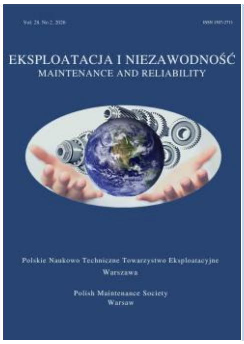

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Dynamic pricing schemes for reliability improvement in demand-responsive feeder transit systems

Indexed by: Web of Science Group

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Highlights

- Flexible scheduling boosts DRFT reliability by aligning with passenger time windows.
- Design dynamic pricing schemes to assess their impact on DRFT system reliability.
- Assessed reliability of integrated dynamic pricing, flexible scheduling & shared rides.

Abstract

This research investigates reliability improvement for demand-responsive feeder transit (DRFT) with simultaneous pick-up and drop-off using dynamic pricing scheme. The fare model adjusts charges based on arrival punctuality-compensating passengers when vehicles miss their time windows, with compensation proportional to delay duration. The flexible departure system is designed to enhance connection reliability. The optimization model maximizes operator profit while minimizing passenger costs, constrained by vehicle operating time, passenger time windows, capacity limits, and drop-off schedules. A multi-chain genetic algorithm solves this multi-objective routing problem. Case studies demonstrate: 1) Flexible scheduling outperforms fixed scheduling in connection reliability and operational profitability; 2) Dynamic pricing scheme surpasses fixed fares in connection reliability, profitability, and resource utilization. The integrated approach significantly enhances overall DRFT system reliability.

Keywords

Demand-Responsive Feeder Transit, public transit system reliability, dynamic pricing scheme, flexible departure

1. Introduction

China's urban expansion has accelerated transport growth at the cost of intensified congestion and pollution, driving demand for personalized feeder solutions in sustainable public transit systems. Demand-Responsive Transit (DRT) emerges as an efficient alternative to conventional fixed-route systems, dynamically matching service supply with passenger demand to minimize resource waste while elevating service quality. This adaptive transit model proves critical for operators seeking competitiveness in modern mobility ecosystems through optimized operations and enhanced passenger experiences.

The service types of DRT encompass a broad range of scenarios, ranging from route deviated mode and station deviated mode to station demand responsive service and regional flexible service mode. Amongst these, demand responsive feeder transit (DRFT) stands as a prominent example[1]. DRFT is a cutting edge public transportation solution that is predominantly deployed at transportation hubs, such as subway stations, high speed rail terminals, and bus interchanges, where passenger density tends to be relatively low[2]. Its core purpose is to serve commuters traveling to and

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from interchange stations, efficiently bridging the last mile gap and tailoring services to meet the diverse and personalized travel needs of passengers. The DRFT system has garnered significant interest in the realm of innovative public transportation solutions. Researchers from across the globe have delved into the intricacies of this system, uncovering valuable insights. This paper examines pivotal topics pertaining to DRFT systems, including pick-up and drop-off modalities, departure time, and dynamic pricing scheme. Through this discussion, we aim to provide a comprehensive overview of the current research landscape, highlighting the advancements and challenges within this rapidly evolving field.

Initially, with regard to pick-up and drop-off modalities, DRFT is categorized into two distinct types: individual pick-up and drop-off and simultaneous pick-up and drop-off. To validate the superior reliability of the latter, an integrated model for DRFT route planning and scheduling under the simultaneous pick-up and drop-off mode has been devised, balancing the interests of enterprises and passengers alike. The model demonstrates significantly improved resource utilization compared to separate pick-up and drop-off modes, clearly showcasing the advantages of simultaneous operations[3]. To further enhance the system reliability, scholars took into account passenger interchange time requirements, stipulating scheduled arrivals at interchange stations and ensuring a reasonable time gap between passenger arrival and the scheduled interchange vehicles[4]. Jiang[5] then introduced game theory into the DRFT system, building a manager led Stackelberg game model that considers the impact of interactions between management and passengers on system reliability under simultaneous pick-up and drop-off operations. Recognizing the limitations of studies focusing on small service areas, Tan[6] expanded the scope to larger regions, exploring through multi-zone partitioning potential routing solutions that could enhance DRFT system reliability under simultaneous pick-up and drop-off operations. Other studies have simply shifted the focus, such as examining the route design of customized buses in the context of simultaneous pick-up and drop-off[7]. The pickup and drop-off modes of DRFT mainly include individual pickup and drop-off and simultaneous pickup and drop-off. With further research, under the simultaneous pickup and drop-off mode, researchers have not only introduced interchange time requirements to optimize passenger experience, but also analyzed the interaction between managers and passengers using game theory models. They have further expanded the research scope to multi-partition planning strategies, significantly enhancing the diversity and practicability of the models. These studies have enhanced DRFT system reliability across multiple dimensions.

In studies on DRFT, departure time optimization is a critical research focus, with two primary scheduling approaches: fixed intervals and flexible departure. Song[8] implemented a flexible departure strategy where vehicles are dispatched either when N passenger requests accumulate at transfer points with available vehicles, or immediately after returning vehicles complete a brief rest period when no idle vehicles exist. He[9] developed a mathematical departure interval function T to determine scheduling, incorporating a demand threshold M that triggers early departures if passenger reservations reach M before interval T elapses. Wang's[10] comparative study demonstrated that flexible scheduling outperforms fixed-interval approaches in DRFT systems, simultaneously reducing operational costs and travel times while significantly enhancing DRFT system reliability. These studies collectively highlight how adaptive departure strategies can enhance DRFT reliability through dynamic response to real-time demand conditions. Wang et al.[11] developed a two-stage coordinated optimization model to enhance public transit system reliability through integrated vehicle routing and scheduling. Their approach demonstrates improved reliability through decoupled optimization of these two interconnected aspects. Alshalalfah et al.[12] highlighted the critical role of slack time allocation in demand-responsive transit systems. Their research indicates that increasing slack time can enhance service flexibility, thereby potentially stimulating higher travel demand due to improved reliability and accessibility. Nourbakhsh et al.[13] conducted a cost-minimization study to determine optimal transit service coverage and departure frequencies. Their findings demonstrate that flexibly scheduled transit systems typically achieve lower operational costs under low-demand conditions, indicating superior reliability in specific demand scenarios.

Multiple factors influence DRFT reliability, with appropriate fare structures representing another critical aspect as previously discussed. Guo[14] established a sophisticated two-stage optimization model incorporating both static fixed fares and dynamic variable fares adjusted based on congestion levels and vehicle detour distances, investigating their impacts on DRFT system reliability. Wang et al.[15] proposed a pricing-based bi-level programming game model considering fare fluctuations while examining competition between DRFT and bike-sharing systems. He et al.[16] conducted an in-depth investigation of the complex interplay between departure schedules and dynamic pricing, developing a bi-level programming model to determine optimal fluctuation ranges for both scheduling and fares that enhance system reliability. Kamel et al.[17] developed a genetic algorithm to optimize time-dependent bus fares and evaluated their impact on passenger mode choice using a multimodal simulation model. Their results demonstrate that time-based optimal fare structures effectively redistribute demand away from peak periods, thereby indirectly enhancing DRFT system reliability. Khattak et al.[18] examined travelers' willingness to use and pay for demand-responsive services, finding users willing to pay premium fares compared to fixed-route transit for greater reliability. Jiang et al.19 considered a service-based fare strategy, dividing the total fare into a base fare and a service fare (an additional charge based on the vehicle's detour distance), thereby enhancing the stability of the DRFT system. Sun et al.20 established a service-level-based fare strategy, first charging personalized fares according to the type of alternative stop selected by passengers, followed by compensating passengers experiencing boarding delays with partial fare adjustments, thereby enhancing the stability of the DRFT system in terms of fare structure. Collectively, these studies reveal the advantages of fare structures in DRFT systems as both revenue management tools and demand-regulation mechanisms for enhancing system reliability.

In other studies, Liu et al.[21] optimized the robot's trajectory by proposing a dynamic two-stage strategy, improving the system's reliability. Skačkauskas[22] proposed an effective path-following replanning method and evaluated its performance and reliability. Jin et al.23 introduced a model predictive control method that adjusts demand-responsive transit scheduling in real-time using predicted passenger flow information for future time periods, significantly enhancing reliability. Huang et al.24 established a mathematical model based on historical route similarity, assessing the similarity between historical route data and current routes to optimize the latter, thereby enhancing the stability of the demand-responsive transit system. Wang et al.[25] proposed a DRT planning strategy to reduce accessibility inequality. It integrates a Continuous Approximation (CA) model for DRT with a graph model for conventional PT. The optimization uses a bilevel structure: the upper level allocates DRT vehicles per zone, while the lower level solves transit assignment iteratively to estimate multimodal traveler distribution. Jiang et al.26 developed an integrated optimization approach using DRT and conventional buses. This model simultaneously generates vehicle scheduling (including DRT/bus deployment and routing) and passenger assignment solutions. An epsilon-constraint algorithm is employed to obtain the Pareto solution set, aiming to achieve efficient and passenger-friendly evacuation of stranded passengers. Hu et al.27 employed an extended Technology Acceptance Model (TAM) to assess DRT acceptance, transcending conventional research limitations by examining the direct impacts of key factors like trust and subjective norms on the public's DRT usage intention. Previous studies have predominantly examined simultaneous pick-up and drop-off services, departure times, and dynamic pricing schemes as independent systems, overlooking their complex interrelationships. This study specifically investigates the interactions among these three critical components. To address existing research gaps, we developed an integrated optimization framework that simultaneously coordinates vehicle fleet composition (single/multiple vehicle types), departure scheduling strategies, fare collection schemes, and simultaneous pick-up and drop-off operations to enhance DRFT system reliability. Our approach establishes a multi-objective optimization model for demand-responsive feeder transit systems, aiming to enhance DRFT system reliability by balancing the interests of both passengers and operators. Furthermore, we propose an innovative multi-chain genetic algorithm to efficiently solve this complex optimization problem.

The remainder of this paper is structured as follows: Section 2 elucidates the DRFT route optimization problem and its corresponding model. Section 3 introduces the algorithm devised to solve this model. An arithmetic example is then employed in Section 4 to scrutinize the model's solution results. Lastly, Section 5 offers a concise summary and outlines potential future research avenues.

2. Methodology

2.1. Problem Description

The demand-responsive feeder transit studied in this paper is in a low-density passenger flow area and is based at the interchange station, which serves as the starting and ending point. It is assumed that there are K_1 shuttle buses available at the interchange station and there are M_1 types of vehicles. Passengers are categorized into two types: alighting and boarding passengers, departing from and arriving at the interchange station. The demand-responsive feeder transit begins its route at the interchange station, passes through a series of demand points, and then returns to the interchange station. During this process, passengers transferring to the interchange station are transported to their respective demand points, and passengers needing to board at the interchange station are picked up, simultaneously serving both types of passengers. The interchange station can be a bus hub, a rail transit station, or other centers for passenger distribution, as depicted in Figure 1.

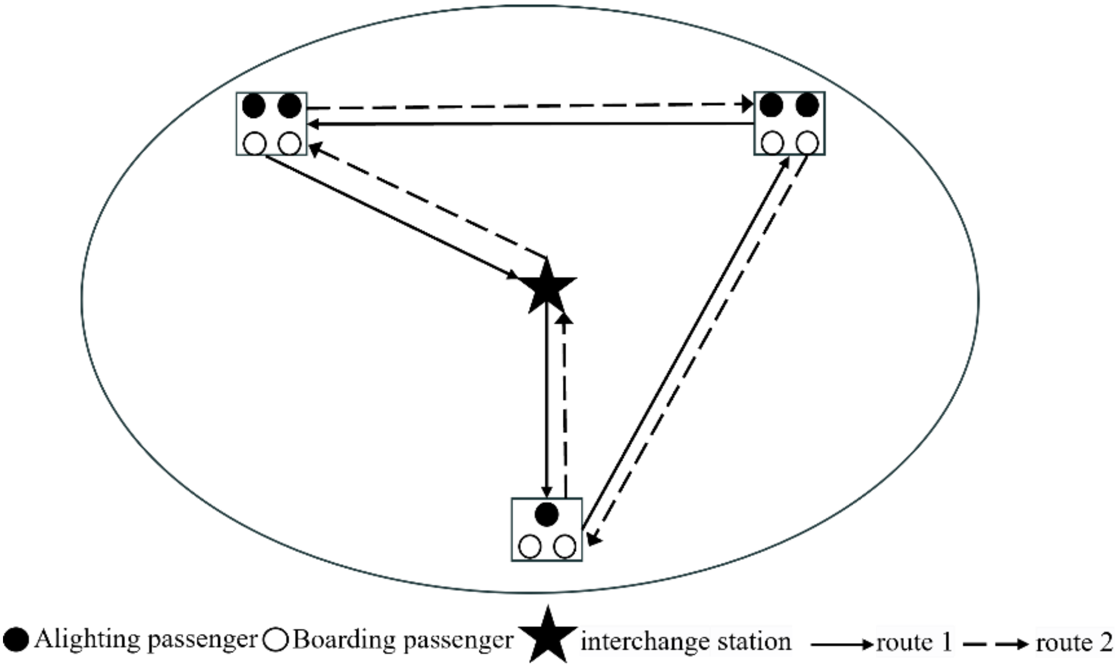

Fig. 1. DRFT route map in simultaneous pick-up and drop-off mode.

2.2. Hypothesis

To solve the problem studied in this paper, the following basic assumptions are made:

(1) The research area for demand-responsive feeder transit is known;

(2) When demand-responsive feeder transit operates on the roads within the service area, traffic conditions such as congestion are not considered, and all vehicles travel at the same speed;

(3) The needs of all pre-booked passengers are met;

(4) The time it takes for vehicles to start and for passengers to board or alight is ignored;

(5) Passengers heading to the interchange station have a boarding time window, and those leaving the interchange station have an alighting time window, both of which are considered soft time windows;

(6) Only the OD (origin-destination) demand between the interchange point and the demand points is considered; the OD demand between demand points themselves is not considered.

2.3 Mathematical Model

The DRFT route optimization problem studied in this paper comprehensively considers the scenarios of simultaneous pick-up and drop-off, dynamic pricing scheme, and flexible scheduling. It aims to maximize the operating profit of the enterprise and minimize the total cost for passengers, with a multi-objective optimization model that considers constraints such as vehicle capacity and maximum travel time. The model's symbols are shown in Table 1.

Table 1 Symbol explanations of the models

Notation	Description
$N=\{1,2,\cdots N_1\}$	Set of passengers
$K^{\omega}=\{1,2,3,\cdots,K_1^{\omega}\}$	Set of Model ω Buses
$M=\{A,B,\cdots M_1\}$	Set of vehicle type
M+1	Transfer station
k	Vehicle k
i,j	Passenger i and j
ω	Vehicle type ω
Q_k	capacity of the vehicle k
d_{ij}	distance between OD pair (i,j)
$Q_{i^-}^k$	Number of people on board when vehicle k leaves node i
$Q_{i^+}^k$	Number of people on board when the vehicle k arrives at node i
N_k	The vector of stations served by the vehicle, ordered by the sequence of service
a_i	The difference between the actual time that passenger i is served and the upper limit of the time window
u_k	The departure time of vehicle k
e_i^k	The scheduled departure time of passenger i in vehicle k
p_i	The fare of passenger i
t_i^k	The time when vehicle k arrives at node i
$[ET_i, LT_i]$	The upper and lower bounds of passenger i's reservation window
V	Vehicle speed
T_{max}	Maximum runtime
θ_1^{ω}	Unit departure cost of vehicle type ω
θ_2^{ω}	Unit travel cost vehicle type ω
h	passenger transit time cost
φ_1	Penalty coefficient for early arrival
φ_2	Penalty coefficient for late arrival
x_{ij}^k	routing variable (equals to 1, if route segment (i,j) is traveled by vehicle k, and 0, otherwise)
y_i^k	passenger type variable(equals to 1, if passenger i boards vehicle k, and -1, otherwise)
s_i^k	request-to-vehicle variable(equals to 1, if passenger i is served by vehicle k , and 0, otherwise)

2.3.1. Objective Function

(1) Enterprise Operational Revenue

Eq. (1) represents the first objective function, which maximizes the total revenue of the enterprise and consists of three parts: Eq. (2) represents the enterprise's departure cost, Eq. (3) is the vehicle operating cost, and Eq. (4) is the total revenue from passenger fares.

$$\mathrm{Max}Z_1 = C_3 - (C_1 + C_2) \tag{1}$$

$$C_1 = \sum_{\omega\in M}\sum_{k\in K^{\omega}}\sum_{j\in N}\theta_1^{\omega}\, x_{(M+1)j}^k \tag{2}$$

$$C_2 = \sum_{\omega\in M}\sum_{k\in K^{\omega}}\sum_{i\in N\cup M+1}\sum_{j\in N\cup M+1}\theta_2^{\omega}\, d_{ij}x_{ij}^k \tag{3}$$

$$C_3 = \sum_{i\in N} p_i \tag{4}$$

(2) Total Passenger Cost

Eq. (5) is the second objective function, which minimizes the total cost for passengers and consists of two parts: Eq. (6) is the total cost of all passengers' time on the bus, and Eq. (7) is the penalty cost for the vehicle's early or late arrival affecting passenger satisfaction.

$$\mathrm{Min}Z_2 = C_4 + C_5 \tag{5}$$

$$C_4 = \sum_{\omega\in M}\sum_{k\in K^{\omega}}\sum_{i\in N\cup M+1}\sum_{j\in N\cup M+1} h x_{ij}^k\, Q_{i^-}^k \frac{d_{ij}}{V} \tag{6}$$

$$C_5 = \sum_{\omega\in M}\sum_{k\in K^{\omega}}\sum_{i\in N} s_i^k\,(Q_{i^+}^k G_i + H_i) \tag{7}$$

2.3.2. Constraints

(1) Vehicle Capacity

Eq. (8) indicates that when the vehicle leaves the subway station, the number of people on board should be less than or equal to the vehicle's capacity; Eq. (9) indicates that the number of passengers on board during the driving process should be less than or equal to the vehicle's capacity.

$$0 \le Q_{M+1^-}^k \le Q_k, \forall k \in K^{\omega}, \omega \in M \tag{8}$$

$$Q_{M+1^-}^k + \sum_{i\in N_k} y_i^k \le Q_k, \forall k \in K^{\omega}, \omega \in M \tag{9}$$

(2) Fleet Size

Eq. (10) is the vehicle availability constraint, meaning that the number of vehicles dispatched from the subway station must not exceed the maximum number of vehicles.

$$\sum_{\omega\in M}\sum_{k\in K^{\omega}}\sum_{i\in N} x_{(M+1)i}^{k} \leq K_{1}^{\omega} \quad (10)$$

(3) Time Window

Eq. (11) is the early arrival penalty value, given if the passenger is a boarding passenger, alighting passengers are not penalized; Eq. (12) is the late arrival penalty value.

$$G_i = \begin{cases} 0, & ET_i \leq t_i^k \leq LT_i or y_i^k = -1 \\ \varphi_1(ET_i - t_i^k), & t_i^k < ET_i and y_i^k = 1 \end{cases} \quad (11)$$

$$H_i = \begin{cases} 0, & ET_i \leq t_i^k \leq LT_i \\ \varphi_2(t_i^k - LT_i), & t_i^k > LT_i \end{cases} \quad (12)$$

(4) Early Arrival Time Value

Eq. (13) is the value of the vehicle's early arrival time. When serving boarding passengers, if arriving at the rendezvous point ahead of schedule, one needs to wait until the lower bound of the time window; when serving alighting passengers, early arrival does not require waiting.

$$f_i^k = \begin{cases} 0, & y_i^k = -1, \forall i \in M, k \in K^{\omega}, \omega \in M \\ ET_i - t_i^k, & y_i^k = 1, ET_i > t_i^k, \forall i \in M, k \in K^{\omega}, \omega \in M \end{cases} \quad (13)$$

(5) Subtour Elimination Constraints

Equation (14) represents the temporal relationship between two sequentially served stations by a vehicle. Equations (15) and (16) ensure that each vehicle can visit a station only once while simultaneously eliminating subtours in conjunction with Equation (14).

$$t_j^k \geq t_i^k + max(0, f_i^k) + t_{ij} - B(1 - x_{ij}^k), \forall i,j \in N \cup M+1, k \in K^{\omega}, \omega \in M \quad (14)$$

$$\sum_{i\in N_1 \cup M+1} x_{ij}^k = 1, \forall k \in K^{\omega}, \omega \in M, j \in N \cup M+1, i \neq j \quad (15)$$

$$\sum_{j\in N_1 \cup M+1} x_{ij}^k = 1, \forall k \in K^{\omega}, \omega \in M, i \in N \cup M+1, i \neq j \quad (16)$$

(6) Maximum Runtime

Eq. (17) is the maximum vehicle driving time constraint. The maximum runtime includes three parts: the time of departure from the transfer station, the time of returning to the transfer station, and the travel time between various stops.

$$\sum_{\omega\in M}\sum_{i\in N}\sum_{k\in K^{\omega}}\left[t_{0i}x_{0i}^k + max(0, f_i^k)\right] + \sum_{\omega\in M}\sum_{i\in N}\sum_{j\in N}\sum_{k\in K^{\omega}}\left[t_{ij}x_{ij}^k + max(0, f_j^k)\right] + \sum_{\omega\in M}\sum_{k\in K^{\omega}}\sum_{j\in N} t_{j0}x_{j0}^k \leq T_{max} \quad (17)$$

(7) Flow Balance Constraints

Eq. (18) indicates that each passenger is served by only one vehicle and all passengers are served; Eq. (19) indicates that the vehicle departs from the interchange point and eventually returns to it. Equation (20) represents flow conservation, ensuring that vehicles depart from the same passenger location after arrival.

$$\sum_{k\in K^{\omega}} s_i^k = 1, \forall i \in N, \omega \in M \quad (18)$$

$$\sum_{i\in N_1} x_{(M+1)i}^k = \sum_{j\in N_1} x_{j(M+1)}^k = 1, \forall k \in K^{\omega}, \omega \in M \quad (19)$$

$$\sum_{j\in N} x_{ij}^k = \sum_{j\in N} x_{ji}^k, \forall i \in N, k \in K^{\omega}, \omega \in M \quad (20)$$

2.4. Dynamic Pricing Scheme

Existing studies on DRFT routing primarily assume fixed fare structures, which neither account for passenger satisfaction nor offer personalized services, ultimately compromising system reliability. To better align passenger interests with operational performance and enhance perceived reliability, this study introduces a dynamic pricing mechanism that adjusts fares based on service delays. Passengers are compensated for delays, thereby improving psychological reliability. Since departure times directly influence passenger waiting times—and consequently fare adjustments—this approach creates an inherent incentive for operational punctuality.

In this paper, the fare for passenger i is denoted by p_i, the maximum payable fare is p_{max}, the minimum payable fare is p_{min}, the per-unit-time compensation cost is τ, and the delay time for bus service to passenger i is a_i.

$$p_i = \begin{cases} p_{max} - \tau a_i, & p_{max} - \tau a_i > p_{min} \\ p_{min}, & p_{max} - \tau a_i \leq p_{min} \end{cases} \quad (21)$$

$$a_i = \begin{cases} 0, & t_i^k \leq LT_i \\ t_i^k - LT_i, & t_i^k > LT_i \end{cases} \quad (22)$$

2.5. Departure Time

Bus departure intervals primarily follow two modes: fixed and flexible schedules. Conventional buses typically operate on fixed intervals in high-demand areas, while DRFT transit serves low-density regions where fixed schedules may compromise punctuality and increase passenger wait times. This study therefore develops a flexible interval model for comparative analysis with fixed scheduling.

This study adopts flexible departure intervals constrained by passenger time windows to ensure solvability. Each vehicle's departure time is determined by its first assigned passenger:

1.For pick up-first passengers, the departure time is calculated backward from the passenger's earliest acceptable pickup time;

2.For drop off-first cases, the departure time is set as the later value between the calculated time and the passenger's requested departure time.

The mathematical formulation is given below, where $N_k(1)$ denotes vehicle k's first served passenger.

$$\begin{cases} u_k = ET_i - \frac{d_{(M+1)i}}{V}, y_i^k = 1, i = N_k(1), \forall k \in K^{\omega}, \omega \in M \\ u_k = max(ET_i - \frac{d_{(M+1)i}}{V}, e_i^k), y_i^k = -1, i = N_k(1), \forall k \in K^{\omega}, \omega \in M \end{cases} \quad (23)$$

3. Solution Algorithm

The multi-objective optimization model established above is a typical vehicle routing problem and is also an NP-hard problem. Since this paper considers the factors of multiple vehicle types, it therefore adopts the multi-chain genetic algorithm for solving the problem. Compared to the traditional single-chain genetic algorithm, the multi-chain genetic algorithm yields higher quality solutions and has higher computational efficiency. The flowchart of the algorithm is depicted in Figure2.

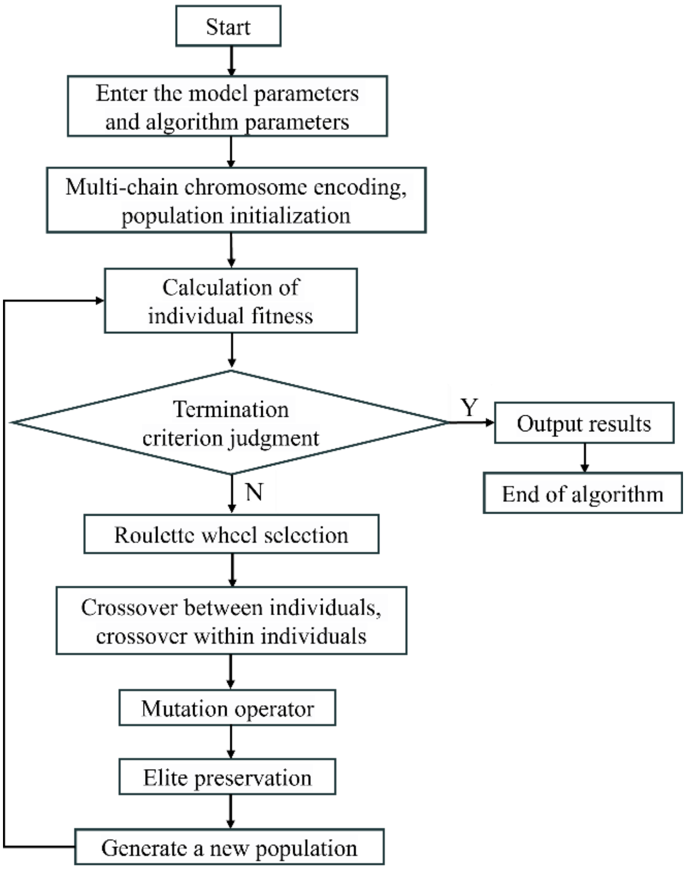

Fig. 2. Algorithm flowchart

The model presented in this paper involves a multi-objective function. Consequently, when calculating individual fitness, this multi-objective function is transformed into a single-objective function to solve the problem. The corresponding coding methods, crossover operators, and mutation operators are described below.

(1) Multi-objective conversion to single objective: due to the different solving directions of objective function 1 and objective function 2, the solving direction of objective function 1 is changed to $\text{Min}\,Z_3 = \text{Max}(-Z_1) = (C_1 + C_2) - C_3$, By linear weighting method, the final objective function is $\text{Min}Z_4 = \lambda_1 Z_3 + \lambda_2 Z_2$, As a fitness function *fit*, since the fitness function is the minimum value, the fitness function is normalized $fit' = \frac{fit_{max}}{fitmin_{max}}$, fit' is used as the fitness value after treatment;

(2) Coding method: Natural number multi-chain coding is adopted, that is, a chromosome contains multiple chains, each chain represents a slimy route, and the vehicle gene and passenger gene in each chain correspond one by one. For example, the interchange station code is 0, the passenger gene is 1~8, and the vehicle gene is 9, 10, so the chromosome contains two chains: 9: 0-1-2-3-4-0, 10: 0-5-6-7-8-0;

(3) Initial population generation: random generation by trial allocation method;

(4) The roulette selection method is adopted to improve the convergence speed of the algorithm;

(5) The crossover operator adopts two methods: inter-individual crossover and intra-individual crossover; Intra-individual Crossover: Select a parent individual based on intra-individual crossover probability. Randomly select two chromosome strands as the target strands for crossover operation. Employing a single-point floating crossover strategy: Generate a random natural number (crossover point) between 1 and the minimum length of the two chromosome strands. Exchange the stop genes after this crossover point between the selected strands. Feasibility Check: If both modified strands satisfy maximum capacity and maximum runtime constraints → Generate new offspring. If either strand violates constraints → Offspring retains the parent's original genetic sequence; Inter-individual Crossover: After selecting two parent individuals based on inter-individual crossover probability:

①. Chromosome Selection

Randomly designate one chromosome strand per parent for crossover (Strand a in Parent A, Strand b in Parent B).

②. Single-Point Fixed Crossover

Crossover point positioned after vehicle genes; Classify stop genes: Shared genes → Gene Pool G_{ab};Unique to a → Set G_a;Unique to b → Set G_b.

③. Gene Exchange & Sanitization

Exchange Strands a and b while preserving gene order;Remove genes from non-crossover strands in Parent A matching Gene Pool G_b; Remove genes from non-crossover strands in Parent B matching Gene Pool G_a.

④. Gene Reinsertion

Randomly insert genes from Set G_a into any position after the first gene of strands in Parent A; Verify feasibility per iteration: If capacity/runtime constraints violated → Reassign gene to alternative strand; Repeat until all genes allocated; Mirror process for Set G_b in Parent B.

(6) The mutation operator adopts the gene segment mutation method, randomly selects a chromosome and a chain in the chromosome, and then randomly generates two numbers q_1, q_2 within the length of the chromosome chain. Scramble the gene sequence within the segment between chromosome strands q_1 and q_2 to generate new offspring. Verify the newly generated offspring against capacity constraints and runtime constraints: if satisfied, retain the offspring; otherwise, re-scramble the gene sequence within the segment to produce new mutated offspring until constraints are met.

4. Case Study

4.1. Data Preparation

This study validates the proposed model and algorithm using an existing benchmark case[3]. The research area is assumed to be a low-density passenger flow zone, with the subway station as the origin and a circular service area of 3.5 km radius. The vehicle fleet consists of 7 Type A vehicles (capacity: 10 passengers) and 7 Type B vehicles (capacity: 15 passengers) stationed at the subway station.

The study period is set from 7:00 to 8:00, during which 80 reservation requests were generated across 25 stops. The demand composition includes 60 passengers traveling to the subway station and 20 passengers departing from it (i.e., 60 boarding and 20 alighting passengers), as illustrated in Figure 3. The coordinates of the 25 demand points are provided in Table 2.

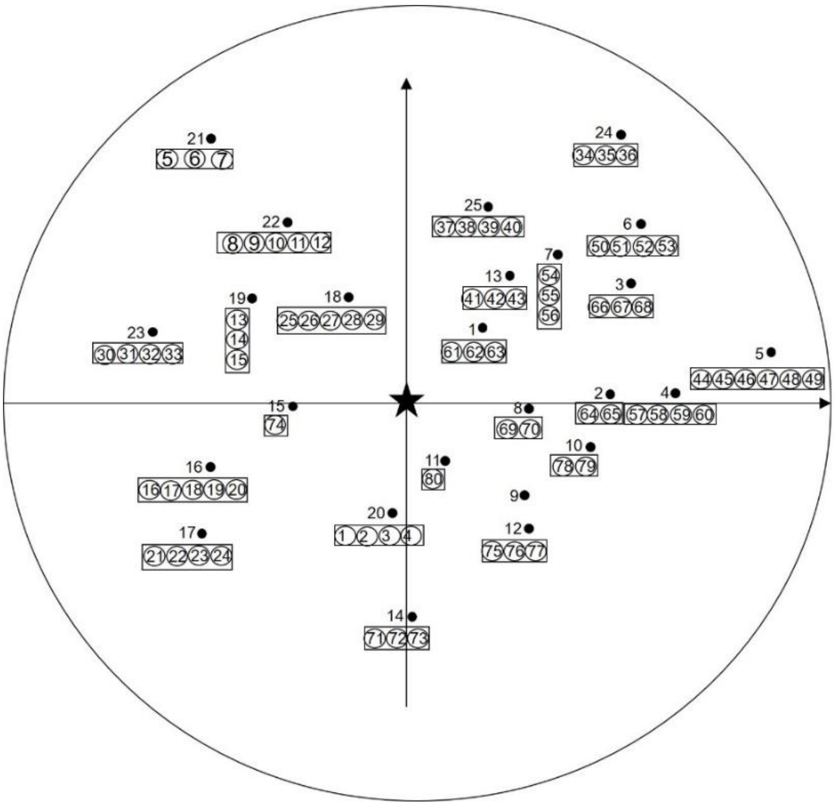

Fig. 3. Service area and demand point location.

Table 2 Coordinates of demand points

Demand point - coordinates	Demand point - coordinates	Demand point - coordinates	Demand point - coordinates
1-（0.87，0.42）	8-（1.44，-0.22）	15-（-1.01，-0.11）	22-（-1.09，1.63）
2-（2.00，0.02）	9-（1.30，-1.31）	16-（-1.56，-1.30）	23-（-2.00，0.58）
3-（2.20，0.90）	10-（1.97，-0.86）	17-（-1.62，-2.58）	24-（1.96，2.33）
4-（2.53，0.14）	11-（0.47，-1.25）	18-（-0.77，0.80）	25-（0.96，1.78）
5-（3.34，0.47）	12-（1.30，-2.08）	19-（-1.21，0.79）	
6-（2.10，1.34）	13-（1.00，1.00）	20-（-0.21，-1.77）	
7-（1.45，1.13）	14-（0.43，-3.50）	21-（-2.11，2.45）	

4.2. Parameter Setting

With reference to relevant literature, the specific parameter values of the model, algorithm and calculation examples in this paper are shown in Table 3.

Table 3. Values of related parameters.

Symbol	Value	Symbol	Value	Symbol	Value
V	35 km/h	p_{min}	1 RMB/person	θ_1	15 RMB/vehicle
T_{max}	40 min	φ_1	0.25 RMB /min	θ_2	25 RMB/vehicle
Q_A	10 Person/vehicle	φ_2	0.35 RMB /min	w_A^L	1.2 RMB /km
Q_B	15 Person/vehicle	τ	0.57 RMB /min	w_B^L	1.5 RMB /km
p_{max}	10 RMB/person	λ_1,λ_2	0.4，0.6		

4.3. Results

4.3.1. Model solution results under simultaneous pick-up and drop-off mode

The algorithm parameters were set as follows: inter-individual crossover probability of 0.8, intra-individual crossover probability of 0.1, mutation probability of 0.1, inertia weight of 0.9, cognitive coefficient and social coefficient both set to 2.0, population size of 100, and maximum iterations of 500, with departure times flexibly adjusted according to passengers' time windows. In Python programming, the scheduling model was solved using both the Multi-chain Genetic Algorithm (MCGA) and Particle Swarm Optimization (PSO), with the comparative results shown in Figure 4. As evident from Figure 4, the MCGA demonstrates superior optimization performance compared to PSO, achieving convergence after approximately 300 generations with an optimal objective function value. The optimal route scheme with the minimal objective function value is presented in Figure 5, while detailed results are shown in Table 4.

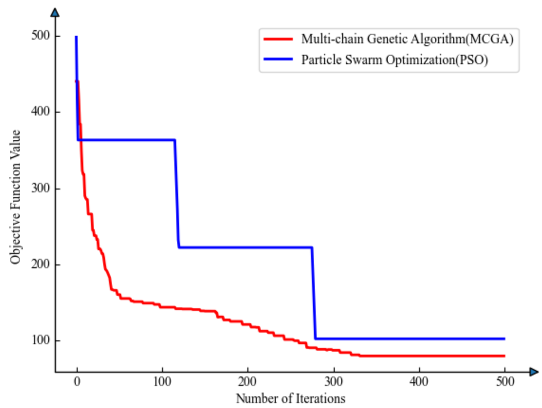

Fig.4. Iterative curve of fitness values.

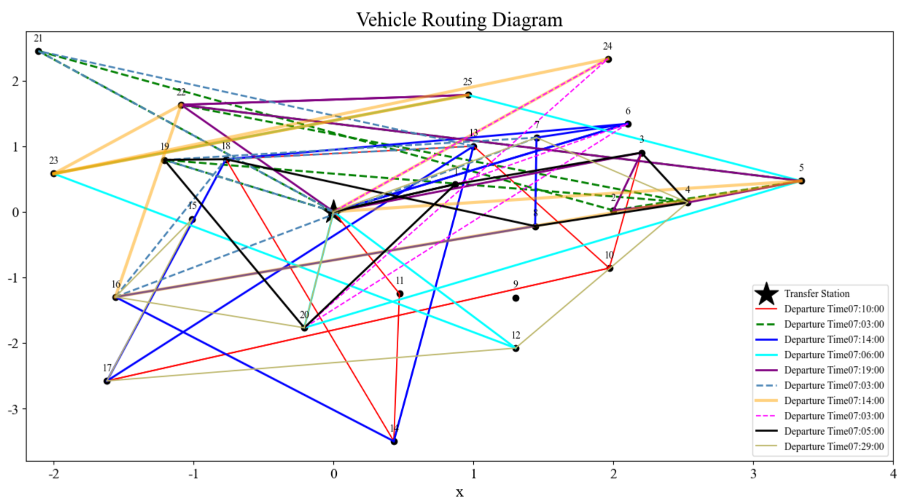

Fig.5. vehicle routing graph.

Figure 5 shows that the optimal number of dispatched vehicles during the 7:00-8:00 period is 7 Type A vehicles and 3 Type B vehicles. In this figure, solid lines represent Type A vehicles, dashed lines indicate Type B vehicles, numbers correspond to station codes, and five-pointed stars denote metro stations, with this graphical convention being consistently applied to all subsequent route diagrams in this study.

Table 4. Travel information.

Vehicle Type	*Vehicle Route*	Travel Distance/km	Passenger Count	Seat Utilization Rate	Travel Time/min
A	*3(66)-10(78)-17(22)-10(79)-13(42)-18(26)-14(72)-11(80)*	16.92	8	80%	35
B	*21(7,6)-2(64)-5(44)-22(9)-4(58)-19(15)*	12.46	7	47%	39
A	*6(50)-7(56)-8(70)-16(19)-14(73,71)-13(43)-17(24)-18(27,28)-6(52)*	15.92	11	110%	36
A	*12(76)-23(33)-25(40)-5(46,49)-20(3)*	21.68	6	60%	37
A	*22(11)-25(39,37)-22(10,12)-5(48,47)-4(60)-2(65)-3(68)*	15.77	10	100%	34
B	*19(13)-7(54)-16(16,18)-18(25)-13(41)-21(5)*	13.60	7	47%	23
A	*5(45)-16(17)-22(8)-23(31,30)-25(38)-23(32)-24(34)*	18.45	8	80%	32
B	*1(61)-6(51)-20(2)-24(35,36)*	11.24	5	33%	30
A	*1(62)-3(67)-4(57)-8(69)-18(29)-19(14)-20(4)-1(63)*	13.47	8	80%	32
A	*7(55)-4(59)-12(77)-17(21,23)-15(74)-16(20)-20(1)*	15.16	8	80%	30

In Table 4, vehicle routes are represented using a combined notation of station numbers and passenger IDs: the station number appears outside the parentheses, while the passenger IDs served at that station are enclosed within the parentheses. This same notation convention applies consistently to Tables 5 and 7. Table 4 shows Type B vehicles consistently exhibit seat utilization below 50%, while Type A vehicles maintain utilization rates above 80%. This disparity stems from Type B's lower passenger volumes despite its larger capacity, coupled with its higher per-kilometer operating cost. The optimization strategy prioritizes allocating passengers to more cost-efficient Type A vehicles when capacity permits, reducing both Type B's active fleet distance and overall system costs. This cost-conscious vehicle assignment enhances the solution's implementation reliability.

4.3.2. Comparison between fixed and flexible departure intervals

Based on flexible departure time adjustments with constrained dispatch intervals, the vehicle routing optimization results under fixed dispatch intervals were obtained using Python programming. The corresponding route diagram is illustrated in Figure 6, with the relevant results summarized in Table 5.

As shown in Figure 6, the optimal solution under fixed dispatch intervals also deploys 10 feeder buses in total, consisting of 7 Type A vehicles and 3 Type B vehicles. The dispatch interval is fixed at 5 minutes, with the first vehicle departing at 7:05 and the last at 7:50.

Table 5. DRFT travel information under fixed departure intervals.

Vehicle Type	*Vehicle Route*	Travel Distance /km	Passenger Count	Seat Utilization Rate	Travel Time /min
A	*1(62)-16(18,16,17)-12(76)-17(22,21)-18(25)-4(58)-22(9)-14(73,71,72)*	20.11	13	130%	36
A	*1(61)-6(51)-7(56)-22(8,11)-5(44)-10(78,79)-16(19)-6(52)-19(15)-20(2)*	15.52	12	120%	34

Vehicle Type	*Vehicle Route*	Travel Distance /km	Passenger Count	Seat Utilization Rate	Travel Time /min
A	*6(53,50)-5(45)-3(67)-21(5)-22(10)-25(38,4*	14.92	8	80%	29
A	*25(39,7)-23(31,33,32)-22(12)-4(57,60)-2(64)*	12.43	9	90%	28
B	*24(35)-23(30)-5(46,49)-21(7)-24(36,34)*	10.66	7	46%	18
B	*20(4,1,3)-7(55)-11(80)-5(48,47)-2(65)*	10.25	8	53%	20
A	*19(13)-18(28,29)-15(74)-13(43,42)-16(20)-8(70,69)*	13.90	9	90%	24
B	*1(63)-4(59)-13(41)-3(68)*	10.11	4	27%	17
A	*18(26,27)-17(23,24)-19(14)-7(54)*	13.23	6	60%	23
A	*12(75,77)-3(66)-21(6)*	10.69	4	40%	18

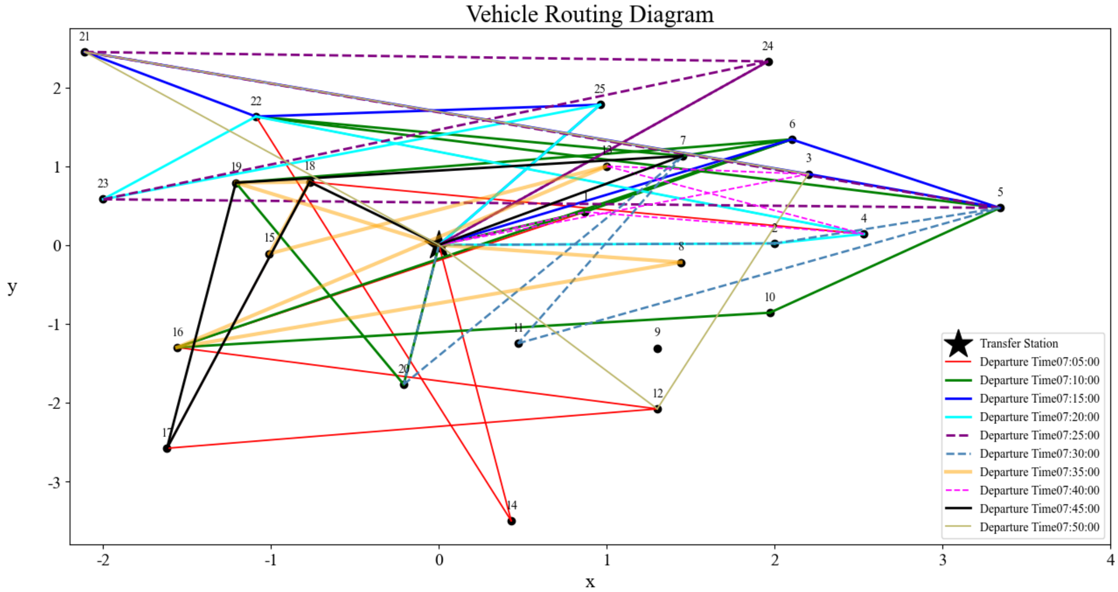

Fig.6. Fixed Interval Vehicle Routing Graph.

Table 5 indicates Vehicle 1 achieves the longest travel time and distance with over 100% seat utilization, while Vehicle 2 shows only 2 minutes less travel time but 5 km shorter distance-suggesting greater passenger wait times. Vehicle 1 demonstrates higher punctuality than Vehicle 2. These metrics (distance, passenger load, seat utilization, and travel time) are compared with flexible scheduling results in Table 6 for multi-criteria reliability analysis.

Table 6. Comparison of DRFT optimization results under different departure modes.

Departure interval form	Number of vehicles in use	Operating income/RMB	Time penalty cost/RMB	Total running time /min	Average seat utilization /%
fixed	10	233.6	255.6	247	73
unfixed	10	365.44	98.65	328	71.7

Table 6 shows both departure modes utilize identical vehicle types and numbers. Compared to fixed scheduling, flexible departure mode reduces time-window penalty costs by 61.4%, increases operating profits by 56.43%, but extends total travel time by 32.79% and slightly decreases seat utilization by 1.78%. The flexible departure mode demonstrates higher reliability in service punctuality (reduced waiting time penalties) and operator profitability, while fixed scheduling proves more reliable in minimizing passenger travel time and maintaining seat utilization efficiency.

The fixed scheduling mode demonstrates shorter total travel time as vehicles rarely arrive early at passenger locations, eliminating waiting time. While early arrivals in flexible scheduling provide reliability benefits for waiting passengers, fixed scheduling shows marginally higher seat utilization (though the difference is negligible). Overall, flexible scheduling offers superior reliability when considering operational performance and passenger service quality.

4.3.3. Comparison between fixed fare and dynamic pricing scheme

Under the fixed fare with flexible departure mode (where all passengers pay a flat rate of 6 RMB per trip), the DRFT route optimization results obtained through Python programming are illustrated in Figure 7, with detailed results presented in Table 7.

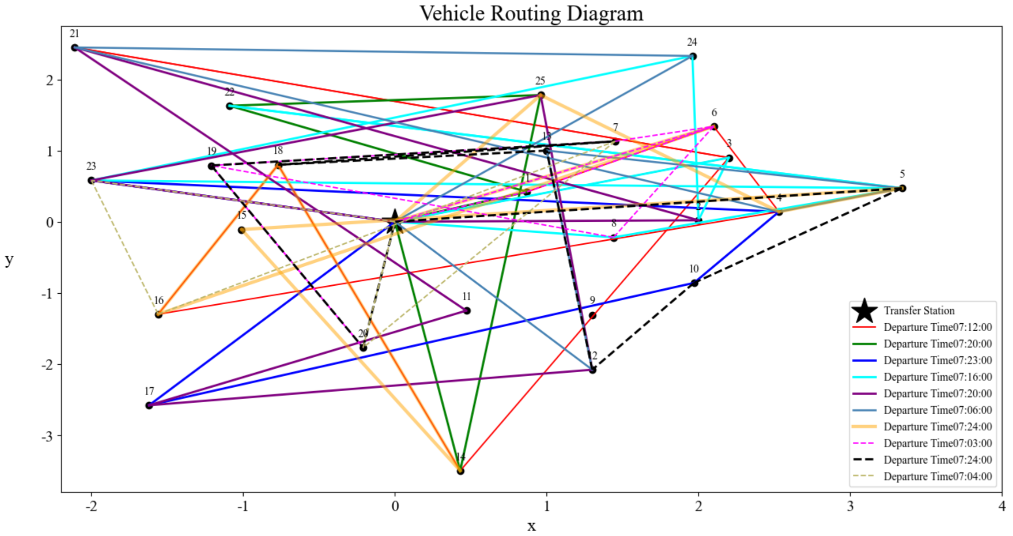

Fig.7. Fixed Fare Vehicle Routing Graph.

Table 7. DRFT travel information under fixed ticket prices.

Vehicle Type	*Vehicle Route*	Travel Distance /km	Passenger Count	Seat Utilization Rate	Travel Time /min
A	*3(67)-21(6)-3(66)-14(73)-18(26)-16(16,19)-4(58)-6(51)-1(62)*	14.57	10	100%	25
A	*14(72)-25(38,40)-22(12)-1(63)*	19.04	5	50%	33
A	*17(24)-10(78)-4(60)-23(32)*	15.23	4	40%	26
A	*8(70)-5(45)-22(9,10)-5(49)-23(31)-24(35,34)-2(64)-3(68)*	16.14	10	100%	39
A	*23(30)-25(37)-12(75)-17(22)-11(80)-21(5)-2(65)*	19.53	7	70%	33
A	*12(76)-13(41)-5(44)-4(57)-21(7)-24(36)*	13.72	11	110%	28
A	*25(39)-4(59)-5(47)-15(74)-14(71)-18(25,29)-16(20)-6(52)*	17.43	9	90%	33
B	*1(61)-6(53)-8(69)-19(13)-20(1,4)-19(14)-7(56)-6(50)*	12.26	9	60%	24
B	*5(46,48)-10(79)-12(77)-13(42,43)-18(27,28)-7(55)-19(15)-20(3)*	13.26	6	40%	22
B	*23(33)-16(18)-7(54)-20(2)*	13.25	4	27%	23

As illustrated in Figure 7, under the fixed fare structure, the optimal solution dispatches 10 feeder buses (including 7 Type A vehicles and 3 Type B vehicles) during the 7:00-8:00 period using the flexible departure mode.

Table 7 shows that Vehicles 1, 4, and 6 achieve seat utilization rates exceeding 100%, demonstrating the efficiency of the simultaneous pickup and drop-off mode in enhancing resource reliability. While Vehicle 5 covers the longest distance, Vehicle 4 has a higher travel time, indicating better punctuality for Vehicle 5. Vehicle 6, however, experiences longer early-arrival waiting times. A comparison with flexible scheduling and dynamic pricing scheme (Table 8) further evaluates the reliability of both modes across multiple performance metrics.

Table 8. Comparison of DRFT optimization results under different fare forms.

Fare form	Number of vehicles in use	Time window penalty cost/RMB	Total passenger cost (including fare)/RMB	Operating income/RMB	Average seat utilization/%
dynamic	10	98.65	1054.36	365.44	71.7
fixed	10	152.65	782.8	110.44	69.3

The comparative analysis in Table 8 reveals that dynamic pricing scheme significantly outperforms fixed fares across multiple operational dimensions while showing one notable trade-off. Specifically, the dynamic pricing scheme reduces time-window penalty costs by 35.37%, boosts operational profits by 231.81%, and improves seat utilization by 3.46%, demonstrating enhanced reliability in terms of service punctuality (through reduced waiting time penalties), operator profitability, and resource efficiency. However, these benefits come at a 34.69% increase in total passenger costs, making the fixed-fare approach more reliable from a user expenditure perspective. This comprehensive comparison underscores the inherent balance required when evaluating transit reliability, where dynamic pricing scheme excels in operational performance while fixed fares maintain advantages in cost predictability for passengers.

The dynamic pricing scheme, despite its higher maximum fares increasing passenger costs, enhances overall DRFT reliability through compensatory mechanisms. When buses miss time windows, passengers may cancel bookings-negatively impacting both operator profits and seat utilization. Dynamic pricing mitigates this by compensating passengers, encouraging them to wait rather than cancel. This dual benefit of maintaining ridership while optimizing operations ultimately makes dynamic pricing more reliable than fixed fares across all performance metrics.

5. Conclusion

This paper focuses on optimizing the routing schemes for demand-responsive feeder transit operating in a simultaneous pickup and drop-off mode, aiming to enhance their reliability in various aspects. The study investigates the reliability of routing outcomes under different scenarios, including whether the departure intervals are fixed and whether the fares are fixed. A routing optimization model is established and validated through case study analysis, yielding relevant findings.

(1) Compared with the fixed departure mode, the flexible departure mode yields higher operational profits for service providers and improves feeder punctuality, thereby enhancing the reliability of DRFT. However, from the perspectives of passenger travel time and resource utilization efficiency, the fixed departure mode demonstrates slightly better reliability.

(2) Compared to the fixed-fare scheme, the dynamic pricing scheme demonstrates superior performance in terms of vehicle punctuality, operational profitability, and seat utilization efficiency, thereby enhancing the overall reliability of DRFT. However, from the perspective of passenger costs, the fixed-fare scheme exhibits marginally better reliability. Nevertheless, given the inherent limitations of fixed pricing (e.g., inflexibility in demand fluctuations), the dynamic pricing scheme approach proves more practical and adaptable to real-world operational conditions.

(3) This study pioneers a unified framework integrating dynamic pricing, mixed pick-up/delivery operations, route planning, dispatching schedules, and fleet sizing—significantly advancing beyond traditional isolated approaches. Our model delivers a synergistically optimized solution that substantially enhances DRFT system reliability. This integrated methodology addresses a critical research gap in combined dynamic pricing and route scheduling while providing theoretical foundations for practical implementations.

(4) This study on DRFT routing optimization has certain limitations. Specifically, it does not account for reliability performance under scenarios involving multiple transfer points or time-varying road networks. Therefore, future research will investigate DRFT route reliability considering both multiple transfer nodes and time-dependent vehicle speeds.

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