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An Efficient Genetic Method for Multi-Objective Location Optimization of Multiple City Air Terminals

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ABSTRACT Some airports construct several buildings in city centre to offer check in and other services, denoted as city air terminals, which help passengers to check in and drop off luggage closer to their residences. Multi-objective location optimization methods play an important role in planning the locations of city air terminals. The objectives are to improve passenger experience and enhance the competitiveness of air transportation. A mathematical model of this problem is introduced. The model takes three factors into accounted as the optimization objectives, including the average path length from passengers to city air terminals, the maximum tolerable distance of passengers, and the service capacity of a station. Secondly, an efficient hybrid evolutionary method is presented for efficiently optimizing the locations of city air terminals, which includes an improved ripple-spreading algorithm for solving the many-to-many path optimization problem and a genetic algorithm for optimizing the facility location problem. Finally, a case study based on a large city in China is performed to test the proposed method for locating city air terminals in urban area and to show its effectiveness and efficiency.

INDEX TERMS Evolutionary computation, genetic algorithm, transportation, ripple spreading algorithm.

I. INTRODUCTION

The concept of city air terminal (CAT) is put forward to provide the air passenger services in urban area of a large city [1]. Generally, a CAT corresponds to a public facility providing a convenient one-stop departure service for airline check-in, immigration clearance, as well as non-stop limousine bus service to the airport. After dropping off luggage and taking a shuttle, the passengers can go through an expedited entry once at the airport, which would greatly reduce the waiting time at airport terminal. The initial objective of CAT is to increase the convenience of the airport by offering airline check-in facilities in city centre. Moreover, the concept of CAT promotes the coordinated development of vehicles, metros, railways, and aviation. For now, the establishment of airport groups in large metropolitans has become the main trend of urban development. The CATs are the important transportation hubs connecting these airports, which help passengers to check in and drop off luggage closer to their residences.

Since 1999, the countries with a high population and a high demand for air transportation started the massive constructions of CATs. Especially in Asia, China, Japan, South Korea, and Malaysia have constructed many CATs, connecting the urban areas and the airports [2]–[4]. For instance, the first CAT in China was built in Shanghai in 2012. And now more than 100 CATs have built in China [5], as illustrated in Fig. 1. Most CATs are constructed in the cities with large populations. According to the CAT development in China, the recent 20 years can be divided into three stages: I. Initial stage (2002-2007): Some airports began to study the new concept of CAT and put it into applications. II. Second stage

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(2007-2010): Some problems appeared during the operation of CATs. Thus, several CATs were closed for various reasons, such as the unreasonable layout of CATs and the limited number of CATs in city centre, leading to a poor service quality. III. Third stage (after 2010): The researchers begin to study the methods for improving the development of CAT. The construction of city air terminals no longer simply pursues the quantity, but pays more attention to the rationality of the CAT layout [5].

Recently, researchers have shown an increased interest in studying the operation mode of intermodal transportation hubs and the location optimization of CATs. The Transportation Research Board (TRB) published two reports about the measures used by some major airports, presenting the urban terminal facilities [6], [7]. Vergin and Rogers [8] applied a simple heuristic for locating economic facilities. In 2011, Goswami *et al.* [9] studied the methods for optimizing off-site passenger service facilities. The optimization of CAT locations is similar to a multiple facility location problem (MFLP) [10] and the best routes between passengers and CATs should be found, which corresponds to a many-to-many path optimization problem [11]. For solving a large-scale problem, heuristic or meta-heuristics algorithms should be adopted. Zhang *et al.* [12] applied a two-phase heuristics algorithm for solving the facility location problem. Liu *et al.* [13] applied Dijkstra in a kNN research based on multi-source query points on road networks. Mei *et al.* [14] utilized a genetic algorithm for finding effective evacuation routes in metro stations. Pour and Nosraty [15] described a heuristic algorithm for solving the plant/facility location problem by applying ant-colony algorithm.

To continue improving the service quality, it is important to optimize the location of CATs by considering multiple objectives, which include:

- Reducing the average distance between the main passenger sources and CATs;
- Balancing the service capacity of CAT and the passenger demands;
- Improving the service quality and increasing the service coverage to attract more passengers.

In this paper, an efficient evolutionary method for locating multiple CATs is proposed. Multiple objectives including the average distance from passenger source locations to CATs, the maximum tolerable distance of passengers, and the service capacity of CAT are accounted for optimizing the CAT locations. This paper is organized as follows. In Section 2, a mathematical model of the problem is introduced. In Section 3, the ripple spreading algorithm is presented. In Section 4, a genetic algorithm is applied for finding the best CAT locations. In Section 5, the method for creating the route network in a large city in China and the method for conducting a survey of the passenger information are presented. In Section 6, the reported method is tested to show its effectiveness and efficiency. The paper ends with a conclusion in Section 7.

FIGURE 1. Distribution of city air terminals in China [5].

II. PROBLEM DESCRIPTION

The main objective is to optimize the CAT locations in a city. The distances between passengers and CATs should be quantified. Thus, the optimization is based on the city road network, in which the main roads should be included. As illustrated in Fig. 2, the problem can be abstracted by a mathematical model, in which a route network $G(V, L)$ is assumed. In $G(V, L)$, $V = \{V_i\}_{i\in[1,N_{\text{node}}]}$ includes all nodes and $L = \{L_j\}_{j\in[1,N_{\text{link}}]}$ includes the links between nodes. Two indicators N_{node} and N_{link} refer to the total numbers of nodes and links.

1) All nodes can be divided into 3 groups:
   - $S = \{S_k\}_{k\in[1,N_{\text{source}}]}$ are the passenger source locations, with N_{source} the total number of passenger sources. The numbers of passengers set off from different passenger source locations are not the same, and the weights $\{w_k\}_{k\in[1,N_{\text{source}}]}$ indicate the degrees of aggregation to passengers.
   - $T = \{T_l\}_{l\in[1,N_{\text{term}}]}$ are CAT locations, with N_{term} the number of CATs. The value of N_{term} is predefined in planning CATs.
   - The others are ordinary nodes, indicating the intersections of main roads.
2) The set L corresponds to city main roads.
3) The optimal routes from passenger sources to city air terminals are illustrated by the red lines in Fig. 2. The corresponding route lengths are included in the set $\{d_k\}_{k\in[1,N_{\text{source}}]}$. Each element d_k is the shortest distance from S_k to its nearest city air terminal, which is expressed by

$$d_k = \min_{l\in[1,N_{\text{term}}]} R_{S_k T_l}, \tag{1}$$

where $R_{S_k T_l}$ denotes the shortest route length from the source S_k to the city air terminal T_l.

In this study, the average path length from passengers to CATs, the maximum tolerable distance of passengers, and the service capacity of CAT are taken into account in the optimization.

The location optimization of CATs can be described as a minimization problem

$$\min V_{\mathrm{OF}}, \text{ with } V_{\mathrm{OF}} = \sum_{i=1}^{3} \alpha_i F_i, \tag{2}$$

where

- F_1 is the average path length from passenger sources to nearest CATs.
- F_2 is the sum of the exceed path lengths which are above the maximum tolerable distance $D_{\max}$. Here, $D_{\max}$ is obtained by a survey to passengers in the airport.
- F_3 is the sum of the exceed passenger numbers above the service capacity of CAT $V_{\max}$.
- α_i ($i \in [1, 3]$) are predefined.

In (2), the first criterion represents the average path length of all sources to their nearest city air terminals, which is expressed by

$$F_1 = \frac{\sum_{k=1}^{N_{\mathrm{source}}} w_k d_k}{\sum_{k=1}^{N_{\mathrm{source}}} w_k}. \tag{3}$$

Secondly, if the distance d_k exceeds the maximum passenger tolerance value, the willingness of passenger for using city air terminals would decrease. The maximum tolerable distance $D_{\max}$ could be defined according to a survey.

In order to reduce the occurrence of cases in which $d_k > D_{\max}$, the second criterion is defined as

$$F_2 = \sum_{k \in [1, N_{\mathrm{source}}]} w_k P_{\mathrm{exc}}(k), \tag{4}$$

with

$$P_{\mathrm{exc}}(k) = \begin{cases} d_k - D_{\max} & \text{if } d_k > D_{\max} \\ 0 & \text{otherwise.} \end{cases}$$

Finally, the maximum service capacity of a city air terminal is limited by $V_{\max}$ and it is predefined. If more passengers get to the city air terminal, the service quality is hard to guarantee and the waiting time becomes much longer, which may result in a negative impact. Therefore, the third criterion to be minimized is

$$F_3 = \sum_{l \in [1, N_{\mathrm{term}}]} w_l V_{\mathrm{exc}}(l), \tag{5}$$

with

$$V_{\mathrm{exc}}(l) = \begin{cases} W_l - V_{\max} & \text{if } W_l > V_{\max} \\ 0 & \text{otherwise,} \end{cases}$$

and $W_l = \sum_{k \in \Omega_l} w_k$, where Ω_l includes the indices of all the passenger sources connected to the city air terminal T_l. In the future study, more aspects could be added in the mathematical model.

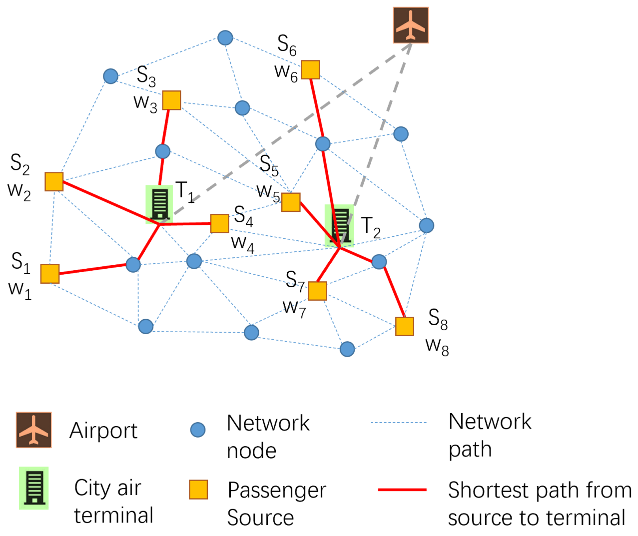


FIGURE 2. Mathematical model of city air terminals location optimization problem.

III. ALGORITHM FOR CALCULATING THE SHORTEST AVERAGE PATH LENGTH

Among the three factors in (2), F_1 is most difficult to be efficiently calculated. To calculate the shortest average distance from multiple passenger locations to multiple CATs, the best paths from all passengers to their nearest CATs should be found. It corresponds to solve a many-to-many path optimization problem (POP), in which the matching information of the passengers and the stations is not pre-acquired. Two questions need to be answered in the optimization. For each passenger, one question is to decide to get to which CAT. The other is to find the best path to arrive that CAT. To guarantee the optimality, a deterministic algorithm should be applied.

One widely-used deterministic algorithm for solving the many-to-many POP is the Dijkstra's algorithm [16]. The Dijkstra's algorithm is a typical greedy algorithm, in which all possible unvisited nodes should be taken into consideration for expanding. The algorithm creates a tree of shortest paths from the starting vertex (source) to all other points in the network. The search continues until the shortest paths to target nodes are determined. This method was originally used for solving one-to-one POP. To solve many-to-many POP, we can simply run Dijkstra's algorithm for every source node. However, to a large-scale network, the computational burden would be heavy.

To solve this problem, we focus on an efficient determinist method, which is the ripple-spreading algorithm [17]–[19]. This method is inspired by a nature phenomenon. If we throw a stone into water, it would create a ripple and it propagates with a constant speed in all directions. Considering a network, several initial ripples are created at the source nodes and these ripples propagate in all directions. When they arrive at unvisited nodes, new ripples are generated at these nodes and they continue to propagate. A ripple is eliminated in the condition that all the nodes connecting to its epicentre are visited. We can see that it imitates the propagations of the ripple fronts. The whole process could be regarded as a relay race of ripples. The process is terminated when each passenger connects to one CAT. The best path is achieved by backtracking these ripple epicentres.

The main advantage of this method is that the many-to-many problems could be solved by a single run of RSA. Multiple ripples propagate simultaneously and the computation time of the optimization is reduced. Thus, RSA is applied in this study for calculating the shortest average path length from passengers to CATs.

IV. GENETIC ALGORITHM FOR LOCATING CITY AIR TERMINALS

The genetic algorithm is a method based on natural selection [20]. The method repeatedly modifies a generation of individual solutions (i.e. chromosomes). At each step, it randomly selects individuals from the current population and produces the next generation. Over successive generations, the population evolves toward an optimal solution [21]. The number of individuals in a generation is denoted by N_I and the total number of generations is denoted by N_G.

In this work, the structure of chromosome and the genetic operations are designed to adapt to the multiple facility location problem. For a layout of CAT locations, N_term positions could be randomly chosen among N_node network nodes. So, each chromosome represents a layout of CAT locations, and each gene of the chromosome corresponds to one node in the network. In addition, by applying genetic operations, one or many terminal locations are changed. The details to the structure of chromosome and the genetic operations are explained as follows.

1) Chromosome: The objective of optimization is to achieve the optimal CAT locations. As illustrated in Fig. 3, one chromosome corresponds to a solution and each gene records a node, which is chosen as CAT location. The length of the chromosome is the predefined number of CATs, which is denoted as N_term. The fitness of a chromosome is defined as

$$F_\mathrm{fit} = \frac{1}{V_\mathrm{OF}}. \tag{6}$$

2) Genetic operations:

a) Mutation: By applying this operation, a chromosome is randomly chosen in a population. The possibility for applying this operation is p_m. Then, one position (or one gene) is chosen to apply the mutation operation. As illustrated in Fig. 4, the CAT location recorded in the second gene is mutated. The new location node number of CAT is 9 after applying the mutation.

In addition, when we choose one gene, we can define an available area. This gene can be mutated by another node number in this area. As illustrated in Fig. 5, the green area corresponds to the available area for mutation. By varying the area size, we can adjust the capacity of jumping out the local optimum.

b) Crossover: Two parent chromosomes are randomly chosen. Then, a random crossover point is selected and the tails of its two parents are swapped to get new off-springs, as illustrated in Fig. 6. The possibility for applying this operation is p_c.

c) Inheritance: In each generation, the chromosomes are sorted based on the fitness values. The best chromosome is directly inherited to the next generation. The possibility for applying this operation is p_i.

d) Random re-initialization: some chromosomes are randomly generated. The possibility for applying this operation is p_rg.

e) Random inheritance: The rest chromosomes are obtained by randomly inheriting chromosomes from the previous generation.

By applying a genetic algorithm with the aforementioned operations, the locations of multiple CATs could be efficiently optimized.

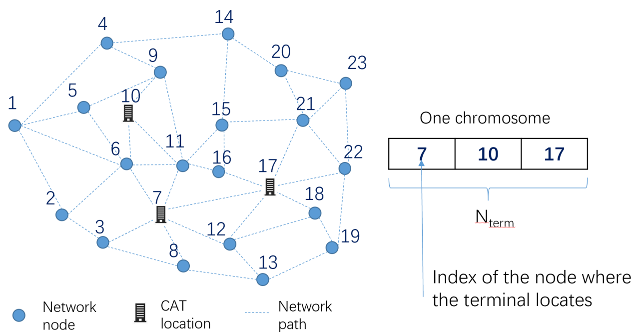


FIGURE 3. Structure of chromosome.

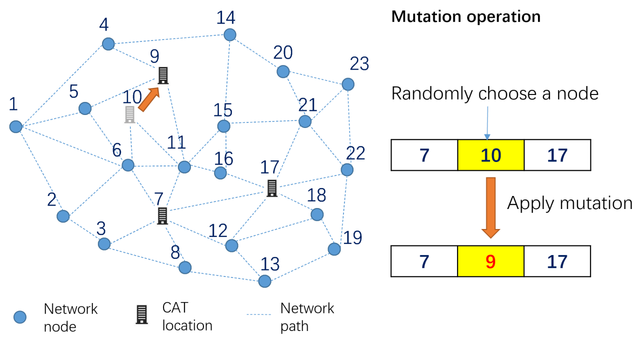


FIGURE 4. Mutation operation.

V. MATHEMATICAL MODEL IN THE CASE OF TIANJIN

Tianjin is the second largest metropolis in northern China with a total population of 14 million. Tianjin borders Beijing municipality and Hebei province. In this area located four large airports, whose total annual air passenger volume reached 350 million. Therefore, there is a strong competition between Tianjin airport and other airports. In order to improve

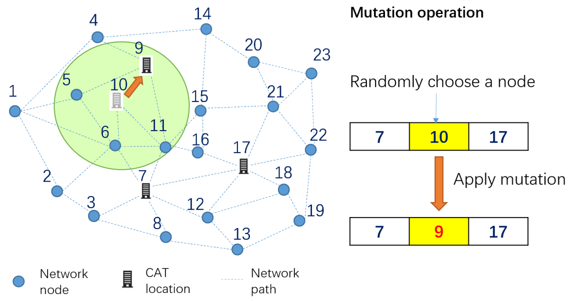


FIGURE 5. Mutation operation with a predefined available area.

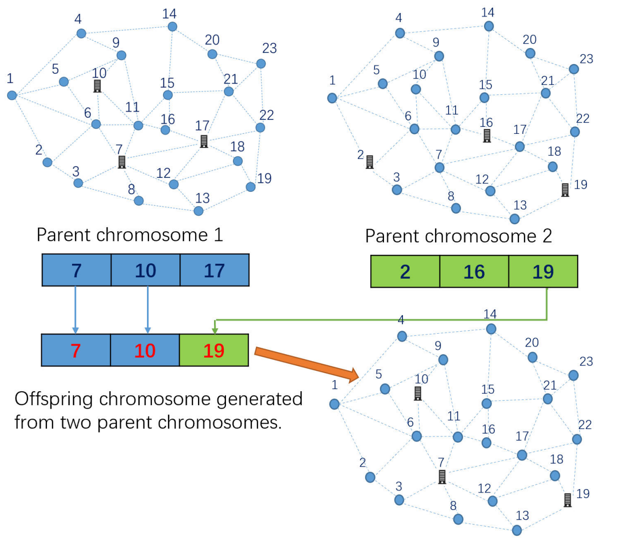


FIGURE 6. Crossover operation.

the competitiveness of the airport and the convenience of passengers, it is of great significance to plan and construct several city air terminals in the city centre of Tianjin. In this section, based on the urban route network of Tianjin and a survey on passenger sources in Tianjin airport, a mathematical model to this case study is set up.

A. ROUTE NETWORK OF TIANJIN

The route network based on a real urban city map of Tianjin (Fig. 7a) is established. The commonly-used transport modes from passengers' dwellings to city air terminals are bus, Uber, and taxi. The trunk roads correspond to the main routes of buses and the routes commonly chosen by taxi drivers. The zoomed network of trunk roads in Tianjin is plotted in Fig. 7b. The locations of the intersections and the turning points of roads are numbered. They form the nodes in the network. The network is created based on the realistic information, as illustrated in Fig. 7c. The total number of nodes is $N_{\text{node}} = 601$ and the number of links is $N_{\text{link}} = 929$. The entire network of Tianjin is plotted in Fig. 7d.

B. A SURVEY TO PASSENGERS IN TIANJIN AIRPORT

To get a sample of passenger sources, a questionnaire survey to the passengers in the waiting hall of Tianjin airport was carried out. The questionnaire concerns how passengers get to airport, e.g., where they live, by which transport mode, duration to the airport, and their opinions about airport shuttle stop locations. Because the survey lasted two days, 210 passengers in total completed and returned the survey forms. The size of survey is relatively small, so here an information diffusion method is applied, as introduced in [1], [20]. The number of the passengers after information diffusion is $N_p = 525$. The network with weights of passengers is shown in Fig. 8. The weights indicate the degrees of aggregation to passengers. Higher the value is, more passengers set off from the corresponding node. The sum of weights in the network is $W_{\text{tot}} = 602.5$.

In addition, we asked the passenger opinion about the maximum tolerable distance from their dwellings to CAT. Among 210 passengers, as illustrated in Fig. 9, 130 passengers chose $1-3$ km, 45 passengers chose $3-5$ km, 21 passengers chose $5-7$ km, and the rests (14 passengers) chose more than 7 km. Thus, in order to balance the passenger convenience and the operational cost of CAT, the maximum tolerable distance $D_{\max}$ is set to 5 km. By setting this value, 83% inquired passengers are satisfied.

TABLE 1. Results of per(β) and average computation time.

	Case 1-1 $N_{\text{I}} = 100$	Case 1-2 $N_{\text{I}} = 200$	Case 1-3 $N_{\text{I}} = 300$	Case 1-4 $N_{\text{I}} = 400$	Case 1-5 $N_{\text{I}} = 500$
per(5%)	0.38	0.71	0.94	0.98	0.98
per(10%)	0.48	0.80	0.96	0.98	1.00
per(20%)	0.72	0.90	1.00	1.00	1.00
Time (s)	376	602	1125	2515	4820

VI. NUMERICAL EXPERIENCE FOR CONFIGURING CITY AIR TERMINALS

Based on the network presented in the previous section, the following parameters are defined: The total number of CAT $N_{\text{term}} = 3$, the maximum tolerable distance $D_{\max} = 5$ km, and the service capacity of CAT $V_{\max} = 210$. Here, $V_{\max}$ is around $W_{\text{tot}}/N_{\text{term}}$, providing an even distribution of service.

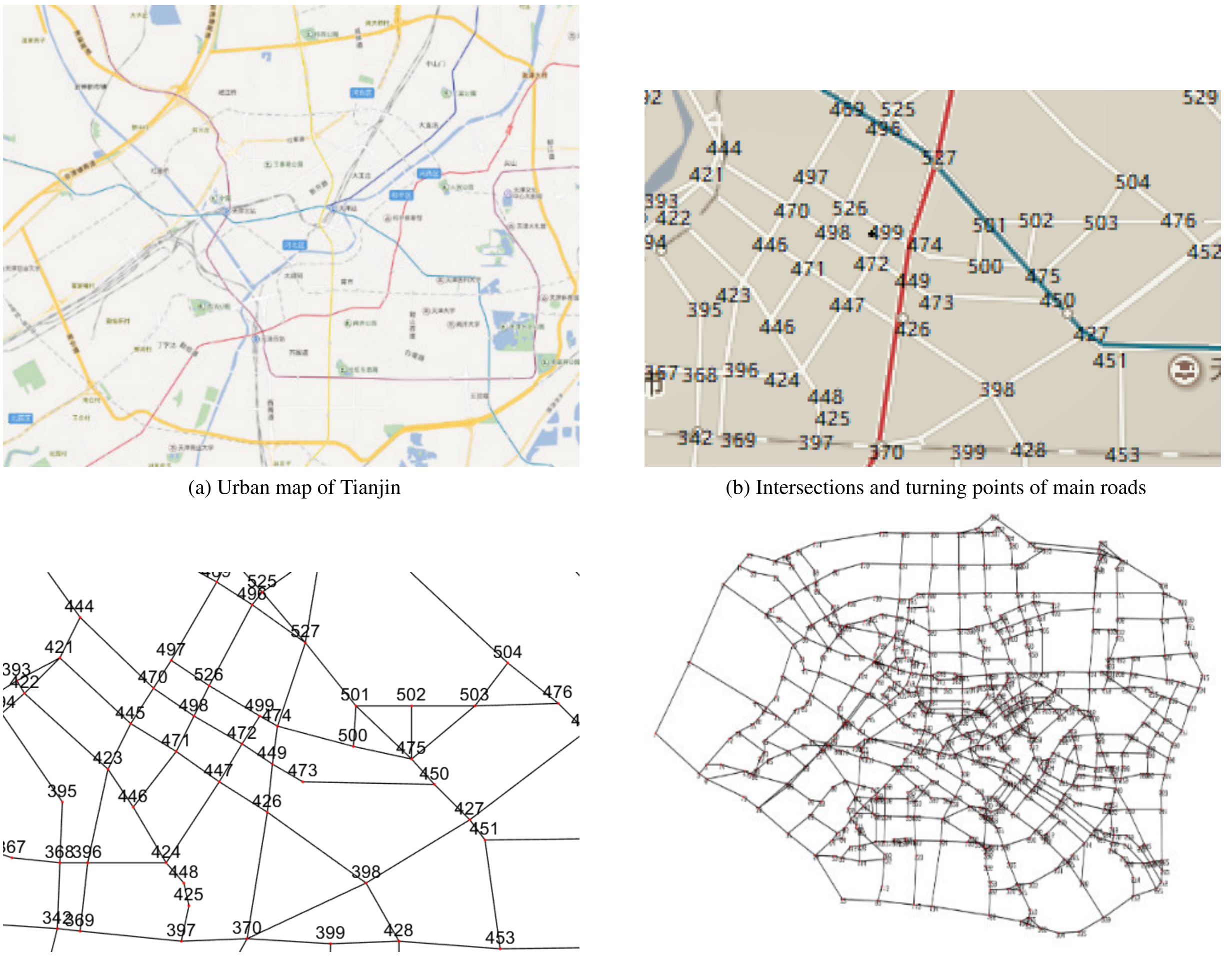
The GA parameters include the size of population N_{I}, the total generation number N_{G}, the possibility of mutation p_{m}, the possibility of crossover p_{c}, the possibility of inheritance p_{i} and the possibility of random re-initialization p_{rg}. The objective is to test the reported method for configuring CATs and find proper parameters to achieve a good balance between solution quality and convergence speed.

A. TESTS OF POPULATION N_I

The operation possibilities are unchanged, and the cases with different population N_{I} are tested. The operation possibilities are $p_{\text{d}} = 0.1$, $p_{\text{m}} = 0.2$, $p_{\text{c}} = 0.6$, and $p_{\text{rg}} = 0.1$. Different N_{I} values 100, 200, 300, 400, 500 are chosen, respectively.

To avoid randomness, we run $N_{\text{test}} = 50$ tests and record the average value. For one single test $p \in [1, N_{\text{test}}]$, the minimum objective function value at the final generation N_{G} is represented by

$$V_{\text{OF}}^{\text{final}}(p) = \min_{n_{\text{i}} \in [1, N_{\text{I}}]} V_{\text{OF}}(N_{\text{G}}, n_{\text{i}}). \tag{7}$$



(a) Urban map of Tianjin

(b) Intersections and turning points of main roads

(c) Network creation

(d) Network of Tianjin

FIGURE 7. Creation process of the network in Tianjin.

TABLE 2. Different combinations of p_m and p_c.

p_c	$X=1$	$X=2$	$X=3$	$X=4$	$X=5$	$X=6$	$X=7$
Case 2-X ($p_m=0.1$)	0.1	0.2	0.3	0.4	0.5	0.6	0.7
Case 3-X ($p_m=0.15$)	0.1	0.2	0.3	0.4	0.5	0.6	0.7
Case 4-X ($p_m=0.2$)	0.1	0.2	0.3	0.4	0.5	0.6	–
Case 5-X ($p_m=0.25$)	0.1	0.2	0.3	0.4	0.5	0.6	–
Case 6-X ($p_m=0.3$)	0.1	0.2	0.3	0.4	0.5	–	–
Case 7-X ($p_m=0.35$)	0.1	0.2	0.3	0.4	0.5	–	–
Case 8-X ($p_m=0.4$)	0.1	0.2	0.3	0.4	–	–	–

These values to N_{test} tests may not be the same. The best one is denoted as

$$V_{\text{BOF}}^{\text{final}} = \min_{p\in[1,N_{\text{test}}]} V_{\text{OF}}^{\text{final}}(p). \tag{8}$$

The percentage per(β) of $V_{\text{OF}}^{\text{final}}(p)$, which is smaller than $(1+\beta)V_{\text{BOF}}^{\text{final}}$ is an important indicator of convergence.

The results and the computation times are recorded in Table 1 and the values of per(β) are illustrated in Fig. 10. In this test, β are chosen as 5%, 10% and 20%. In Cases 1-1 and 1-2, per(β) are small, which means that the optimization results in N_{test} tests are obviously differed. This is mainly because N_{I} is not large enough, which makes it hard to achieve a best solution. In Cases 1-3, 1-4, and 1-5, per(β) are all close to 100%, which implies that GA has well converged to the optimal solution at the end of evolutionary process. It is observed in Fig. 10 that the curves are gently changed with $N_{\text{I}} \geq 400$. On the other hand, the computation time is almost proportional to N_{I}. Considering these two aspects, $N_{\text{I}} \geq 400$ could be an appropriate choice, which can achieve good solutions with a reasonable computational time.

B. TESTS OF GENETIC OPERATIONS POSSIBILITIES

Different possibilities of genetic operations in GA have major impacts on the optimization results and convergence speed,

TABLE 3. Percentage per(β) of objective function values which are smaller than $(1+\beta)V_{\mathrm{BOF}}^{\mathrm{final}}$ and convergence generation N_{cg}.

Cases	2-1	2-2	2-3	2-4	2-5	2-6	2-7	3-1	3-2	3-3	3-4	3-5	3-6	3-7
per(5%)	0.20	0.62	0.76	0.76	0.80	0.80	0.54	0.38	0.38	0.51	0.76	0.66	0.78	0.68
per(10%)	0.50	0.82	0.84	0.91	0.86	0.88	0.84	0.74	0.62	0.68	0.88	0.8	0.96	0.84
per(20%)	0.86	0.92	1.00	1.00	1.00	0.98	0.96	0.90	0.92	0.95	1.00	0.94	1.00	0.96
N_{cg}	–	–	–	89	–	–	–	–	–	–	–	–	65	–
Cases	4-1	4-2	4-3	4-4	4-5	4-6	5-1	5-2	5-3	5-4	5-5	5-6	6-1	6-2
per(5%)	0.08	0.40	0.56	0.66	0.76	0.84	0.14	0.42	0.68	0.74	0.82	0.88	0.22	0.44
per(10%)	0.44	0.62	0.84	0.84	0.88	0.90	0.44	0.64	0.86	0.88	0.90	0.94	0.66	0.66
per(20%)	0.72	0.84	0.94	0.98	0.98	0.98	0.78	0.92	0.98	1.00	0.96	1.00	0.90	0.92
N_{cg}	–	–	–	–	–	65	–	–	–	–	89	61	–	–
Cases	6-3	6-4	6-5	7-1	7-2	7-3	7-4	7-5	8-1	8-2	8-3	8-4		
per(5%)	0.66	0.82	0.84	0.18	0.42	0.70	0.84	0.84	0.20	0.42	0.72	0.88		
per(10%)	0.82	0.88	0.88	0.56	0.60	0.90	0.94	0.88	0.50	0.72	0.86	1.00		
per(20%)	0.96	0.96	1.00	0.86	0.80	1.00	1.00	1.00	0.86	0.96	1.00	1.00		
N_{cg}	–	55	–	–	–	102	68	–	–	–	–	66		

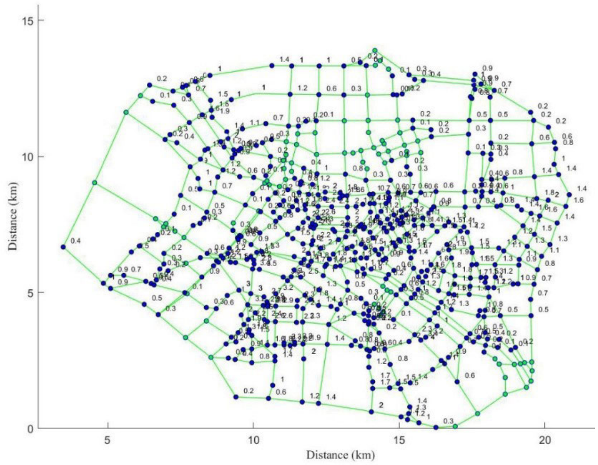


FIGURE 8. Urban network with passenger sources according to a survey in the airport.

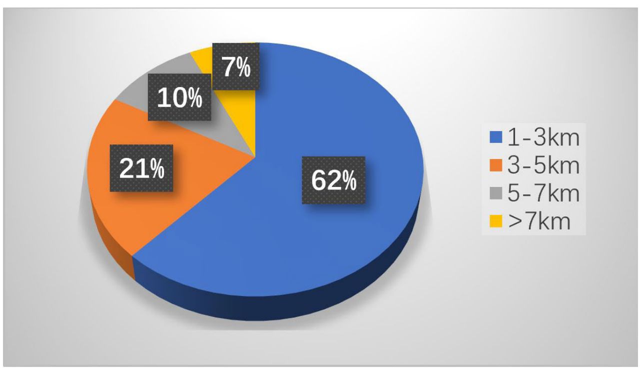


FIGURE 9. The maximum tolerable distances based on a survey to passengers.

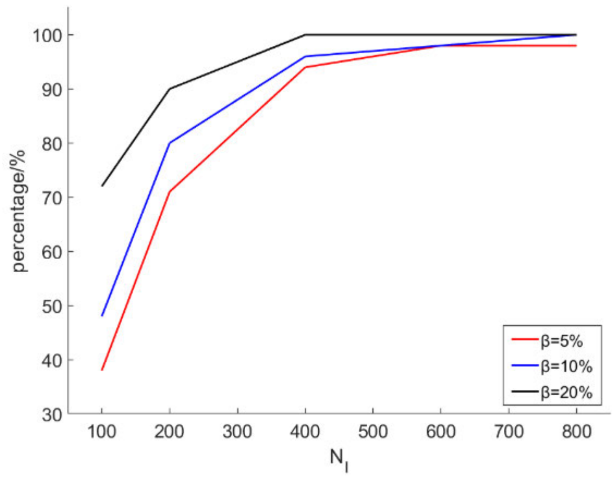


FIGURE 10. Illustration of percentage per(β) of objective function values which are smaller than $(1+\beta)V_{\mathrm{BOF}}^{\mathrm{final}}$, with $\beta = 5\%, 10\%, 20\%$.

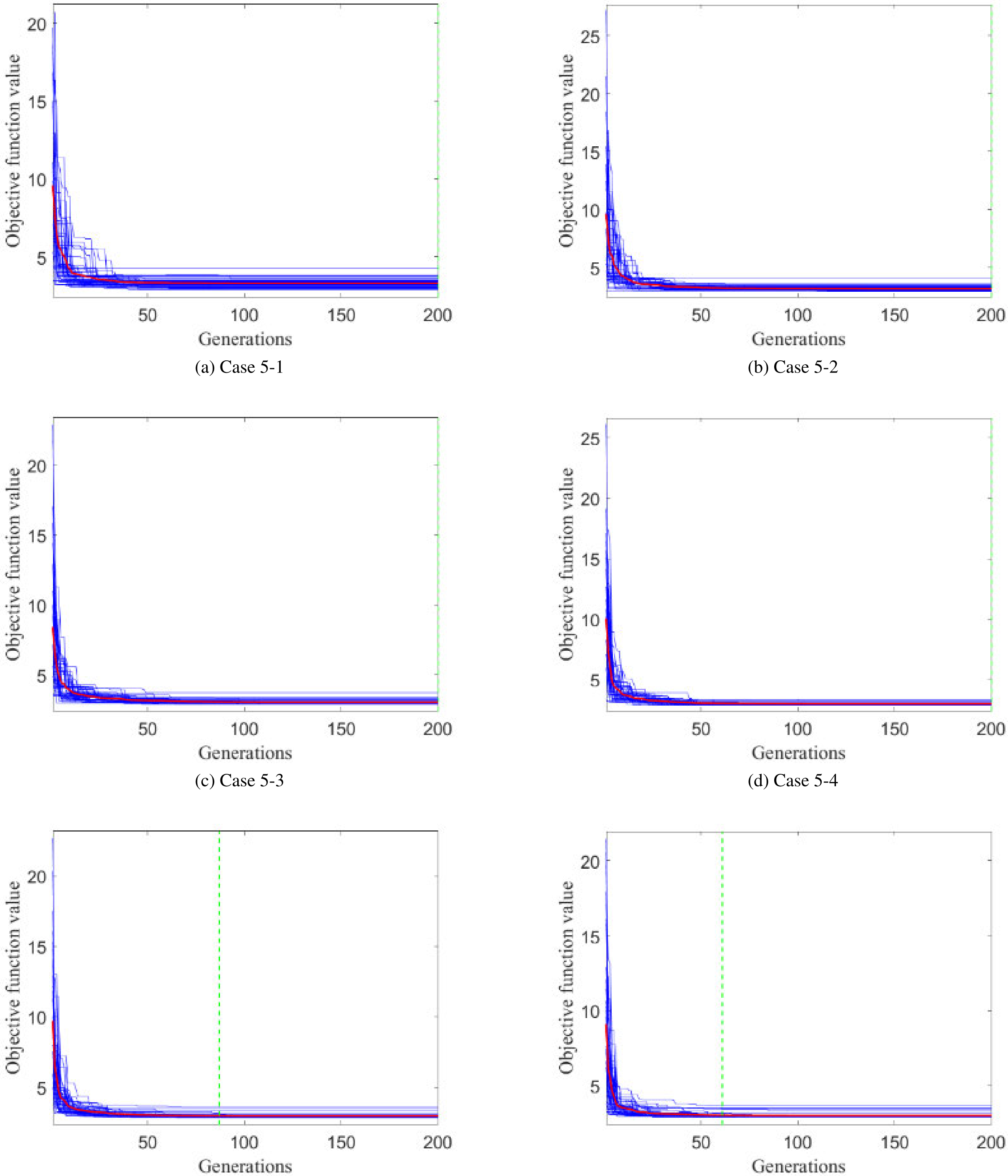
especially the possibility of mutation p_{m} and the possibility of crossover p_{c}.

In this experiment, different parameters combinations are tested. The possibility of elite inheritance is fixed to 5%, and the possibility of random re-initialization is 10%. The combinations of p_{m} and p_{c} are presented in Table 2, while the rest corresponds to the random inheritance operation. The range of p_{m} is from 0.1 to 0.4, spacing 0.05, and the range of p_{c} is from 0.1 to 0.7, spacing 0.1.

For each combination of p_{m} and p_{c}, $N_{\mathrm{test}} = 50$ tests are performed to avoid the randomness. To illustrate the evolution in terms of generations, the cases with $p_{\mathrm{m}} = 0.25$ are plotted in Fig. 11, where each blue line illustrates the evolution of $V_{\mathrm{OF}}^{\mathrm{min}}(n_{\mathrm{g}}) = \min_{n_{\mathrm{i}}\in[1,N_{\mathrm{I}}]} V_{\mathrm{OF}}(n_{\mathrm{g}}, n_{\mathrm{i}})$ in terms of generation $n_{\mathrm{g}} \in [1, N_{\mathrm{G}}]$.

In all, there are N_{test} blue lines and the evolution of the average values for all tests is illustrated by the red line. The average values of $V_{\mathrm{OF}}^{\mathrm{min}}$ decrease along with generations.

The results are recorded in Table 3, and per(β) values with $\beta = 5\%, 10\%, 20\%$ are listed. The curves of per(β) are plotted in Fig. 12. Different colours correspond to different mutation possibilities, and the x-axis represents crossover possibilities. In general, for p_{c} in $[0, 0.6]$, the solutions become better when p_{c} increases. A higher crossover possibility helps to converge efficiently towards the optimal solution. When $p_{\mathrm{c}} = 0.7$, it corresponds to 2 special cases: Case 2-7 and Case 3-7. The values of p_{m} are 0.1 and 0.15, respectively. The results are not as good as the ones with $p_{\mathrm{c}} = 0.6$ and the percentages decrease. This is because in these two cases, the capability of jumping out of local optimal

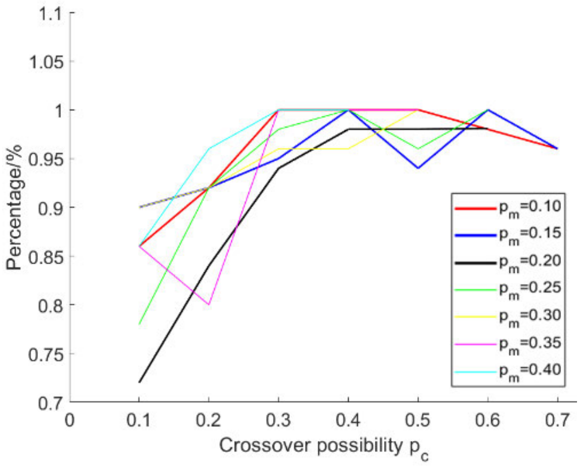


(a) Case 5-1 (b) Case 5-2 (c) Case 5-3 (d) Case 5-4 (e) Case 5-5 (f) Case 5-6

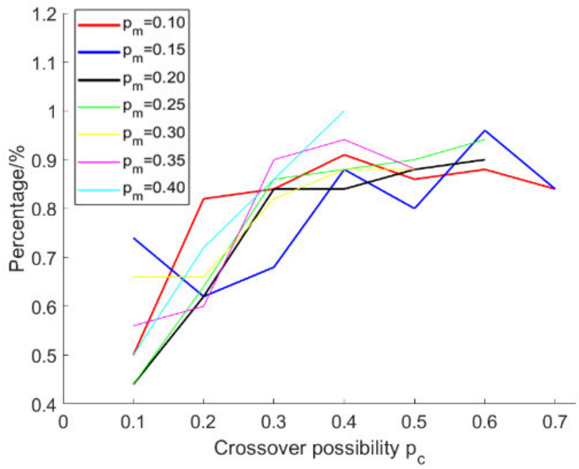
FIGURE 11. Cases with $p_m = 0.25$: Objective function value curves for N_{test} tests in blue, the average objective function value in red, the number of generations needed for convergence N_{cg} represented by the green dotted line.

areas is not satisfactory. And Case 5-6 with $p_m = 0.25$, $p_c = 0.6$ and Case 8-4 with $p_m = 0.4$, $p_c = 0.4$ give the best results.

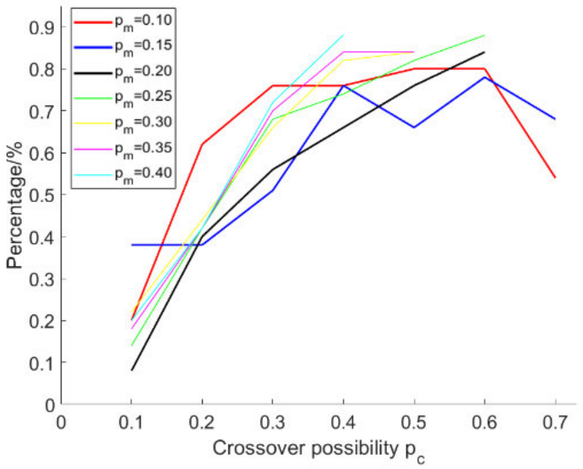
Another important performance indicator is the number of generations needed for convergence, denoted as N_{cg}. It represents the generation index after which 90% of the objective function values $\{V_{OF}^{final}(n_g)\}_{n_g \in [1, N_{test}]}$ are smaller than $(1 + 10\%)V_{BOF}^{final}$. Different to per($\beta$), N_{cg} mainly reflects the convergence speed. In fact, these two indicators are related to each other. In general, the larger per(β) is, the smaller N_{cg} is. In Fig. 11, the green vertical dotted lines indicate the values of N_{cg} for the cases with $p_m = 0.25$. For all the cases, N_{cg} values are listed in Table 3, and the symbol '–' means $N_{cg} > N_G = 200$ (i.e., in N_G generations, the criterion of N_{cg} is not satisfied). Only Cases 2-4, 3-6, 4-6, 5-5, 5-6, 6-4, 7-3, 7-4, and 8-4 satisfy $N_{cg} < N_G$. The value of N_{cg} indicates



(a) $\beta = 20\%$



(b) $\beta = 10\%$



(c) $\beta = 5\%$

FIGURE 12. Curves of the percentages per(β) with different β values.

the convergence speed and the capability of jumping out of local optimal areas. Case 5-6 with $p_\mathrm{m} = 0.25$ and $p_\mathrm{c} = 0.6$ achieves the best result.

To sum up, the combination with $p_\mathrm{m} = 0.25$ and $p_\mathrm{c} = 0.6$ is the best choice for optimizing the configuration of CATs. The locations of city air terminals optimized with these GA parameters are plotted in Fig. 13. The minimum objective function value is 2.85 with $F_1 = 2.70$, $F_2 = 0.15$, $F_3 = 0$. It means that the average distance between passenger sources and city air terminals is 2.70 km. There are a few sources of which the distances exceed $D_\mathrm{max} = 5$ km. The exceeded distances are no more than 0.15 km. And the number of passengers to each terminal is within the service capacity. The reported method shows its efficiency in solving the optimization problem of CAT configuration.

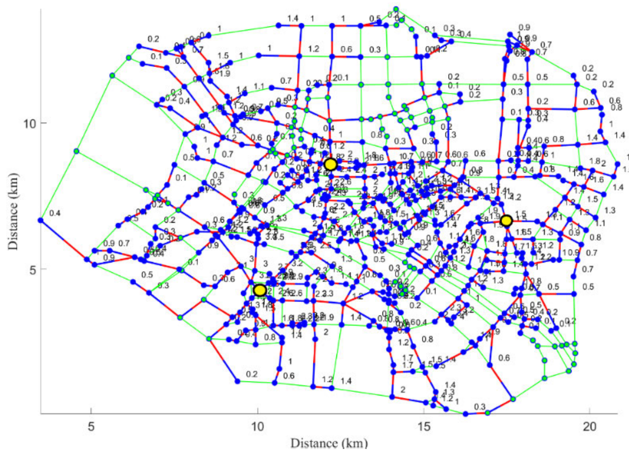


FIGURE 13. Optimized locations of CATs (represented by the yellow circles) with $p_\mathrm{m} = 0.25$ and $p_\mathrm{c} = 0.6$.

VII. CONCLUSION

By accounting three aspects as optimization objectives, an efficient genetic algorithm combined with the ripple spreading algorithm is proposed for optimizing the locations of city air terminals. Firstly, a new mathematical model of the problem is established based on the information diffusion theory. Three aspects including the average distance from passengers to city air terminals, the maximum tolerable distance, and the service capacity are considered in the optimization objective function. Then, an evolutionary method for solving the problem is developed. In the hybrid method, the ripple-spreading algorithm is applied for solving the many-to-many path optimization problem and a genetic algorithm is used for determining the locations of city air terminals. In the case study, the route network of Tianjin, China is used, and the passenger source locations are obtained by a survey carried out at Tianjin airport. The reported method is tested for configuring CATs in Tianjin. The results prove that the method exhibits obvious advantages in terms of effectiveness and efficiency.

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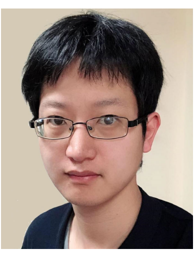

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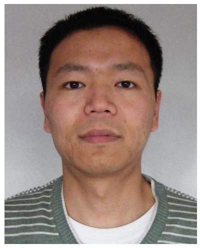

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