Robust Optimization of Customized Electric Bus Routes in Village-town Areas

Yuduan Jiao, Yongpeng Zhao, Changxi Ma

Abstract—**Village-town passenger transportation resources have a low utilization rate, and most passengers cannot achieve their riding purposes within a reasonable time period. Considering the impact of fuel vehicles on the environment and cost, electric buses responsive to urban and rural demand are presented as a solution to these problems in this study: passenger demand information is collected and used to formulate a realistic optimization problem in which both the total cost of the bus company and the total travel time of passengers, are minimized. That is, a robust optimization model for the routes of urban and rural customized electric buses is constructed to meet passenger ride demand using the vehicle travel time on the road section as an uncertainty value. Passenger stations are numbered by using the improved NSGA-II algorithm; natural number coding, a simulated annealing fitness function, the order crossover method, and a specially designed mutation operation are also used. Considering practical scenarios, the times for getting on and off the bus are added to the total travel time of passengers to verify the rationality of the model and algorithm. The results show that using the proposed improved NSGA-II algorithm (improved fast non-dominated multi-objective optimization algorithm with elite retention strategy) reduces the average travel time was by 14.47% and the computing time by 39.81% compared to using the multi-objective genetic algorithm NPGA. For route optimization of passenger demand-responsive electric buses in village-town areas, the proposed improved NSGA-II algorithm produces more accurate solutions with a higher efficiency and performance than the multi-objective genetic algorithm NPGA. To minimize the cost of passenger buses, the total travel time of passengers should be reduced to the largest possible extent. This consideration is extremely important for optimizing long-distance passenger routes of demand-responsive electric buses in village-town areas.**

Index Terms—Village-town passenger transportation, Customized electric buses, Simulated annealing fitness function, Robust optimization, The improved NSGA-II algorithm.

Manuscript received April 13, 2022; revised April 21, 2023.

This research was funded by the National Natural Science Foundation of China Grant (No.71861023, No.52062027), the Program of Human-ities and Social Science of Education Ministry of China Grant (No.18YJC630118), Foundation of a Hundred Youth Talents Training Program of the Lanzhou Jiaotong University, Philosophy and Social Science Foundation of Ningbo (No. G20-ZX37), and the "Double-First Class" Major Research Programs, Educational Department of Gansu Province (No. GSSYLXM-04).

Yuduan Jiao is an undergraduate student of Lanzhou Jiaotong Univ-ersity, Lanzhou,730070 China. (phone:+86 15620210307;e-mail:631100579@qq.com).

Yongpeng Zhao is a PhD student of Lanzhou Jiaotong University, Lanzhou,730070 China. (e-mail: 13210007@stu.lzjtu.edu.cn).

Changxi Ma is a professor and doctoral supervisor of Lanzhou Jiaotong University, Lanzhou,730070 China. (Corresponding author, phone: +86 13109429716, e-mail: machangxi@mail.lzjtu.cn).

I. INTRODUCTION

Current rapid economic and social development in China has enabled unprecedented construction and development of urban transportation. Although urban public transport systems are being rapidly upgraded, development of public transport in vast rural areas has stagnated. Although the requirement of providing buses to all villages has already been met in some rural areas, mismatch between low passenger demand and an excessive supply of public transport has resulted in an enormous waste of resources. During peak periods, a fixed number of passenger buses cannot carry all the passengers that wish to use public transport. In recent years, a call to dissolve the original urban–rural dual structure has ushered in a new stage in the integration of urban–rural development. To facilitate travel of urban and rural residents and make public transport in rural areas more attractive, the state has begun to advocate coordinated development of urban and rural passenger transport resources and to extend urban bus lines to remote areas, such as urban–rural junctions, thereby transcending traditional geographical restrictions. Thus, there is steady promotion of operation and management of rural passenger transport areas for the improvement of the scale and efficiency of rural passenger transport. Current transportation modes for village and town areas mainly include traditional fixed-point and fixed-line buses and urban and rural long-distance passenger buses. The traditional modes of fixed-point and fixed-line buses are services that transport passengers from towns to towns, towns to villages, and villages to villages. The stations and routes are fixed, and the routes are generally linear or radial. Urban-rural long-distance passenger buses depart from a passenger transport center in the city or county and arrive between towns or villages. There are generally stops in route, and the operation mode is similar to that of urban public transport. However, service areas have different economic development levels and service objects, and the aforementioned two types of bus operation modes have difficulty maintaining a high level of vehicle operation efficiency under different passenger flow conditions. Therefore, setting up demand-response buses in rural areas would provide an effective solution under these diverse conditions. Customized bus is a kind of public transportation service mode intermediate between conventional bus and taxi. This mode can meet the requirements of high-quality travel in the form of multi-person shared transportation. The price is slightly higher than that of ordinary buses but remains within an acceptable range. To provide demand-response buses to rural areas, we first collect information on the departure and arrival stations of passengers through the "Rural Passenger Transport to Villages and Villages" program, adjust the bus routes scientifically and reasonably, maximize the convenience of passenger services and minimize the passenger travel time. This method improves the utilization rate of resources and meets the needs of passengers, while making travel convenient and reducing costs. Demand-response buses provide an effective solution for ensuring basic bus service for individuals, reducing waste, and saving costs for bus companies.

To reduce environmental pollution, ease pressure on local oil resources and reduce dependence on imported oil, many cities in China, such as Suzhou, Yangzhou, Changshu, prefecture-level cities in Jiangsu Province, and Zibo and Weifang in Shandong Province, have successively invested in the operation of new-energy buses.

New-energy buses have been introduced in cities, as well as to rural passenger lines in many areas, such as Yichang, Langzhong, Huzhou, Chibi, and Chongming Island. New-energy buses contribute to improving the rural ecological environment and provide excellent economic benefits. The use of fuel vehicles in Beijing suburban passenger lines has resulted in year-round losses. Overall operating conditions have improved considerably since the replacement of fuel vehicles with new-energy passenger vehicles, which has been supported by purchase and operating subsidies, coupled with the lower operating costs of electric vehicles. The use of new-energy and clean-energy, energy-saving and environmentally friendly vehicles suitable for rural traffic conditions and that meet the travel needs of the masses in areas where conditions permit is effectively promoting the green and low-carbon development of rural passenger transport.

To sum up, the operation of electric customized passenger buses in urban and rural areas can not only effectively reduce pollution, but also reduce costs and reduce the waste of resources in urban and rural areas.

At present, there are few studies on the route optimization of customized electric passenger buses in urban and rural areas, but there are also a lot of studies on customized passenger transportation in rural areas and route optimization of urban electric vehicles.

Fang Chen et al. [1] analyzed the status quo of rural passenger transport development. And they pointed out that the unbalanced development of rural passenger transport and the deficiencies in economic benefits. Cunye Lu [2] optimized the rural passenger transport system in the context of low-carbon economy from the layout optimization of rural passenger transport line network and hub stations. Kunpeng Hu [3] established an urban-rural integrated transportation organization framework through the trunk and branch line planning method and passenger transportation forecast. Tong An [4] used AP clustering algorithm, designed a two-level constraint programming model, and used simulated annealing algorithm to pair rides The station layout is optimized; Fengyan Zhang [5] established a traffic compactness model to optimize rural highway passenger routes. Guo Qiu [6] built a two-level programming model based on the results of passenger travel mode selection and used the branch and bound algorithm to solve the upper model. The improved allocation algorithm combined with the mean algorithm (MSA) solves the lower model. Yan Gao [7] established fixed route planning and variable route models of rural passenger vehicles that concurrently operate express delivery, and used tabu search algorithm to solve them, and worked out rural passenger vehicles Scale and route plan. Rongrong Xu [8] studied the route optimization of demand-responsive transit in rural areas and demonstrated that demand-responsive transit in rural areas can effectively utilize transportation resources and reduce operating costs. Yanguang Cai [9] established a single-model open-cooperative vehicle path mathematical model for the vehicle leasing model, taking into account factors such as the frequency of rural population travel during morning and evening peak periods, and the longest tolerance time for passengers. The main characteristics of algorithm, scanning algorithm and genetic algorithm, construct a hybrid ant colony solution algorithm and simulate an example to obtain the optimal solution. Liangping Liu [10] took Rural passenger transport in Chongqing as the research object and studied the development status, operation mode and promotion method of rural passenger transport from three aspects, considering the characteristics of residents' scattered residence, irregular travel rules and diversified demands. The function model of rural passenger transport cost minimization is established. Chan Shen [11] established the objective function with the lowest total cost based on the shortest circuit with the highest reliability and adopted the emergency algorithm to obtain more reliable results than the shortest circuit scheme. Hangqi Zhang [12] used improved AP clustering and ant colony algorithm on the basis of granular computing methodology to obtain 3 customized bus routes. Wenwen Guo [13] proposed the layout method of rural township passenger stations by dividing the level of road network within the layout region based on the position and layout of rural township passenger stations. Finally, combined with quantitative and qualitative analysis, the number of passenger stations in the layout area is determined, which provides reference for the layout method of rural passenger stations. Ruiqin Zhang [14] started from the rural passenger transport in towns and villages, combined with the theory and practice of the existing passenger terminal facility configuration scale, and carried out a systematic study on the scale of township facilities. Through investigation and analysis of the existing basic conditions of my country's township passenger transport, combined with the actual situation, the empirical research is carried out with Jiangzhang Town as an example. Yeqian Lin et al. [15] described the variable line bus scheduling model from the perspective of mixed integer programming, mainly considering the problems of bus operation cost and passenger travel cost and establishing the model with the optimization goal of the lowest system cost. Faroqi H [16] used GIS technology to optimize demand-responsive bus routes and collected network data and commuting times in 6 areas of Tehran City, and finally evaluated and analyzed the analysis results. Erdogan and Miller-Hooks [17] consider the possibility of having fuel constraints and alternative fuel stations (AFS) and built an objective function that minimizes the total distance traveled. Mathematical programming model. A fixed value is assumed for each customer service time and refueling time. Hoog J D [18] studied the vehicle path planning problem of a mixed fleet of traditional fuel vehicles and electric vehicles, but it did not involve charging stations in the modeling. Hiermann et al. [19] introduced a multi-model electric vehicle path planning problem with time constraints and constructed a model with the minimum travel distance and vehicle usage cost. Jin-Quan Li [20] studied the electric bus scheduling problem with battery capacity constraint and used branch pricing and local search algorithms to solve it. Huaxu Liu [21] constructed a path planning model in line with pure electric vehicles according to the short cruising range of electric vehicles and added cruising range constraints and designed an effective ant colony algorithm to solve the problem. Rongge Guo [22] studied the optimization problem of customized electric bus routes with multi-path selection, the model aims at maximizing the total operating revenue, and considers such constraints as vehicle capacity, passenger travel time window, cruising range, and the number of visited sites. Customize the characteristics of public transportation, design a new adaptive large neighborhood search algorithm, propose the corresponding initial solution generation rules and neighborhood search operators, and verify the effectiveness of the algorithm through an example. Geoke D [23] and others applied a neighborhood search algorithm to solve the vehicle routing problem of mixed fleet vehicles with time windows, and analyzed the impact of different target costs, including the cost of electric vehicles, on the routing. Jun Yang et al. [24] used the improved Clarke-Wright two-stage tabu search algorithm to solve the vehicle routing problem, and the comparison with the calculation results of CPLEX proved that the algorithm is more effective and reliable. Youjun Deng et al. [25] established an electric vehicle path planning and charging navigation model based on the time cost and the optimization goal of minimizing the sum of the waiting time cost, fast charging cost and battery loss cost. Wanchen Jie, Jun Yang et al. [26] used branch pricing algorithm with preprocessing lower bound value to solve the multi-vehicle vehicle routing problem with time window, and the improved algorithm has superiority in solving speed. Yan-e Hou et al. [27] set up hybrid iterative algorithms to solve real school bus problem cases in several schools in China for finite and infinite heterogeneous school bus fleet path problems with the objective of minimizing the sum of fixed and variable costs. Changxi Ma et al. [28] proposed a three-stage hybrid coding method based on the NSGA-II algorithm to deal with custom bus route optimization under uncertainty. The paper constructs a robust optimization model with the objectives of minimizing passenger travel time and carbon emissions of custom buses, and finally, solves a practical problem including three custom bus parking lots and 20 boarding and alighting stations to validate the rationality of the model and algorithm. Lan-xue Dang et al. [29] set up a hybrid meta-heuristic algorithm to solve the school bus routing problem (SBRP) with the objectives of minimizing the number of school buses and the total trips, respectively, and finally, an efficient perturbation method based on ruin and recreate is also adopted. The developed algorithm is tested on a benchmark instance and the results show that the proposed algorithm is effective.

The literature on routing demand-response vehicles in urban and rural areas is not in a mature stage, and few studies have been performed on the routing optimization of electric passenger vehicles. First, most studies on path optimization of electric vehicles are based on single-objective models; second, most studies are based on path optimization in a certain environment and do not consider vehicle operation in an uncertain environment, as is the case with actual road environments. In real urban and rural long-distance passenger transport, electric buses departing from passenger stations in cities and towns carry passengers to various destination stations in rural areas, at which passengers are picked up with destinations at stations in cities and towns. Consequently, a real-life scenario is used as a starting point in this study, and the characteristics of urban and rural long-distance passenger transport are used to model the uncertainty in the road travel time: the minimum total travel time of passengers and the minimum cost to passenger transport companies are taken as optimization goals, and the problem of charging electric buses in constructing custom urban and rural transportation schemes is also considered. The multi-objective robust optimization model of electric passenger buses is solved using an improved NSGA-II algorithm.

II MULTI-OBJECTIVE ROBUST MODELING OF CUSTOMIZED ELECTRIC BUSES IN VILLAGE-TOWN AREAS

A. Problem Description

A passenger reas a ride, and a fully charged electric bus carries the passenger from a passenger station in a town to a station in a rural area and returns to the initial passenger station. That is, passengers get on the bus at a station in town and get off at a station in a rural area, and passengers get on the bus at a station in a rural area with the initial station in town as their destination. The demand for rides at rural stations is not excessive, and the vehicle must finish unloading and loading all passengers at the rural station and return to the initial station immediately. As an electric bus has a limited battery capacity, the power level of the bus must be checked after arriving at a station, and it must be determined whether the bus needs to be recharged in real time. An electric vehicle that exceeds the driving range constraint must go immediately to a charging service facility. The vehicle is charged at a high rate, and the fully charged vehicle resumes its task.

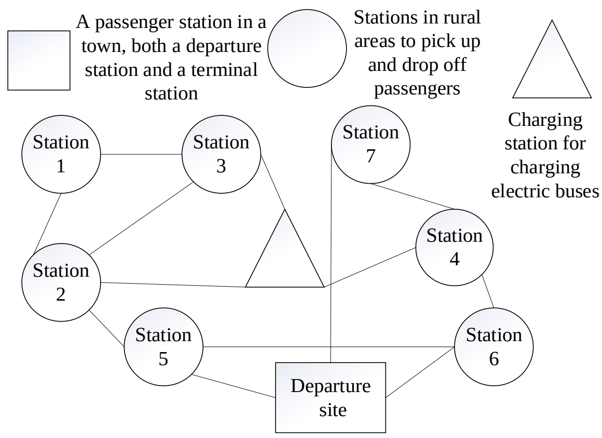

Fig.1. Schematic diagram of vehicle service route

B. Assumptions

According to the situation of transporting passengers in rural areas, some simplifications are made to the model, and the following assumptions are set:

1) The passenger station has the number of passenger buses that can meet the demand of all passengers in the road

network, and each bus is of the same type and the same approved capacity.

2) Except for the departure station and charging station, the rest of the stations can only be served once.

3) Each bus can serve multiple stations.

4) The number of passengers at the boarding and alighting stations is set and the total number of boarding passengers at each station does not exceed the authorized capacity of a single bus.

5) The distances between different nodes are known.

6) Passengers do not get off the bus until they reach the stop they need to reach.

7) The electric bus has a small battery capacity.

TABLE I

SYMBOL DEFINITION

Symbol	The meaning of the symbol or related factors	Type
S_0	Collection of stations that electric buses need to reach in rural areas, including charging stations.	set
S	The passenger station in the town is the starting point and the terminal station.	set
d_{ijk}^{s}	The distance of the $k-th$ bus from station S from station i to station j .（unit: km）	parameter
k	Passenger buses carrying passengers in the road network.	parameter
f	Electricity required by electric bus per kilometer. （unit: kWh/km）	parameter
g	Unit price of electricity， unit: yuan/kWh	parameter
f_0	Flat fee per electric bus.	parameter
q_{ik}	Remaining power of electric bus k when it arrives at station i .	parameter
t_{io}	Time it takes to get off each passenger who gets off at stop i	parameter
t_{ib}	The time it takes for each passenger who gets on the bus at station i to get on the bus	parameter
N_{io}	Number of people getting off at station i .	parameter
N_{ib}	Number of people picking up at station i .	parameter
w	The collection of all road segments in the passenger network	set
d_{ij}	Distance of road segment (i, j) .	Parameter
C	Nuclear occupancy of an electric bus.	parameter
Q_{pk}	Number of passengers on vehicle k in line p	parameter
V_s	$V_s = \{k \mid k = 1, 2, ..., K\}$ represents the set of vehicles departing from the passenger station S , and k is the maximum number of vehicles.	set
x_{ijk}^{s}	$x_{ijk}^{s} = \begin{cases} 1, \textit{The } k-th \textit{ electric bus starting from the} \\ \textit{passenger station s will pass through the} \\ \textit{road segment } (i,\ j), \textit{ that is, directly} \\ \textit{from station i to station j} \\ 0, \textit{otherwise} \end{cases}$	variable
$E_{ijk}^{'}$	Number of passengers in vehicle k in road segment (i, j)	parameter
I_{ijk}^{s}	$I_{ijk}^{s} = \begin{cases} 1, E_{ijk}^{'} > 0 \\ 0, E_{ijk}^{'} = 0 \end{cases}$	variable
R	A collection of road segments whose travel time changes due to uncertain factors.	set
Γ	Time Robust Control Parameter.	parameter
t_{ij}	The nominal value of the travel time of the electric bus on the road segment (i, j) , $t_{ij} = \frac{d_{ij}}{v}, (i, j) \in w$	parameter
$\hat{t}_{ij}$	The deviation of the nominal value of the travel time of the electric passenger buses on the road section (i, j) .	parameter
T_{ij}	$T_{ij} \in [t_{ij}, t_{ij} + \hat{t}_{ij}]$, travel time of electric bus on road segment (i, j) , $(i, j) \in w$	parameter
v	The driving speed of the electric bus is a fixed value	parameter
a	Charging station a , $a \in S_0$. a is a special site in S_0 .	parameter
h_a	Time it takes to charge at charging station a .	parameter

C. Model building

Various factors need to be taken into account when building a route optimization model for rural or urban–rural areas. The shortest path must meet the travel needs of passengers while reducing the operating costs of bus companies. In addition, road conditions in rural areas are different from those in cities and may consist of uneven or even rugged roads, numerous curves, and poor infrastructure in areas through which vehicles pass, which can increase travel time, create difficulties for driving vehicles and make travel arduous for passengers. Therefore, it is more realistic to set the travel time for the passenger bus to an uncertain value. By optimizing the two goals of the lowest cost and the shortest passenger total travel time, one or more scientific and reasonable paths can be found to reduce the costs to the bus company while meeting passengers' needs, enabling all passengers on board to reach their destinations as fast as possible.

Robust optimization is a kind of uncertain optimization, and it is also a kind of pre-analysis method, which has a wide range of applications in many fields. Robust optimization fully considers the uncertainty in the modeling process and describes the variables in the form of sets. In 1973, Soyster used the idea of robust optimization to solve the uncertainty in linear programming for the first time. Although it was initially considered on the worst basis, the result was too conservative, but it opened up the road of robust optimization. Mulvey et al. first proposed the concept of robust optimization in 1995 [30]. They gave a general model framework based on scenario set robust optimization and proposed the concepts of solution robust and model robust and eliminated the inconsistency by splitting the objective function into an aggregate function and a penalty function. Determine the influence of the parameters on the results. The Israeli scholars Ben-Tal and Nemirovski [31,32] and the University of Berkeley's Ghaoui [33] put forward a foundational work on robustness in the 1990s. Ben-Tal proved that if the set U of uncertainty is an ellipsoid Uncertain sets, then for some of the most important general convex optimization problems (linear programming, quadratic constrained programming, semi-definite programming, etc.), the robust equivalence is either accurate or can be approximated as a solvable problem: Algorithms such as interior point method can be used to solve in polynomial time. In addition, Ben-Tal gave an approximate robust equivalence that can be handled in the calculation of general uncertain semi-definite programming problems. After that, Ben-Tal et al. put forward concepts such as adjustable robust optimization concepts, which were widely used in all walks of life. Later, Bertsimas and Sim [34] proposed a new robust optimization framework based on the research of Soyster, Ben-Tal and Nemirovski. The robust optimization of Bertsimas and Sim covers discrete optimization. The main feature is that the established robust equivalence does not increase the complexity of problem solving. On the other hand, the robust optimization of Bertsimas and Sim allows the occurrence of constraint violation (Constraint Violation), in which case the robust solution obtained is feasible with high probability. The theories of Bertsimas and Sim have been widely recognized by the academic circles due to their ease of processing and practicality.

A robust optimization model for route optimization of customized electric buses in urban and rural areas is established as follows.

$$\begin{aligned}\min z_1 = &\sum_{K\in V_s}\sum_{(i,j)\in w} x_{ijk}^s t_{ij} E_{ijk}^{'} + \\ &\max_{\{R|R\in w,|R|=T\}} \sum_{K\in V_s}\sum_{(i,j)\in w} \hat{t}_{ij} x_{ijk}^s t_{ij} E_{ijk}^{'} + \\ &\sum_{K\in V_s}\sum_{(i,j)\in w} \begin{matrix} y_{jk}^s\{(E_{ijk}^{'} + N_{jb} - N_{jo})\times \\ [\max(t_{jo}\cdot N_{jo}, t_{jb}\cdot N_{jb})] \end{matrix} \\ &+(N_{jo}\cdot t_{jo} + N_{jb}\cdot t_{jb})\} + \sum_{i,a\in S_0} E_{iak}^{'} h_a\end{aligned} \tag{1}$$

$$\begin{aligned}z_1 = &\Gamma t_{IJ} + \min\{[\sum_{K\in V_s}\sum_{i=1:(i,j)}^{I:(I,j)}\sum_{j=1:(i,j)}^{J:(i,J)} t_{ij} x_{ijk}^s E_{ijk}^{'} \\ &+\sum_{K\in V_s}\sum_{i=1:(i,j)}^{I:(I,j)}\sum_{j=1:(i,j)}^{J:(i,J)} (t_{ij} - t_{IJ}) x_{ijk}^s E_{ijk}^{'}] + \\ &\sum_{K\in V_s}\sum_{(i,j)\in w} \begin{matrix} y_{jk}^s[(E_{ijk}^{'} + N_{jb} - N_{jo})\times \\ \max(t_{jo}\cdot N_{jo}, t_{jb}\cdot N_{jb}) \end{matrix} \\ &+(N_{jo}\cdot t_{jo} + N_{jb}\cdot t_{jb})] + \sum_{i,a\in S_0} E_{iak}^{'} h_a\}\end{aligned} \tag{2}$$

Since the objective function (1) contains an uncertain max term, it needs to be equivalently transformed according to the robust optimization theory of Bertsimas and Sim, and equation (2) is obtained.

$$\min z_2 = f\bullet g\begin{pmatrix} \sum_{r\in p_s}\sum_{i\in S}\sum_{j\in S_0} d_{ijk}^s x_{ijk}^s \\ +\sum_{r\in p_s}\sum_{i\in S_0}\sum_{j\in S_0} d_{ijk}^s x_{ijk}^s \\ +\sum_{r\in p_s}\sum_{i\in S_0}\sum_{j\in S} d_{ijk}^s x_{ijk}^s \end{pmatrix} + Kf_0 \tag{3}$$

s.t.

$$E_{ij}^{'} \le C, \forall i, j\in S_0\cup S \tag{4}$$

$$\sum_{k\in K} y_{ik}^s = 1, \forall k\in K, \quad \forall i\in\{m \mid m\ne a,\ \text{and } m\in S_0\} \tag{5}$$

$$x_{iak}^s = \begin{cases} 1, d_{iak}\cdot f < q_{ik} \leqslant \max(d_{ijk} + d_{jak})\cdot f \\ 0, q_{ik} > d_{ijk}\cdot f + d_{jak}\cdot f \end{cases} \tag{6}$$

when i is not the last mission site of bus k, $j\ne s$ $\forall k\in K, (i,j,a)\in w$.

$$x_{iak}^s = \begin{cases} 1, q_{ik} < d_{isk}\cdot f \\ x_{isk}^s - 1, q_{ik} \ge d_{isk}\cdot f \end{cases} \tag{7}$$

when i is the last mission site of bus k.

$$0 < q_{ik} \le q_{\max},\ \ \forall i\in S_0\cup S \tag{8}$$

In the above model, x_{ijk}^s and y_{ik}^s are both 0-1 decision variables. Equation (1) and equation (2) is the objective function with the goal of minimizing the total travel time of passengers, which is the sum of the total time for each passenger to arrive at the station after getting on the bus. In the actual scenario application of the customized bus problem, the maximum value of the time it takes for passengers to get on and off the bus at station i is a definite value. Equation (3) and equation is the cost function of the passenger bus company, which includes the electricity consumption cost determined according to the length of the running distance, and the fixed cost of the passenger bus. Equation (4) is the passenger capacity constraint. Equation (5) represents the constraint that each non-charging station in the rural area can only be served once by one vehicle during the operation. Equation (6) is the constraint on whether to go to the charging station to charge; When the remaining power of the bus arriving at the point is greater than the sum of the power required to reach the next station from station j and the power required to reach the charging station from station j, the bus continues to operate to complete the service task and temporarily does not need to go to the charging station for charging; When the remaining power of the vehicle arriving at the point is greater than the required power from the station to the charging station and less than or equal to the sum of the required power from the station to the next station and the required power from the station to the charging station, it must go from the point to the charging station to charge. Equation (7) indicates that when the vehicle arrives at the current last mission site, if the remaining power does not support it returning to the starting point, it must go to the charging station for charging immediately. Equation (8) indicates that the remaining power of the electric bus must be greater than 0 and must be less than or equal to its full power when the electric bus arrives at a certain station.

Γ is the time robust control parameter, which is used to control the conservative degree of the solution. Under different values of Γ, the obtained solutions are different, and the degree of conservation is also different.

Ⅲ. SOLVING ALGORITHMS

As it is not possible to optimize two objective functions at the same time for a robust model with multiple objective functions, a multi-objective solution algorithm is used. Unlike single objective functions, multiple objective functions conflict with each other, and the optimization of one objective may deteriorate the value of another objective, making it impossible optimize multiple objectives at the same time. Multi-objective optimization yields a set of noninferior solutions, and the elements in the set are called Pareto optimal solutions. Pareto solutions are also called nondominated solutions: for multiple objectives, a solution may be optimized one objective and result in the worst values of other objectives due to the existence of conflicts among objectives and the phenomenon of noncomparability. Solutions that improve any objective function while necessarily weakening at least one other objective function are called nondominated solutions or Pareto solutions. The desired solution is to obtain as many and as widely distributed Pareto optimal solutions as possible. In this paper, a modified NSGA-II fast nondominated ranking algorithm is used to solve the multi-objective optimization problem.

A. Simulates the adaptability function of the improved annealing thought

The idea of simulated annealing is used to stretch the adaptability with the number of iterations. Genetic algorithm in the early stage of operation of individual differences, if the use of roulette method to choose the generation and adaptability proportional, you can get a better selection effect, but in the later stage of the algorithm, the degree of adaptation tends to be consistent, the advantages of excellent individuals are insufficient, then the adaptability to a certain "stretch", the specific formula is as follows:

$$f_i = \frac{e^{f_i/T}}{\sum_{i=1}^{M} e^{f_i/T}} \tag{9}$$

$$T = T_0(0.99^{g-1}) \tag{10}$$

Where is the $f_i\, i-th$ individual's fitness, M is population size, g is genetic algebra, T is temperature, is initial T_0 temperature.

B. Fast non-dominant sorting and crowding

1) Fast non-dominant sorting method

For each individual i, there are two parameters $n(i)$ and $S(i)$. $n(i)$ is the number of solved individuals that dominate individual i in the population. $S(i)$ is a collection of dissolved individuals governed by individual i.

a) First, find all the $n(i)$ and 0 individuals in the population and store them in the current collection $F(1)$.
b) For each individual j in the current collection $F(1)$, examine the individual set $S(j)$ at its disposal and subtract n(k) of each individual k in set $S(j)$ by 1, i.e. the number of individuals that dominate individual k minus 1 (because the individual j that governs individual k has been deposited in the current set $F(1)$.
c) If $n(\mathrm{k})-1=0$ is deposited in another set of H. Finally, $F(1)$ is given as the first level of non-dominant individual collection, and given the individual within the collection the same non-dominant order $i(rank)$, and then continue to do the above classification of H and give the corresponding non-dominant order until all individuals are graded. The computational complexity is m as the number of target functions and N as the population $O(\mathrm{m}N^2)$ size.

2) Determine congestion

a) Determine the degree of congestion

The congestion degree $\mathrm{i_d}$ of each point is set to 0.

For each optimization goal, the population is sorted non-dominantly, so that the crowding degree of the two individuals on the boundary is infinite. $\mathrm{o_d} = \mathrm{l_d} = \infty$.

Calculate the crowding degree of other individuals in the population.

$$i_d = \sum_{j=1}^{m} (| f_j^{i+1} - f_j^{i-1} |) \tag{11}$$

b) Congestion degree comparison operator

After fast non-dominated sorting and crowding calculation, each individual i of the population has two attributes: Non-dominated order determined by non-dominated order $i(rank)$, and Crowdedness i_d.

When any one of the following two conditions is met, individual i can be selected to win.

Condition 1: $i(rank) < j(rank)$.

Condition 2: $i(rank) = j(rank)$ and $i_d > j_d$.

Condition 1 is used to ensure that the selected individual belongs to the superior non-inferior level in the population. Condition 2 is to select two individuals at the same dominance level based on the crowded distance, and the less crowded individual (that is, the more crowded) will be selected According to these two selection conditions, the winning individual in the population is selected.

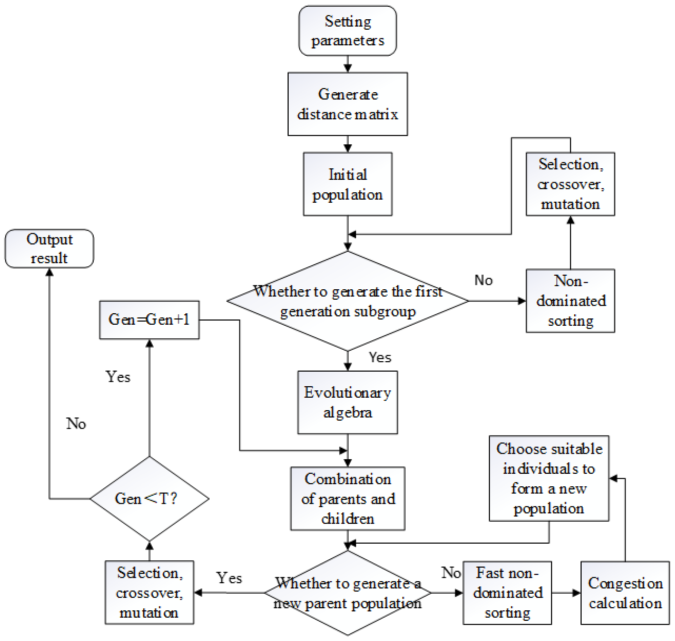

Fig. 2. Improved NSGA-II algorithm flowchart

C. Algorithm steps

Step1 Set parameters such as the number of individuals in the population and the maximum number of iterations.

Step2 After initializing the population, determine whether to generate the first generation on subgroup. If the first generation subpopulation is generated, then proceed to step3, if not, then return to step2 by using non-dominated sorting and related selection, cross , variation operations.

Step3 Evolve the generations.

Step4Merge the parent and child populations, and then judge whether to generate a new parent population; if a new parent population cannot be generated, then carry out a fast non-dominated sorting method to select suitable individuals to form a new population through crowding calculation, and then judge whether to generate a new population. If a new parent population can be generated, the selection, crossover and mutation operations are carried out directly to step5.

Step5 Judge whether the number of iterations reaches the maximum, if not reached, then return to step4; if it has been reached, then output the result.

D. Coding, Crossover, Variation Operation

1) Coding operation

The model encodes chromosomes by natural number coding and directly number passenger stations in towns and villages and stations in rural areas. Set the passenger station number to 0, the station or drop-off station number is 1,2, ..., n.

2) Order cross operator

If you adopt point intersection directly, a site may be missing, so the order crossover method is used. First, randomly select two hybrid points among the parents, and then exchange the hybrid segment, the other location is determined according to the relative location of the parent site. The crossover process is shown in the figure.

Before the cross:

Parent 1

0	3	2	5	[7	8	1	9]	6	4

Parent 2

2	9	5	3	[4	7	6	8]	0	1

Setting the intersection to 4,7 Then the child chromosome is

Child 1

&	&	&	&	[4	7	6	8]	&	&

Child 2

&	&	&	&	[7	8	1	9]	&	&

Starting with the second hybrid segment of parent 1 6-4-0-3-2-5-7-8-1-9, removing the elements in the hybrid segment to get 0-3-2-5-1-9, and then filling in the chromosomes of the two children from the second hybrid point as follows.

After crossing

Child 1

2	5	1	9	4	7	6	8	0	3

Child 2

3	4	6	0	7	8	1	9	2	5

3) Variation Operation

According to the given mutation rate, the three integers within the interval are randomly taken for the individuals with the selected variation. For example： 1<a<b<c<10, and insert the gene segment between a and b into the back of c and 10 front

Ⅳ CASE STUDY

A. Case Scenario Description

This paper selects the road network in a certain area of Linxia City, Gansu Province as the research object. After the bus is fully charged and loaded with passengers, it departs from the initial station, goes to various stations in rural areas to complete the pickup and delivery of passengers, and then returns to the departure station. Since it is a customized electric bus, the pick-up and drop-off points for passengers will be determined before departure. When the electric bus runs out of power, it will go to the charging station for charging. The distance between sites is detailed in Table Ⅱ. Site 0 is a departure station located in the town area, station a is a charging station located in a rural area, and the rest are stations that need to be served by electric buses. Table Ⅲ lists various types of information for passengers getting on and off the bus.

B. Description of parameters and operation

Setting the nuclear capacity of electric buses is 45 people/bus; the full charge is 70kwh;Power consumption rate f is 2kwh/km; charging rate 6 kwh/min; electricity price g=0.6 $yuan/kwh$; The nominal value of the electric bus travel time on the road section (i,j) is $t_{ij}=d_{ij}/v$, $i,j\in w$.And setting the deviation value of the time when the bus travels on the road segment (i,j) is $\hat{t}_{ij}\,(0\le\hat{t}_{ij}\le 0.5t_{ij})$ which is a randomly generated real number. The fixed fee per bus is 50 yuan, fixed speed is $v=30km/h$, the boarding time for each passenger is 2s, and the alighting time for each passenger is 1s.

TABLE II

DISTANCE BETWEEN SITES UNIT:KM

OD	0	1	2	3	4	5	6	7	a	8	9	10	11	12	13	14	15	16	17	18	19	20
0	0	8	5	6	7	5	8	5	9	5	7	9	6	7	6	5	8	7	9	10	15	8
1	8	0	7	6	5	5	7	6	6	4	5	4	10	5	5	9	6	8	7	6	8	7
2	5	7	0	6	5	7	8	8	6	7	6	8	9	6	6	5	5	4	8	6	7	5
3	6	6	6	0	8	5	4	6	7	5	4	6	4	6	5	7	4	5	9	7	6	6
4	7	5	5	8	0	6	8	5	9	6	7	6	5	9	6	7	5	5	6	8	7	9
5	5	5	7	5	6	0	5	4	7	6	5	7	6	5	6	8	5	6	7	5	10	6
6	4	7	8	4	8	5	0	5	5	9	6	4	7	4	7	6	5	7	11	6	8	5
7	5	6	8	6	5	4	5	0	6	6	7	9	5	5	5	7	4	7	6	7	7	5
a	9	6	6	7	9	7	10	6	0	8	7	8	6	6	10	6	9	7	5	7	6	8
8	5	4	7	5	6	6	9	6	8	0	7	4	7	6	4	5	6	5	6	8	5	7
9	7	5	6	4	7	5	6	7	7	7	0	6	5	6	7	4	7	5	6	5	11	6
10	9	4	8	6	6	7	4	9	8	4	6	0	8	7	8	6	5	7	8	8	6	9
11	6	10	9	4	5	6	7	5	6	7	5	8	0	4	6	5	6	7	5	4	7	11
12	7	5	6	6	9	5	4	5	6	6	6	7	4	0	4	6	4	8	6	7	8	5
13	6	5	6	5	6	6	7	5	10	4	7	8	6	4	0	6	7	9	6	8	7	9
14	5	9	5	7	7	8	6	7	6	5	4	6	5	6	6	0	6	8	9	5	4	7
15	8	6	5	4	5	5	5	4	9	6	7	5	6	4	7	6	0	4	9	7	8	5
16	7	8	4	5	5	6	7	7	7	5	5	7	7	8	9	8	4	0	7	5	6	4
17	7	7	8	9	6	7	11	6	5	6	6	8	5	6	6	9	9	7	0	8	6	5
18	10	6	6	7	8	5	6	7	7	8	5	8	4	7	8	5	7	5	8	0	10	7
19	15	8	7	6	7	10	8	7	6	5	11	6	7	8	7	4	8	6	6	10	0	5
20	8	7	5	6	9	6	5	5	8	7	6	9	11	5	9	7	5	4	5	7	5	0

TABLE III

NUMBER OF PEOPLE WHO NEED TO PICK UP AND DROP OFF AT EACH STOP IN RURAL AREAS

Site number	Number of passengers getting off at this stop	Number of passengers getting on at this site	$\max(t_{jo}\cdot N_{jo},\ t_{jb}\cdot N_{jb})$
1	6	5	10s
2	5	4	8s
3	3	2	4s
4	5	6	12s
5	6	5	10s
6	4	4	8s
7	3	2	4s
a	0	0	-
8	5	0	5s
9	6	5	10s
10	6	4	8s
11	7	6	12s
12	5	4	8s
13	6	6	12s
14	10	9	18s
15	5	3	6s
16	2	2	4s
17	4	5	10s
18	6	4	8s
19	5	4	8s
20	3	2	4s

Using PyCharm as the operating platform, the python version is 3.8.3, using the improved NSGA-II algorithm to solve the problem, setting the initial population number is 150, the number of iterations is 150, the initial temperature is $T_0 = 500$ in the simulated annealing fitness function, and the variation The probability is 0.3, the crossover probability is 0.8, and the robust control parameters Γ are set to 0, 20, and 40, respectively. The results obtained by running the program multiple times are shown in Table Ⅳ, Table Ⅴ, Table Ⅵ. In the case of Γ =0, 20, and 40, respectively 3, 3, 3 groups of pareto optimal solutions. Figure 4, Figure 5, and Figure 6 show the distribution of effective occupancy rate of buses for Γ=0, Γ=20, and Γ=40.

TABLE Ⅳ

RESULTS OF THE BUS PATH SCHEME FOR Γ = 0

pareto solution	Bus routing plan	Effective occupancy rate	Operating mileage /km	Bus company cost /yuan	Total travel time of passengers /h
	Bus1:0-7-4-15-12-11-14-9-0	85.01%			
1	Bus2:0-8-16-2-20-18-19-a-17-10-6-3-0	77.65%	121	295.2	70.7318
	Bus3:0-5-1-13-0	37.14%			
	Bus1:0-6-3-13-12-18-20-17-a-19-2-0	74.96%			
2	Bus2:0-8-10-1-9-14-11-0	72.72%	119	292.8	78.9003
	Bus3:0-5-7-15-16-4-0	41.38%			
	Bus1:0-8-10-1-18-15-19-a-7-4-16-0	66.49%			
3	Bus2:0-5-6-12-11-3-9-14-0	85.08%	118	291.6	80.2561
	Bus3:0-2-20-17-13-0	37.78%			

TABLE Ⅴ

RESULTS OF THE BUS PATH SCHEME FOR Γ = 20

pareto solution	Bus routing plan	Effective occupancy rate	Operating mileage /km	Bus company cost /yuan	Total travel time of passengers /h
	Bus1:0-5-1-10-18-2-14-0	77.54%			
1	Bus2:0-11-9-3-7-20-17-a-19-15-16-4-0	86.63%	121	295.2	79.9758
	Bus3:0-6-12-13-8-0	41.07%			
	Bus1:0-3-15-19-18-12-17-a-16-2-13-0	80.42%			
2	Bus2:0-8-10-1-4-11-9-14-0	78.67%	119	292.8	83.6572
	Bus3:0-5-6-20-7-0	32.44%			
	Bus1:0-8-17-20-18-5-7-a-19-15-16-2-0	87.83%			
3	Bus2:0-13-12-6-10-1-3-11-0	76.37%	118	291.6	89.1280
	Bus3:0-14-9-4-0	44.25%			

TABLE Ⅵ

RESULTS OF THE BUS PATH SCHEME FOR Γ = 40

pareto solution	Bus routing plan	Effective occupancy rate	Operating mileage /km	bus company cost /yuan	Total travel time of passengers /h
	Bus1:0-14-9-19-18-10-6-12-0	54.03%			
1	Bus2:0-5-4-11-3-8-1-a-17-20-13-0	89.22%	117	290.4	98.7521
	Bus3:0-2-16-15-7-0	29.29%			
	Bus1:0-2-4-13-12-6-9-14-0	88.95%			
2	Bus2:0-8-10-1-15-19-18-17-a-7-0	67.5%	120	294.0	94.6181
	Bus3:0-11-3-16-20-5-0	42.22%			
	Bus1:0-12-18-6-15-19-9-14-0	83.52%			
3	Bus2:0-13-8-1-4-10-3-11-a-5-0	84.32%	122	296.4	89.3486
	Bus3:0-2-16-20-17-7-0	35.17%			

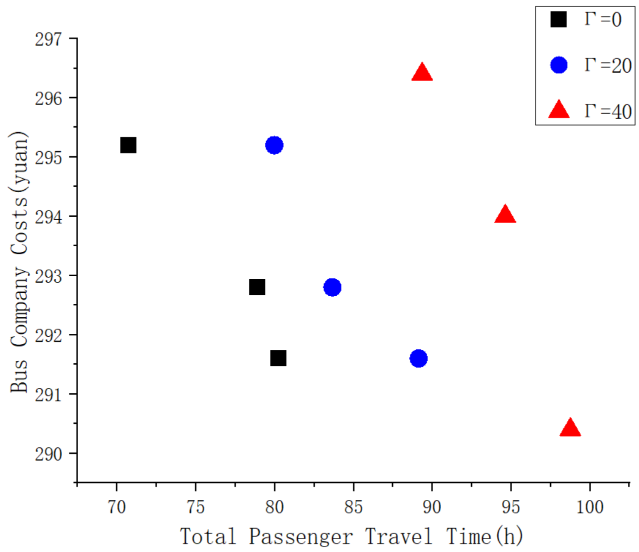

Fig.3. The pareto optimal solution at different Γ values

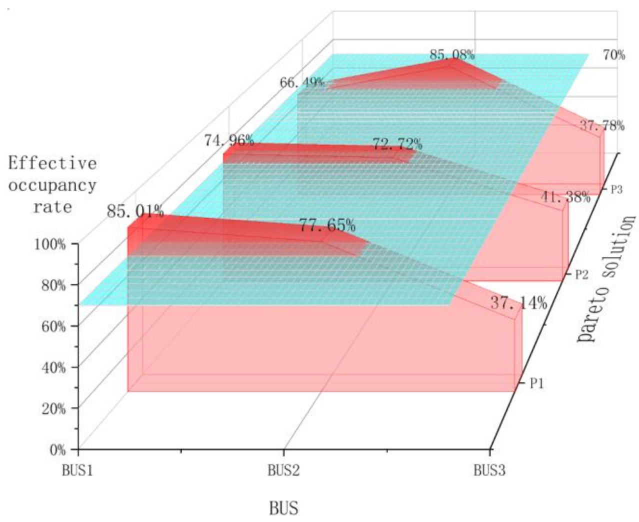

Fig.4. Distribution of effective attendance results for Γ = 0

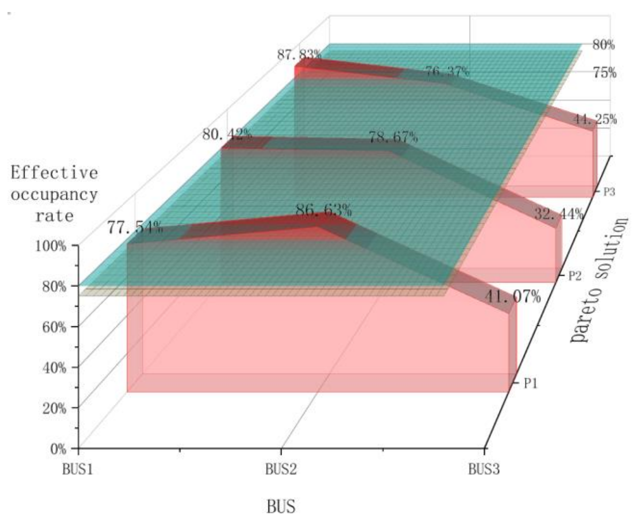

Fig.5. Distribution of effective attendance results for Γ = 20

C. Analysis of operation results

Table Ⅳ, Table Ⅴ, Table Ⅵ and Figure 3 show the results of runs, where the target-value of individual Pareto solutions, as well as the shortest path, vary with the Γ value. With increasing Γ, the target value of the total travel time of passengers increases and there is a slight change in the target values of the shortest distance and cost. The model is the most sensitive to uncertain risks at Γ=0. A change in the weight of a particular road segment of the bus route may affect the optimal solution obtained by the model.

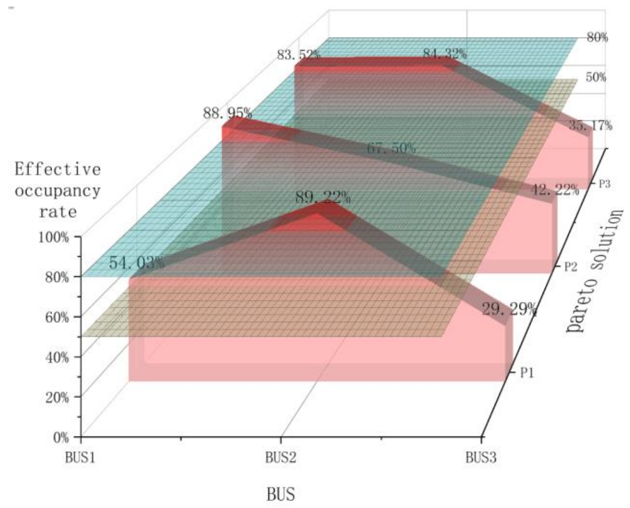

Fig.6. Distribution of effective attendance results for Γ = 40

However, the model gradually becomes conservative with gradually increasing Γ and therefore has some level of robustness. At Γ=40, the model is the least sensitive to uncertain changes, the most conservative solution is obtained, and the resulting passenger company costs and total passenger travel time are also relatively larger. Observation of the changes in the solution show that as the value of the cost objective function increases, the total passenger travel time decreases and vice versa. This result shows that the travel distance of the passenger bus is reduced, resulting in an increase in the total travel time of passengers. Besides, the optimal path for a specific problem should be chosen by comprehensively considering the influence of other factors, such that decision-making is based on a large quantity of data and the actual situation.

For the bus mentioned in this thesis, there are passengers getting on and off the bus during the journey, so its occupancy rate is different from the fixed occupancy rate of a bus where passengers do not need to get on and off the bus in the middle of the journey, but the effective occupancy rate. The effective occupancy rate is the ratio of the distance travelled by the bus when the seats are occupied to the distance travelled by the bus when the seats are vacant and occupied.

The effective occupancy rates of all buses obtained at different values of Γ are shown in Fig. 4, Fig. 5, and Fig. 6. From these figures, it can be concluded that different buses have different effective occupancy rates, and there are many buses with occupancy rates close to 90%. In Figure 4, the effective occupancy rate of most buses is higher than 70%. In Figure 5, six buses have an effective occupancy rate above 75% and three buses have an effective occupancy rate above 80%; in Figure 6, four buses have an effective occupancy rate above 80% and two are between 50% and 80%. These conclude that the customized electric bus route optimization scheme obtained from the solution can make most of its buses make good use of its resources, and thus can reduce the waste of customized passenger transportation resources.

D. Comparative Analysis of Algorithms

Table Ⅶ compares the results obtained using the improved NSGA-II algorithm and the multi-objective genetic algorithm NPGA at Γ=0. The improved NSGA-II algorithm outperforms the multi-objective genetic algorithm NPGA in terms of all comparison indicators. Compared with the results for the multi-objective genetic algorithm NPGA, using the improved NSGA-II results in a lower operating mileage and cost, a 14.47% lower average passenger travel time, and a 39.81% lower computing time. In addition, Figure 7 and Figure 8 conclude more clearly from the perspective of the objective function values that the improved NSGA-II algorithm outperforms the multi-objective genetic algorithm NPGA. Thus, compared with the multi-objective genetic algorithm NPGA, the proposed improved NSGA-II algorithm is more inventive, produces better results, and completes the task for urban and rural demand-response buses more effectively.

E. Conclusion

From the actual case results and comparative analysis, it can be seen that the different Γ values in uncertain environments have different degrees of influence on the calculation results. How to choose the right bus path solution also needs to be based on the actual needs. Secondly, the results of the effective occupancy rate obtained from the calculation can also surface that the proposed bus route optimization scheme can effectively utilize the traffic resources and reduce the waste of resources. Finally, the algorithm comparison also proves that the algorithm proposed in this paper also has better calculation results and calculation time compared with NPGA, which is certainly more superior.

TABLE Ⅶ

(Γ=0) ALGORITHM COMPARISON TABLE

Compare metrics	The Improved NSGA-II algorithm			Multi-objective genetic algorithm NPGA		
Bus routing plan	Bus1:0-7-4-15-12-11-14-9-0 Bus2:0-8-16-2-20-18-19-a-17-10-6-3-0 Bus3:0-5-1-13-0	Bus1:0-6-3-13-12-18-20-17-a-19-2-0 Bus2:0-8-10-1-9-14-11-0 Bus3:0-5-7-15-16-4-0	Bus1:0-8-10-1-18-15-19-a-7-4-16-0 Bus2:0-5-6-12-11-3-9-14-0 Bus3:0-2-20-17-13-0	Bus1:0-14-9-1-4-15-12-11-0 Bus2:0-8-16-2-20-18-19-a-17-10-6-3-0 Bus3:0-7-13-5-0	Bus1:0-12-18-6-15-19-9-14-0 Bus2: 0-13-8-16-4-2-20-17-a-1-10-3-0 Bus 3:0-11-7-5-0	Bus1：0-12-18-6-15-19-9-14-0 Bus2：0-13-8-10-5-3-11-a-1-4-0 Bus3：0-7-20-16-4-2-0
Operating mileage	121 km	119 km	118 km	120 km	121 km	123 km
Average operating mileage		119.3333 km			121.3333 km	
Company cost	295.2 yuan	292.8 yuan	291.6 yuan	294 yuan	295.2 yuan	297.6 yuan
Average company cost		293.2 yuan			295.6 yuan	
Total passenger travel time	70.7318 h	78.9003 h	80.2561 h	95.1589 h	90.1586 h	83.4561 h
Mean value of total passenger travel time		76.6294 h			89.5912 h	
Computing time		6.2s			10.3s	

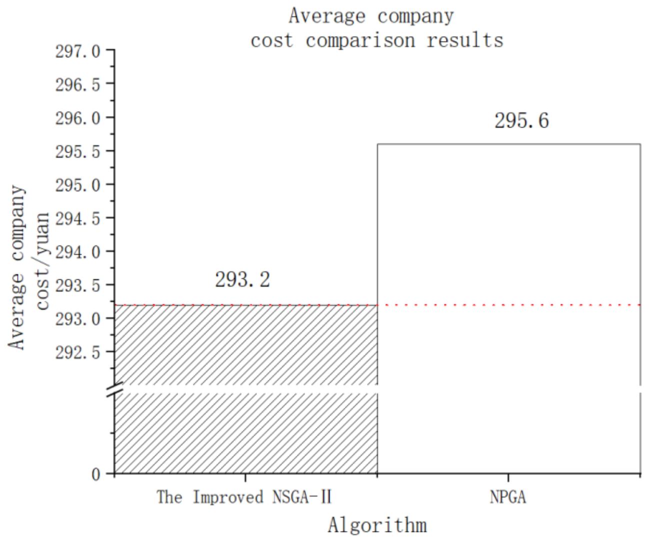

Fig.7. Average company cost comparison results

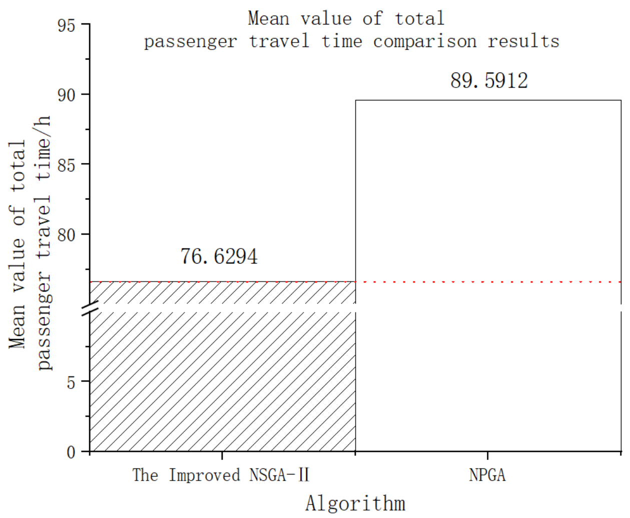

Fig.8. Mean value of total passenger travel time comparison results

V. CONCLUSIONS AND PROSPECTS

1) As relatively backward urban and rural areas have immature passenger transportation systems, demand-responsive buses provide an efficient and convenient service for those with definite destinations by compiling and fulfilling the needs of all passengers, which has not been possible previously. In rural areas with poor road operating environments, an effective and comprehensive solution is provided in this study to the mismatch between low passenger demand and an excessive supply of buses, which significantly wastes resources, and the inability of a fixed number of buses for mass transit to accommodate all passengers during peak periods.
2) The operation of electric buses in rural areas is not fully mature but is practically functional in many areas. As the routes of custom electric buses must be planned in advance, it is challenging to formulate charging strategies. The charging strategy proposed in this study is as follows: the remaining power of the vehicle in operation is detected; if the current station is not the final task station, the power required to go the next station and then go to the charging station is compared with the power required to reach the charging station directly to determine whether to go to the charging station immediately or continue to complete the task. When the last rural station is reached, it must be determined whether the current remaining power can support return to the initial passenger station.
3) In this study, a robust optimization model of electric passenger transport for urban–rural response is established with the objectives of minimizing the cost to the bus company and the total travel time of passengers, while fully considering the uncertainty in the running time of the electric bus caused by uneven and rugged roads. The model is optimized using the improved NSGA-II algorithm to obtain a Pareto optimal solution that minimizes both the total travel time of passengers and the cost to the bus company. This solution is economically beneficial to the bus company and considers the impact of travel time on the passengers. The multi-objective function considered in this study is a more useful reference than a single-objective function or line optimization in a deterministic environment.
4) Application of the proposed improved NSGA-II algorithm results in a lower total passenger bus operating mileage and cost to the bus company (where the average total passenger travel time is reduced by 14.47%, and the computing time is reduced by 39.81%) compared to those obtained using the multi-objective genetic algorithm NPGA. This result shows that the improved NSGA-II designed in this paper is superior to the multi-objective genetic algorithm NPGA in terms of the results and efficiency of the solution, while being more practical.
5) Multiple departure stations and other uncertain environments in rural roads have not been considered in this study and will be addressed by performing a robustness study in the future.

REFERENCES

[1] Fang Chen, Hao Qiu, Xiaoli Fan, "Study of Rural Passenger Transport Development from Perceptive of Human Residence," Acta Agriculturae Jiangxi, vol.26, no.02, pp.140-143+147, Feb.2014.
[2] Lu Cunye, "Research on Development Mode of Rural Passenger Transport System under Low-Carbon Economy," M.S. thesis, Dept. Trans. Eng., Chang'an Univ., Shanxi, China, 2011.
[3] Kunpeng Hu, "Application research on county rural passenger transportation planning method," M.S. thesis, Dept. Trans. Eng., South China University of Technology., Guangdong, China, 2014.
[4] Tong An, "The Research on The Operating System And Route Design of Urban Customized Bus," M.S. thesis, Dept. Trans. Eng., Changsha University of Technology., Hunan, China, 2016.
[5] Fengyan Zhang, Wei Zhou, "Optimization of Rural Bus Route Based on Traffic Compactness," J Highw Transp Res Dev, vol.27, no. 09, pp.111-116, Sept, 2010.

[6] Guo Qiu, “Research on Optimizing Design Method of Customized Bus Route Based on Bassenger Mod-e Choice,” Ph.D. dissertation, Dept. Trans. Eng., Beijing Jiaotong Univ., Beijing, China, 2019.
[7] Yan Gao, “Route Design of Village-town Passenger Transport Operating Express Delivery,” M.S. thesis, Dept. Trans. Planning and management., Beijing Jiaotong Univ., Beijing, China, 2020.
[8] Rongrong Xu, “Research of DRT Application in Rural Passenger Transport,” M.S. thesis, Dept. Trans. Eng., Chang'an Univ., Shanxi, China, 2015.
[9] Yanguang Cai. Yalian Tang, Jun Zhu. “Research of collaborative vehicle routing problem for bus in countries,” Application Research of Computers, vol 32, no.6, pp.1657-1662, Jun.2015.
[10]Liangping Liu, “Chongqing rural passenger transport operation mode and method research,” M.S. thesis, Dept. Trans. Eng., Chongqing Jiaotong Univ., Chongqing, China, 2014.
[11]Chan Shen, Cui Hongjun, “Optimization of Real-time Customized Shuttle Bus Lines Based on Reliability Shortest Path,” J Transp Syst Eng Inf Technol, vol.19, no.06, pp.99-104, Dec.2019.
[12]Hangqi Zhang, “Research on customized bus route planning based on granular computing,” M.S. thesis, Dept. Sw. Eng., Hangzhou Dianzi Univ, Zhejiang, China, 2019.
[13]Wenwen Guo, “Study on the layout of rural township passenger station,” M.S. thesis, Dept. Trans. Eng., Chang'an Univ., Shanxi, China, 2012.
[14]Ruiqin Zhang, “Study on construction scale of the township passenger station based on the rural public passenger transportation,” M.S. thesis, Dept. Trans. Eng., Chang'an Univ., Shanxi, China, 2013.
[15]Yeqian Lin, Li Wenquan, Qiu Feng. “An Optimal Model for Flex-route Transit Scheduling Problem,” Journal of Transport Information and Safety, vol.30, no.05, pp.14-18+33, Oct.2012.
[16]Faroqi H, Sadeghiniaraki A, “Developing Gis-Based Demand-Responsive Transit System in Tehran City,” ISPRS. vol. XL-1-W5,pp.189-191, Jan.2015.
[17]Sevgi Erdogan,Elise Miller-Hooks. “A green vehicle routing problem”. Transportation Research Part E:Logistics and Transportation Review, vol 48,no.1,pp: 100-114, Jan.2012.
[18]J. de Hoog, T. Alpcan, M. Brazil, D. A. Thomas and I. Mareels, "Optimal charging of electric vehicles taking distribution network constraints into account," 2017 IEEE Power & Energy Society General Meeting, 2017, pp.1-1.
[19]Gerhard Hierman. Jakob Puchinger, Richard F.Hartl. “The Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows and Recharging Stations,” European Journal of Operational Research, vol.252, no.3, pp.995-1018, Aug.2016.
[20]Jing-Quan Li. “Transit bus scheduling with limited energy,” Transportation Science, vol.48, no.4, pp.521-539, Nov.2013.
[21]Huaxu Liu. “Research on scheduling optimization common deliver based on electric vehicle technical feature,” Dept. Trans., M.S. thesis, Beijing Jiaotong Univ., Beijing, China, 2012.
[22]Goeke D, Schneider M. “Routing a mixed fleet of electric and conventional vehicles,” Publications of Darmstadt Technical University Institute for Business Studies, vol.245, no.1, pp.81-99, Aug.2015.
[23]Rongge Guo, Wei Guan, Wenyi Zhang, Mengyua Duan. “Customized Electric Bus Routing Optimization Considering Multi-Path Selection,” Journal of Transportation Systems Engineering and Information Technology, vol.21, no.2, April.2021, pp.133-138.
[24]Jun Yang, Pengxiang Feng, Hao Sun, Chao Yang. “Battery Exchange Station Location and Vehicle Routing Problem in Electric Vehicles Distribution System,” Chinese Journal of Management Science, vol.23, no.9, pp.87-96 Sept.2015.
[25]Youjun Deng, Ming Li, Qian Yu, “Logistics Distribution Route Optimization and Charging Navigation of Electric Vehicle Based on Real-Time Information Sensing,” Southern Power System Technology, vol.11, no.2, pp.41-49, Feb.2017.
[26]Wanchen Jie, Jun Yang, Chao Yang. “Branch-and-price algorithm for heterogeneous electric vehicle routing problem,” Systems Engineering-Theory＆Practice,vol.26, no.7, Jul.2016, pp.1795-1805.
[27] Yan-e Hou, Lanxue Dang, Yunfeng Kong, Zheye Wang, and Qingjie Zhao, "A Hybrid Metaheuristic Algorithm for the Heterogeneous School Bus Routing Problem and a Real Case Study," IAENG International Journal of Computer Science, vol. 47, no.4, pp775-785, 2020.
[28]Changxi Ma, Chao Wang, Xuecai Xu. A Multi-Objective Robust Optimization Model for Customized Bus Routes. IEEE Transactions on Intelligent Transportation Systems, 2021, vol. 22, no. 4, pp. 2359-2370. DOI: 10.1109/TITS.2020.3012144.
[29]Lan-xue Dang, Yan-e Hou, Qing-song Liu, and Yun-feng Kong, "A Hybrid Metaheuristic Algorithm for the Biobjective School Bus Routing Problem," IAENG International Journal of Computer Science, vol. 46, no.3, pp409-416, 2019
[30]Mulvey, J.M., Vanderbei, R.J. and Zenios, S.A., “Robust optimization of large-scale systems,” Operations Research, vol.43, no.2, pp.264–281, Aug.1995.
[31]Ben-Tal, A. and A. Nemirovski, “Robust Convex Optimization,” Mathematics of Operations Research, vol.23, no.4, pp.769-805, Nov,1998.
[32]Ben-Tal, A. and A. Nemirovski, “Robust solutions of uncertain linear programs,” Operations Research Letters, vol.25, no.1, pp.1-13, Jun.1999.
[33]ElGhaoui L, Lebret H, “Robust solutions to least-squares problems with uncertain data,” SIAM Journal on Matrix Analysis and Applications, vol.18, no.4, pp.1035-1064, Oct 1997.
[34]Bertsimas, D. and M. Sim, “The Price of Robustness,” Operations Research, vol.52, no.1, pp.35-53, Feb,2004.