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An Improved Genetic Evolutionary Algorithm for Commuter Route Optimization

Xiaohong Qian
College of Information Engineering, Wuhan Huaxia University of Technology
Wuhan, China
21424691@qq.com

Linlin Liu
College of Information Engineering, Wuhan Huaxia University of Technology
Wuhan, China
12831991@qq.com

***Abstract*—Commuter route problem is a very wide range of intelligent optimization problems in the field of public transport research. Solving route optimization problems is of great significance. Genetic algorithm (GA) is one of the effective methods to solve this kind of problem. The standard genetic algorithm has some limitations. In order to solve the problems that the standard genetic algorithm is easy to be premature and easy to fall into the local optimal solution, an improved genetic evolutionary algorithm(IGEA) is constructed by using adaptive neighborhood method to construct initial population, adaptive crossover mutation probability function and evolutionary reversal etc. to improve standard GA, which improves the quality of the population, enhances the local search ability of genetic algorithm and increases the probability that the offspring will inherit the high quality gene from the father. The simulation results show that the IGEA has better ability to search the optimal solution, the convergence effect is better and the calculation result is more stable.**

Keywords-* *genetic algorithm, route optimization, convergence, optimal solution

I. INTRODUCTION

Commuter shuttle bus is one of the public transport modes in urban areas. This paper studies the commuter bus route planning for the e-bus of industrial park. It is not only the key issue encountered by the staff traveling but also the key research topic of the public transport network optimization. The traditional query of single target route such as the shortest distance and the quest of the least time route can no longer meet the realistic needs of passenger travel under the modern urban three-dimensional traffic system. From a passenger's point of view, a multi-objective commute solution allows passengers to get to and from the company nearest and cost less time. From commuter bus company's perspective, the multi-objective route optimization takes full account of experiences of passengers and the use of buses, and also ensures that the company commuter operating costs the lowest.

As one of the most important research hotspots in the field of artificial intelligence, route planning [1] is more and more concerned by relevant researchers at home and abroad. It is one of the most important components in the field of optimal control robotics intelligent transportation and artificial intelligence-related technologies [2].With the development of research for route planning, there are more and more researches for solving route planning. Different planning problems need to be solved by different methods. Many researchers have proposed different ideas. Wang [3] proposed a multi-objective genetic algorithm. Szeto[4] putted forward the idea of improving genetic algorithm based on domain search algorithm for the design and optimization of urban public transportation network. A new method to calculate the fitness function of genetic algorithm is given by Biellia[5] and applied to the bus network optimization problem. Wang [6] proposed an improved multi-objective ant colony optimization algorithm. Li [7] proposed the shortest path optimization algorithm. Emel [8] presented a hybrid genetic algorithm using fuzzy rule for classifying high dimensional problems. In literature [9], the author used the local optimization ability of adaptive domain method to improve the initial population of the algorithm and adjusted the genetic probability dynamically to balance the global searching ability and local search ability of the algorithm. The genetic algorithm (GA) is a heuristic search method in which the error of the optimal solution and the actual optimal is smaller and has higher global search performance and higher convergence speed than the simulated annealing method. In practice, the corresponding algorithms need to be selected according to the needs of the problems. In the planning of intelligent commuter bus routes, the actual coverage of the upper and lower passengers, the running track of the commuter vehicle and the occupancy rate are taken into consideration. In this paper, IGEA is proposed. In view of the fact that traditional commuter vehicles can't meet the individual needs of passengers and can't make the best use of vehicle utilization, an optimized algorithm named IGEA is proposed which aims to choose an optimal value to balance the number of vehicles and travel time of staff, using the least vehicles to cover the largest population and reducing travel costs while ensuring staff travel time.

II. PROBLEM DESCRIPTION AND MODEL ESTABLISHMENT

The model is described as follows.

Set the number of passengers is m (1, 2,⋯,m). Each passenger's location and destination (arriving at a industrial park) are given. The number of commuter buses required is n(1,2,⋯,n).The number of sits with a bus is μ.Each bus is noted as v. The industrial park is known as D. In order to reasonably arrange the routes and the use of commuter buses,

this paper used the following formula (1) to solve the required number of vehicles.

$$n=[m/\mu]+1 \quad (1)$$

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Where n denotes the number of buses required. [] denotes rounding and α is a parameter where 0 <α <1 and a is related to the restriction situation, such as time constraints of passengers and road conditions. The more restrictions, the smaller is α is. You can adjust the value of the parameter α according to the actual situation.

The transport cost of passenger i to passenger j (including travel time travel, distance, freight costs, and so on.) is represented as $p_{i,j}$ and the cost of the passenger i to the industrial park D is noted as pi， D(i=1,2,⋯,m), T is the longest time that the first passenger can tolerate from getting on the bus to the park. Define the following variables.

$$x_{ijv} = \begin{cases} 1, \text{vehicle v from passenger i to passenger j} \\ 0, \text{otherwise} \end{cases}$$

$$y_{iv} = \begin{cases} 1, \text{passenger i is [illegible] by vehicle v} \\ 0, \text{otherwise} \end{cases}$$

$$z_{iv} = \begin{cases} 1, \text{passenger i [illegible] by v directly to D} \\ 0, \text{otherwise} \end{cases}$$

To meet the maximum commuter demand, the minimum operating costs and to achieve the least line optimization, a mathematical model of the objective function is defined as follows.

$$\min z = [illegible] \quad (2)$$

$$[illegible] \quad v = 1,2,\cdots,n \quad (3)$$

$$[illegible] \quad (4)$$

$$[illegible] \quad (5)$$

$$[illegible] \leq T \quad (6)$$

III. IGEA

GA is a powerful global search algorithm for solving combinatorial optimization problems [9]. It simulates the evolutionary process of the natural world. By initializing population, selection, crossover and mutation operations, the genetic algorithm follows the global law of "survival of the fittest" .GA has good robustness and global search ability but also has some shortcomings. For example GA has low optimization efficiency of search efficiency and is easy to fall into local optimum.GA needs to be improved continuously to meet the time and efficiency, at the same time getting the optimal solution. Thus, to overcome the faults of GA and to meet the requirement of intelligent commuter for passengers, the IGEA is proposed here.

A. Chromosome Coding

Chromosomal coding is to transform the problem to be solved from phenotypic space to genotype for genetic manipulation. There are many different coding methods in GA including symbolic coding, floating-point coding and binary coding etc. In the running process of GA, it does not directly manipulate the actual decision variables of the problem to be solved but manipulate individuals such as selection, crossover, mutation and other operations, continuing to search for individuals with higher fitness and gradually increase the number of groups until the best solution to find the problem or approximate optimal solution. In order to study simply, this article uses the symbol coding method. Set the passenger point sequence coding using symbolic set, such as {A, B, C, D....} or {1, 2, 3, 4….} and etc. Each symbol represents a passenger point and chromosomes are encoded as M integer sequences [1, M], where M> 20, as is shown below.

3	5	10	11	15	···	M	16	6

B. Initial Population Construction

Multi-objective optimization problem using a simple random method to generate the initial population has some problems, such as large search space, long time and prone to premature convergence. In order to overcome these problems, a kind of initial population strategy is used to improve the genetic algorithm and adaptive domain method is used to generate the initial population which is generated by a simple stochastic method. The size of the population generally varies with the problem and there is no clear indicator to define the appropriate number of the population. But the quality of the initial population often affects the convergence rate and efficiency of the genetic algorithm. First of all, getting the number of initial population according to the number of customer points based on experience is needed. After determining the initial population number M and then starting from a point, it randomly select the point within the field slightly farther than its nearest point as the next point and as the current point continues to search to add not admitted points until the traversal of all the points, getting optimized M individuals. This method is not only random but also improves the quality of initial population.

C. Fitness Function

A constrained optimization route scheme can be used as a chromosome. In this paper the reciprocal of the objective function formula (2) is used as the chromosome fitness function.

$$F(R_i) = 1/[illegible] \quad (7)$$

$F(R_i)$ is the reciprocal of the sum of the cost of travel distance and the cost of travel time for all passenger points.

D. Choice Operation

The selection operation is to select individuals with high fitness function from the current population to a new group with a certain probability. The probability that an individual is selected is related to the fitness value of the individual. The main purpose is to try to transfer the excellent gene to the next generation and improve algorithm efficiency and global convergence probability. The proportion of wheel and disc and the best way to save individuals are combined to use for individual selection. The probability of selection is calculated using the following formula.

$$P_i = F(R_i) \Big/ \sum_{i=1}^{M} F(R_i) \quad (8)$$

Where $F(R_i)$ is the fitness of the ith gene in the population. Since to get the minimum value of the target seeking function (2),it selects the parent population fitness relatively large as the next route optimization individual and remove individual with relatively small fitness in the offspring population. The individual with the largest fitness value go straight into the next generation, making excellent genes uninterrupted and mutated. In addition, proportional selection is used to avoid the difficulty of jumping out of the local optimal solution caused by the optimal individual save strategy. This way provides outstanding genes to the evolution of the next generation and also provides good basis for global outstanding solution.

E. Crossover and Mutation Operation

Crossover and mutation use the above individual selection method and then randomly select the matching crossover and mutation point. The crossover operation of multi-objective commuter route optimization uses a cross operation between two points such as a pair of individuals q1 and q2.Then randomly generate two intersections s1 and s2 (s1 <s2) within the chromosome range [1, M]. Substitution of the genes of individuals between the crossover points with the corresponding mapped genes and if the genes other than the crossover point are the same as those between the crossover points, then this gene is replaced using evolutionary reversing mapping.

Evolutionary reversal operation can improve the local search ability of genetic algorithm. In this paper we use evolutionary reversing mutation operation for individuals after crossover which enlarges the selection source of parent individual gene information and prevent the algorithm from premature convergence. "Evolution" refers to the reversal of an individual who can increase the fitness value after a reversal of an operation. The reverse operation is as follows.

- It randomly selects two numbers n1 and n2 of the chromosomes, determine two positions c and d where c = 4 and d = 9 are defined.
- Reversing the chromosome between the 4th and 9th positions of the selected position results in the next generation of offspring.

5 1 2 |4 3 7 9 8| 6

After reverse the chromosome is as follows.

5 1 2 |8 9 7 3 4|6

The fitness value of the new individual after the reversal is calculated. If the fitness value is higher than before the reversal, then the new individual is retained, otherwise the original individual is retained. After the evolution reversal, the individual with the higher fitness value is retained; otherwise the original individual is retained. The optimal objective function is selected from the generated offspring that is the global optimal solution of the commuting route.

In order to improve the effectiveness of crossover and mutation, this paper adopted changing adaptively the probability of crossover and mutation. When population fitness tended to coincide or local optimum, the initial crossover rate p_c and the initial mutation rate p_m were increased, improving the probability of individuals to cross and mutation. When the population difference in fitness is large, the lower p_c and p_m was adopted as shown in formula (9) and (10).

$$p_c = \begin{cases} k_1(f_{max} - f') \big/ (f_{max} - f_{avg}), & f' \ge f_{avg} \\ k_1, & f' < f_{avg} \end{cases} \quad (9)$$

$$p_m = \begin{cases} k_2(f_{max} - f), & f \ge f_{avg} \\ k_2, & f < f_{avg} \end{cases} \quad (10)$$

f', f_{max}, f_{avg}, f respectively represent the larger fitness to be crossed parents, the maximum fitness in the population, the average fitness of the population and the individual fitness to be mutated; k1 and k2 respectively represent the maximum crossover probability and the maximum mutation probability.

IV. SIMULATION TEST AND RESULT ANALYSIS

According to the above steps to solve the commuter route optimization problem, the basic flow of the designed algorithm is shown in Fig.1.

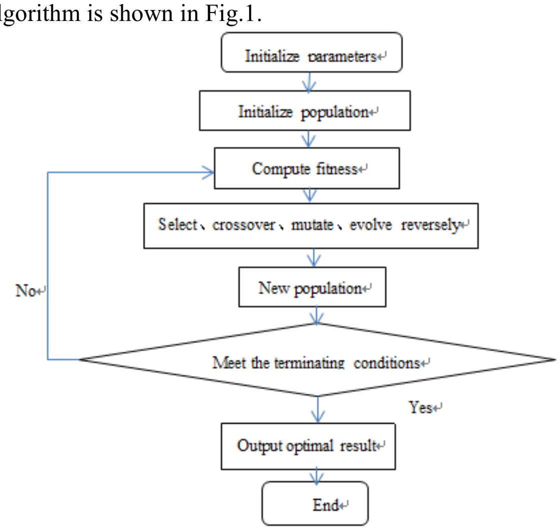

Figure 1. The flow chart of IGEA

In order to verify the performance of the IGEA, we simulated commuter situation to get optimized commuter schema. According to the commute of an industrial park, the park now has some commuter buses with a carrying capacity of 30 and now there are 25 passenger points and 132 passengers who use these commuter buses. The passenger points are noted as 1, 2, 3,⋯, 25. The industrial park number recorded as 0. In order to facilitate the calculation, each passenger's actual geographic location is reduced to xy coordinates according to a certain scale. The location coordinates of the park and each passenger point are shown in Tab.I. We required the least commuter buses to be used and the shortest total route to meet customers' arrival in the park.

TABLE I. THE COORDINATE OF INDUSTRIAL PARK AND CUSTOMER

passenger point number	0	1	2	3	4	5	6	7	8	9	10	11	12
X-axis/km	16	19	22	17	14	6	19	20	14	12	23	8	15
Y-axis/km	22	18	23	18	15	8	17	33	6	16	7	9	11
passenger point number	13	20	25	16	17	18	19	20	21	22	23	24	25
X-axis/km	15	13	17	14	20	19	13	21	30	25	26	29	11
Y-axis/km	19	20	28	22	21	20	15	17	32	22	28	20	13

The parameters of IGEA are set as follows: the initial population size is 200 and the maximum number of iterations is 100. The algorithm runs 10 times in total. The experiment results of using IGEA to solve commutation route optimization problems are shown in Tab.II.

TABLE II. TEST RESULTS OF COMMUTER BUS ROUTING OPTIMIZATION

times	1	2	3	4	5
transportation distance/km	39.4	38.8	38.3	38.1	37.8
Number of buses	5	5	5	5	5
transportation time/s	2.8	3.0	2.9	2.6	2.7
times	6	7	8	9	10
transportation distance/km	37.6	37.0	36.8	36.8	36.7
Number of buses	5	5	5	5	5
transportation time/s	2.9	2.7	2.6	2.8	2.7

Fig.2 is a comparison of convergence effect between the improved genetic algorithm of this paper and the standard genetic algorithm. The improved genetic algorithm can speed up the search for the optimal solution and reduce the number of iterations compared with the standard genetic algorithm and the calculation result is stable.

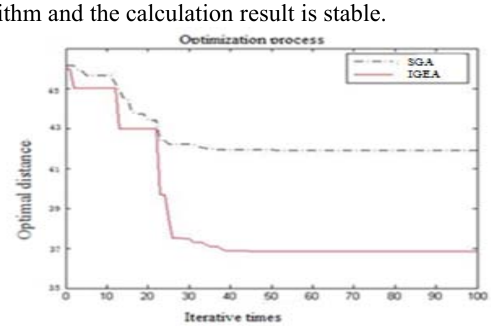

Figure 2. The iterative curve of standard GA and IGEA

V. CONCLUSION

Commuter bus route optimization is a very wide range of intelligent optimization problems in the field of public transport research. In this paper, we design an improved genetic algorithm to solve it. The problem model is constructed according to the objectives and limitations of the multi-objective commuter bus route optimization problem. According to the characteristics of commuting route multi-objective optimization problem, in order to avoid the problem that the initial population generated by simple random method is large in search space, long in time and easy to premature convergence, an adaptive domain method is used to generate the initial population of genetic algorithm. In order to preserve the diversity of population, roulette selection strategies and elite strategy retention is implemented before crossover. The introduction of the adaptive crossover mutation probability function not only speeds up the convergence of the optimal solution but also makes the algorithm difficult to fall into precocity.

The simulation results show that the optimized genetic algorithm can search the optimal solution more quickly and converge quickly. Future research on commuter routing optimization will consider adding more constraints and integrating the optimized genetic algorithm with other algorithms such as ant colony algorithm and simulated annealing algorithm so that when the passenger point size and passenger size are relatively large, optimal solution will also be solved.

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