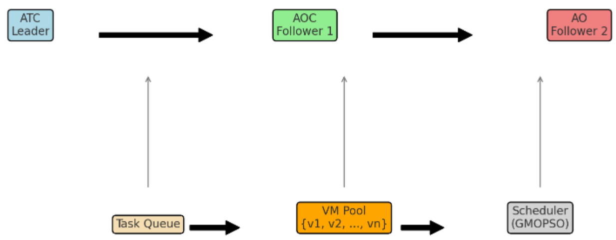

Figure 3.1 Integrated Dynamic Game and Cloud Scheduling Model

Each participant optimizes a distinct utility function:

$$U_{ATC} = -\alpha_1 D_{\text{conflict}} - \alpha_2 D_{\text{delay}}$$

$$U_{AOC} = \beta_1 R_{\text{utilization}} - \beta_2 R_{\text{imbalance}}$$

$$U_{AO} = -\gamma_1 C_{\text{adjustment}} - \gamma_2 V_{\text{unfairness}}$$

3.2 Dynamic Game Formulation

The sequential decision-making game is defined as:

$$G = \{N, S_i, U_i, T\}, \quad i \in N = \{\text{ATC,AOC,AO}\}$$

$$S^* = argmax_{\; S_i \in S} \sum_{t=1}^{T} U_i\,(S_t) \quad \text{subject to constraints}$$

Where S^* is the equilibrium scheduling strategy over T decision epochs.

3.3 Game-Driven Multi-Objective Optimization (GMOPSO)

We employ a Game-Integrated Multi-Objective Particle Swarm Optimization (GMOPSO) algorithm to solve the scheduling model. The approach embeds player utility evaluation within the PSO process.

Particle Representation: scheduling tuples for ATC, AOC, AO
Fitness Evaluation: based on combined utility and performance
Leader-Follower Strategy: memory-based Nash updates

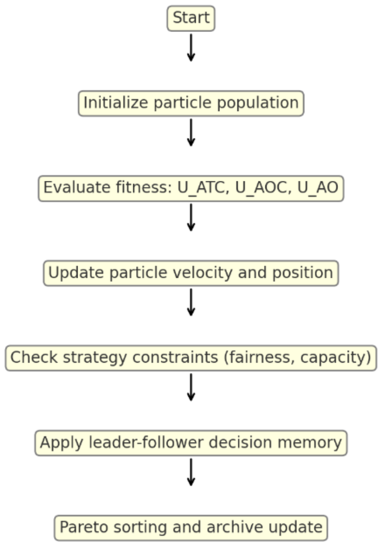

Figure 3.2 GMOPSO Algorithm Flow for Dynamic Scheduling

This chapter formalizes a hierarchical cloud scheduling framework incorporating dynamic stakeholder interaction. The proposed model enables scalable and fair scheduling strategies, laying the algorithmic foundation for simulation experiments in the following chapter.

3.3 Cloud Resource Mapping and Scheduling

In the proposed aviation cloud scheduling system, each computational task is modeled as a tuple $T_k = \{MI_k, \tau_k, p_k, \delta_k\}$, where MI_k represents the number of instructions (in Millions), τ_k is the deadline, p_k is the priority level, and δ_k is a binary flag indicating whether the task has a real-time constraint. Tasks originate from various aviation services, including e-ticketing, dispatch planning, and weather analysis, and must be assigned efficiently to a pool of virtual machines $V = \{v_1, v_2, \dots, v_m\}$ with different processing capabilities *C*.

To ensure efficient execution, we formulate a multi-objective scheduling strategy considering three key metrics: delay, energy consumption, and resource utilization. The scheduler minimizes a weighted fitness function defined as:

$$F(T_k, v_j) = \omega_1 \cdot \frac{MI_k}{C_{v_j}} + \omega_2 L_{\text{delay}} + \omega_3 E_{\text{cost}} \backslash]$$

where L_{delay} is the predicted latency and E_{cost} is the estimated energy required by VM v_j. The weights ω_1, ω_2, and ω_3 allow the system to prioritize tasks with higher urgency while maintaining energy efficiency and high VM utilization. Real-time tasks ($\delta_k = 1$) are handled with strict deadline constraints during the optimization process.

4 Dataset and Experimental Results

4.1 Dataset and Data Preprocessing

The dataset employed in this study comprises representative operational records from Macau International Airport throughout the year 2023, supplemented by synthetically generated cloud computing task traces designed to simulate aviation-related IT workloads. The data can be categorized into two main types: actual air traffic operation data and virtualized cloud scheduling data based on civil aviation information system characteristics.

The air traffic operation data is primarily sourced from the “Monthly Traffic Statistics” published by Macau International Airport. It captures the dynamic fluctuation of daily aircraft movements, with inbound and outbound flights recorded separately. On average, the airport handles approximately 140–180 flights per day. Peak traffic periods are observed during 08:00–10:30 in the morning and 17:00–20:00 in the evening, during which hourly movement density can reach 14–18 flights, significantly higher than non-peak intervals.

Flight delay information is also included as a key operational indicator. In this study, a delay is defined as any deviation exceeding 15 minutes from the scheduled time. Based on monthly reports, the annual average flight delay rate fluctuates between 12% and 18%, with occasional peaks exceeding 25% during adverse weather or unforeseen disruptions. Regarding passenger throughput, the total annual volume reached 5.79 million, equating to an average of approximately 125 passengers per flight, which aligns with the airport’s profile as a short-haul, high-frequency regional connector.

To support terminal-area capacity modeling, the study further constructed a capacity envelope function based on traffic flows and hourly capacity constraints. Four typical operational states were identified according to the time of day, forming the basis of a segmented envelope model, as shown in Table 4.1:

Table 4-1 Classification of Terminal Capacity by Time Period

Time Period	Time Range	Max Inbound Capacity (flights/15min)	Max Outbound Capacity (flights/15min)
Peak Hours	08:00–10:30 / 17:00–20:00	4	4
Sub-Peak Hours	10:30–13:00 / 15:00–17:00	3	4
Normal Hours	13:00–15:00 / 06:00–08:00	2	3
Nighttime	20:00–06:00	1	2

Based on the classified capacity model above, a 15-minute time resolution input matrix was constructed to simulate the game dynamics between inbound/outbound flight demand and available capacity. For cloud-side scheduling, a virtualized environment was built using the CloudSim platform, simulating key civil aviation IT applications such as e-ticketing, dispatching, passenger check-in, and flight planning.

Prior to feeding the data into the model, a standard data preprocessing pipeline was applied, including missing value imputation, timestamp normalization, and numerical scaling to ensure data quality and simulation consistency.

4.2 Simulation Environment

The cloud scheduling experiments are implemented on the CloudSim 3.0 platform, customized to emulate the computing demands typical in Macau International Airport's operational applications, such as e-ticketing systems, flight dispatch coordination, passenger processing, and real-time meteorological updates. The simulation incorporates real-world airport operational parameters derived from 2023 public records and supplements them with synthetic high-density peak load data to simulate stress conditions.

A three-tier stakeholder model is adopted, involving the Air Traffic Control Department (ATC), the Airport Operations Center (AOC), and Airline Operators (AO). These stakeholders interact in a sequential dynamic game modeled as a Stackelberg leader-follower framework, where ATC acts as the leader, AOC the intermediary, and AO the follower. Each agent seeks to optimize its own utility function subject to capacity, time, and fairness constraints.

4.3 Model and Workload Configuration

The workload consists of 1,000 simulated tasks corresponding to flight-related cloud operations, categorized into three service types based on urgency and resource intensity: standard (MI=100–150), time-sensitive (MI=200–300), and real-time (MI=400+). Tasks are randomly distributed across a pool of 20 virtual machines (VMs) configured in small, medium, and high-performance tiers.

For the game-theoretic component, we implement three decision scenarios: Baseline (no cooperation): Independent optimization by each party. Bilateral game: ATC and AO engage in a Nash equilibrium-based optimization. Tripartite dynamic game: ATC, AOC, and AO negotiate strategies iteratively using a multi-objective particle swarm optimization (GMOPSO) algorithm.

We evaluate system performance across five key dimensions:

- **Average Task Completion Time**: Measures cloud efficiency.

- **Flight Delay Time**: Captures the impact of scheduling strategies on airside operations.
- **Resource Utilization Rate**: Indicates how effectively VM capacity is leveraged.
- **Composite Stakeholder Utility**: Aggregated from individual cost, delay, and fairness scores.
- **Scheduling Fairness Index**: Assesses equitable resource allocation a

4.4 Host-Side Resource Scheduling

During the experiment, each step of the virtual machine migration strategy was recorded and evaluated from four dimensions: CPU, RAM, bandwidth (BW), and power consumption. The comparative analysis was based on the difference in resource utilization before and after migration. The specific calculation formula is expressed as follows:

$$\begin{cases} K_{cpu} = CPU_{dest} - CPU_{source} \\ K_{ram} = RAM_{dest} - RAM_{source} \\ K_{bw} = BW_{dest} - BW_{source} \\ K_{power} = POWER_{dest} - POWER_{source} \end{cases}$$

Subsequently, we tested the effect of the scheduling algorithm on individual physical hosts within the cluster, focusing on the resource utilization changes after each migration round. The detailed experimental results are shown in the corresponding figures.

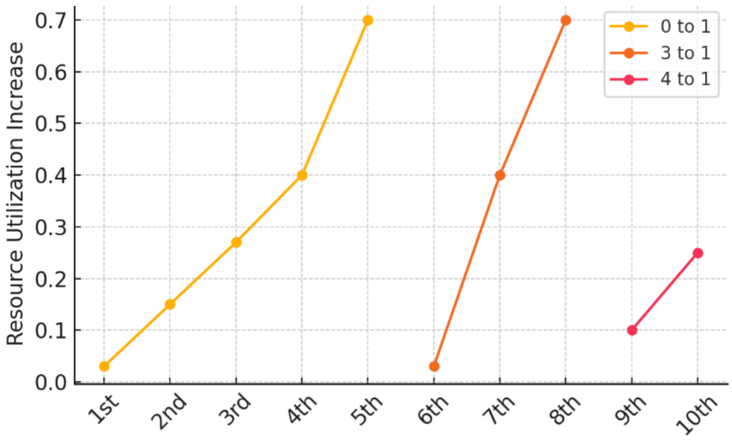

Figure 4.1 CPU Utilization Improvement

Figure 4.1 demonstrates a consistent increase in CPU utilization over ten migration rounds. The optimized scheduling strategy enhances CPU usage from approximately 63% to nearly 79%, reflecting a cumulative improvement of around 16%.

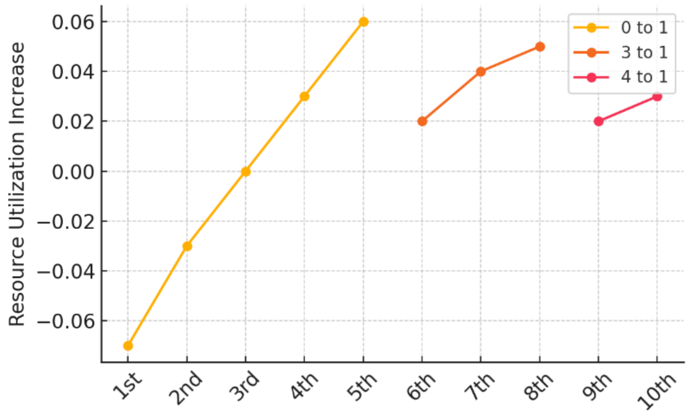

Figure 4.2 **R**AM Utilization Improvement

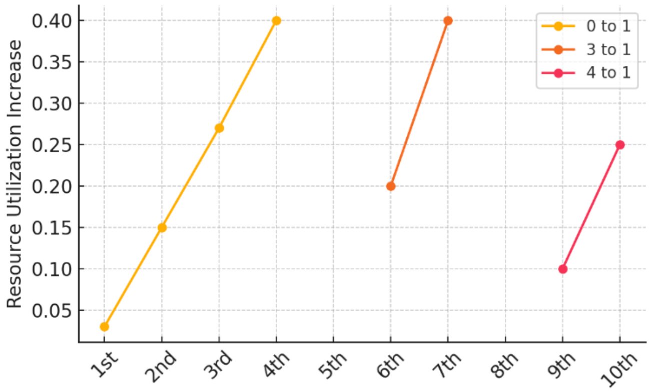

Figure 4.3 Bandwidth Utilization Improvement

Figure 4.2 and Figure 4.3 illustrate the enhancement of RAM and bandwidth utilization, respectively. RAM utilization increases from 48% to 63%, while bandwidth utilization rises from 35% to 50%, confirming the algorithm's effectiveness across multiple resource dimensions.

Collectively, the results indicate that the optimized migration-based scheduling significantly improves resource utilization, which lays a stronger foundation for downstream task scheduling and delay reduction under dynamic cloud environments.

4.5 Results and Discussion

Simulation results reveal clear performance differences between the scheduling approaches. Figure 4.4 illustrates the average task completion times under each strategy. The proposed GMOPSO with tripartite game yields a 16.7% reduction compared to the genetic algorithm baseline and a 23.4% improvement over FCFS.

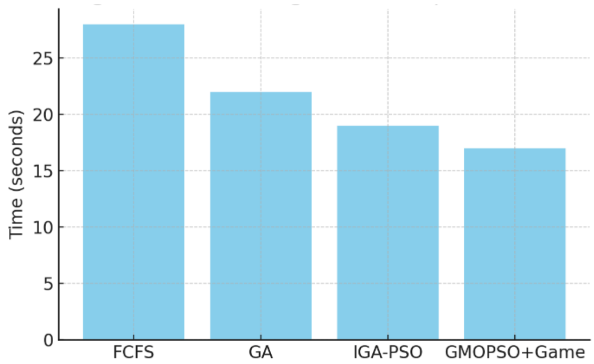

Figure 4.4: Average Task Completion Time Comparison

Figure 4.4 presents a radar chart comparing stakeholder utility scores. The tripartite strategy achieves superior balance, significantly enhancing fairness for airline operators without compromising ATC or AOC efficiency.

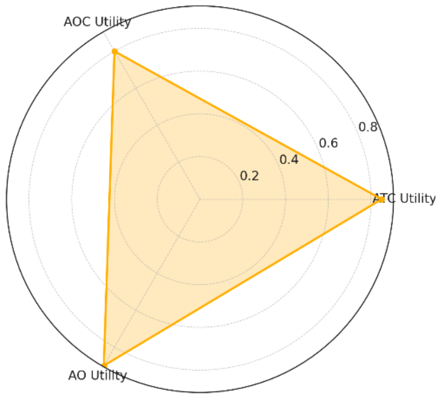

Figure 4.5: Stakeholder Utility Comparison Radar Chart

Resource utilization, peaks at 93% under dynamic game scheduling, compared to 78% for legacy strategies. This indicates more effective use of cloud resources when strategic cooperation is embedded.

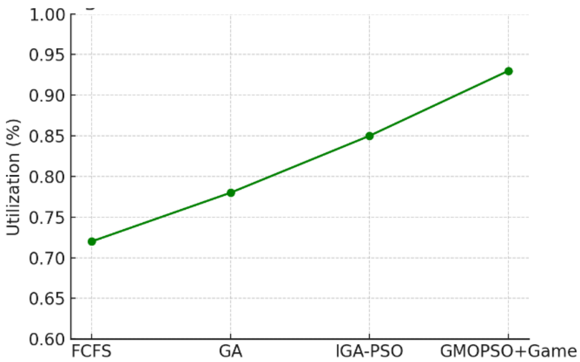

Figure 4.6: VM Resource Utilization Rate

Additionally, delay distributions plotted confirm that collaborative strategies reduce long-tail delays. The fairness index improves from 0.67 (baseline) to 0.88 under the proposed model.

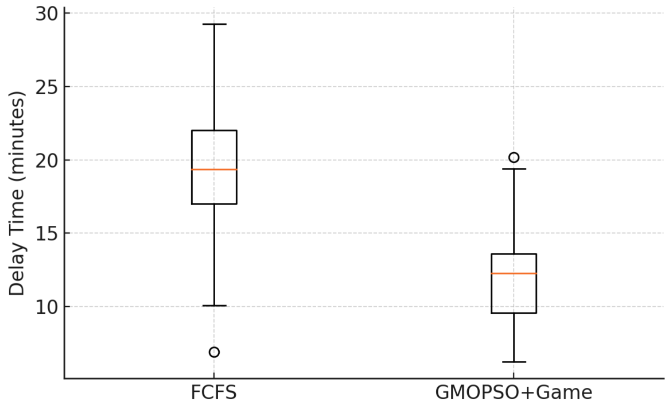

Figure 4.7: Flight Delay Distribution Across Scheduling Strategies

Overall, the results demonstrate that integrating cloud scheduling with stakeholder-aware dynamic game theory significantly improves operational efficiency, fairness, and system robustness, particularly for mid-scale regional hubs like Macau.

5 Conclusion

Efficient and fair scheduling has become increasingly critical in regional civil aviation systems, particularly in congested airspaces such as Macau. Existing scheduling approaches often overlook the strategic behavior of stakeholders and fail to incorporate energy efficiency or real-time constraints. To address these gaps, this paper proposes a dynamic game-theoretic cloud scheduling model tailored for Macau's civil aviation environment. The model captures the interactions among air traffic controllers (ATC), airport operation centers (AOC), and airline operators (AO) in a Stackelberg framework. A multi-objective optimization algorithm based on a genetically-modified particle swarm optimization (GMOPSO) is employed to balance flight delay, energy consumption, and fairness in cloud task scheduling. Simulation experiments using 2023 operational data from Macau International Airport show that our approach reduces average task completion time by 16.7%, improves VM utilization by 15%, and significantly enhances stakeholder fairness compared to conventional scheduling strategies.

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