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RESEARCH ARTICLE

An Optimization Model for the Demand-Responsive Transit With Non-Fixed Stops and Multi-Vehicle Type

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ABSTRACT As a new type of public transportation, demand responsive transit has gradually attracted attention for its flexibility and efficiency. In order to solve problems such as single-vehicle type and fixed stop, and improve its operation efficiency, a collaborative scheduling method combining multi-occupancy vehicle type with non-fixed stop is proposed. Different from the previous studies on scheduling problems of demand responsive transit, which only focused on stop modes such as fixed or non-fixed stop or vehicle types containing single-occupancy or multi-occupancy, this paper also studies the vehicle scheduling of demand responsive transit from the perspective of combination of non-fixed stop and multi-vehicle type. In addition, carbon emission cost is innovatively added into the scheduling model, and an improved genetic algorithm with multiple crossovers within individuals is designed to accelerate the convergence speed of the algorithm and improve the solution efficiency. Finally, taking Shijiazhuang downtown regional road network as an example, the validity of the proposed scheduling method is verified. The results show that compared with the single-occupancy vehicle scheduling method, the operating costs of the multi-occupancy vehicle scheduling method can be reduced by up to 25.0%, and the average passenger in-vehicle time is decreased by up to 8.8%, which could significantly reduce the system operating costs on the premise of ensuring shorter total passenger travel time. Compared with the mode with fixed stops, the average full load ratio of the mode with non-fixed stops increased by 21.7%. Besides, the convergence speed and solving speed of the proposed improved genetic algorithm are increased by 31.7% and 4.8%, compared with the traditional genetic algorithm.

INDEX TERMS Urban traffic, demand responsive transit, genetic algorithm, vehicle scheduling, multi-vehicle type, non-fixed stop.

I. INTRODUCTION

Demand Responsive Transit (DRT) is a kind of public transportation service system that does not operate using fixed routes and timetables. The system offers a more flexible approach for operations that determine the scheduling plan and operating routes according to the individual spatial and temporal information submitted by passengers, which could effectively reduce detours and deadhead where traditional public transit does not perform well in low density or large-variance areas [1], [2]. In the post-epidemic era, the DRT system could be much more popular for providing personality service for individuals and improving efficiency of bus company, as well as limiting the number of in-vehicle passengers. In DRT system, reasonable vehicle route scheduling could significantly reduce the vehicle operating costs and improve the efficiency of public transit operations [3]. DRT service usually involves non-fixed stop, fixed stop and other service modes. In the fixed stop mode service, the vehicle route passes through not only demand points from occasional requests but also several presetting fixed stops providing picking-up and delivering services. However, as for

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the non-fixed stop service mode, vehicle routes are completely determined by demand points from passenger requests distributed stochastically in the region.

Currently, most research focuses on constructing models for DRT vehicle route scheduling problems. Sun et al. [4] optimized customized bus routes with the goal of minimizing operators' operating costs, and introduced random travel time constraints into the model, which could better meet the travel demands of passengers. Narayan et al. [5] set up a model with the goal of minimizing passengers' travel benefits and proposed a route selection approach combining fixed stop with DRT services. which can effectively reduce the average waiting time. Only one single objective that maximizes the benefit of enterprises or passengers is involved in the above studies. In order to obtain better scheduling results, the multi-objective model is established considering both passengers' traveling costs and operating costs [6], [7]. Ayadi et al. [8], [9], Jin et al. [10] and Guan et al. [11] solved DRT scheduling problem by introducing penalty function into the proposed model, aiming at maximizing benefits of both enterprises and passengers, which could significantly improve passengers' travel satisfaction. A model aiming at maximizing operator profits, maximizing the number of boarding passengers and minimizing total travel costs of passengers is established to optimize the vehicle route [12], [13], [14], [15]. Above models only take into account the benefits of enterprises and passengers, but regardless of the social benefits, especially environmental factors. Recent research studied the eco-oriented DRT vehicle route scheduling problems, and established scheduling models considering vehicle fuel consumption/ carbon emission [16], [17].

Most of the current studies constructed vehicle route scheduling models based on single-type vehicle. Shen et al. [18] established a model with the goal of maximizing enterprises' revenue with single occupancy vehicles. Sun et al. [19] studied the DRT feeder service based on ride-sharing and established a model aiming at minimizing the total travel time of passengers. Based on the optimum routes by solving the proposed model, the service could accurately provide individual and vehicle guidance. A multi-objective model is constructed by taking into account the benefits of enterprises and passengers with a single-vehicle type [20], [21], [22]. However, single-vehicle type is not suitable when travel demand has a large variance, especially in peak and off-peak hours, resulting in in-vehicle congestion and vehicle deadhead. Besides, low vehicle capacity generally means high comfort for passengers but high travel cost for the bus company. On the contrary, high vehicle capacity reduces cost for bus company, but is not friendly to passengers. Therefore, multi-occupancy vehicle type service needs to be offered in this trade-off. Wang et al. [23] investigated two vehicle types in the feeder bus route vehicle scheduling problem. Zhang et al. [24] established a model considering the coordination between rental vehicles and DRT in suburban areas, aiming at minimizing total vehicle travel costs of both vehicles of DRT and rental vehicles. Zhao et al. [25] studied the coordinated optimization problems of conventional public transit and DRT, and established a model with the objective of minimizing passengers' total travel time as well as the total fleet size.

In order to solve the DRT optimization model, genetic algorithm is a common method [28]. For solving the bus line design or optimization model, Johar et al. [29] summarized and concluded the research based on genetic algorithm to solve this kind of problem, and concluded that genetic algorithm is an effective optimization technology. Chakrobority et al. [30] showed the effectiveness of genetic algorithm in solving urban public transport network design and optimization problems, and designed a set of programs for solving such problems based on genetic algorithm. Genetic algorithm is used to optimize the departure schedule of public transportation vehicles to reduce the transfer time of passengers, to generate bus lines with the goal of decreasing passenger travel time in public transit vehicle scheduling problems [31], [32], [33], [34]. It is concluded that genetic algorithm performs much better in computation efficiency and applicability in solving public transit problems, especially in vehicle scheduling problems.

Most of models are established based on the optimal benefits of enterprises and passengers, however, social benefits are rarely considered. Single-vehicle type is largely used in vehicle scheduling model, while few studies focus on multi-occupancy vehicle type. Besides, the non-fixed stop DRT service usually involves fixed stops, just like conventional transit stops, lacking of the flexibility. In order to fill those gaps, the DRT service combines with non-fixed stops, multi-objective of combining benefits of passengers, operators and carbon emission, and multi-vehicle type is presented in this paper. In addition, an improved genetic algorithm is also proposed to solve the DRT vehicle problems.

The rest of this paper is organized as follows: The first section describes the model parameters and constructs the DRT scheduling model. A heuristic algorithm is proposed in the second section. The third section gives an illustrative case to demonstrate the validity of the model and effectiveness of the heuristic algorithm. The fourth section draws the conclusions and outlooks future research.

II. SCHEDULING MODEL OF DRT WITH NON-FIXED STOPS AND MULTI-VEHICLE TYPE

A. PROBLEM DESCRIPTION

The fixed stops are generally supermarkets, schools and other large passenger demand points or some regular bus stops, where passengers do not need to submit requirements. Meanwhile, vehicles must stop at fixed stops regardless of whether there is demand. The non-fixed stops are meeting points of passenger demand, and vehicles will provide service only when the passengers submit their demands. In this paper, passengers submit information involving boarding and alighting points, as well as expected departure and arrival time, to the system before trips, and the dispatch center could

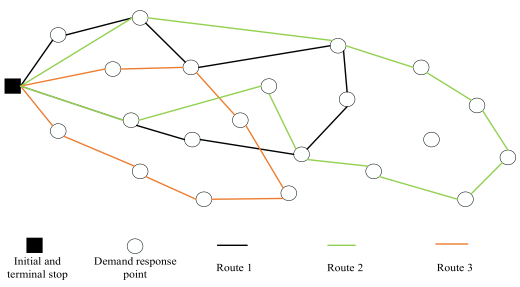

FIGURE 1. Vehicle routes for DRT with non-fixed stops.

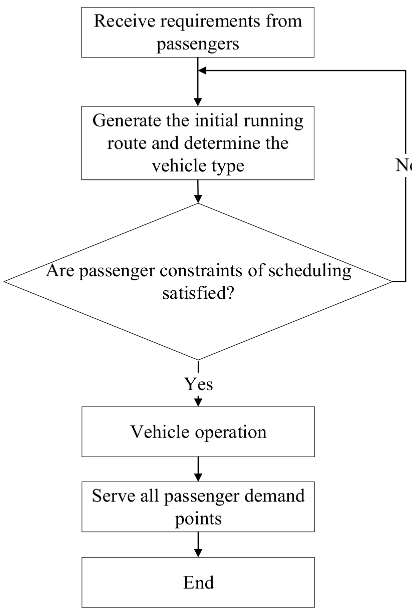

FIGURE 2. The operating flowchart of DRT system with non-fixed stops.

flexibly determine vehicle types and driving routes according to receiving demand. Only passengers who submit their demands are required to take a ride. The driving routes with one terminal is shown in Fig. 1 and the workflow is shown in Fig. 2.

B. MODEL ASSUMPTIONS

The DRT scheduling model with non-fixed stops and multi-vehicle type studied in this paper has the following assumptions [19], [35]:

(1) The vehicle speed is assumed to be constant, without considering the influence of other occasional factors such as congestion;

(2) Passengers' boarding and alighting vehicle time is assumed to be constant;

(3) Passengers are not allowed to modify their travel information once submitting reservations;

(4) Each passenger is assumed to be served by one vehicle without transfer;

(5) Vehicle must arrive at the departure point within the time windows required by the passengers;

(6) All riding requests of passengers must be served, and each passenger can only be visited at once;

(7) The distance between stops is calculated by actual distance;

(8) The vehicles are dispatched from the original depot and are terminated at the same depot.

C. MODEL PARAMETERS

The notations used in the model formulations are shown in Table 1, together with their description.

D. PENALTY FUNCTION

In order to ensure service quality and passenger satisfaction, passenger time window is considered as a strict constraint, that is, the vehicle must arrive at the demand point within the boarding time window required by the passengers to provide services. If not, the penalty cost is extremely high.

The formula of penalty function is shown in Eq. (1) below:

$$f(t) = \begin{cases} 0 & e_{qi} \le t_{ki}^{p} \le l_{qi} \\ M & t_{ki}^{p} < e_{qi}, t_{ki}^{p} > l_{qi} \end{cases} \tag{1}$$

E. CONSTRUCTION OF DRT VEHICLE SCHEDULING MODEL WITH NON-FIXED STOPS

According to the above parameters, the scheduling model is constructed, the benefits of passengers, enterprises, and society are considered comprehensively, and the constraints of passenger travel time window, vehicle capacity and maximum vehicle travel time are used to establish the DRT vehicle scheduling model with non-fixed stops and multi-vehicle type.

(1) Vehicle setup cost C_1

$$C_1 = \sum_{k\in K}\sum_{p\in P}\sum_{j\in N_1^+} G_p X_{kOj}^{p} \tag{2}$$

(2) Vehicle operating cost C_2

$$C_2 = \sum_{k\in K}\sum_{p\in P}\sum_{i\in N_1\cup\{O\}}\sum_{j\in N_1\cup\{O\}} C_p d_{ij} X_{kij}^{p} \tag{3}$$

(3) Carbon emission reduction cost C_3

Carbon emission reduction cost is the difference of the total carbon emission cost of DRT and the counterpart of private car.

$$C_3 = C_a\left(\sum_{k\in K}\sum_{p\in P}\sum_{i\in N_1\cup\{O\}}\sum_{j\in N_1\cup\{O\}} W_{Ga}^{p} d_{ij} X_{kij}^{p} - W_{Ca}\times\sum_{q\in Q} h_q\right) \tag{4}$$

Travel distance of passenger:

$$h_q = \sum_{i\in N_1^+}\sum_{j\in N_1^-} d_{ij} Z_{uqi} Z_{bqj} \tag{5}$$

TABLE 1. Notations.

Notation	Description	Notation	Description
N_1^+	The set of passengers booking demand	C_2	Vehicle operating cost
N_1^-	The set of alighting demand	C_3	Carbon emission cost
N_1	The set of total boarding and alighting demand points	C	Total system cost
N'	The set of all demand points preceding the demand point $i\{1,2,...,i-1\}$	G_p	Unit setup cost value for vehicle type p $p \in P$
q	Passenger index $q \in Q$	C_p	Unit transportation cost of vehicle type p $p \in P$
Q	Set of passengers	C_a	Unit cost value of carbon emission cost
O	Vehicle depot index $\{O\}$	d_{ij}	The distance between demand points i and j. $i, j \in N_1$
i, j	Passenger demand point index $i, j \in N_1$	v	Vehicle speed
k	Vehicle index $k \in K$	M	A large enough positive value
K	Set of vehicles	D_{pki}	The number of boarding passengers in vehicle k for type p when it arrives at the demand point i $p \in P$ $i \in N_1$
p	Vehicle type index $p \in P$	u_i	The number of boarding passengers at the demand point i $i \in N_1$
P	Set of vehicle types	b_i	The number of alighting passengers at the demand point i $i \in N_1$
$t_{u(q)}$	Boarding time of passenger q $q \in Q$	λ_1、λ_2、λ_3	Weight coefficient
$t_{d(q)}$	Alighting time of passenger q $q \in Q$	T_k^p	The total travel time for vehicle k of type p $k \in K$ $p \in P$

TABLE 1. *(Continued.)* Notations.

Notation	Description	Notation	Description
t_i	Vehicle arrival time at demand point i $i \in N_1$	$f(t)$	Time window penalty cost
t_a	Average boarding or alighting time	$[e_{qi}, l_{qi}]$	The time window of passenger q at the demand point i, e_{qi} is the earliest boarding time of passenger q at the demand point i, and l_{qi} is the latest boarding time of passenger q at the demand point i. $i \in N_1$ $q \in Q$
$T_{\max}$	Maximum DRT operating time	$[y_{ki}^p, g_{ki}^p]$	The arrival and departure times of vehicle k for type p serving the demand point i $p \in P$ $i \in N_1$
R_p	The number of vehicles for each type p $p \in P$	X_{kij}^p	Binary variable, 1, vehicle k of type p will visit j after i, 0, otherwise. $p \in P$ $i, j \in N_1$ $k \in K$
Q_p	The capacity of vehicle for type p $p \in P$	Z_{uqi}	Binary variable, 1, when passenger q gets on at demand point i, 0, otherwise. $q \in Q$ $i \in N_1$
W_{Ga}^p	Unit carbon emission of vehicle for type p $p \in P$	Z_{bqi}	Binary variable, 1, when passenger q gets off at demand point i, 0, otherwise. $q \in Q$ $i \in N_1$
W_{Ca}	Unit carbon emission of car	Y_{kq}^p	Binary variable, 1, when passenger q chooses vehicle k of type p, 0, otherwise. $p \in P$ $q \in Q$ $k \in K$
C_1	Vehicle setup cost		

By integrating Eq. (2)-(4), the objective function of the scheduling model can be obtained as follows:

$$\min C = \lambda_1 C_1 + \lambda_2 C_2 + \lambda_3 C_3 \tag{6}$$

The constraints are as follows:

$$\sum_{j \in N_1^+} X_{kOj}^p = 1 k \in K, p \in P \tag{7}$$

$$\sum_{i \in N_1^-} X_{kiO}^p = 1 k \in K, p \in P \tag{8}$$

$$\sum_{k \in K} \sum_{j \in N_1^+} X_{kOj}^p \leq R_p p \in P \tag{9}$$

$$0 \leq D_{pki} \leq Q_p i \in N_1, k \in K, p \in P \tag{10}$$

$$D_{pki} = \sum_{i \in N'} X_{kij}^p (u_i - b_i) \tag{11}$$

$$u_i = \sum_{q \in Q} Z_{uqi} Y_{kq}^p \tag{12}$$

$$b_i = \sum_{q \in Q} Z_{bqi} Y_{kq}^p \tag{13}$$

$$0 < t_{d(q)} - t_{u(q)} \leq T_q q \in Q \tag{14}$$

$$t_{u(q)} = \sum_{i \in N_1^+} Z_{uqi} y_{ki}^p \tag{15}$$

$$t_{d(q)} = \sum_{j \in N_1^-} Z_{bqj} y_{kj}^p \tag{16}$$

$$T_k^p \leq T_{\max}, k \in K, p \in P \tag{17}$$

$$T_k^p = \sum_{i \in N_1 \cup \{O\}} \sum_{j \in N_1 \cup \{O\}} \frac{d_{ij} X_{kij}^p}{v} + t_a \sum_{i \in N_1} \max(u_i, b_i) \tag{18}$$

$$\sum_{i \in N_1 \cup \{O\}} X_{kij}^p = 1 \; k \in K, p \in P, j \in N_1, i \neq j \tag{19}$$

$$\sum_{j \in N_1} X_{kij}^p = \sum_{j \in N_1} X_{kji}^p k \in K, p \in P, i \in N_1 \cup \{O\} \tag{20}$$

$$\sum_{j \in N_1} X_{kij}^p = \sum_{j \in N_1} X_{kji}^p k \in K, p \in P, i \in N_1 \cup \{O\} \tag{21}$$

$$\frac{d_{ij} X_{kij}^p}{v} + g_{ki}^p \leq y_{kj}^p, k \in K, p \in P, i \in N_1 \cup \{O\}, j \in N_1 \cup \{O\} \tag{22}$$

$$y_{kj}^p = \sum_{i \in N_1 \cup O} \sum_{j \in N_1 \cup O} \frac{d_{ij} X_{kij}^p}{v} + t_a \sum_{i \in N_1} \max(u_i, b_i) \tag{23}$$

$$g_{kj}^p = y_{kj}^p + t_a \max(u_j, b_j) \tag{24}$$

$$Z_{uqi} Y_{kq}^p = X_{kij}^p i \in N_1, q \in Q, p \in P, k \in K, \forall j \in N_1 \tag{25}$$

$$Z_{bqj} Y_{kq}^p = X_{kij}^p j \in N_1, q \in Q, p \in P, k \in K, \forall i \in N_1 \tag{26}$$

$$e_{qi} \leq t_{ki}^p \leq l_{qi} \; i \in N_1 \tag{27}$$

Eq. (6) is the objective function. Objective C_1 is the vehicle setup cost, objective C_2 is the vehicle operating cost, and objective C_3 is the carbon emission cost. Eqs. (7)-(27) are related formulas of constraint conditions. Eq. (7) and Eq. (8) indicate that vehicles can only start from the depot O and return to the same depot. Eq. (9) ensures that the number of vehicles participating in scheduling does not exceed the total number of vehicles available. Eq. (10) ensures that the number of passengers in vehicle does not exceed the vehicle capacity. Eq. (11) calculates the number of people in the car when the k bus of model p reaches the demand point i. Eq. (12) and Eq. (13) calculate the number of people boarding and alighting at the demand point i. Eq. (14) is the boarding and alighting time limitation for each passenger. Eq. (15) and Eq. (16) calculate the actual boarding and alighting time of passenger$q$. Eq. (17) is the maximum operation time constraint for each vehicle. Eq. (18) calculates the one-way travel time of the k type p bus. Eq. (19) and Eq. (20) ensure that each demand point can only be visited once by one vehicle. Eq. (21) ensures that each vehicle that arrives at the demand point must leave from the same demand point. Eq. (22) is the vehicle arrival time limitation. Eq. (23) and Eq. (24) calculate the time for the k type bus to arrive and leave the demand point j. Eq. (25) and Eq. (26) ensure vehicle that stops at a pick-up point must stop at the corresponding drop-off point for each passenger. Eq. (27) ensures that the vehicle arrives at demand point within the time window that the passenger is willing to board.

III. SOLUTION OF DRT VEHICLE SCHEDULING MODEL WITH NON-FIXED STOPS

The DRT vehicle scheduling model with non-fixed stops established in this paper has many constraints, complex objective functions, and a large amount of data at the base, so many factors such as time and space need to be considered at the same time. Given the complexity of the problem, this paper aims to utilize a genetic algorithm to address the model, based on the characteristics of the model, the traditional genetic algorithm is briefly modified.

The algorithm flowchart is shown in Fig. 3.

As can be seen from Fig. 3, the specific steps of the genetic algorithm in this paper are as follows:

(1) Input information of stops, vehicle capacity, passenger travel demand, and other parameters.

(2) Coding design. In this paper, points involving demand points and vehicle depot are encoded into the chromosome structure by natural number coding. Firstly, passengers that meet the requirements of the time window constraints are attempted to be put in the same vehicle. Then, remove the repeated-location demand points. Finally, if the number of passengers exceeds the capacity of the vehicle, another vehicle will be dispatched to provide delivering service until all passengers are allocated.

The genes for each trip chromosome include the departure depot, demand points, and returning depot. The coding method is shown in Fig. 4. 0 and 9 represent the starting and ending points of vehicles (0 and 9 represent the same station in this paper, and are represented by different numbers to easily distinguish). The chromosome code below indicates that vehicle 1 departs from station 0 and returns to station

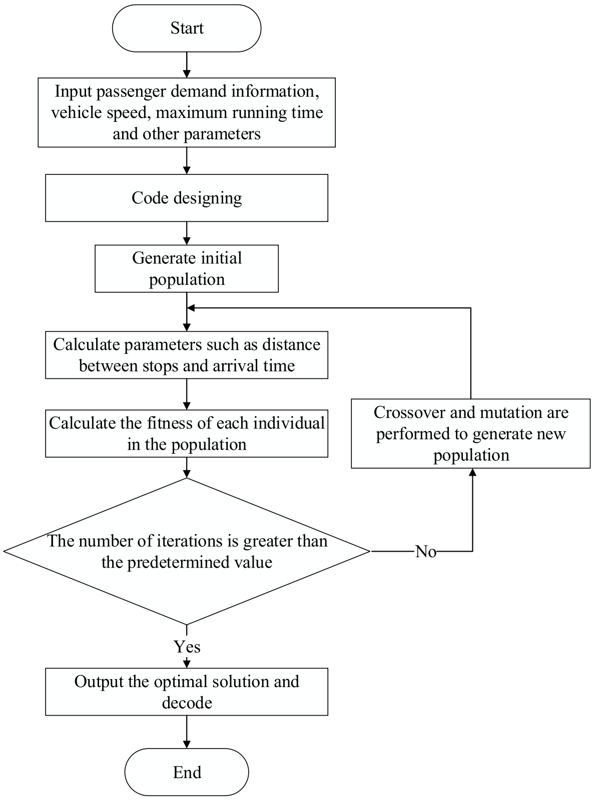

FIGURE 3. The flowchart of improved genetic algorithm.

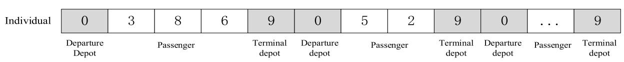

FIGURE 4. Encoding method.

9 after serving passengers 3, 8, and 6, while vehicle 2 departs from station 0 and returns to station 9 after serving passengers 5 and 2. The boarding and alighting sequences of the passengers are determined by the constraints of maximum in-vehicle time, departure time window, and other factors.

(3) Set algorithm parameters. The maximum evolutionary iterations, cross mutation probability, and other parameters are defined.

(4) Initial population. Generate an initial population with random size.

(5) Fitness function. In this paper, the objective function is selected as the fitness function to solve the optimal value.

(6) Crossover operation. Crossover operation is carried out within individuals. Starting from the first chromosome, it is judged whether there is a point that can be crossed in subsequent chromosomes according to the passenger's boarding time window. If exists and satisfies the constraints, the two chromosomes can be crossed. If not, crossover will not be carried out, and the next chromosome will continue to be selected until all chromosomes are checked. If no point can be crossed, the chromosome will remain unchanged. The crossing points in each chromosome do not include the first and last points. The cross-operation diagram is shown

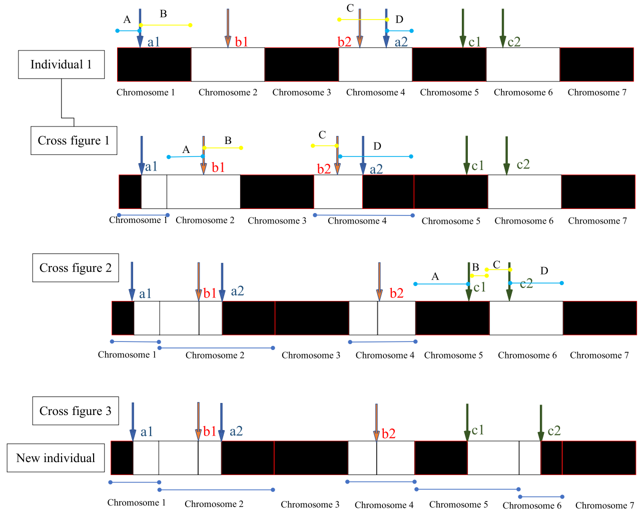

FIGURE 5. Intra-individual crossover.

in Fig. 5. For example, for individual 1, the point a1 in chromosome 1 can be crossed with point a2 in chromosome 4. Then, fragment A and fragment D constitute a new chromosome 1, and fragment B and fragment C constitute a new chromosome 4. Then continue to seek for points that can be crossed in subsequent chromosomes. If point b1 in chromosome 2 and point b2 in chromosome 4 can be crossed, then fragment A and fragment D constitute a new chromosome 2, and fragment B in chromosome 2 and fragment C in chromosome 4 constitute a new chromosome 4. The population after crossing is shown in Crossover figure 2. Each chromosome is judged in turn until all chromosomes are finished, and finally a new individual is obtained, presented in Crossover figure 3.

(7) Mutation operation. A local search algorithm is selected for mutation. Two positions referred to randomly generated natural numbers in the randomly selected chromosome from parent chromosome are exchanged while the remaining maintains unchanged, so as to obtain a new offspring.

(8) Calculate the initial fitness of each schedule and select the optimal one to put into the iteration list.

(9) Cross-mutation operation is carried out on each population successively to obtain a series of vehicle schedules, then calculate the fitness of each population and select the best one and put it into the iteration list, afterwards, set gen=gen+1, and finally exit until the maximum number of iterations is reached or the difference between the global optimal values in the nearest two iterations is very low.

Compared with the traditional genetic algorithm, the genetic algorithm designed in this paper has the following improvements:

(1) Vehicle capacity, time window and picking-up and delivering location constraints are considered in the improved algorithms, instead of only regarding to capacity in the traditional algorithm. Therefore, it is easier to get a better solution.

(2) The cross operation of traditional genetic algorithm adopts external cross for two individuals in a population, resulting in spending a lot to solve thousands of the duplicate

FIGURE 6. Figure of real road network.

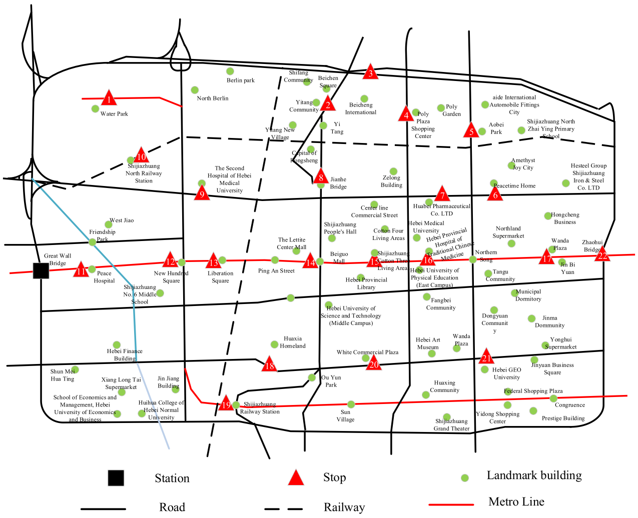

FIGURE 7. Topology diagram of road networks.

segments. However, inter cross is utilized in improved genetic algorithm, ensuring that each gene code is different.

(3) The traditional genetic algorithm adopts out-of-order mutation, while the improved genetic algorithm adopts 2-opt for mutation with higher solution efficiency.

IV. CASE ANALYSIS

A number of demand points from the downtown area in Shijiazhuang (mainly including residential communities, schools, commercial facilities and entertainment venues, etc.) is selected to verify the capability and applicability of DRT with non-fixed stops. The proposed solution algorithm is programmed in python 3.8. The real road network in the specific area is shown in Fig. 6, and the topology diagram with non-fixed DRT stops grouped by the K-means clustering method based on the submitted demand points is shown in Fig. 7.

A. PARAMETERS DESCRIPTION

In order to verify the effectiveness of the model, two types of vehicles are referred to provide travel services for passengers. The parameters of the two types of vehicles are shown in Table 2:

The shortest distance between each demand point is calculated using Amap. The parameters of the vehicle initial route optimization model are set as follows:

TABLE 2. Vehicle type and related parameters.

Vehicle type	Vehicle capacity	Setup cost	Fuel cost (yuan/km)	Carbon emission cost (yuan/km)
A	10	15	2.1	3.9
B	25	25	2.7	4.9

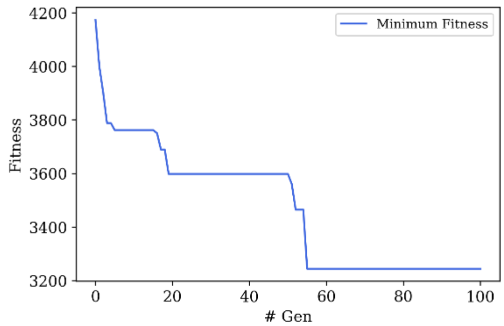

FIGURE 8. Results of improved genetic algorithm solution.

The weight coefficients in the objective function are set to 1. The passenger average boarding or alighting time is 3 seconds per person. The unit driving cost of 10-seat vehicle is set as 2.1 yuan per kilometer, and that of 25-seat vehicle is 2.7 yuan per kilometer [37]. The number of vehicles for type A and B is set to 20 respectively. Vehicle running time is no more than 120 minutes, the passenger travel time window is set to 5 minutes, the number of potential points (or stops) providing service is set to 22, and the departure and terminal depot is Great Wall Bridge Stop. The locations of all points are shown in Table 3 below.

The parameters of the genetic algorithm are set as follows: The population size is 100, the crossover probability is 0.8, the mutation probability is 0.1, and the number of evolutionary iterations is set as 100.

B. RESULT ANALYSIS AND EVALUATION

239 passenger demands are assumed to be submitted to the DRT system from 8 a.m. to 9 a.m. on working days. The vehicle route and number of passengers served for each vehicle are obtained using the improved genetic algorithm, as shown in Table 4. All demands submitted are fully served within the given constraints delivered by 20 vehicles, among which 9 vehicles of type A and 11 vehicles of type B are used, and the number of iterations reaches 100, as shown in Fig. 8. The population has almost converged to the optimal solution at the 60th iteration, and the optimal objective function value is 3244.4 yuan. The vehicle routing topology of all scheduling vehicles is shown in Fig. 9, where lines of different colors represent the travel paths of different vehicles. (The horizontal coordinate and vertical coordinate represent transformed geographical coordinate values of stop locations).

The parameters of the GA are set as follows: the population size is 100, the crossover probability is 0.8, the mutation probability is 0.1, and the evolution generation is 100. The

TABLE 3. Stop location.

Stop	Name	Longitude	Latitude	X-coordinate	Y-coordinate
0	Starting point (Great Wall Bridge)	114.4430987	38.0510734	36329.73466	4255.527898
1	Water Park	114.4639732	38.0851563	36331.18264	4259.511919
2	Beichen Square	114.5196051	38.0829736	36336.10425	4259.773869
3	Beicheng International	114.5268908	38.0842869	36336.7304	4259.986481
4	Poly Plaza Shopping Center	114.5410834	38.0794787	36338.03514	4259.580454
5	Aobei Park	114.5520976	38.0742343	36339.06528	4259.096994
6	Peace Time Home	114.5561755	38.0600226	36339.58857	4257.551591
7	Huabei Pharmaceutical Co. LTD	114.5413042	38.0595904	36338.28414	4257.367659
8	Jianhe Bridge	114.5181182	38.0603775	36336.23356	4257.244015
9	The Second Hospital of Hebei Medical University	114.4877208	38.0635379	36333.5209	4257.319736
10	Shijiazhuang North Railway Station	114.4720535	38.0727896	36332.03554	4258.207964
11	Peace Hospital	114.458774	38.0510662	36331.11504	4255.668727
12	New Hundred Square	114.4843399	38.0496875	36333.38209	4255.746707
13	Liberation Square	114.4935221	38.0498603	36334.18869	4255.849254
14	Beiguo Mall	114.5177321	38.0488929	36336.33175	4255.961562
15	Shijiazhuang Cotton Three Living Areas	114.532638	38.0490996	36337.64202	4256.120341
16	Hebei Hospital of Traditional Chinese Medicine/ Hebei Medical University	114.5436559	38.049109	36338.61218	4256.221877
17	Wanda Plaza	114.5704956	38.0504927	36340.95978	4256.621265
18	Huaxia Homeland	114.5001932	38.0300217	36335.00397	4253.700594
19	Shijiazhuang Railway Station	114.4903978	38.0185987	36334.27216	4252.339612
20	White Commercial Plaza	114.5326654	38.0286093	36337.88057	4253.838732
21	Hebei GEO University	114.5546366	38.0278885	36339.82431	4253.958935
22	Zhaohui Bridge	114.5825692	38.0535036	36341.98813	4257.067151
0	End point (Great Wall Bridge)	114.4430987	38.0510734	36329.73466	4255.527898

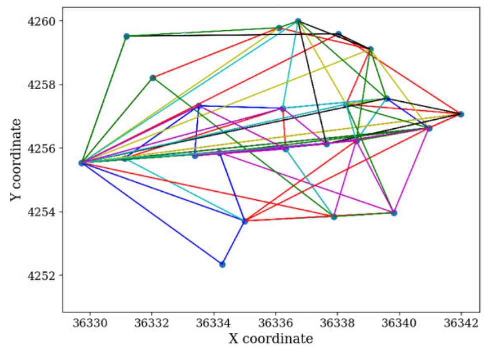

FIGURE 9. Figure of the driving routes.

TABLE 4. Vehicle optimization routing schemes.

Vehicle	Route	Number of Served
1	0→17→22→15→12→9→0	5
2	0→ 16→ 20→ 21→13→ 0	7
3	0→ 10→ 2→ 5→ 7→ 22→4→ 0	23
4	0→ 18→ 13→ 11→0	10
5	0→ 22→ 17→ 15→ 0	9
6	0→ 7→ 6→ 16→ 17→ 13→0	10
7	0→ 11→ 8→ 14→ 20→18 →16→17→0	16
8	0→ 2→ 3→ 7→ 6→ 5→17→0	7
9	0→ 11→ 9→ 8→ 0	6
10	0→ 9→ 14→ 20→ 18→11→0	18
11	0→ 20→ 21→18→ 17→ 0	6
12	0→ 11→ 9→ 8→ 6→ 17→ 0	16
13	0→ 3→ 8→6→ 16→ 17→0	8
14	0→ 19→ 18→ 13→ 0	10
15	0→ 5→ 6→ 7→16 →17→15→22→0	9
16	0→ 10→ 20→ 21→7→ 17→0	11
17	0→ 1→ 4→ 5→ 3→ 15→ 22→6→0	25
18	0→ 1→ 2→ 3→ 6→5→16→17→13→0	18
19	0→ 7→ 16→ 13→ 11→ 0	13
20	0→ 8→ 15→ 17→ 21→16→ 12→ 14→9→0	12

change of the optimal fitness value of each generation is shown in Fig. 8, where the algorithm reaches the state of local convergence at the time of 20th-50th, so the fitness shows a straight-line state, and then jumps out of the local convergence in the iterative mutation process, and reaches the convergence state again after the 85th generation.

1) COMPARATIVE EXPERIENMENTS OF DIFFERENT VEHICLE TYPES

In order to verify the superiority of the multi-vehicle type in this paper, 239 demands are served by vehicles of type A

TABLE 5. Comparison results for different vehicle types.

Vehicle type	Total cost value /yuan	Vehicle operating cost /yuan	Number of trips	Number of people served	Average in-vehicle time of passenger /min	Total travel time /min	Average load ratio/%	Passenger service rate/%
A/B	3244.4	1589.6	20	239	19.8	1327.6	74.0	100
A	4861.0	2118.3	29	239	18.9	2017.4	82.4	100
B	3859.5	1789.8	19	239	21.7	1291.4	50.9	100

TABLE 6. Comparison of results for different vehicle types.

Vehicle type	Total cost value /yuan	Vehicle operating cost /yuan	Number of trips	Number of people served	Average in-vehicle time of passenger /min	Total travel time /min	Average load ratio/%	Passenger service rate/%
A/B	2309.5	1083.9	15	144	10.2	951.6	71.2	100
A	2719.0	1222.4	17	144	8.4	1164.2	84.7	100
B	2750.4	1222.6	14	144	8.2	905.6	45.4	100

and B respectively. The parameters are the same as above. Results for each iteration and vehicle routes of different vehicle types are obtained from 8 a.m. to 9 a.m. on working days.

From the results in Table 5, compared with the mode of multi-vehicle type, total cost value in the result of type A increases by 33.3%, the total travel time increases by 34.2%, and the average load ratio of vehicles increases by 8.4%. Although the average load ratio is improved due to the smaller capacity, more trips are increased, resulting in additional vehicle setup cost and total travel time. Counter-intuitively, vehicles of type B reduce one trip, the total cost value increases by 15.9%, the total travel time reduces by 2.7%, the average load ratio reduces by 23.9%. It is shown that the average load ratio is decreased sharply, which is easy to cause the waste of in-vehicle space and the increase of operating cost. Therefore, the multi-vehicle type operating mode could effectively reduce the total cost and improve the vehicle utilization rate.

In order to further verify the superiority of the multi-vehicle type operating mode in this paper, 144 and 336 demand points are provided, and the results are shown in Table 6 and Table 7. It can be seen that the results are almost consistent under different requirements. Therefore, it is verified that the service mode of multi-vehicle type is better than the service mode of single-vehicle type with lower total cost and relatively higher average load ratio.

2) COMPARATIVE EXPERIMENTS OF DIFFERENT SERVICE MODES

In order to verify the advantages and effectiveness of DRT with non-fixed stops, the service mode of DRT with fixed stops [26], [27], [36] is selected in the comparative experiment. In the downtown area of Shijiazhuang defined in Fig. 6, 17 public transit lines are concluded in the service area. The locations of fixed stops and demand points are shown in Fig. 10, where the yellow stops are fixed stops and the red ones are non-fixed stops. The experiments using two service modes with the same submitted demand information are performed and results are shown in Table 9. The service route and number of passengers of each vehicle are shown in Table 8.

As can be seen from Table 9, compared with the service mode of DRT with fixed stops, the non-fixed stops service mode requires 3 more trips, 52 more passengers to serve, and the objective function value is reduced by 293.9 yuan. It is evident that the service mode with non-fixed stops has significant improvements in both the passenger service rate and the average load ratio. This is because a more reasonable schedule is created based on the actual travel information submitted prior to the traveling. Besides, some unnecessary detours can be reduced and more travel time can be saved, thus more passengers can be served in a trip. The same conclusion can be obtained from experiments with the different number of requirements, seen from Table 10 and Table 11.

TABLE 7. Comparison of results for different vehicle types.

Vehicle type	Total cost value /yuan	Vehicle operating cost /yuan	Number of trips	Number of people served	Average in-vehicle time of passenger /min	Total travel time /min	Average load ratio/%	Passenger service rate/%
A/B	3588.8	1893.3	27	336	16.6	1579.6	68.4	100
A	6634.0	2905.1	41	336	21.9	2766.8	82.0	100
B	4059.8	2037.9	26	336	15.6	1509.6	45.4	100

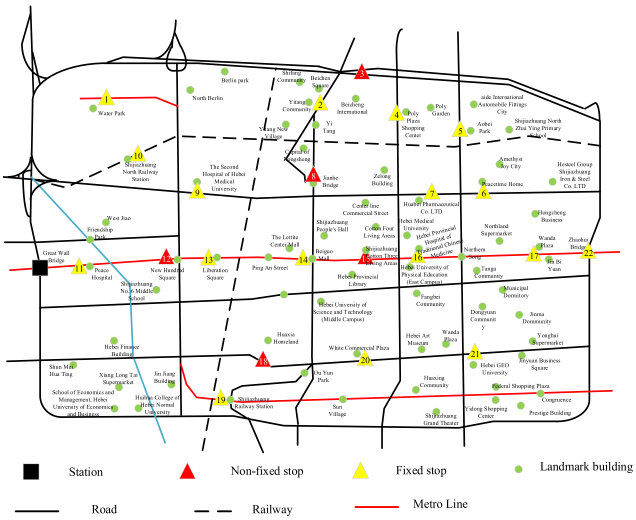

FIGURE 10. Distribution of public transit line stops.

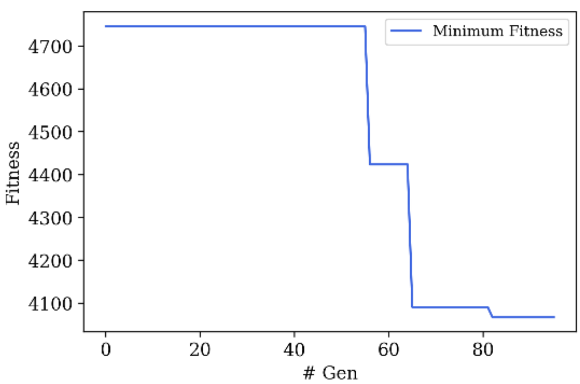

FIGURE 11. Results of traditional genetic algorithm.

TABLE 8. Vehicle routes.

Vehicle	Route	Number of Served
1	0→10→11→4→8→14→13→0	14
2	0→ 20→ 21→ 18→ 17→ 16→ 14→ 0	8
3	0→6→ 22→ 16→ 15→ 14→11→ 0	5
4	0→ 19→ 18→ 13→ 11→ 0	24
5	0→ 5→ 7→ 16→15→14→11→ 0	7
6	0→ 1→ 10→ 2→ 6→14→11→ 0	9
7	0→ 2→ 7→ 6→ 5→16→18 →17→0	4
8	0→ 1→ 10→ 5→ 15→22 →4→6→0	12
9	0→ 4→ 14→ 15→ 18→ 11→0	16
10	0→ 20→ 18→ 21→ 11→ 0	17
11	0→ 3→ 9→ 17→ 20→19→18→ 0	5
12	0→ 4→ 8→ 15→ 16→ 17→ 0	8
13	0→ 3→ 2→ 5→ 17→16 →11→0	11
15	0→ 6→ 17→ 16→ 15→18→11→ 0	8
16	0→ 6→ 16→ 17→ 13→ 0	15
17	0→ 10→ 16→ 17→ 7→13→11 →0	13

3) EXPERIMENTS WITH TWO ALGORITHMS

In order to verify the superiority of the improved genetic algorithm proposed in this paper, the traditional genetic algorithm is selected to solve the vehicle scheduling problems under the service mode of DRT with non-fixed stops, and the solution results are compared. The parameters of the two algorithms are the same, population size is 100, crossover probability is 0.8, mutation probability is 0.1, and number of evolutionary iterations is 100. The results of the two algorithms are shown in Fig. 11 and 12, respectively.

TABLE 9. Comparison of two service modes.

Service mode	Total cost value /yuan	Vehicle operating cost /yuan	Number of trips	Number of people served	Average in-vehicle time of passenger /min	Total travel time /min	Average load ratio/%	Passenger service rate/%
Non-fixed stop	3244.4	1589.6	20	239	15.6	1327.6	74.0	100
Fixed stop	3538.3	1437.1	17	187	17.9	1195.2	63.0	79.3

TABLE 10. Comparison of two service modes under 144 requirements.

Service mode	Total cost value /yuan	Vehicle operating cost /yuan	Number of trips	Number of people served	Average in-vehicle time of passenger /min	Total travel time /min	Average load ratio/%	Passenger service rate/%
Non-fixed stop	2309.5	1083.9	15	144	10.2	951.6	71.2	100
Fixed stop	2436.7	947.5	10	99	19.4	904.8	61.8	68.8

TABLE 11. Comparison of two service modes under 337 requirements.

Service mode	Total cost value /yuan	Vehicle operating cost /yuan	Number of trips	Number of people served	Average in-vehicle time of passenger /min	Total travel time /min	Average load ratio/%	Passenger service rate/%
Non-fixed stop	3588.8	1893.3	27	336	16.6	1579.6	68.4	100
Fixed stop	4029.0	1501.6	17	236	18.3	1371.6	72.1	70.2

TABLE 12. Comparison results of different algorithms.

Solving algorithm	Total cost value /yuan	Number of trips	Number of people served	Average in-vehicle time of passenger /min	Total travel time /min	Average load ratio/%	Passenger service rate/%
The traditional genetic algorithm	4066.8	27	239	15.3	1528.1	56.7	100
The improved genetic algorithm	3244.4	20	239	15.6	1327.6	74.0	100

It can be seen from Figs. 11 and 12 that the improved genetic algorithm proposed in this paper has great advantages in terms of convergence speed and objective function results. As shown in Table 12, compared with the traditional genetic

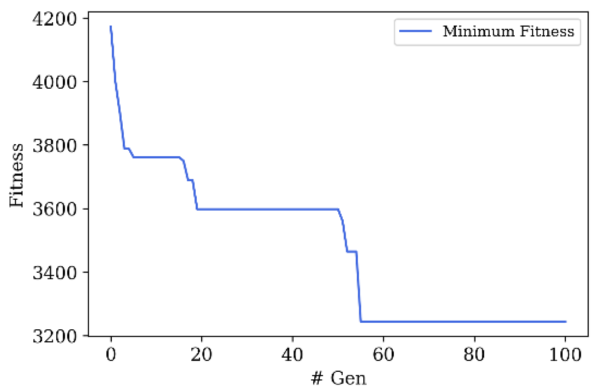

FIGURE 12. Results of improved genetic algorithm.

algorithm, although the average passenger in-vehicle time is increased by 1.9%, the number of trips and the total travel time are significantly reduced by 25.9% and 13.1% respectively, which can effectively improve the vehicle utilization rate. The running time of the improved genetic algorithm is 4.8% lower than the traditional algorithm, which indicates the effectiveness of the proposed method.

V. CONCLUSION

This paper presents a scheduling system of DRT by considering passengers' submitting information before trips based on the advantages of the Internet environment. The strategies combining non-fixed stops and multi-vehicle type are introduced into the developed DRT system, and a scheduling model is adopted to decrease the total system cost, involving vehicle setup cost, operating cost and carbon emission cost. An improved genetic algorithm is then developed to solve the problem and enhance actual applications of the DRT service. A case study in Shijiazhuang downtown area is carried out to verify the effectiveness of the proposed DRT service with non-fixed stops and the computing efficiency of the improved algorithm. Results show that the multi-vehicle type scheduling method significantly reduces the vehicle operating cost by 25.0% and the number of trips by up to 31.0% compared with single small-capacity vehicle type, and the average load ratio is reduced by 23.9% compared with single large-capacity vehicle type. DRT with non-fixed stops increases the average load ratio by 11.0% and the passenger service rate by 21.7% compared with fixed stops service mode. It can be seen that vehicle scheduling of DRT with non-fixed stops and multi-vehicle type performs better in reducing total travel time as well as increasing average load ratio. The operating mode of public transit and scheduling method proposed in this paper is expected to enhance both vehicle utilization efficiency and the operational efficiency, which can help operators and administrators assess the quality of service, user satisfaction and social efficiency, especially under environmental concerns. In order to verify the superiority of the improved genetic algorithm in this paper, the comparison with the traditional genetic algorithm shows that the proposed improved genetic algorithm has great advantages in convergence speed and solving accuracy. Although this study provides a new DRT service mode combining both non-fixed stops and multi-vehicle type considering operators, passengers and social benefits, the following limitation should be concerned: The vehicle operating speed in this paper is selected as a fixed value in vehicle scheduling, instead of dynamic vehicle speed; Only the subscription demand is considered, but it fails to consider real-time or short-time demand. Further research will be conducted in these aspects.

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