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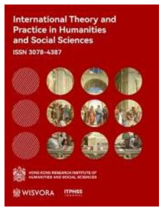

Optimization of Flight Frequency for an eVTOL Network Connecting Disconnected High-Speed Rail Corridors and Urban Area

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Abstract

The rapid advancement of eVTOL technology offers a novel solution for enhancing commuting efficiency across complex geographical barriers, thereby accelerating the construction and development of 3D transportation infrastructure. However, the planning and development of an eVTOL operational network rely heavily on detailed passenger flow analysis and strategic decision-making regarding flight frequencies. This paper integrates the classic Multinomial Logit model from transportation planning to estimate route-specific passenger demand. With the objective of maximizing the global unit profit for the eVTOL operator, an optimization model for flight frequency scheduling is established. A Genetic Algorithm, tailored to the model's structure, is designed to calculate the dispatch headways for eVTOLs on each route. A case study, based on the "Xiangtan Urban Area - Zhuzhou West Railway Station - Xiangtan North Railway Station" bidirectional loop eVTOL network, validates the approach. The optimal flight frequencies for each route are derived through computations that account for competition with various transportation modes. Sensitivity analysis reveals that operators must prioritize marketing effectiveness for highly time-sensitive passengers. Furthermore, performing more flexible, dynamic flight adjustments based on accurate predictions of commuter flow is essential for comprehensively improving operational performance.

1 Introduction

In recent years, with the rapid advancement of global aviation technology and the gradual liberalization of low-altitude airspace management policies, the low-altitude economy has become an important direction for transportation system transformation and industrial upgrading in many countries. Since 2020, the U.S. Federal Aviation Administration (FAA) has released multiple guidance policies on Advanced Air Mobility (AAM), actively promoting pilot operations of Electric Vertical Takeoff and Landing (eVTOL) aircraft in urban commuting and short-haul transport scenarios (Federal Aviation Administration, 2020). In Europe, the European Union Aviation Safety Agency (EASA) has established airworthiness and operational standards for eVTOL aircraft (European Union Aviation Safety Agency, 2023), with several member states launching urban air mobility corridor construction and validation projects. Since 2023, China has successively issued national-level policy documents such as the Guidelines for High-Quality Development of the Low-Altitude Economy and the Implementation Plan for the Innovative Application of General Aviation Equipment (2024–2030), positioning the low-altitude economy as a key strategic emerging industry (State Council Office, 2023). These policies explicitly call for accelerating the establishment of a new type of air transportation system represented by eVTOL, promoting the construction and demonstration of low-altitude route networks within urban clusters. Consequently, the low-altitude economy has entered a stage of unprecedented development opportunities, with eVTOL-based short-distance passenger transport emerging as a key pathway to enhance the efficiency and spatial connectivity of urban agglomerations. Many regions are now actively building eVTOL take-off and landing infrastructure, and low-altitude short-haul aviation networks are gradually taking shape.

As a critical component of the low-altitude economy, eVTOL aircraft, characterized by vertical take-off and landing capability, low noise, zero emissions, and high maneuverability, exhibit distinct advantages in short-distance passenger transportation. Compared with traditional ground-based transportation, eVTOLs can traverse natural and man-made obstacles along direct, high-speed trajectories, achieving point-to-point connectivity. This advantage is particularly pronounced in regions with complex topographical conditions. For example, between certain cities along the Yangtze River, eVTOLs can fly directly across the river, avoiding time-consuming detours via bridges or ferries (Ministry of Industry and Information Technology et al., 2024); in northwestern areas such as Qingyang and Yan'an (Qingyang Local News, 2025), where loess plateaus are deeply dissected by valleys, eVTOLs can effectively connect dispersed counties, significantly improving travel efficiency; and in coastal and island regions, such as the Zhoushan Archipelago or around Shenzhen's Dapeng Peninsula (Tencent News, 2024), eVTOL routes can enable rapid inter-island commuting, offering convenient options for tourism, emergency response, and daily transportation (Liu, 2021). Meanwhile, human-made barriers in urban areas have also become increasingly severe. By bypassing ground-level congestion, eVTOLs can establish aerial express routes between urban cores and peripheral districts, providing high-value services for time-sensitive business travel, medical transport, and daily commuting (Guangdong Trans., 2024).

However, despite the rapid development of China's high-speed rail and trunk transport systems, some regions still face local bottlenecks characterized by "macro-level connectivity but micro-level constraints." Although many high-speed rail lines intersect at major hubs, interconnection between adjacent stations on different lines remains incomplete, limiting regional transfer efficiency. For instance, in Hunan Province, Xiangtan North Station and Zhuzhou West Station lie on two separate high-speed rail lines, which are the Beijing–Guangzhou and Shanghai–Kunming lines respectively, only 30 km apart, yet without a direct railway link. Passengers transferring between these two lines must typically detour via larger junctions such as Changsha South Station, increasing travel time and operational costs. Geographically, Xiangtan North Station is located in Yisuhe Town (northern Xiangtan County), while Zhuzhou West Station is situated in Lukou Town (west of Lusong District). Though the two are connected by expressway, ground traffic is often hindered by congestion and interregional restrictions, making it difficult to meet the high-efficiency demands of high-speed rail transfers and regional travel. This phenomenon, as spatial proximity but functional disconnection, is common across multiple Chinese urban clusters, constraining both high-speed rail network synergy and urban integration.

Furthermore, most high-speed rail stations in China are located in peripheral or suburban areas due to geographical, cost, and planning factors, forcing passengers to spend significant time on surface transfers before and after train travel. This not only raises passengers' time and financial costs but also diminishes the overall timeliness and attractiveness of the high-speed rail system. As urban integration accelerates, improving connectivity between city centers and high-speed rail stations has become a key challenge. Therefore, it is imperative to explore a new transportation mode that combines flexibility and speed advantages to shorten ground transfers, enhance travel experience, and promote coordinated development between air and rail systems.

Against this backdrop, establishing eVTOL routes between high-speed rail stations and major urban passenger hubs and organizing a low-altitude commuter shuttle network covering key travel corridors, as illustrated in Figure 1, is a novel attempt to construct a three-dimensional transportation system with significant practical relevance and application value. On one hand, such a network can serve as an efficient supplement to existing rail and ground transport systems, bridging gaps between trunk lines and enabling integrated "air-ground" mobility within urban clusters. On the other hand, eVTOL routes possess adjustable operational flexibility, allowing scheduled or on-demand dispatching based on passenger demand patterns. From an investment and operations standpoint, several scientific questions must be addressed: How can eVTOL flight frequencies be optimally scheduled across routes according to predicted passenger flow to simultaneously satisfy demand balance, ensure inter-route capacity equilibrium, and maximize overall network profitability? This paper proposes an optimization model and solution approach to address this issue, demonstrating the feasibility and economic potential of eVTOL applications within urban transportation systems, while providing theoretical support for policymaking and operational planning in low-altitude passenger transport.

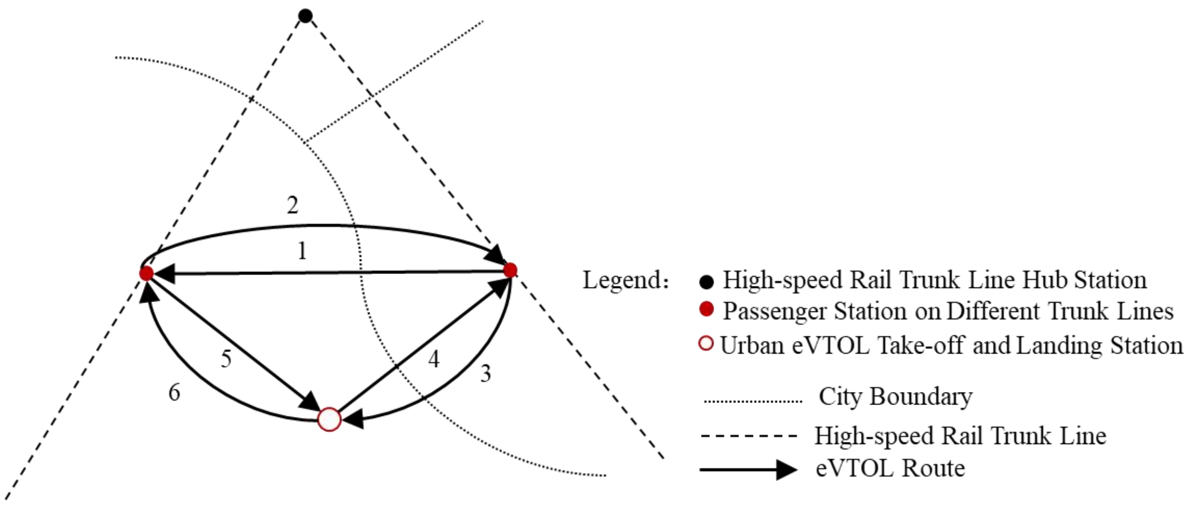

Figure 1: eVTOL Route Network Between Urban Areas and High-speed Rail Stations

2 Mathematical Model

2.1 Problem Description

In the eVTOL route network shown in Figure 1, round-trip flights are established between one urban eVTOL vertiport and two high-speed rail trunk stations, forming six routes labeled by the set $I=\{1,2,3,4,5,6\}$ The total commuter traffic flow between the origin and destination of each route is $\pi_i, \forall i \in I$, and the average utility loss due to commuting time is τ .The eVTOLs on the routes fly at a constant cruise speed v_0 on route i, which has a length of $l_i, \forall i \in I$. The pricing for all routes is based on a fare calculated using an average distance of f_0 . The set of all transportation modes alternative to route i is defined as $K_i, \forall i \in I$, and the transportation mode with the worst utility is denoted as $k^* = arg\min_{k \in K_i} u_{i,k}, \forall i \in I$. The set of transportation modes competing on route i in the operational network planning is $K_i^- = K_i \backslash \{k^*\}, \forall i \in I$. The fare for competing modes is $f_{i,k}, \forall i \in I, \forall k \in K_i^-$, and the commuting time is $t_{i,k}, \forall i \in I, \forall k \in K_i^-$. To ensure operational safety, the minimum safe flight time interval between two consecutive eVTOL flights on the same route is set to τ_0 and the maximum passenger capacity per eVTOL flight is σ_0 . The eVTOL operator needs to meet customers' safe commuting demands while maximizing operational profit by reasonably planning the optimal dispatch frequency for each route circuit.

We define a decision variable as follow:
T_i： The time interval between departures of eVTOL flights on route i， $\forall i \in I$.

To better study the eVTOL dispatch frequency problem refined in this paper, the following assumptions need to be made:

(1) Due to the low altitude of the routes and the use of vertiports for takeoff and landing, the climb and approach/descent times of the eVTOL are negligible;
(2) To improve eVTOL operational efficiency, dwell time at the vertiport is only for necessary boarding and alighting of passengers. This time is very short and negligible in the operational network planning;
(3) Commuting customers are homogeneous, rational decision-makers sensitive to price and commuting time.

2.2 Route Passenger Flow Estimation

To appropriately schedule eVTOL flights for each route, it is necessary to estimate in advance the probability of route i being selected among the passenger group with commuting demands. This probability can be estimated by introducing the classic Multinomial Logit Model (MNL), which was proposed by Lo et al.(2004), from the field of transportation planning. Drawing on the commuter demand estimation framework of Wang et al.(2022), preparatory work for the MNL model estimation involves calculating passenger utilities for different transportation modes: specifically, using the highest utility among existing transportation modes as the upper bound of customer choice utility, and using the difference between this upper bound and the transportation mode with the smallest absolute utility as the relative utility for the remaining modes. The calculation methods for absolute utility and relative utility are as follows:

$$u_{i,k} = -f_{i,k} - \tau t_{i,k}, \quad \forall i \in I, \forall k \in K_i \tag{1}$$

$$U_{i,k} = -f_{i,k} - \tau t_{i,k} - \min_{k \in K_i} u_{i,k}, \quad \forall i \in I, \forall k \in K_i^- \tag{2}$$

Different from the relative utility estimation for transportation modes in K_i^- , the passenger relative utility for eVTOL routes must consider not only the flight time but also the maximum passenger waiting time at the vertiport, expressed by the decision variable T_i . Therefore, it is calculated as follows:

$$U_{i,0} = -f_{i,k} - \tau\left(T_i + \frac{l_i}{v_0}\right) - \min_{k \in K_i} u_{i,k}, \quad \forall i \in I \tag{3}$$

Drawing on the MNL model, the passenger choice probability for each route in the competitive market can be calculated:

$$p_i(T_i) = \frac{e^{U_{i,0}(T_i)}}{e^{U_{i,0}(T_i)} + \sum_{k \in K_i^-} e^{U_{i,k}}}, \quad \forall i \in I \tag{4}$$

Consequently, the commuter flow after the opening of route i can be estimated by $p_i(T_i)\pi_i$.

2.3 Route Cost Estimation

The route operating cost for eVTOLs comprises six major categories: energy consumption cost $c_{i,1}$, maintenance and repair cost $c_{i,2}$, operational support and management cost $c_{i,3}$, takeoff and landing infrastructure fees $c_{i,4}$, route insurance premium $c_{i,5}$, and aircraft depreciation cost $c_{i,6}$. The detailed basis for calculation, calculation methods, and numerical values are shown in Table 1 below.

Table 1 Operational Cost Structure of eVTOL Routes

Cost Category	Calculation Method	Sub-item Parameters	Value	Reference Basis
Energy consumption cost $c_{i,1}$	Average energy consumption × Electricity rate	Energy consumption: 0.4 kwh/km; Industrial electricity price: RMB. 1 Yuan/kwh	RMB. 0.1 Yuan/km	German Aerospace Center. (2019); China EV100. (2020)
Maintenance and repair cost $c_{i,2}$	Battery amortization cost + Scheduled maintenance cost	Battery cycle cost RMB. 300,000 Yuan/2,000 times; Single charge range under frequent take-offs and landings:150km; Regular maintenance costs: RMB. 0.5 Yuan/km	RMB. 1.5 Yuan/km	Morgan Stanley. (2021); Xpeng Aeroht.(2024)
Operation and management cost $c_{i,3}$	Single pilot daily salary / Daily flight legs	The daily wage for drivers: RMB. 1,000 Yuan. The maximum daily flight range is 50	RMB. 20 Yuan/Flight range	Civil Aviation Administration of China. (2023)
Takeoff and landing base cost $c_{i,4}$	Per takeoff and landing fee	Initiation and reduction fee: RMB. 300 Yuan	RMB. 300 Yuan/flight range	Shenzhen Urban Transport Planning Center Co., Ltd. (2022)
Trip insurance premium $c_{i,5}$	Annual total premium / Annual flight kilometers	eVTOL: RMB. 200,000 Yuan per aircraft; Annual premium rate: 5% The planned annual flight is 240,000 km	RMB. 0.4 Yuan/km	Joby Aviation. (2024); Lilium. (2024)
Aircraft depreciation cost $c_{i,6}$	(Aircraft price - Residual value) / Depreciation period / Annual flight kilometers	eVTOL: RMB. 200,000 Yuan per aircraft; Residual value at scrapping: 10%; Depreciation period: 8 years; Annual flight distance: 240,000 km	RMB. 1.4 Yuan/ km,	Roland Berger. (2021); McKinsey & Company. (2022)

Based on the cost values in Table 1, the operating cost per flight segment can be calculated as:

$$c_i = (c_{1,i} + c_{2,i} + c_{5,i} + c_{6,i})l_i + c_{3,i} + c_{4,i}, \quad \forall i \in I \tag{5}$$

2.4 Frequency Decision Model

In the low-altitude commuting operational network, eVTOLs are scarce resources and should circulate non-stop among various routes as much as possible. Therefore, the operational network structure needs to be represented by the connectivity specifying the immediate predecessors and successors of each route. Consequently, the route connectivity parameter is defined as follows:

$$\delta_{i,j}=\begin{cases} 0, & \text{Upon completing route } i, \text{ the eVTOL is assigned to route } j. \\ 1, & \text{The eVTOL cannot be assigned to route } j \text{ after completing route } i. \end{cases}, \forall i\in I, \forall j\in I$$

Using the estimated route passenger flow, a frequency decision model is established to maximize the eVTOL operator's profit while satisfying passenger travel demand. The specific model is as follows:

$$\max\sum_{i\in I}\left[f_i p_i(T_i)\pi_i-\frac{c_i}{T_i}\right] \tag{6}$$

$$\text{s.t.}\quad p_i(T_i)\pi_i-\frac{\sigma_0}{T_i}\leqslant 0,\quad \forall i\in I \tag{7}$$

$$v_0 T_i\leqslant M,\quad \forall i\in I \tag{8}$$

$$\sum_{j\in I}\frac{\delta_{i,j}}{T_j}=\frac{1}{T_i},\quad \forall i\in I \tag{9}$$

$$\sum_{j\in I}\frac{\delta_{j,i}}{T_j}=\frac{1}{T_i},\quad \forall i\in I \tag{10}$$

$$T_i\in\mathbb{R}^+,\ \forall i\in I \tag{11}$$

Where Eq.(6) is the objective function, representing the eVTOL operator's goal of maximizing the total profit from all operational routes; Eq.(7) is the constraint for meeting passenger commuting demand on each route, i.e., the total transport capacity per unit time period after the route is opened must be greater than or equal to the estimated passenger flow for that route; Eq.(8) is the safe flight separation constraint on a route, meaning the time interval between two consecutive eVTOL flights on the same route must be greater than the upper bound M for safe flight separation; Eq.(9) and Eq.(10) form the flow balance constraint set. Eq.(9) states that the number of eVTOL flights departing from route i must equal the sum of flights entering all routes connected as successors to route i. Similarly, Eq.(10) states that the number of eVTOL flights entering route i must equal the sum of flights departing from all routes connected as predecessors to route i. Eq. (11) defines the range of the decision variables.

3 Solution Algorithm

Since the objective function expressed by Eq.(6) is non-convex and nonlinear, and it inherently involves a complex fractional structure, while constraints equations, such as Eq.(7), Eq.(9), and Eq.(10), are also fractional. The DFDM model is difficult to solve quickly and effectively using conventional optimization methods. Therefore, this paper designs a suitable genetic algorithm (Sergio et al., 2016) for its solution.

3.1 Solution Encoding and Initial Solution Generation

As the decision variable is a positive real number belonging to continuous variables, this paper adopts the floating-point encoding method to improve the decision-making accuracy of the DFDM model. A feasible solution for the DFDM model can be represented as a string of floating-point numbers, where the flight frequencies for the six routes are designed in ascending order of route number to satisfy constraint Eq.(8), with values within the range. This is illustrated in Figure 2 below.

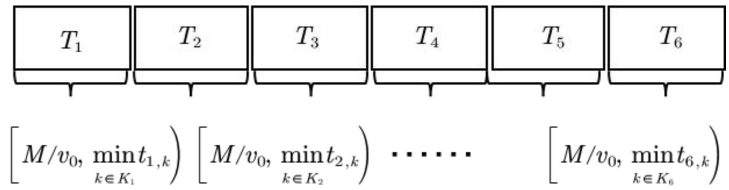

Figure 2 Code Structure of a Gene

However, if an initial feasible solution is generated by randomly selecting a value within the decision variable's range defined by Eq.(8) to enter the genetic evolution framework, the algorithm's convergence might be affected by the poor quality of the initial solution. Therefore, a warm-start method (Zhou et al., 2001) needs to be designed to find a better solution as the initial solution. Referring to Section 2.2, where the worst utility is used as the upper bound for relative utility calculation, using the longest commute time among the alternative transportation modes for a specific route as the upper bound for the decision variable is relatively appropriate. Thus, the initial solution can be calculated by the following Eq.(12):

$$T_i^0 \longleftarrow Rand\left[M/v_0,\ \min_{k\in K_i} t_{i,k}\right),\ \forall i\in I \qquad (12)$$

3.2 Evolution Strategy

Using the objective function, i.e., Eq.(6), as the fitness function, the selection, crossover, and mutation operations were designed. For the selection strategy, a tournament approach was employed to choose 60% of the individuals from the current population to advance to the next iteration. This involved repeatedly sampling a specific number of individuals at random from the current generation and selecting the one with the highest fitness until the quota was filled. Subsequently, in the crossover strategy, two individuals were randomly selected, and genes from three randomly chosen positions were exchanged between them, as depicted in Figure 3. Finally, for the mutation strategy, one individual was randomly chosen, and the genes at two randomly selected positions were regenerated according to the rules shown in Figure 4.

However, new solutions generated by crossover and mutation strategies may not satisfy constraints Eq.(9) and Eq.(10). Therefore, based on the first altered gene point in the original individual, a deduction calculation according to Eq.(9) and Eq.(10) can be performed, gradually adjusting genes at other points to form a new feasible solution before it enters the next iteration.

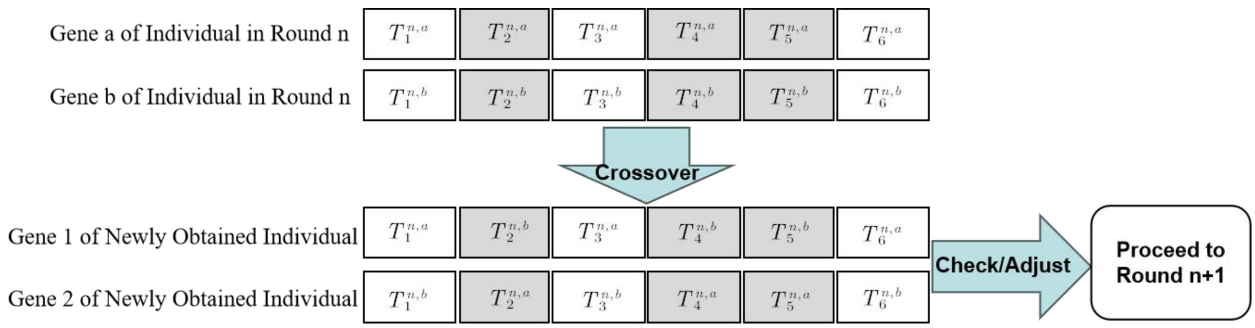

Figure 3 Operational of Crossover

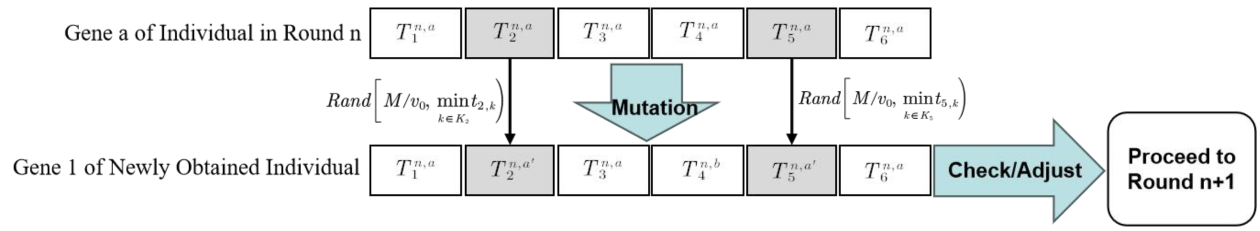

Figure 4 Operational of Mutation

The choice of which strategy to use for evolutionary operations in each iteration is selected using a roulette wheel method. The probabilities for selection, crossover, and mutation operations are set as p^{select}, p^{cross} and p^{muta}, respectively, with $p^{select}+p^{cross}+p^{muta}=1$. A random number between 0 and 1 is generated. If the number falls within the interval $[0,\ p^{select})$ selection is performed; if it falls within $[p^{select},\ p^{select}+p^{cross})$, the crossover is performed; If it falls within the remaining interval, the mutation operation is performed.

3.3 Genetic Algorithm

Setting the stopping iteration count to, the genetic algorithm for solving the DFDM model can be executed according to the computational flowchart shown in Figure 5 below:

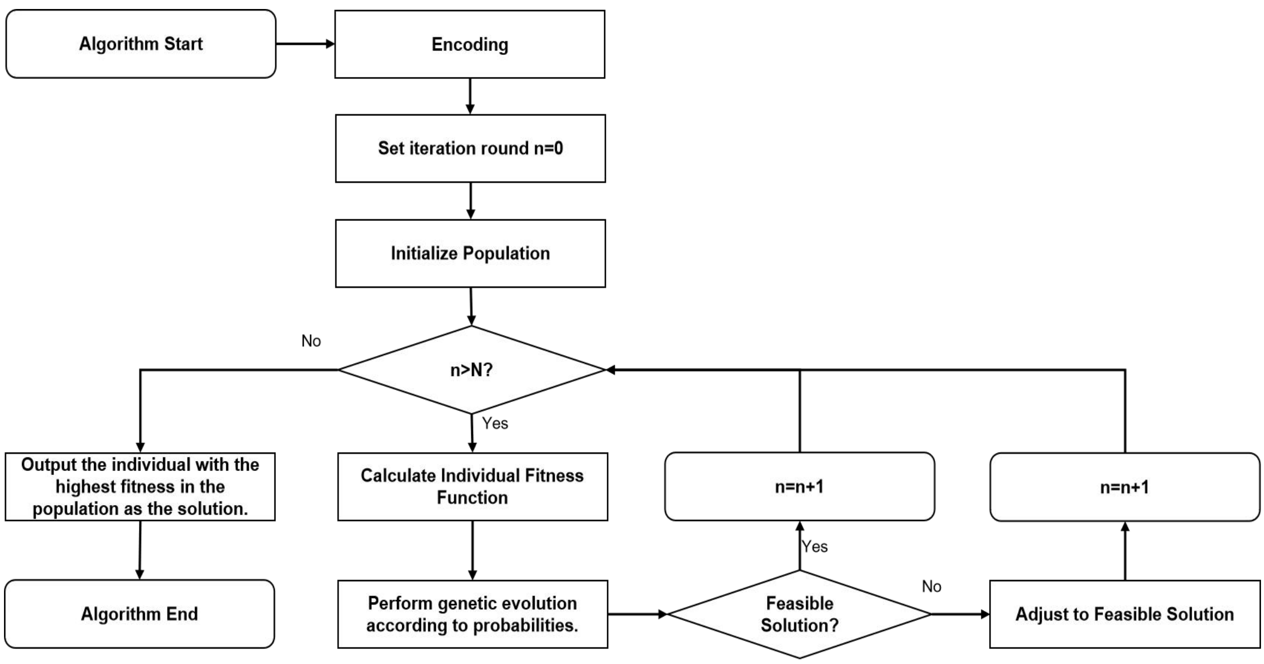

Figure 5 Flowchart of Genetic Algorithm

4 Case Study Verification

A passenger flow of 100 passengers per hour for each route was selected as the baseline commuter passenger flow. Simultaneously, the annual GDP per capita for Xiangtan City in 2024 was converted into the hourly GDP on a workday to serve as the value for. Using the competing transportation modes for each route shown in Table 2 and setting the genetic algorithm's convergence iteration count to 800, a case study verification was conducted. The calculated hourly profit after the operation of the "Xiangtan North Railway Station - Xiangtan City Center - Zhuzhou West Railway Station" loop route reaches RMB. 21,851.05 Yuan, indicating that the short-distance low-altitude commuter service for eVTOL operators between the two high-speed rail trunk stations in Xiangtan has certain development potential. To test potential scenarios after route inauguration, sensitivity analyses were performed on the one-way and round-trip passenger flows for the " Xiangtan North Railway Station - Zhuzhou West Railway Station " route. The test results are reported in Sections 4.1 and 4.2.

Table 2 Competing Transportation Modes for eVTOL Routes

eVTOL Route	Alternative Transportation Modes	Fare Cost/ RMB. Yuan	Commute Time /min	Relative Utility
Xiangtan North - Zhuzhou West (Routes 1 & 2)	Mode 1*: HSR transfer via Changsha South	68.2	57.0	-241.3
	Mode 2: Ride-hailing/Taxi	112.0	35.0	-176.4
	Mode 3: Ride-Passenger Train-Ride Intermodal	90.0	84.0	-244.6
	Mode 4: Bus-Passenger Train-Bus Intermodal	13.0*	141.0*	-272.4*
	Mode 5: eVTOL Route	89.0	$7.0+T_i$	$-101.9-1.84T_i$
Xiangtan City Center - Zhuzhou West (Routes 3 & 4)	Mode 1*: Ride-hailing/Taxi	54.0	23.0	-96.3
	Mode 2: Ride-Passenger Train-Ride Intermodal	66.0*	86.0*	-224.2*
	Mode 3: Bus-Passenger Train-Bus Intermodal	13.0	113.0	-220.9
	Mode 4: eVTOL Route	78.0	$4.0+T_i$	$-85.4-1.84T_i$
Xiangtan City Center - Xiangtan North (Routes 5 & 6)	Mode 1*: Ride-hailing/Taxi	51.0*	25.0*	-97.0*
	Mode 2: Direct Bus	3.0	47.0	-89.5
	Mode 3: eVTOL Route	81.0	$5.0+T_i$	$-92.0-1.84T_i$

Note: * indicates the transportation mode serving as the lower bound for relative utility, with $\tau=1.84$.

4.1 Sensitivity Analysis of Passenger Flow Change on a Single Route

The hourly passenger flow for the "Zhuzhou West Railway Station - Xiangtan North Railway Station" (Route 1) was set to eight different values: 20, 40, 60, 80, 100, 120, 140, and 160. These were sequentially numbered from 1 to 8, and the DFDM model was calculated accordingly. The results obtained are shown in Figure 6 below.

Observation of Figure 6 shows that the change in unit operating profit increases with the increase in passenger flow on the single route, but the growth rate first increases and then slows down. The inflection point of the growth rate change occurs between the two groups with hourly passenger flows of 80-100 people. This indicates that when the total passenger flow is relatively small, the eVTOL operator can adopt marketing methods such as advertising to increase the overall commuter passenger flow across routes and achieve greater profits. When the total passenger flow is relatively large, the eVTOL operator can overcome the profit bottleneck encountered later due to safety capacity constraints by expanding safe capacity through methods such as opening a second route parallel to this one.

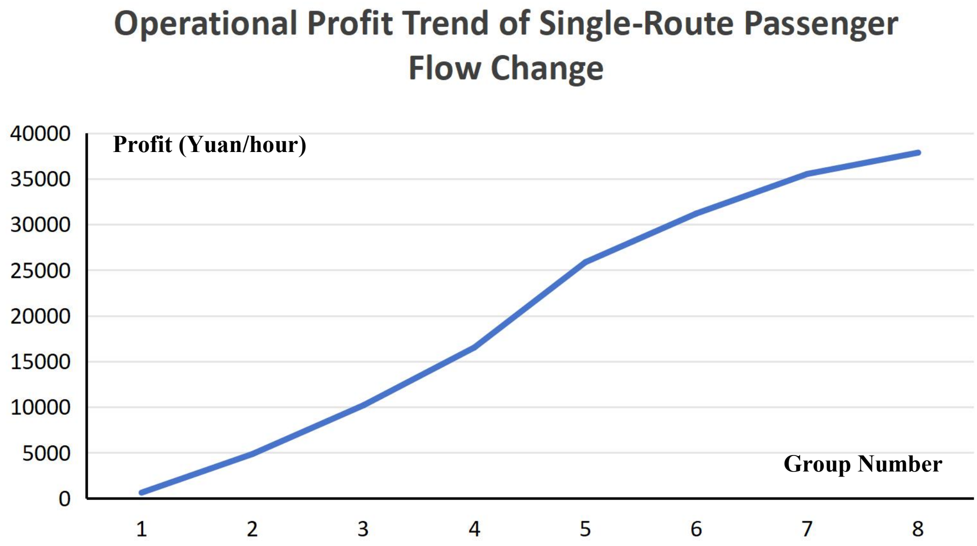

Figure 6 Sensitivity Analysis Results of Passenger Flow Change on a Single Route

4.2 Sensitivity Analysis of Passenger Flow Change on a Round-Trip Route

The passenger flow ratio for the " Zhuzhou West Railway Station - Xiangtan North Railway Station " round-trip routes (Route 1 and Route 2) was varied from 1:1 to 15:1. The specific hourly passenger flow values are shown in Table 3 below. These were sequentially numbered from 1 to 8, and the DFDM model was calculated accordingly. The results obtained are shown in Figure 7 below.

Table 3 Parameter Settings for Passenger Flow Change on a Round-Trip Route

Group Number	Passenger Flow on Route 1 (persons/hour)	Passenger Flow on Route 2 (persons/hour)	Passenger Flow Ratio (Route 1/Route 2)
1	80	80	1：1
2	90	70	9：7
3	100	60	5：3
4	110	50	11：5
5	120	40	3：1
6	130	30	13：3
7	140	20	7：1
8	150	10	15：1

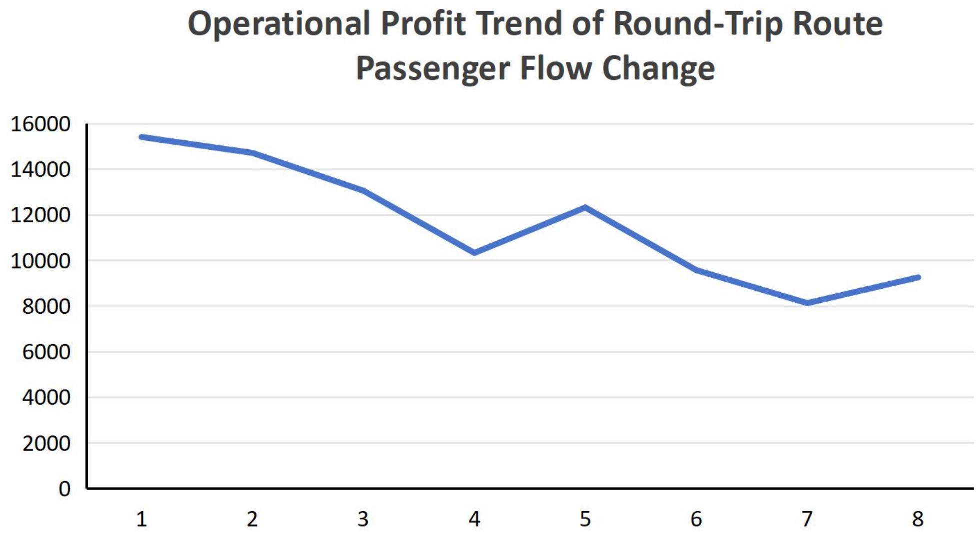

Figure 7 Sensitivity Analysis of Passenger Flow Change on a Round-Trip Route

Observation of Figure 7 shows that the change in unit operating profit decreases as the difference in the passenger flow ratio for the round-trip route increases. This indicates that passenger flow imbalance generally has a negative effect on route frequency design. However, the unit operating profit increases slightly as the round-trip passenger flow ratio approaches 3:1 and 15:1. This reflects the global adjustment effect of the DFDM model; that is, under conditions of extreme passenger flow imbalance, the routes can achieve profitability by optimizing the matching of flight frequencies with other routes to utilize excess capacity. Therefore, eVTOL operators need to flexibly adjust flight frequencies based on short-term, more accurate predictions of the overall commuter passenger flow for the routes to obtain greater profits.

5 Conclusion

The study on eVTOL flight frequency optimization for routes between stations without high-speed rail connections and urban areas reveals that short-distance shuttle routes can constitute a significant market for eVTOL operators. However, this market still faces intense competition from various traditional ground transportation modes (such as taxis/ride-hailing, buses, and intermodal transport). Due to the inclusion of relatively high fixed costs per trip, such as infrastructure costs for take-off and landing and operational management costs, short-distance shuttle routes do not hold a pricing advantage. Relying on the DFDM model established in this study, which integrates market competition and passenger flow prediction for route frequency optimization, and verified through case studies, it is evident that eVTOL operators need to prioritize the marketing quality towards time-sensitive passengers. This should be supplemented by data-driven accurate predictions of route-specific commuter passenger flow to enable more flexible and dynamic flight frequency adjustments, thereby enhancing operational performance. Future research could incorporate robustness analysis of frequency adjustments and explore more complex eVTOL network operation management optimization that integrates dynamic pricing, utilizing accumulated passenger flow data.

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