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Research on airport reservation bus scheduling

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Abstract
Passengers face high costs or multiple transfers when they arrive or depart from the airport. In addition, most transportation modes in a city typically stop operating from midnight to early morning, making it impossible for passengers to enjoy quality and inexpensive services. Considering the passenger detour and muti-types, this paper sets up the passenger detour rebate mechanism and constructs the Airport Reservation Bus (ARB) scheduling model to maximize the profit of ARB enterprise. Meanwhile, an Improved Adaptive Genetic Algorithm (IAGA) is designed to solve the model, where the crossover and mutation operations are optimized to prevent it from falling into local optimum. Finally, a case study shows that ARB costs at least 39% less than taxis, with slightly longer travel time. Compared to traditional GA, IAGA reduced running time by more than 12%, showing faster convergence.

Keywords: airport reservation bus; differential pricing; vehicle scheduling; improved adaptive genetic algorithm.

Investigación sobre la programación de autobuses de reserva en aeropuertos

Resumen
Los pasajeros afrontan altos costos o múltiples trasbordos al viajar al aeropuerto. Además, la mayoría de los medios de transporte urbano cesan su operación de medianoche a primera hora, privando a los pasajeros de servicios económicos y de calidad. Considerando desvíos y tipos mixtos de vehículos, se propone un mecanismo de reembolso por desvío y un modelo de programación de autobuses de reserva aeroportuaria (ARB) para maximizar la rentabilidad. Se diseña un Algoritmo Genético Adaptativo Mejorado (IAGA) optimizando cruce y mutación para evitar el óptimo local. Los casos muestran que el ARB cuesta 39% menos que los taxis con un ligero aumento de tiempo. En comparación con el AG tradicional, el IAGA redujo el tiempo de ejecución en más del 12%, lo que demuestra una convergencia más rápida.

Palabras clave: autobús con reserva de aeropuerto; tarificación diferencial; programación de vehículos; algoritmo genético adaptativo mejorado.

1 Introduction

If the airport connection service is not good enough, it would be inconvenient for passengers. Currently, the public transportation modes from airport to urban area mainly include ‘airport bus + bus/subway’, ‘railway + bus/subway’ and cab, etc., which are difficult to balance the convenience, economy and comfort of travel. Nevertheless, the Airport Reservation Bus in this paper strives for a compromise among the three, while reducing the total social cost, easing traffic pressure and improving the efficiency of passenger distribution.

Fare studies are mainly divided into two categories, fixed fare and differential fare. Regarding fixed fare, Zhou (2001) [1] et al developed a bi-level transit fare optimization method based on line capacity constraints. Borndörfer (2012) [2] et al proposed a nonlinear fare optimization method based on a discrete choice model. However, these studies predominantly adopted fixed fares and overlooked the impact of detours on passenger cost. Due to the unfairness of fixed fare, differential pricing is attracting more and more attentions. Emele (2013) [3] et al introduced a variable pricing mechanism into the fare planning for flexible transport

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services. Kamel (2020) [4] et al constructed a platform for optimizing time-based transit fares in large multimodal transportation networks. Guo (2021) [5] et al established a time-dependent transit pricing model considering elasticity and time-distributed demand. While these studies explored dynamic pricing mechanisms, they seldom connected fare adjustments with detour distances.

Vehicle scheduling is categorized into single-vehicle type and multiple-vehicle type. Concerning the single-vehicle type, Smith (2003) [6] et al established a bi-objective scheduling optimization model based on balancing the maximum number of deviations and minimum unused slack time. Gebeyehu (2008) [7] et al applied the GIS technology to the design of Demand Responsive Transit routes. Ye (2015) [8] et al constructed an optimization model for taxi ridesharing routes. Li (2024) [9] et al proposed a real-time dynamic route planning algorithm for DRT. Notably, these single-vehicle studies overlooked the efficiency potential of mixed fleets, a research dimension that subsequent multi-fleet studies have begun to address. In terms of multi-vehicle type, Golden (1984) [10] et al first proposed the multi-vehicle route planning problem. Tarantilis (2003) [11] et al designed a metaheuristic algorithm to solve it with a fixed vehicle size. Dondo (2008) [12] et al, Barkaoui (2013) [13] et al and Goeke (2015) [14] et al proposed a hybrid local improvement algorithm, improved adaptive genetic algorithm, and hybrid heuristic algorithm respectively. Gasque (2022) [15] et al established two mixed-integer programming models for taking delivery without separation as well as taking delivery with separation and proposed an adaptive large-neighborhood search element heuristic algorithm. Although these multi-vehicle studies optimized routes, they rarely combined mixed types with detour management.

Though existing research has made significant progress in fares and scheduling models, there remain the following problems: the fixed fare is typically adopted, without considering the effect of detours. Concerning vehicle scheduling, scholars pay less attention to the variability of vehicle types. With respect to algorithms, the Adaptive Genetic Algorithm (AGA) is more widely used because of its high robustness and efficiency, while suffers from problems such as premature convergence and local optimization. Aiming at the above problems, this paper simultaneously considers the passenger detour and the mixed vehicle types and proposes a passenger detour rebate mechanism. With the goal of maximizing the profit of the Airport Reservation Bus (ARB) enterprise, then the ARB scheduling model is constructed. Finally, an Improved Adaptive Genetic Algorithm (IAGA) is designed to solve it.

2 Airport reservation bus scheduling model based on passenger detour compensation

2.1 Problem description

The problem is divided into the delivery stage and pick-up stage, described as follows: the delivery stage involves transporting passengers boarding at the airport. In this stage, the origin is fixed at the airport. The pick-up stage is to collect passengers alighting at the airport. According to distance of detours, a fare discount is rebated to detour passengers.

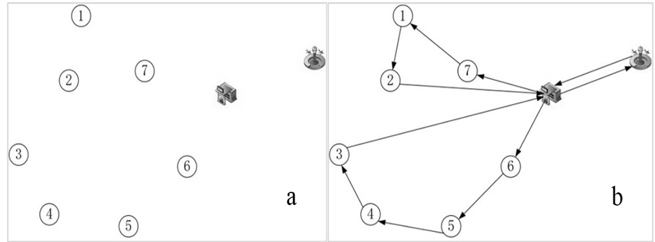

Figure 1. Passengers boarding at the airport and their routes a) Passengers; b) Routes for them
Source: Own elaboration.

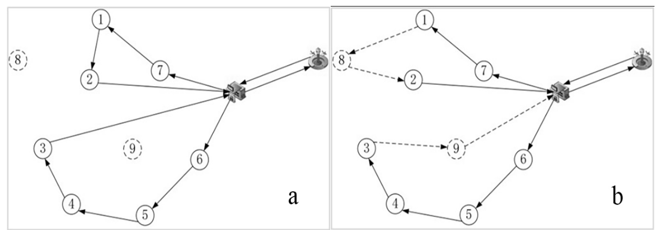

Figure 2. Add passengers alighting at the airport a) Add passengers; b)Final routes
Source: Own elaboration.

The process of generating the routes of the ARB is shown in Fig. 1 (a) – 2 (b). The demands of passengers boarding at the airport and their routes are in Fig. 1 (a) - (b). Based on this, taking passengers alighting at the airport into routing consideration, the final planning is in Fig. 2 (a) - (b).

The solid area in the above figure is for passengers boarding at the airport and the dashed is for passengers alighting at the airport. The ARB delivers passengers to the destination while picking up passengers to the airport. Upon completion of the pick-up and drop-off, the bus returns to the terminal to wait for the next round of pick-ups and drop-offs.

2.2 Model building

2.2.1 Model assumptions

(1) The seat reservations are accepted only between the airport and the points of demand, not between points of demand;

(2) For passengers alighting/boarding at the airport, only their arrival/departure time window at the airport is considered.

(3) The vehicle type and fleet size are known;

(4) Vehicle speed is constant and known.

(5) There is only one airport within the service area.

(6) The vehicle makes only one round trip at a given time.

2.2.2 Definition of parameters

The definition of the parameters involved are in Table 1.

Table 1.
Parameter Definition.

Symbol	Definition
J	Airport.
G	Freeway entrance/exit.
M	The set of boarding and alighting points, m is the total number of points.
K	The set of vehicle types, $K=\{1,2,\dots,h\}$, h is the sequence of the vehicle type.
K_h	The set of the number for vehicles type h, $K_h=\{1,2,\dots,k\}$, k is sequence of the vehicle.
Q	The set of passengers.
Q_a	The set of passengers alighting at the airport.
Q_b	The set of passengers boarding at the airport.
i	The sequence of the point, $i \in M$.
q	The sequence of the passenger, $q \in Q$.
l_{ij}	Ideal distance traveled from point i to point j.
Q_{iJ}^k	Number of passengers for vehicle k from i to the J.
p^k	Fare per kilometer of vehicle k in the urban area.
$g(l_{iJ}^{kf})$	Floating fare for vehicle k from i to J.
C_v	Value of time for passengers.
L_{ij}^k	Actual distance traveled by vehicle k from i to j.
λ_{lim}	Passenger detour coefficient.
C_{h0}	Fixed costs of type h.
N	The service life of the vehicle.
C_{h1}	Variable cost of unit distance for vehicle type h.
C_d	Wage for driver.
V	Speed of vehicle.
t_0	Individual passenger boarding or alighting time.
φ	Penalty cost factor for late arrival of vehicles at the airport.
Q_l^k	Number of passengers late arrival for vehicle k.
T_{dJ}^k	Departure moment of vehicle k from J.
$[T_q^e, T_q^l]$	Expected arrival time window, $q \in Q_a$.
	Expected departure time window, $q \in Q_b$.
Q_{ik}	Number of passengers in vehicle k arriving at point i.
Q_k	Capacity of vehicle k.
T_q^w	Waiting time of passenger q.
T_q^{max}	Maximum tolerated waiting time for passenger q.
T_{max}	Maximum travel time of vehicle.
Y_{ij}^k	1, vehicle k traveling from i to j.
	0, otherwise.
Y_q^k	1, passenger q served by vehicle k.
	0, otherwise.

Source: Own elaboration.

2.2.3 Model assumptions

Route planning is a major task of vehicle scheduling. This paper formulates a route planning model to maximize the profit of ARB enterprises by optimizing operational efficiency. The model introduces a differential pricing mechanism that rebates passengers for detours and imposes penalty fees if their time requirements are unmet. The objective function is defined as:

$$max\, P = R - C_1 - C_2 - C_3 - C_4 \tag{1}$$

Where P, R, C_1, C_2, C_3, C_4 mean profit, fare revenue, fixed cost, variable cost, penalty cost for late arrival and for late departure respectively.

1. Fare revenue R

The fare revenue R consists of the basic fare R_{bf} and the rebate R_r based on mileage pricing.

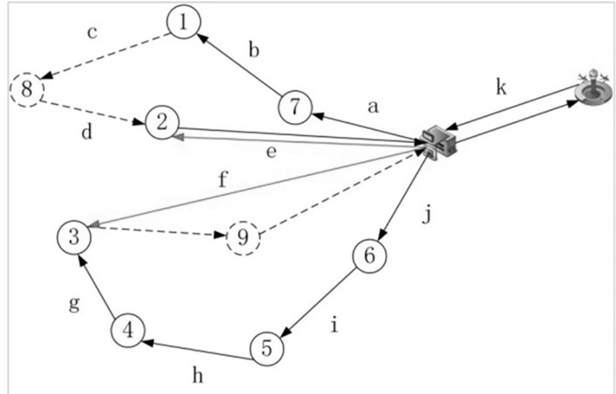

Figure 3 Shortest and actual routes.
Source: Own elaboration.

$$R = R_{bf} - R_r \tag{2}$$

The basic fare R_{bf} is a primary function proportional to the ideal distance of passengers [16-18].

$$R_{bf} = \sum_{h\in K}\sum_{k\in K_h}\sum_{i\in M}\sum_{j\in M}[p^k \cdot l_{iJ} \cdot (Q_{iJ}^k + Q_{Ji}^k)] \tag{3}$$

The rebate R_r is related to the passenger detour distance. The formula proposed in this paper is as follows.

$$R_r = \sum_{h\in K}\sum_{k\in K_h}\sum_{i\in M}[(g(l_{iJ}^{kf}) \cdot Q_{iJ}^k + g(l_{Ji}^{kf}) \cdot Q_{Ji}^k] \tag{4}$$

$$g(l_{iJ}^{kf}) = \begin{cases} [C_v \cdot (L_{iJ}^k - \lambda_{lim} \cdot l_{iJ})]/V, L_{iJ}^k/l_{iJ} \geq \lambda_{lim} \\ 0, L_{iJ}^k/l_{iJ} < \lambda_{lim} \end{cases} \tag{5}$$

When a passenger detour is greater than or equal to λ_{lim}, passenger time delayed by the detour is converted into money and rebated to him. The shortest and actual distance for passengers are shown in Fig. 3.

For passenger 6, the actual distance is ideal distance, so detour does not exist. For passenger 3, whose ideal distance is $f+k$, the actual distance is $g+h+i+j+k$. If $(g+h+i+j+k)/(f+k) > \lambda_{lim}$, it is necessary to rebate him.

2.Fixed cost C_1

Fixed cost C_1 is related to the number of vehicles and their service life [16-18].

$$C_1 = \frac{\sum_{h\in K}\sum_{k\in K_h} C_{h0}}{365N} \tag{6}$$

3. Variable cost C_2

Variable cost C_2 includes fuel consumption and driver cost, which are related to distance [16-18].

$$C_2 = \sum_{h\in K}\sum_{k\in K_h}\sum_{i\in M}\sum_{j\in M}(C_{h1} \cdot l_{ij} \cdot Y_{ij}^k + C_d \cdot (\frac{l_{ij} \cdot Y_{ij}^k}{V} + \frac{\sum_{i\in M} max(Q_{iJ}^k, Q_{Ji}^k) \cdot t_0}{60})) \tag{7}$$

4. Penalty cost for late arrival at the airport C_3

C_3 is the penalty cost for vehicles arriving late at the airport. Since airport passengers are highly time sensitive, late arrival may cause passenger miss their flights and incur a great loss [16-18].

$$C_3 = \begin{cases} \sum_{q\in Q_a}\sum_{h\in K}\sum_{k\in K_h}(\varphi\cdot Y_q^k),(T_{X1} > T_q^l) \\ 0,(T_{X1}\le T_q^l) \end{cases} \quad (8)$$

$$T_{X1} = T_{dJ}^k + \frac{\sum_{i\in M}\sum_{j\in M} l_{ij}Y_{ij}^k}{V} + \frac{\sum_{i=1}^m max(Q_{iJ}^k, Q_{Ji}^k)\cdot t_0}{60} \quad (9)$$

5. Penalty cost for late departure from the airport C_4

C_4 is the penalty cost for a vehicle departing the airport late. If a vehicle leaves the airport later than T_q^l, it will cause the passenger wait too long. The formula proposed is as follows.

$$C_4 = \begin{cases} 0.5\sum_{q\in Q_a}\sum_{h\in K}\sum_{k\in K_h} C_{X2},(0 < T_{dJ}^k - T_q^l \le 5) \\ 0.73\sum_{q\in Q_a}\sum_{h\in K}\sum_{k\in K_h} C_{X2},(5 < T_{dJ}^k - T_q^l \le 20) \\ 100\sum_{q\in Q_a}\sum_{h\in K}\sum_{k\in K_h} C_{X2},(T_{dJ}^k - T_q^l > 20) \end{cases} \quad (10)$$

$$C_{X2} = \left(T_{dJ}^k - T_q^l\right)\cdot Y_q^k \quad (11)$$

2.2.4 Constraints

1. Origin and destination constraints

Vehicles entering and exiting a point of demand are the same.

$$\sum_{i\in M} Y_{ij}^k \le 1,(j\in M, k\in K_h) \quad (12)$$

2. Vehicle capacity constraints

The number of passengers in a vehicle is less than or equal to the its capacity.

$$\begin{cases} Q_{ik}\le Q_k \\ Q_{ik} + Q_{iJ}^k - Q_{Ji}^k \le Q_k \end{cases},(k\in K_h, i\in M) \quad (13)$$

3. Connection service supply constraints

Each demand is served by only one vehicle.

$$\sum_{h\in K}\sum_{k\in K_h} Y_q^k = 1,(q\in M) \quad (14)$$

4. Maximum travel time of vehicle

$$\frac{\sum_{i\in M}\sum_{j\in M} l_{ij}\cdot Y_{ij}^k}{V} + \frac{\sum_{i\in M} max(Q_{iJ}^k, Q_{Ji}^k)\cdot t_0}{60} \le T_{max},(k\in K_h) \quad (15)$$

5. Passenger detour constraints

$$\lambda = \left(\frac{L_{iJ}^k}{V} + \frac{\sum_{i\in M} max(Q_{iJ}^k, Q_{Ji}^k)\cdot t_0}{60}\right)\Big/\frac{l_{iJ}}{V} \le \lambda_{lim} \quad (16)$$

3 Improved adaptive genetic algorithm

The problem studied in this paper is the Vehicle Routing Problem with Time Window constraints, which is a well-known NP-hard problem solved by heuristic algorithms efficiently. Genetic Algorithm (GA) has the advantages of parallelism and global optimization. It continuously generates new individuals and populations in the process of reproduction, and seeks a better solution, which is applicable to the solution of complex optimization problems.

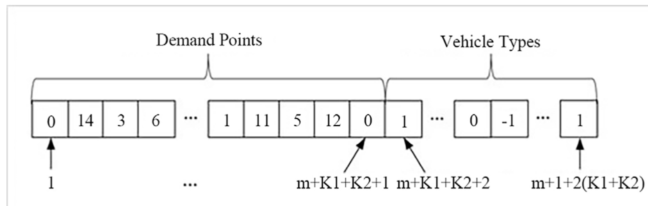

Figure 4 Chromosome coding schematic.
Source: Own elaboration.

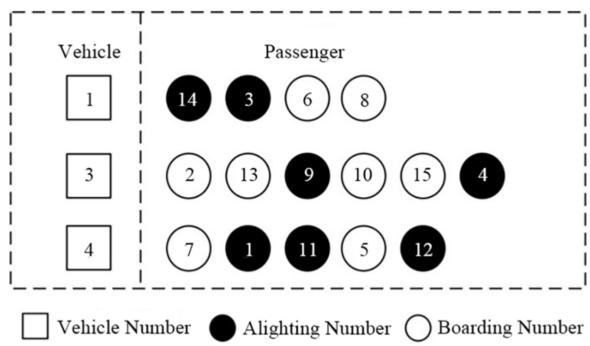

Figure 5 Chromosome coding forms.
Source: Own elaboration.

In the traditional GA, the crossover probability P_c and mutation probability P_m are fixed values. In the process of large-scale problem, the early maturity often occurs. This paper proposes an IAGA to set P_c and P_m as dynamic values, which improves the solving efficiency while setting the minimum value of P_c and P_m to ensure the evolution speed in the early stage is high enough to avoid falling into the local optimal solution.

3.1 Chromosome coding and population initialization

3.1.1 Chromosome coding

Considering mixed vehicle types, it is necessary to add vehicle type auxiliary codes for chromosome coding. The chromosome is encoded into individuals of length $m + 1 + 2(K_1 + K_2)$. The coding scheme is shown in Fig. 4.

In this paper, there are two vehicle types. Where 1 in the vehicle types represents the type a, -1 is the vehicle type b, and 0 means the vehicle is not being used. The demand point 0 is the airport.

Taking (0,14,3,6,8,0,0,2,13,9,1,4,0,7,1,11,5,12,0,1,0,-1,-1) as an example, the chromosome coding form is shown in Fig. 5. There are 15 demand points and 4 vehicles, with two each of vehicle type a and b.

Vehicle 1 (a): Airport - Point 14 - Point 3 - Point 6 - Point 8 -Airport

Vehicle 2 (a): Non-operational

Vehicle 3 (b): Airport - Point 2 - Point 13 - Point 9 - Point 10 - Point 15 - Point 4 - Airport

Vehicle 4 (b): Airport - Point 7 - Point 1 - Point 11 - Point 5 - Point 12 – Airport

3.1.2 Population initialization

In this paper, a randomized generation method was chosen to generate the initial population. A passenger is randomly selected and assigned to a vehicle. If the number of passengers does not exceed the capacity, add the point into the route. Otherwise, re-select a vehicle among the rest and determine whether it is overcrowded until the passenger is assigned to a particular vehicle. Repeat until all demands are met.

3.2 Genetic operation

3.2.1 Selection operation

In this paper, the selection operation is based on Monte Carlo Method, and the selection probability of a chromosome is the ratio of its fitness value to the sum of the fitness values of all chromosome. Therefore, the larger the fitness value, the greater the probability of being selected.

3.2.2 Crossover operation

The Adaptive Genetic Algorithm (AGA) proposed by M. Srinivas makes the crossover probability P_c relevant to the fitness value, which can solve the problem of premature convergence effectively. However, in the early stage of AGA, the evolution speed of good individuals is slow, which reduces the operational efficiency and even leads to the local optimum.

This paper improves the crossover probability P_c of AGA, which ensures that the fitness value can flexibly change the crossover probability to improve the operational efficiency. Meanwhile, the minimum crossover probability is set to ensure that it evolves quickly in the early stage, to avoid falling into the local optimum. The improved formula are as follows.

$$P_c = \begin{cases} P_{c_1} - \dfrac{(P_{c_1} - P_{c_2})(f_{up} - f_{mean})}{f_{max} - f_{mean}}, f_{up} \geq f_{mean} \\ P_{c_1}, f_{up} < f_{mean} \end{cases} \tag{17}$$

Where

f_{max}——Maximum fitness value of all chromosomes

f_{up}——Larger fitness value in two chromosomes

f_{mean}——Mean of all chromosome fitness values

P_{c_1}——Maximum crossover probability

P_{c_2}——Minimum crossover probability

When chromosome X and Y perform crossover operation, point chain 1 of vehicle i is randomly selected from X, and point chain 2 of vehicle j is randomly selected from Y. The type of vehicle i and j may be the same or different.

(1) The same vehicle type.

In this case, it does not need to consider vehicle type crossover and only chain crossover can be considered.

Step 1: add the points in chain 2 to chain 1 sequentially. For each point, conduct a feasibility test of the corresponding vehicle type on chain 1. If the constraints are satisfied, insert it into chain 1 and delete points duplicated with chain 1 on other chains of the X chromosome. Otherwise, remain in chain 2.

Step 2: update the chromosome X.

Step 3: set the operated vehicle in chain 2 on chromosome Y to 0, complement missing demand points and randomly select an assigned vehicle to deliver the demand points. If points cannot be assigned to them, arrange for a new vehicle. If it is not available, keep the original chromosome Y to enter the offspring.

(2) The different vehicle types.

Step 1: if vehicle i and j are type a and b respectively, draw out the points in chain 1, and sequentially place the drawn points into chain 2 until the constraint of type b is satisfied.

Step 2: conduct the aforementioned procedure for the same vehicle type according to the case where both vehicles are type a and both are type b respectively, to obtain temporary chromosome X_1 and X_2.

Step 3: calculate the fitness f_1 and f_2 for X_1 and X_2. Generate a random number γ, if $\gamma \leq \frac{f_1}{f_1+f_2}$, remain X_1 into the offspring, otherwise remain X_2. Swap the sequence of chromosomes X and Y and perform the above operation.

3.2.3 Mutation operation

The improved mutation probability P_m of AGA proposed by M. Srinivas plays the same role as P_c. Therefore, it is necessary to set a minimum mutation probability. The improved formula are as follows.

$$P_m = \begin{cases} P_{m_1} - \dfrac{(P_{m_1} - P_{m_2})(f_{up} - f_{mean})}{f_{max} - f_{mean}}, f_{up} \geq f_{mean} \\ P_{m_1}, f_{up} < f_{mean} \end{cases} \tag{18}$$

Where

P_{m_1}——Maximum mutation probability

P_{m_2}——Minimum mutation probability

The mutation operation is divided into two stages, point mutation and vehicle type mutation. The procedure is as follows:

Step I: select individuals in turn from the crossover operation.

Step II: determine whether the individual is mutated or not. If mutated, turn to step III. Otherwise, turn to step V.

Step III: Stage 1 - Point Mutation.

Step 1: randomly select an assigned vehicle and record its point chain.

Step 2: randomly choose a point x in the chain and remove it.

Step 3: add point x to the chain of another assigned vehicle, if the new chain satisfies the capacity constraints of the corresponding vehicle type, then the insertion is successful. Otherwise, search for the next vehicle. If fail to assign it, then determine whether a vehicle is available. If there is, assign the point to the new vehicle, otherwise turn to Step IV;

Step 4: update the chromosome.

Step IV: Stage 2 - Vehicle type mutation.

Step 5: randomly select a vehicle and record its chain and type.

Step 6: determine whether the chain satisfies the constraints of the other vehicle type. If so, turn to Step 8, otherwise, turn to the next step.

Step 7: draw out all points in the chain sequentially until the capacity constraint of the other type is satisfied. Then, assign the drawn points to other assigned vehicles for the other type. If failed, arrange a new vehicle. If there are no available vehicles, readjust the point drawn scheme. If all schemes can not satisfy the constraints, the mutation fails and remain the chromosome. Otherwise, turn to the next step.

Step 8: replace the vehicle type with the other one.

Step V: update the chromosome.

3.3 Solution flow

The IAGA is used for model solving, and the specific flow is shown in Fig. 6.

3.4 Algorithm comparison

In order to verify the advantages of the IAGA, the algorithms are compared with 20 and 30 demands

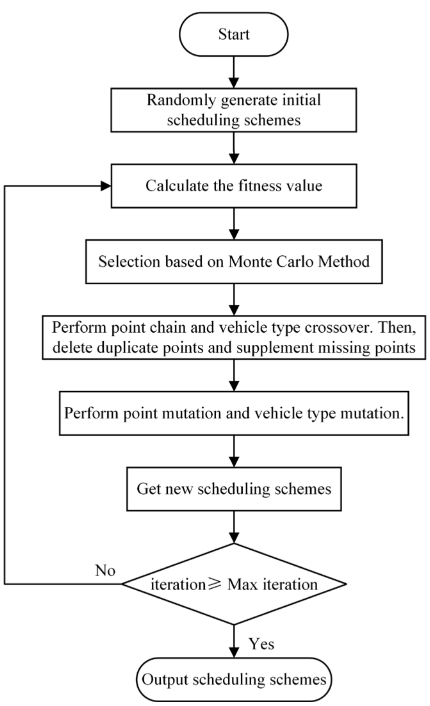

Figure 6 Schematic diagram of the IAGA.
Source: Own elaboration.

Table 2.
Algorithm comparison data.

Demand	Longitude	Latitude	Time	Demand	Longitude	Latitude	Time
1	101.27	31.05	13:45	16	101.29	31.07	14:00
2	101.3	31.02	13:50	17	101.24	31.02	14:30
3	101.21	31.06	13:45	18	101.24	31	13:55
4	101.25	31.03	13:45	19	101.2	31.04	14:15
5	101.21	31.02	13:50	20	101.27	31.03	14:25
6	101.23	31.1	14:25	21	101.28	31.04	14:30
7	101.22	31.01	14:30	22	101.25	31.02	14:15
8	101.25	31.01	13:55	23	101.27	31.04	14:05
9	101.22	31.08	13:30	24	101.29	31.09	13:50
10	101.22	31.02	14:25	25	101.23	31.04	14:00
11	101.2	31.05	13:55	26	101.3	31.03	13:55
12	101.2	31.05	14:30	27	101.28	31.05	13:45
13	101.21	31.05	14:00	28	101.28	31.02	14:10
14	101.27	31	13:25	29	101.26	31.06	14:05
15	101.3	31.09	14:25	30	101.27	31.03	14:00

Source: Own elaboration.

respectively. The fitness of the traditional GA is set as the value of the objective function and the algorithm parameters are the same as the IAGA. Taking the arrival time window at the airport as an example, the data in the table is T_q^l, and T_q^e is 15 minutes in advance, shown in Table 2. The 20 demands are the top 20 data in Table 2.

The changes in the objective function values for each group are in Fig. 7 (a), 7 (b) and the results is in Table 3, 4.

Compared with the traditional GA, the running time of the IAGA corresponding to 20 and 30 demands decreased by 12.02% and 14.08% respectively and the number of iterations has been reduced by 23.6% and 35.7%.

4 Case study

4.1 Service areas and example profiles

Take Changchun Nanguan District, an area with high density passenger flow, as the object.

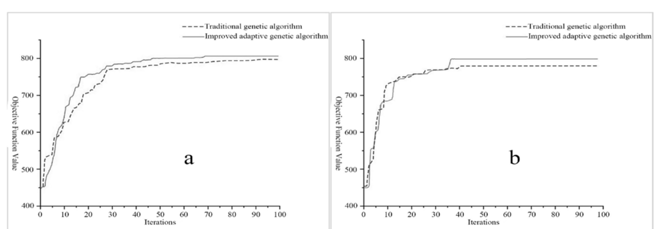

Figure 7 Different demands a) Demands = 20; b) Demands = 30.
Source: Own elaboration.

Table 3.
Comparison of the results of 20 demands.

Algorithm	Running time (s)	Iterations	objective function value
Traditional GA	43.76	89	797.66
IAGA	38.5	68	806.3
Change (%)	-12.02	-23.6	+1.08

Source: Own elaboration.

Table 4.
Comparison of the results of 30 demands.

Algorithm	Running time (s)	Iterations	objective function value
Traditional GA	49.08	42	1094.0
IAGA	42.17	27	1131.3
Change (%)	-14.08	-35.7	+3.41

Source: Own elaboration.

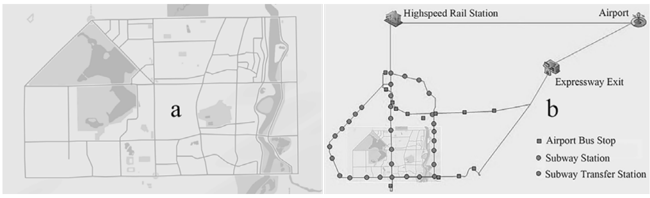

Figure 8 Road information a) Road network; b) Public transportation.
Source: Own elaboration.


Figure 9 Reservation demand distribution.
Source: Own elaboration.

The road network is in Fig. 8 (a), and the coverage of public transportation around the area is shown in Fig. 8 (b). The existing transportation modes from urban area to Changchun Longjia International Airport (International Air Transport Association: CGQ) are in Fig. 8 (b)

Taking arrival flights of 19:00-22:30 and departure flights of 22:30-00:30 as an example, 50 passenger demand points are randomly generated. The total number of passengers is 58, where 44 passengers board at airport and 14 passengers alight at airport. The distribution of demand points are in Fig. 9 and the demand data is shown in Table 5, in which point 51 and 52 are freeway entrance/exit and airport.

Table 5.
Passenger travel data.

No.	Longitude	Latitude	Expected time window		Number of passengers	
			Arrival	Departure	Boarding	Alighting
1	125.316731	43.860387	-	20:15-20:20	1	0
2	125.319349	43.861980	-	20:05-20:10	1	0
3	125.324971	43.861299	-	19:35-19:40	1	0
4	125.324628	43.859814	21:00-21:15	-	0	1
5	125.320465	43.855977	-	20:20-20:25	1	0
6	125.331581	43.858541	-	20:35-20:40	1	0
7	125.334927	43.860804	-	20:40-20:45	1	0
8	125.329863	43.862197	-	20:10-20:15	1	0
9	125.333983	43.854801	-	20:05-20:10	2	0
10	125.339648	43.858576	20:50-21:05	-	0	1
11	125.328876	43.858515	-	19:55-20:00	2	0
12	125.348403	43.860031	-	20:20-20:25	1	0
13	125.341665	43.855296	-	20:35-20:40	2	0
14	125.357851	43.863526	-	19:10-19:15	1	0
15	125.359611	43.857728	-	19:55-20:00	1	0
16	125.354776	43.862816	-	20:30-20:35	1	0
17	125.359396	43.848783	-	20:05-20:10	2	0
18	125.346879	43.848828	-	19:00-19:05	1	0
19	125.340528	43.85053	21:10-21:25	-	0	1
20	125.339305	43.848333	-	20:15-20:20	1	0
21	125.334412	43.849757	21:30-21:45	-	0	1
22	125.327803	43.849076	-	20:10-20:15	1	0
23	125.330335	43.845795	21:45-22:00	-	0	1
24	125.335206	43.843195	22:15-22:30	-	0	1
25	125.327775	43.855069	-	19:10-19:15	1	0
26	125.323619	43.848271	-	20:30-20:35	1	0
27	125.322503	43.843474	22:40-22:55	-	0	1
28	125.325529	43.847861	22:00-22:15	-	0	1
29	125.291347	43.845888	21:30-21:45	-	0	1
30	125.29787	43.844278	21:05-21:20	-	0	1
31	125.300273	43.841369	-	19:35-19:40	1	0
32	125.297628	43.846277	-	20:20-20:25	1	0
33	125.299694	43.848287	-	20:40-20:45	2	0
34	125.305144	43.834249	-	20:30-20:35	1	0
35	125.296861	43.834125	-	19:00-19:05	1	0
36	125.293965	43.838057	22:10-22:25	-	0	1
37	125.306467	43.845906	-	20:35-20:40	1	0
38	125.310582	43.845887	-	19:10-19:15	1	0
39	125.320104	43.846667	-	20:20-20:25	1	0
40	125.311192	43.851894	-	19:05-19:10	2	0
41	125.314478	43.837229	21:15-21:30	-	0	1
42	125.309758	43.834102	-	19:10-19:15	2	0
43	125.310594	43.838707	-	20:15-20:20	1	0
44	125.331036	43.840939	-	20:35-20:40	1	0
45	125.330659	43.846738	21:05-21:20	-	0	1
46	125.326877	43.845568	-	19:35-19:40	1	0
47	125.332513	43.837778	22:10-22:25	-	0	1
48	125.34159	43.840317	-	20:20-20:25	1	0
49	125.341247	43.835673	-	19:05-19:10	2	0
50	125.347856	43.836292	-	20:05-20:10	1	0
51	125.470987	43.903319	-	-	-	-
52	125.705079	43.998125	-	-	-	-

Source: Own elaboration.

Table 6.
Model parameters.

Parameter	Definition	Value
h	1, fleet size of vehicle type a (vehicle)	10
	2, fleet size of vehicle type b (vehicle)	10
p^k	Fare per kilometer of vehicle k (yuan/PAX)	$\begin{cases} 1.3\ (daytime), k \in K_1 \\ 1.6\ (evening), k \in K_1 \\ 1.5\ (daytime), k \in K_2 \\ 1.8\ (evening), k \in K_2 \end{cases}$
C_v	Value of time for passengers (yuan/h)	43.78
λ_{lim}	Passenger detour coefficient	1.2
C_{h0}	Fixed cost of vehicle k (yuan/h)	$\begin{cases} 32.5, k \in K_1 \\ 40, k \in K_2 \end{cases}$
C_{h1}	Variable cost of unit distance for vehicle k (yuan/km)	$\begin{cases} 1, k \in K_1 \\ 1.2, k \in K_2 \end{cases}$
C_d	Wage for driver (yuan/h)	33
V	Speed of vehicle (km/h)	55
t_0	Passenger boarding or alighting time (min)	1/6
φ	Penalty cost factor for late arrival (yuan/PAX)	10000
Q_k	Capacity of vehicle k (PAX)	$\begin{cases} 7, k \in K_1 \\ 12, k \in K_2 \end{cases}$
T_{max}	Maximum driving hours per vehicle (h)	2
NP	Initial population	300
F	Maximum Iterations	300

Source: Own elaboration.

4.2 *Scheduling and planning analysis*

The parameter calibration is shown in Table 6.

The evolutionary iteration process is shown in Fig. 10, which illustrate the relationship of the iterations and optimal value. The objective function value increases with the number of iterations and stabilizes after 210 iterations.

The routes and corresponding vehicle allocation scheme are shown in Table 7. According to Table 7, a total of six vehicles are assigned, including two 7-seat and four 12-seat vehicles. 58 passengers are all delivered to their destinations. Specific route information is illustrated in Table 8, which shows that all vehicles return CGQ within 2h.

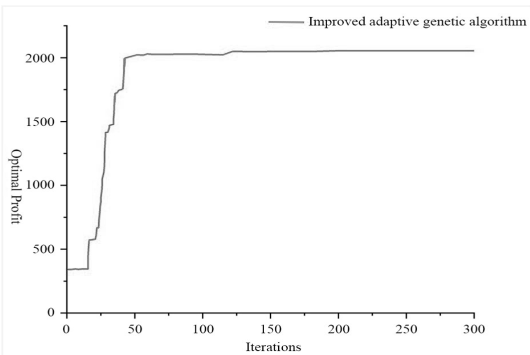

Figure 10 Iterative diagram of the evolution of the optimal solution.
Source: Own elaboration.

Table 7.
Solution results.

No.	Vehicle type	Route	Number of passengers (PAX)	Route length (km)	Average travel time (min)
1	b	52-51-14-18-49-42-35-38-40-25-4-10-51-52	13	104.6	47.11
2	a	52-51-3-30-31-41-46-45-19-51-52	7	96.54	44.13
3	a	52-51-11-15-29-21-51-52	5	99.4	43.66
4	b	52-51-12-1-5-20-48-43-39-32-36-28-47-24-51-52	12	106.51	46.59
5	b	52-51-8-2-9-22-23-50-17-51-52	9	100.64	49.36
6	b	52-51-16-13-7-6-26-33-37-34-44-27-51-52	12	100.22	46.78

Source: Own elaboration.

Table 8.
Route information.

Route	Point	Boardings or alightings	Persons in vehicle	Travel distance (km)	Detour factor	Basic fare (yuan)	Rebate (yuan)	Final Fare (yuan)	Arrival time
1	52	+11	11	-	-	-	-	-	19:10
	51	-0	11	-	-	-	-	-	19:40
	14	-1	10	35.40	1.00	52.30	0.00	52.30	19:53
	18	-1	9	36.60	1.00	54.10	0.00	54.10	19:55
	49	-2	7	38.70	1.00	57.25	0.00	57.25	19:57
	42	-2	5	43.00	1.01	62.95	0.00	62.95	20:02
	35	-1	4	45.90	1.06	63.85	0.00	63.85	20:05
	38	-1	3	47.60	1.11	63.40	0.00	63.40	20:07
	40	-2	1	50.70	1.28	58.60	2.53	56.07	20:10
	25	-1	0	53.10	1.33	58.90	4.25	54.65	20:13
	4	+1	1	40.80	1.04	57.85	0.00	57.85	20:15
	10	+1	2	37.20	1.00	55.00	0.00	55.00	20:19
	51	-0	2	-	-	-	-	-	20:35
	52	-3	0	-	-	-	-	-	21:04
2	52	+3	3	-	-	-	-	-	19:35
	51	-0	3	-	-	-	-	-	20:05
	3	-1	2	35.40	0.91	59.47	0.00	59.47	20:22
	30	+1	3	44.74	1.05	63.89	0.00	63.89	20:27
	31	-1	2	39.96	0.94	64.15	0.00	64.15	20:27
	41	+1	3	41.98	1.01	62.46	0.00	62.46	20:30
	46	-1	2	42.69	1.09	59.47	0.00	59.47	20:30
	45	+1	3	40.90	1.05	59.47	0.00	59.47	20:31
	19	+1	4	37.50	1.00	57.39	0.00	57.39	20:35
	51	-0	4	-	-	-	-	-	20:51
	52	-4	0	-	-	-	-	-	21:20
3	52	+3	3	-	-	-	-	-	19:55
	51	-0	3	-	-	-	-	-	20:25
	11	-2	1	38.20	1.00	58.30	0.00	58.30	20:41
	15	-1	0	40.70	1.11	56.22	0.00	56.22	20:44
	29	+1	1	44.50	1.09	61.68	0.00	61.68	20:50
	21	+1	2	38.50	1.00	58.69	0.00	58.69	20:57
	51	-0	2	-	-	-	-	-	21:14
	52	-2	2	-	-	-	-	-	21:43
4	52	+8	8	-	-	-	-	-	20:20
	51	-0	8	-	-	-	-	-	20:50
	12	-1	7	35.00	1.00	54.14	0.00	54.14	21:03
	1	-1	6	38.40	1.02	57.78	0.00	57.78	21:07
	5	-1	5	40.20	1.05	58.56	0.00	58.56	21:09
	20	-1	4	43.80	1.19	56.61	0.00	56.61	21:13
	48	-1	3	45.40	1.19	58.30	0.00	58.30	21:14
	43	-1	2	48.25	1.15	63.11	0.00	63.11	21:18
	39	-1	1	48.76	1.23	60.38	0.80	59.58	21:18
	32	-1	0	51.66	1.12	68.83	0.00	68.83	21:21
	36	+1	1	43.85	1.00	65.84	0.00	65.84	21:24
	28	+1	2	40.55	1.02	60.25	0.00	60.25	21:27
	47	+1	3	38.75	0.95	61.81	0.00	61.81	21:29
	24	+1	4	37.90	1.00	57.91	0.00	57.91	21:30
	51	-0	4	-	-	-	-	-	21:47
	52	-4	0	-	-	-	-	-	22:15
5	52	+8	8	-	-	-	-	-	20:10
	51	-0	8	-	-	-	-	-	20:40
	8	-1	7	38.10	1.00	58.17	0.00	58.17	20:56
	2	-1	6	41.40	1.10	57.52	0.00	57.52	21:00
	9	-2	4	40.70	1.09	57.13	0.00	57.13	21:03
	22	-1	3	44.30	1.16	58.17	0.00	58.17	21:07
	23	+1	4	39.54	1.02	59.08	0.00	59.08	21:09
	50	-1	1	53.80	1.38	59.34	5.57	53.77	21:12
	17	-2	2	54.34	1.45	57.52	7.34	50.18	21:12
	51	-0	2	-	-	-	-	-	21:29
	52	-2	0	-	-	-	-	-	21:59
6	52	+11	11	-	-	-	-	-	20:40
	51	-0	11	-	-	-	-	-	21:10
	16	-1	10	34.80	1.00	51.40	0.00	51.40	21:23
	13	-2	8	37.60	1.02	54.40	0.00	54.40	21:26
	7	-1	7	41.40	1.10	55.60	0.00	55.60	21:30
	6	-1	6	42.90	1.13	56.05	0.00	56.05	21:32
	26	-1	5	43.49	1.10	58.45	0.00	58.45	21:33
	33	-2	3	45.99	1.08	62.95	0.00	62.95	21:35
	37	-1	2	46.32	1.09	62.95	0.00	62.95	21:36
	34	-1	1	49.02	1.15	63.10	0.00	63.10	21:39
	44	-1	0	50.82	1.24	60.55	1.38	59.17	21:40
	27	+1	1	38.70	1.00	57.25	0.00	57.25	21:43
	51	-0	1	-	-	-	-	-	22:00
	52	-1	0	-	-	-	-	-	22:30

Source: Own elaboration.

The cost and revenue for each route is illustrated as Table 9. The total profit is 2033 yuan and total cost is 1363 yuan. All of the penalty cost for vehicle is 0 and there are no passengers arriving late at the airport. In addition, a majority of passenger time window are met.

Table 9.
Rebate and cost of each route.

Route	R	C_1	C_2	C_3	C_4	P
1	753.69	40	188.46	0	5	520.23
2	426.3	32.5	154.56	0	0	239.24
3	293.19	32.5	159.11	0	0	101.58
4	722.72	40	223.84	0	0	458.88
5	501.34	40	211.46	0	0	249.88
6	698.67	40	180.56	0	14.8	463.31
Total	3395.91	225	1117.99	0	19.8	2033.12

Source: Own elaboration.

Fare rebate is given to some passengers due to detours, shown in Table 10.

Table 10.
Rebate passenger information.

Route	Point	Distance (km)		Basic fare (yuan)	Rebate (yuan)	Final fare (yuan)
		Ideal	Actual			
1	40	39.6	50.70	58.60	2.53	56.07
	25	39.8	53.10	58.90	4.25	54.65
4	39	39.8	48.76	60.38	0.80	59.58
5	17	37.6	54.33	57.52	7.34	50.18
	50	39	53.80	59.34	5.57	53.77
6	44	40.9	50.81	60.55	1.38	59.17

Source: Own elaboration.

The layout of each route is shown in Fig. 11 (a) - 13 (b).

4.3 Comparison of connection methods

In order to compare different connection modes, it assumes the distribution of demand remains the same. Point 44 is taken as an example to compare each connection mode, and the calculation results are in Table 11. Due to the inability to measure the walking and waiting time of passengers, The travel time of airport bus and railway are its running time.

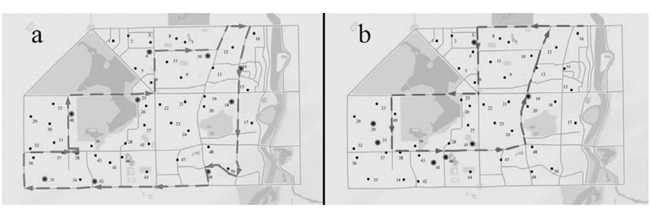

Figure 11 Vehicle routes 1-2 a) Route 1; b) Route 2.
Source: Own elaboration.

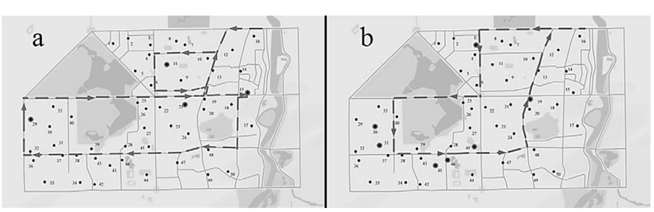

Figure 12 Vehicle routes 3-4 a) Route 3; b) Route 4.
Source: Own elaboration.

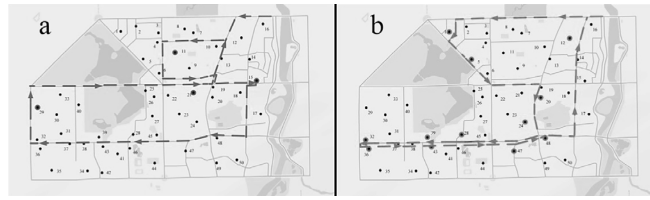

Figure 13 Vehicle routes 5-6 a) Route 5; b) Route 6.
Source: Own elaboration.

Table 11.
Comparison of each mode.

Indicator		Airport bus	Railway	Cab	ARB
Daytime	Travel time (min)	46	30	45	55
	Fare (yuan)	27	13	76	39
Night	Travel time (min)	-	-	45	55
	Fare (yuan)	-	-	76	48
Convenience		2	2	1	1

Note. '1': door-to-door, '2': non-door-to-door.
Source: Own elaboration.

No matter during the daytime or at night, even though ARB has a small increase in travel time compared to cab, the former is at least 39% less than the latter in terms of fare. As a consequence, ARB can attract most of the passengers. During the daytime, although the travel time for airport bus and railway is less than that of ARB, the former does not take walking time and waiting time into account, so it is highly likely that the former's is greater than that of the latter. Moreover, ARB offers door-to-door transportation compared to the other two modes, and despite the fact that its fare is relatively higher, it is still a good choice for those seeking efficiency or persons with large luggage.

5 Discussion

5.1 The ARB model balances cost and convenience.

The proposed ARB achieves a fare reduction of more than 39% compared with taxis through a bypass rebate mechanism and mixed vehicle scheduling, while the door-to-door service makes up for the shortcomings of traditional public transportation that requires walking, which verified the feasibility of "low cost + high adaptability".

5.2 A double breakthrough in pricing and algorithms

The pricing mechanism breaks through the limitations of traditional fixed fares and combines detour distance with time value, which solves the defect that dynamic pricing proposed by Emele [3] et al does not consider detours. Compared with traditional GA, the IAGA reduces the running time by 12%/14% and the number of iterations by 23%/35%, effectively avoiding the problem of premature convergence.

5.3 Limitations and future directions

The model assumes that there is no traffic congestion, but it is inevitable in practice. Future research will consider integrating real-time traffic data to improve the model's adaptability.

As the case study with concentrated demand points, future research may partition cities into districts to set differentiated vehicle round-trip time limits based on demand distribution.

6 Conclusion

In order to meet the personalized travel demands and improve the quality and efficiency of airport connections, this paper proposes ARB mode, which improves convenience for passengers, avoids high fares, and provides a new choice. The main research content and innovation points of the paper are summarized as follows.

(1) This paper incorporates rebate mechanism into the model. The rebate mechanism makes it possible to accommodate benefits of both passengers and enterprise in the same objective function, which makes the model more reasonable.

(2) An IAGA is proposed. Setting the minimum crossover probability and mutation probability improves the evolutionary speed in the early stage and avoid it falling into local optimum while producing a better and faster result.

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