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Research Article

Transit Route Network Design for Low-Mobility Individuals Using a Hybrid Metaheuristic Approach

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This paper follows the previous effort of authors and builds the model of transit route network design for low-mobility individuals, proposing an appropriate solution methodology. Firstly, a desired objective, whose priority is to meet transit demands of low-mobility individuals followed by those of general public, is presented to minimize the weighted sum of direct traveler, transfer, and unsatisfied demand costs. Then, a hybrid metaheuristic approach based on ant colony and genetic algorithms is formulated to solve the proposed model in accordance with current conditions (i.e., existing routes that may need to undergo configuration adjustments to different degrees). Finally, the case study of Wenling is presented to highlight the performance and benefits of the proposed model and solution methodology.

1. Introduction

Given that many individuals are unable to access all benefits of transportation services due to their limited mobility and the low-mobility population is large in China, some researchers started focusing on low-mobility individuals (LMIs, e.g., older adults, low-income individuals, and individuals with disabilities) in various fields, such as policy development [1], traffic data collection [2], and modeling mode choice [3].

In a previous paper, the authors analyzed the transportation demands of LMIs in Wenling, China [4], following the results of Jansuwan et al., [5] as a reference. Results of the demand analysis show that: (a) the transit share of LMI respondents (15.26%) is larger than that of general public (GP) respondents (6.53%) in China (respondents were asked to provide their traffic information in the previous survey). The main reason is that LMIs have to make mid- and long-distance trips using a bus due to financial or physical limitations, while the GP has access to more transportation options (e.g., private car and bus) to complete mid- and long-distance trips; (b) due to inadequate national financial investment, most Chinese cities' bus transit services lack the resources to meet the demands of many individuals, particularly of LMIs; (c) considering the high population density in most Chinese cities, planners and policymakers should develop the public transportation actively by learning from the experiences of other developed countries (e.g., Japan and Singapore), and take the special conditions of their own country into account to meet the transit demands of LMIs. Furthermore, an efficient transit system is urgently needed to ensure access to transportation for citizens, and contribute in improving mobility, mitigating traffic congestion, reducing energy consumption, and air pollution, etc. [6]. Therefore, this paper pays attention to the transit demands of LMIs and presents the next stage of research efforts: a transit route network design model for LMIs with the same case study of Wenling, China.

Exiting studies related to transit route network design (TRND) have been presented by many researchers in different public transportation networks. For example, transit network accessibility [7, 8], multi-user class transit network design [9, 10], feeder network design [11, 12]. However, most of exiting studies related to public transportation for LMIs mainly focus on public transit accessibility (i.e., walking to the bus stop) [4, 5, 13, 14], rather than on the TPND. Hence, modeling transit route network design for LMIs (TRNDLMI) is necessary and essential, since this is the theoretical basis in order to improve travel conditions of LMIs. Furthermore, different routes must be subject to varying degrees of configuration adjustments for real-world optimization, but traditional TRND algorithms cannot achieve this requirement. As a result, a suitable solution algorithm, which can meet the requirements and be applied on TRNDLMI, is a significant challenge for researchers.

This article aims to solve the TRNDLMI problem, i.e., to aid the design of transit networks that are more conducive to travel demands, and in particular those of LMIs. In this paper, the adjustments of stops and headway of routes are mainly dealt with, and a hybrid metaheuristic approach is adopted to compensate for the shortcomings of existing algorithms. In addition, we show the effectiveness and precision of the proposed model and methodology through the following: (1) a comparison between the original and optimal solutions, (2) a sensitivity analysis of different weights, (3) an evolution analysis from ACA to GA, and (4) a comparison to other approaches.

The rest of this paper is organized as follows. The literature review is given in Section 2. The proposed model and methodology to the problem are shown in Sections 3 and 4, respectively. The results and analyses from an application in the case study of Wenling are provided in Section 5. Finally, we conclude the paper and give future research directions in Section 6.

2. Literature Review

In general, TRND models can be organized using a three-layer structure (objectives, parameters, and methodology). The definition of parameters is related to the technical implementation details and usually considered during the formulation of the problem [15]. Objectives refer to a metric that describes the TRND as an optimization problem, such as a cost function, while methodology refers to the approach that is used to formulate the TRND model. Therefore, the literature review is divided into two parts, a review of approaches based on their objectives and a review of approaches based on their methodology approaches.

2.1. Objectives. The objectives of the TRND have been summarized as follows: (a) user benefit maximization, (b) operator cost minimization, (c) total welfare maximization, (d) network capacity maximization, (e) energy conservation and protection of the environment, and (f) individual parameter optimization [15]. These objectives have been widely used by many publications to solve various TRND problems, e.g., considering variable demand [16], sustainability [15], direct traveler density [17, 18], and transfer [6, 19].

A multi-objective nonlinear mixed integer model was formulated by Fan and Machemehl [6, 19], considering user costs, operator costs, and unsatisfied demand costs based on different weightings for those costs. Given that different weights might result in different optimal results using the same methodology, they analyzed the sensitivity of user cost weights and found that the smaller the value of user cost weight, the better results they can obtain. In this paper, we also form a multi-objective optimization function based on user benefit and capacity maximization, to further consider different user class costs (direct travel, transfer, and unsatisfied demand) and the relationship between three transit travel demands of LMIs and GP. Furthermore, a reasonable weight set is chosen according to results of weight analysis presented by Fan and Machemehl [6, 19] and our optimization goal (i.e., the priority of our optimal transit route network) is to meet more travel demands, particularly those of LMIs.

2.2. Methodological Approaches. Given that the metaheuristic algorithms have proven to be a flexible and practical method, many researchers have recently presented various such approaches to solve TRND problems, such as those based on simulated annealing (SA) [20], tabu search (TS) [19], genetic algorithms (GA) [21–23], and ant colony algorithms (ACA) [17, 18]. However, the ACA and GA are the most well-known, and can obtain good solutions for transit networks at reasonable computational cost.

The ACA, proposed primarily by Dorigo et al., [24], does not focus on mathematical descriptions of specific problems, but rather on overall optimization ability and parallelization capacity. The principle of the ACA is that ants communicate with one another via pheromones along their way from the food source to the nest. The ACA has received considerable attention with respect to its potential as an alternative algorithm for solving hard combinatorial optimization problems. Most researchers have generally applied the ACA to single path design problems; for example, in transit feeder network design [11, 25, 26] and school bus routing [27, 28]. However, ACAs applied on TRND problems require the original and terminal stops of routes beforehand, which limits the interrelation between different routes.

GAs, first presented by Holland [29], are a class of intelligent search heuristics inspired by Darwin's theory about evolution. According to the evolution theory, only the best-fit individuals will survive and create new offspring, whereas the least-fit individuals will be eliminated. GAs have high efficiency and adaptability, combining with their ability for massive parallel computing, makes them suitable for non-linear combinatorial problems. Therefore, GAs have been successfully implemented in a number of papers for addressing TRND problems [21–23, 30, 31]. However, GAs applied in the TRND problems produce the same degree of configuration adjustment for all transit routes, which is not a viable approach for TRND, as mentioned in the Section 1.

Different metaheuristic approaches can be used for solving different TRND problems. With the increase of transit route network scale and optimization requirements, some researchers gradually tend to use hybrid metaheuristic approaches for solving complex TRNDLMI problems [32]. The present paper integrates the ACA and GA approaches to solve the TRNDLMI problem, with the purpose of leveraging the advantages of each algorithm and making up for their shortcomings. Given that existing routes may need to produce different degrees of variations in the configuration, we use the existing transit route network as the input and then make the configuration of some routes change, mainly through the direct traveler density of routes using the ACA (see Section 4.2); afterwards, we utilize the GA design all routes with fine configuration changes and then output the optimal transit route network (see the Section 4.3).

3. Model

A transit route network design model for low-mobility individuals is proposed to solve TRNDLMI problem faced by major Chinese transit networks. In our solution, the length, headway, and stop configuration of routes are actually being optimized to meet more transit travel demands, particularly the direct travel demand of LMIs. Some assumptions we adopted are as follows:

(i) The number of routes is constant;
(ii) The origin and destination stops of each transit route are known;
(iii) The maximum transit fleet size available for public transportation is fixed;
(iv) The load capacity of each vehicle is same;
(v) The average speed of each operating vehicle is fixed;
(vi) Any transit trips that require more than one transfer will be considered as trips not served by the transit transportation;
(vii) Road congestion is not substantial;
(viii) Each route has the same headway and operating line with its reverse route.

3.1. Setting. We formulate the traffic network as a directed graph $G(V, E)$, which is denoted by a stop set V and a link set E consisting of feasible links $(i, j) \in E$ connecting stops i and $j(i, j \in V, i \neq j)$. The following notations for parameters and decision variables are used:

Parameters

M: Number of routes,
d_{ij}: Total travel demand from stops i to j (persons),
d_{ij}^{g}: Total travel demand of different groups from stops i to j (person), where g is either LMIs or GP; note that $d_{ij} = d_{ij}^{\mathrm{LMI}} + d_{ij}^{\mathrm{GP}}$,
l_{ij}: Length of the link (i, j) (km),
L_{ij}: Minimum possible route length from stop i to j (km),
$L_{\max}$: Maximum route length (km),
$L_{\min}$: Minimum route length (km),
$h_{\max}$: Maximum headway required for any route (min/vehicle),
$h_{\min}$: Minimum headway required for any route (min/vehicle),
Q: Maximum load capacity of each operating vehicle (persons/vehicle),
W: Fleet size available for operations in an hour (vehicles/h),
v: The average speed of each operating vehicle (km/h),
C_x: Weights reflecting the relative importance of three components: direct traveler costs, transfer costs and unsatisfied demand costs, respectively, $x = 1, 2, 3$,
C_{d}^{g}: Weights reflecting the relative importance of direct traveler costs between low-mobility individuals and general public, respectively, g is LMIs and GP
C_{t}^{g}: Weights reflecting the relative importance of transfer costs between low-mobility individuals and general public, respectively, g is LMIs and GP,
T_{d}^{g}: Time value of each unsatisfied travel demand of different groups (min), g is either LMIs or GP.

Decision Variables

m: The mth route of a solution, $m = 1, 2, \ldots, M$,
tr: Transfer paths that use more than one route,
L_m: Overall length of the route m (km),
h_m: Headway of route m (min/vehicle),
d_{ij}^{m}: Transit passengers from stops i to j on route m (persons) travelling directly,
$d_{ij,g}^{m}$: Transit passengers of different groups from stop i to j on route m (person); g stands for LMIs or GP; note that $d_{ij}^{m} = d_{ij,\mathrm{LMI}}^{m} + d_{ij,\mathrm{GP}}^{m}$,
d_{ij}^{tr}: Transit passengers from stop i to j on path tr (persons) transferring to another route,
$d_{ij,g}^{tr}$: Transit passengers of different groups from stops i to j on path tr (persons), g is LMIs or GP; note that $d_{ij}^{tr} = d_{ij,\mathrm{LMI}}^{tr} + d_{ij,\mathrm{GP}}^{tr}$,
DR_{ij}: Set of direct routes used to serve demand from stop i to j
TR_{ij}: Set of transfer paths used to serve the demand from stops i to j,
L_{ij}^{m}: Length from stops i to j on the route m (km),
L_{ij}^{tr}: Length from stops i to j along transfer path tr (km),
t_{ij}^{m}: Total travel time from stop i to j on route m (min), $t_{ij}^{m} = L_{ij}^{m}/v$,
t_{ij}^{tr}: Total travel time from stop i to j along transfer path tr (min), $t_{ij}^{tr} = L_{ij}^{tr}/v$,
F_m: Maximum carried flow occurring on route m (persons/h).

3.2. Objective Function. The objective is to minimize the sum of direct travel, transfers, and unsatisfied demand costs for the studied transit route network, taking into account the trade-off between transit trips of LMIs and GP. The objective function is as follows:

$$\begin{aligned}\min Z = {} & C_1 \times \begin{pmatrix} C_{\mathrm{d}}^{\mathrm{LMI}} \times \sum_{i\in V}\sum_{j\in V}\sum_{n\in DR_{ij}} d_{ij,\mathrm{LMI}}^{m} \times t_{ij}^{m} \\ + C_{\mathrm{d}}^{\mathrm{GP}} \times \sum_{i\in V}\sum_{j\in V}\sum_{n\in DR_{ij}} d_{ij,\mathrm{GP}}^{m} \times t_{ij}^{m} \end{pmatrix} + C_2 \times \begin{pmatrix} C_{\mathrm{t}}^{\mathrm{LMI}} \times \sum_{i\in V}\sum_{j\in V}\sum_{tr\in TR_{ij}} d_{ij,\mathrm{LMI}}^{tr} \times t_{ij}^{tr} \\ + C_{t}^{\mathrm{GP}} \times \sum_{i\in V}\sum_{j\in V}\sum_{tr\in TR_{ij}} d_{ij,\mathrm{GP}}^{tr} \times t_{ij}^{tr} \end{pmatrix} \\ & + C_3 \times \begin{bmatrix} T_{d}^{\mathrm{LMI}} \times \left(\sum_{i\in V}\sum_{j\in V} d_{ij}^{\mathrm{LMI}} - \sum_{i\in V}\sum_{j\in V}\sum_{n\in DR_{ij}} d_{ij,\mathrm{LMI}}^{m} - \sum_{i\in V}\sum_{j\in V}\sum_{tr\in TR_{ij}} d_{ij,\mathrm{LMI}}^{tr} \right) \\ + T_{d}^{\mathrm{GP}} \times \left(\sum_{i\in V}\sum_{j\in V} d_{ij}^{\mathrm{GP}} - \sum_{i\in V}\sum_{j\in V}\sum_{n\in DR_{ij}} d_{ij,\mathrm{GP}}^{m} - \sum_{i\in V}\sum_{j\in V}\sum_{tr\in TR_{ij}} d_{ij,\mathrm{GP}}^{tr} \right) \end{bmatrix}, \end{aligned} \quad (1)$$

subject to

$$L_{\min} \le L_m \le L_{\max}, \tag{2}$$

$$h_{\min} \le h_m \le h_{\max}, \tag{3}$$

$$\frac{F_m \le 60^* Q}{h_m}, \tag{4}$$

$$\sum_{m=1}^{M} \frac{2^* 60}{h_m} = W. \tag{5}$$

Objective function (1) seeks to minimize the weighted sum of different kinds of costs, including direct travel (the first term), transfer (the second part), and unsatisfied demand (the third component) costs. Parameters C_1, C_2, and C_3 reflect the tradeoffs among different costs, making TRNDLMI a multi-objective optimization problem. In the first term, parameters $C_{\mathrm{d}}^{\mathrm{LMI}}$ and $C_{\mathrm{d}}^{\mathrm{GP}}$ are introduced to formulate the relationship between the direct travel costs of LMIs and GP. Parameters $C_{\mathrm{d}}^{\mathrm{LMI}}$ and $C_{\mathrm{d}}^{\mathrm{GP}}$ are similar to parameters $C_{\mathrm{t}}^{\mathrm{LMI}}$ and $C_{\mathrm{t}}^{\mathrm{GP}}$ (in the second part), and parameters $T_{\mathrm{d}}^{\mathrm{LMI}}$ and $T_{\mathrm{d}}^{\mathrm{GP}}$ (in the third component). The values of these parameters, the constraints of which are shown in Equations (6)–(10), depend on planners' experience and experts' judgment to meet more travel demands (Equation 6), more direct travel demand of LMIs (Equation 7), more transfer travel demand of LMIs (Equations 8 and 9), and reduce the unsatisfied demand of LMIs (Equation 10). Note that Equation 9 shows that transit travel is the main transportation mode among LMI transfers due to the less alternative modes, but GP transfers may easily stop the transit travel because of the inconvenience of transferring. Constraint (2) is the route length constraint. This avoids routes that are too small or long to guarantee the efficiency of transit route networks. Constraint (3) is the route headway (frequency) constraint, which reflects the necessary usage of policy headways on extreme situations. Constraint (4) ensures that the maximum carried flow on any route cannot exceed the maximum load capacity of vehicles. Constraint (5) shows the resource limits of the transit company and guarantees that each transit route network uses the same fleet size. Note that for Constraints (4) and (5), 60 is cited because 1 h is equal to 60 min.

$$C_1 + C_2 + C_3 = 1,\ 0 < C_1 < C_2 < C_3, \tag{6}$$

$$C_{\mathrm{d}}^{\mathrm{LMI}} + C_{\mathrm{d}}^{\mathrm{GP}} = 1,\ 0 < C_{\mathrm{d}}^{\mathrm{LMI}} < C_{\mathrm{d}}^{\mathrm{GP}}, \tag{7}$$

$$C_{\mathrm{t}}^{\mathrm{LMI}} + C_{\mathrm{t}}^{\mathrm{GP}} = 1,\ 0 < C_{\mathrm{t}}^{\mathrm{LMI}} < C_{\mathrm{t}}^{\mathrm{GP}}, \tag{8}$$

$$C_{\mathrm{t}}^{\mathrm{LMI}} < C_{\mathrm{d}}^{\mathrm{LMI}}, \tag{9}$$

$$0 < T_{\mathrm{d}}^{\mathrm{GP}} < T_{\mathrm{d}}^{\mathrm{LMI}}. \tag{10}$$

4. Solution Methodology

In this section, according to the proposed methodology, we force the optimal transit route network to retain the high occupancy links of the existing transit route networks as far as possible, so as to not affect people's travel habits as much as possible. Three degrees of configuration adjustments, including the length and stops of routes, are presented: major (many stops are adjusted), fine (a few stops are adjusted) and no adjustments.

To meet three degrees of configuration adjustments, the proposed approach incorporates ACA into GA, named ACA–GA, including two processes: major tuning and fine tuning. This is depicted in Figure 1. Note that the major and fine tuning processes may not necessarily result in a change of a route's configuration.

During major tuning, we optimize the "original solution" (existing transit route network) based on the ACA, which instigates large changes in the configuration of some routes.

In fine tuning, the transit route network after the major tuning process is optimized using the GA to output the "optimal solution" (ACA–GA transit route network), where all routes may produce subtle configuration variations.

This approach (i.e., ACA–GA) not only reduces the search scope and improves the quality, but also inherits many good genes (high occupancy links) from the existing transit route network. The following notations for parameters and decision variables are used:

Parameters

- N: Maximum number of iterations,
- K: Number of vehicles assigned to the origin in the beginning of each ant activity,
- D_{t}: Threshold of direct traveler density of routes,
- α: Pheromone influence coefficient,
- β: Visibility influence coefficient,
- δ: Adjustment coefficient,
- ρ : Evaporation parameter.

Decision Variables

- n: The nth iteration of a computational cycle, $n = 1, 2, ..., N$,
- k: The kth vehicle of an ant activity, $k = 1, 2, \ldots, K$,
- Dd_m: Direct traveler density of route m (persons/km),
- τ_{ij}: Pheromone from stop i to j
- η_{ij}: Visibility from stop i to j,
- d_j^m: All upstream travel demands of stop j on route m,
- p_{ij}^k: Probability of vehicle k moving from stop i to j,
- u: Stop adjacent to i
- $tabu_k$: Set of unfeasible stops for vehicle k,
- m_k: Route m found by the vehicle k,
- $\Delta\tau_{n(ij)}^k$: Increase in pheromone on link (i, j) of route m_k,
- Dd_m^k: Direct traveler density on route m_k,
- $f_{m,ij}^k$: Carried flow of link (i, j) on route m_k,
- n_s: Number of stops on route m_k,
- τ_{ij}^{new}: Pheromone on link (i, j) after updating,
- τ_{ij}^{old}: Pheromone on link (i, j) before updating.

4.1. Representation. A solution can be described by M (i.e., number of routes) different integer series of variable length,

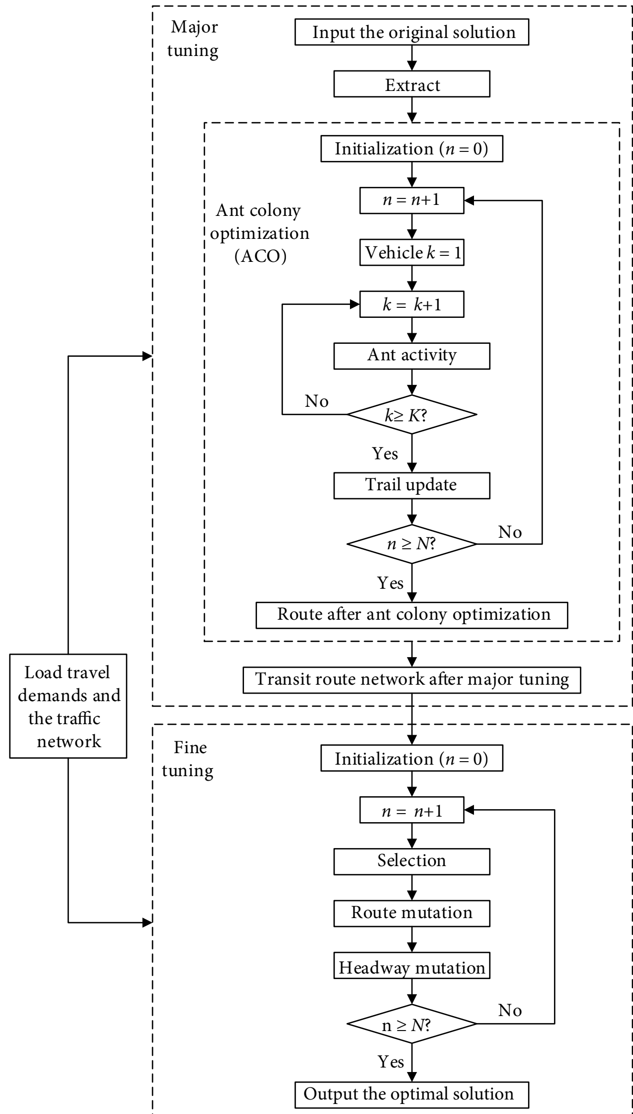


Figure 1: Flowchart of the ACA–GA.

known as a route set (each series is a route). The same network as in Wan and Lo [33] is used to illustrate our model, as shown in Figure 2(a). There are 10 stops (corresponding to the number of node) and 19 links. An example solution having 3 routes is shown in Figure 2(b).

4.2. Major Tuning. In this process, the configuration of different transit routes should be optimized individually when the origin and terminal stops are known. Consequently, we use the ACA to complete the larger-scale configuration adjustment of the transit route network.

Based on the study presented by Yu et al., [17, 18], our ACA considers vehicles as ants, the origin stop as the nest, and the terminal stop as the food source. The colony needs to find the route with the shorter distance and meet more travel demands from the origin to the terminal stop using the pheromone. Some improvements were made on the proposed ACA: (1) we only need to find a route using the ant colony optimization (ACO) process (see Figure 1); (2) we consider the carried flow of the link (i, j) on the route as the local pheromone.

The procedure of major tuning based on the ACA is as follows.

Step 1. Load the original solution, travel demands and traffic network.

Step 2. Obtain routes in need of the larger-scale configuration adjustment through the extract scheme (described in Section 4.2.1).

Step 3. Optimize routes in need of larger-scale configuration adjustment individually using the ACO process, as follows.

Step 3.1. Input the origin and terminal stops of a route;

Step 3.2. Initialize, set iteration number $n = 0$;

Step 3.3. Initialize, set vehicle $k = 0$;

Step 3.4. Find the route for vehicle k through the ant activity scheme (Section 4.2.2);

Step 3.5. If $k < K$, then $k = k + 1$, otherwise return to step 3.4;

Step 3.6. Accumulate experiences of many ant activities through the trail update scheme (Section 4.2.3);

Step 3.7. If $n < N$, then $n = n + 1$ otherwise return to step 3.3;

Step 3.8. Obtain the optimal route after larger-scale configuration adjustment.

Step 4. Obtain the ACO solution (i.e., transit route network after larger-scale configuration adjustment).

4.2.1. Route Extraction. The direct traveler density is taken as the index to judge whether each route in the original solution produces a large change in configuration. We extract those routes with low direct traveler density ($< D_t$) to be optimized using the ACO process. The direct traveler density of route m is defined as:

$$Dd_m = \sum_{i\in V}\sum_{j\in V}\frac{d_{ij}^m}{L_m}. \tag{11}$$

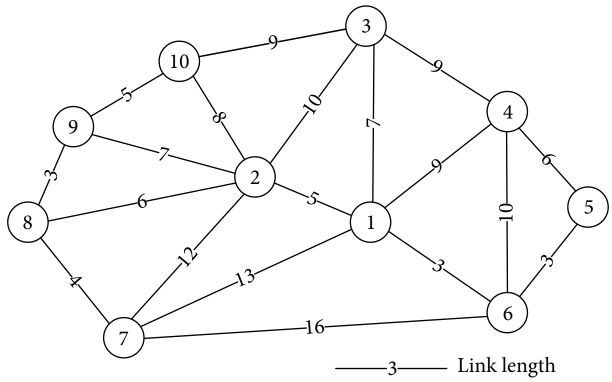
4.2.2. Ant Activity. Ant activity is influenced mainly by the pheromone (continuously updated with the increase of iterations) and visibility (which remains comparatively stable among iterations).

The initial pheromone from stop i to j is defined by:

$$\tau_{ij} = \frac{d_{ij}}{L_{ij}}. \tag{12}$$

Visibility encourages a vehicle to visit a stop locally according to a greedy method. The visibility from stop i to j is defined as:

$$\eta_{ij} = \frac{d_j^m}{l_{ij}}. \tag{13}$$



(a)

No.	Display	Symbol
1	$7 \xrightarrow{12} 2 \xrightarrow{10} 3 \xrightarrow{7} 1 \xrightarrow{3} 6$	7,2,3,1,6
2	$9 \xrightarrow{5} 10 \xrightarrow{8} 2 \xrightarrow{10} 3 \xrightarrow{9} 4$	9,10,2,3,4
3	$8 \xrightarrow{4} 7 \xrightarrow{13} 1 \xrightarrow{9} 4 \xrightarrow{10} 6$	8,7,1,4,6

(b)

FIGURE 2: Illustration of example network. (a) Transit network and (b) Route representation.

A search rule is then given to vehicles, where a vehicle tends to choose the better path, using the pheromone and visibility as variables. The probability of the vehicle k moving from stop i to j is defined by:

$$p_{ij}^{k} = \begin{cases} \dfrac{\left(\tau_{ij}\right)^{\alpha} * \left(\eta_{ij}\right)^{\beta}}{\sum_{u \notin tabu_k} \left(\tau_{iu}\right)^{\alpha} * \left(\eta_{iu}\right)^{\beta}} & \text{if } j \notin tabu_k, \\ 0 & \text{otherwise.} \end{cases} \tag{14}$$

4.2.3. Trail Update. The experience of the ant colony search (which comprises many ant activities) is reflected by the pheromone of the links, so update methods of the pheromone affect the process and result of the ant colony search directly. We improve the update strategy of the increased pheromone presented by Yu et al., [17, 18], taking the direct traveler density of a route and the carried flow of a link as the global and local pheromone, respectively.

The improved update strategy is as follows:

$$\Delta\tau_{m,ij}^{k} = \begin{cases} \dfrac{Dd_m^k + f_{m,ij}^k / L_{ij}}{\delta * \left(n_s + 2\right)} & \text{if link } (i, j) \text{ on the route } m_k, \\ 0 & \text{otherwise.} \end{cases} \tag{15}$$

If all vehicles complete route searches, the pheromone matrix is updated as:

$$\tau_{ij}^{\text{new}} = (1 - \rho) * \tau_{ij}^{\text{old}} + \sum_{k=1}^{K} \Delta\tau_{m,ij}^{k} \quad \rho \in (0, 1). \tag{16}$$

4.3. Fine Tuning. In this process, the interrelationship of different routes must be considered. Therefore, we use the GA to perform fine configuration adjustment of the transit route network.

Judging from previous experiences, the GA includes selection, crossover, and mutation schemes. The selection scheme is to select routes or the transit route network in need of crossover and mutation; the crossover scheme exchanges stops between two different routes optionally, resulting in large-scale configuration changes of routes; the mutation scheme adjusts the stops on a single route, only resulting in subtle variations of route configuration. Due to the optimization requirements of fine tuning in this case, our GA does not include the crossover scheme; we increase the selection probability in the selection scheme, and design an advanced route mutation scheme. In addition, the proposed GA adds a headway mutation scheme to adjust the headway of each route, while taking into account the interrelationship of different routes.

The procedure of fine tuning based on the GA is as follows.

Step 1. Load travel demands and the traffic network, set the transit route network after large-scale configuration adjustment as the current solution.

Step 2. Initialize, set iteration number $n = 0$.

Step 3. Execute the selection scheme on the current solution (Section 4.3.1).

Step 4. Execute the route mutation scheme on routes obtained during step 3 (Section 4.3.2).

Step 5. Execute the headway mutation scheme on the current solution after step 4 (Section 4.3.3).

Step 6. If $n < N$, then $n = n + 1$, otherwise return to step 3.

Step 7. Output the ACA–GA solution by comparing objective function values.

4.3.1. Selection. A random selection strategy was used to select routes. The selection probability is reduced as the scale of the network increases.

Table 1: Relevant parameters.

Parameters	Value
M, W, K	13, 77, 100
$L_{\max}, L_{\min}$	10, 30
$h_{\max}, h_{\min}$	20, 7.5
Q, υ	75, 30
C_1, C_2, C_3	0.15, 0.3, 0.55
$C_{\mathrm{d}}^{\mathrm{LMI}}, C_{\mathrm{d}}^{\mathrm{GP}}$	0.45, 0.55
$C_{\mathrm{t}}^{\mathrm{LMI}}, C_{\mathrm{t}}^{\mathrm{GP}}$	0.4, 0.6
$T_{\mathrm{d}}^{\mathrm{LMI}}, T_{\mathrm{d}}^{\mathrm{GP}}$	80, 40
$D_t, \alpha, \beta, \delta, \rho$	10, 0.9, 0.2, 0.1, 0.3

4.3.2. Route Mutation. The route choice is governed mainly by travel demands. Therefore, we give priority to stops with more travel demands for selection as mutated stops. Note that this scheme only considers the mutation of intermediate stops.

4.3.3. Headway Mutation. Under the precondition of steady fleet size, this scheme increases the headway of routes whose direct traveler density is smaller, and decreases headways whose direct traveler density is larger.

5. Case Study

The approaches described in this paper were coded in MATLAB software and ran on an Intel 4Ghz PC under Windows 7. In this section, we examine our proposed model initially on the traffic network of Wenling city, using data obtained in the previous survey of the authors [1] to demonstrate the computational efficiency and solution optimality.

5.1. Scenarios. The total population of the survey region is approximately 442.6 thousand and the build-up area is about 61.55 km^2. As shown in Figure 3, the traffic network of Wenling has 259 stops (corresponding to the node number) and 406 links (the length can be obtained based on the scale). In our previous survey [1], the total survey results (12,013) consisted of 4,319 low-mobility respondents and 7,694 general respondents. Here, we used two parts of trip O–D (Origin–Destination) from survey results to formulate our travel demands: (1) transit trip O–D of respondents; (2) trip O–D of low-mobility respondents who made mid- and long-distance travels (at least 20 minutes) by riding a bicycle, electric bicycle or motorcycle. The actual travel demand matrix (259^*259) was generated according to calculations based on the proportion of respondents in the survey region (i.e., the sum of two parts of trip O–D divided by the proportion of respondents). The number of iterations of ACA and GA were 100 and 400, respectively. Table 1 lists the values of the other parameters related to the proposed model according to the actual state, the optimization requirements, and Equations (6–10).

5.2. Result Analysis

5.2.1. Comparison between Original and ACA–GA Solutions. The results of the route optimization are listed in

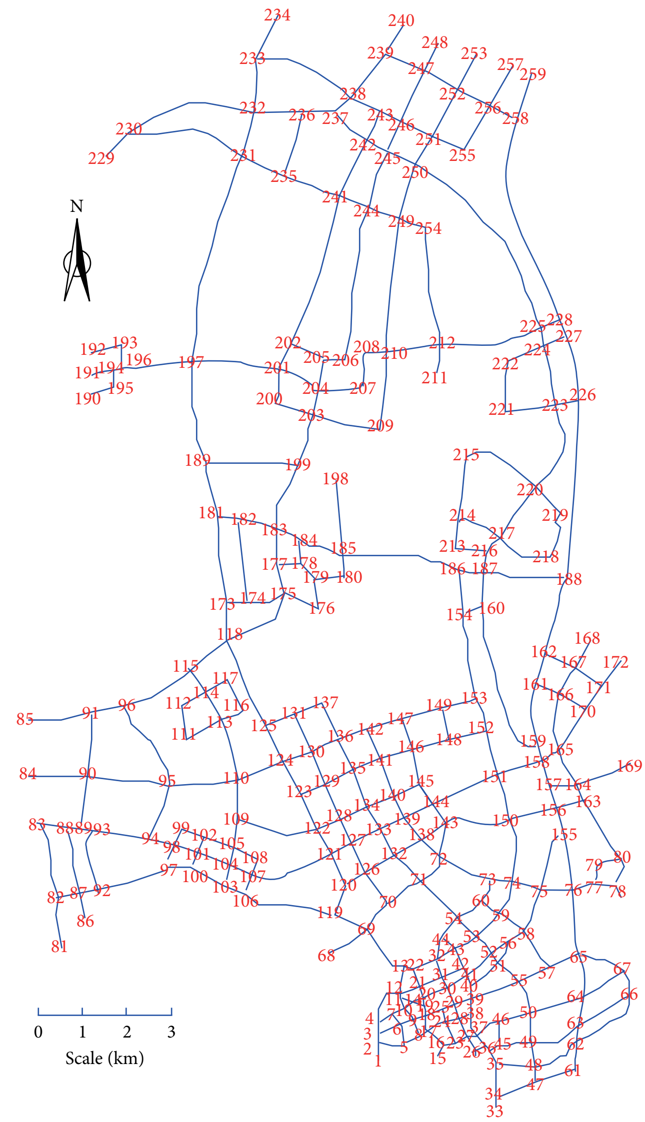


Figure 3: Layout of stops and links in Wenling.

Table 2, where we see that the configuration drift from original to ACA–GA routes takes place according to the three degrees of configuration adjustments (major, fine and no adjustments). Routes 1, 2, 6, 7, 9, 10, 11 and 12 were optimized by the ACO and their configuration was changed to a large extent; routes 4 and 13 only have subtle configuration variations; others routes retain the original path and were not adjusted at all. In the optimal routes, direct traveler densities of all routes are no less than 10 persons/km; the larger the direct traveler density of a route is, the smaller the headway of the route. These results indicate that all ACA–GA routes are based on available configurations and inherit many high occupancy links from original routes.

Table 3 presents the results of the original and ACA–GA transit route network solutions, including the number of direct travelers (N_{DT}), the average travel time ratio of LMI and GP direct travelers (AR_{DT}), the number of transfers (N_T), average travel time ratio of LMI and GP transfers (AR_T), the number

Table 2: Results of original and ACA–GA routes.

No.	Type	Configuration of stops	Dd_m	L_m	h_m	ACO?
1	Original	59, 53, 54, 71, 132, 126, 120, 121, 122, 123, 124, 125, 118, 173, 181, 189, 197, 231, 235	5.4	30.4	12	Yes
	ACA–GA	59, 60, 73, 74, 75, 155, 156, 157, 158, 159, 160, 154, 186, 187, 216, 217, 220, 223, 221, 222, 224, 225, 250, 245, 244, 241, 235	18.7	40.6	7.5	
2	Original	3, 6, 9, 18, 25, 29, 39, 55, 57, 58, 75, 74, 73, 72, 138, 139, 140, 141, 142, 147, 149	8.0	21.3	10	Yes
	ACA–GA	3, 6, 9, 10, 14, 20, 19, 18, 25, 29, 30, 31, 32, 13, 69, 70, 71, 72, 143, 144, 145, 146, 148, 149	42.9	16.0	7.5	
3	Original	3, 4, 7, 10, 14, 20, 30, 31, 32, 44, 54, 60, 73, 74, 75, 76, 77, 78	32.9	11.3	15	No
	ACA–GA	3, 4, 7, 10, 14, 20, 30, 31, 32, 44, 54, 60, 73, 74, 75, 76, 77, 78	30.2	11.3	20	
4	Original	33, 34, 35, 36, 37, 27, 23, 16, 17, 8, 5, 2, 3, 6, 9, 18, 25, 29, 39, 55, 57, 65, 67	8.9	16.4	7.5	No
	ACA–GA	33, 34, 35, 36, 37, 27, 23, 16, 17, 8, 5, 2, 3, 6, 9, 18, 25, 29, 39, 55, 57, 65, 67	10.4	16.4	20	
5	Original	66, 63, 49, 45, 36, 26, 27, 28, 29, 30, 31, 32, 43, 53, 59, 74, 150, 156, 157, 158, 165, 166, 167, 171, 172	20.6	24.3	7.5	No
	ACA–GA	66, 63, 49, 45, 36, 26, 27, 28, 29, 30, 31, 32, 43, 53, 59, 74, 150, 156, 157, 158, 165, 166, 167, 171, 172	20.9	24.3	10	
6	Original	47, 48, 49, 45, 36, 26, 27, 23, 24, 25, 18, 19, 20, 21, 22, 13, 69, 119, 106	0.2	15.0	7.5	Yes
	ACA–GA	47, 48, 49, 45, 46, 37, 38, 28, 27, 23, 16, 17, 8, 5, 2, 3, 4, 7, 10, 14, 20, 30, 31, 32, 44, 54, 71, 70, 126, 120, 119, 106	35.2	25.7	7.5	
7	Original	67, 64, 50, 55, 51, 56, 58, 59, 60, 73, 72, 143, 144, 145, 140, 134, 128, 129, 130, 124, 110, 113, 114	4.1	27.4	7.5	Yes
	ACA–GA	67, 66, 62, 48, 49, 50, 55, 51, 56, 52, 53, 59, 60, 54, 71, 72, 138, 132, 126, 70, 69, 119, 106, 107, 104, 105, 109, 110, 113, 111, 112, 114	20.1	40.6	12	
8	Original	67, 65, 57, 58, 56, 52, 41, 42, 43, 32, 22, 13, 69, 119, 120	11.0	13.8	10	No
	ACA–GA	67, 65, 57, 58, 56, 52, 41, 42, 43, 32, 22, 13, 69, 119, 120	28.4	13.8	10	
9	Original	3, 6, 9, 18, 25, 29, 39, 40, 41, 52, 53, 59, 74, 150, 151, 152, 153	2.2	11.9	15	Yes
	ACA–GA	3, 4, 7, 10, 14, 11, 12, 21, 20, 19, 18, 25, 29, 30, 41, 40, 51, 56, 58, 75, 76, 77, 78, 80, 163, 156, 157, 158, 151, 152, 153	32.8	20.2	20	
10	Original	3, 2, 5, 8, 17, 24, 28, 38, 39, 40, 51, 52, 56, 58, 75, 155, 156, 163, 164, 169	14.4	15.8	20	Yes
	ACA–GA	3, 4, 12, 11, 14, 19, 20, 30, 41, 40, 51, 55, 57, 65, 76, 77, 78, 80, 163, 164, 169	29.0	18.4	8.5	
11	Original	58, 59, 53, 54, 71, 132, 133, 134, 135, 136, 137	0.3	11.5	10	Yes
	ACA–GA	58, 56, 51, 40, 39, 29, 25, 18, 19, 14, 10, 11, 12, 13, 69, 70, 126, 127, 128, 134, 140, 141, 142, 136, 137	46.8	19.0	7.5	
12	Original	47, 61, 62, 63, 64, 65, 76, 155, 156, 157, 158, 159, 161, 162	0.8	16.2	10	Yes
	ACA–GA	47, 61, 62, 66, 67, 65, 76, 77, 78, 80, 163, 164, 165, 170, 166, 161, 162	12.4	20.4	15	
13	Original	57, 58, 59, 74, 150, 151, 152, 153, 154, 160, 187, 216, 217, 218, 219, 220, 223, 224	26.7	28.0	12	No
	ACA–GA	57, 58, 75, 74, 150, 151, 152, 153, 154, 160, 187, 216, 217, 218, 219, 220, 223, 224	36.5	28.0	7.5	

of unsatisfied demands (N_{UD}), and the value of the objective function (V_{OF}). Compared to the original transit route network, it can be seen that the ACA–GA transit route network (Solution-b) produces more direct travelers and transfers, and reduces the unsatisfied travel trips; at the same time, the average travel time ratios between LMI to GP direct travelers and transfers are both increased. These results indicate that the proposed model can obtain a better transit route network than the original transit route network, particularly for LMIs.

5.2.2. Sensitivity Analysis of Different Weights. The sensitivity analysis of weights among direct travel, transfer, and unsatisfied demand costs is similar to that presented by Fan and Machemehl [6, 19]. In consideration of our study for LMIs, the sensitivity of weights between LMIs and the general public was analyzed using the ACA–GA. Three different weights were extracted: (a) the tendency for LMIs (parameters $C_{\mathrm{d}}^{\mathrm{LMI}}$, $C_{\mathrm{d}}^{\mathrm{GP}}$, $C_{\mathrm{t}}^{\mathrm{LMI}}$, $C_{\mathrm{t}}^{\mathrm{GP}}$, $T_{\mathrm{d}}^{\mathrm{LMI}}$, and $T_{\mathrm{d}}^{\mathrm{GP}}$, listed in Table 1); (b) equitableness for LMIs and GP (parameters $C_{\mathrm{d}}^{\mathrm{LMI}}$, $C_{\mathrm{d}}^{\mathrm{GP}}$, $C_{\mathrm{t}}^{\mathrm{LMI}}$, and $C_{\mathrm{t}}^{\mathrm{GP}}$ are all 0.5, parameters $T_{\mathrm{d}}^{\mathrm{LMI}}$ and $T_{\mathrm{d}}^{\mathrm{GP}}$ are both 60); (c) tendency for general public (parameters $C_{\mathrm{d}}^{\mathrm{LMI}}$, $C_{\mathrm{d}}^{\mathrm{GP}}$, $C_{\mathrm{t}}^{\mathrm{LMI}}$, $C_{\mathrm{t}}^{\mathrm{GP}}$, $T_{\mathrm{d}}^{\mathrm{LMI}}$, and $T_{\mathrm{d}}^{\mathrm{GP}}$ are 0.55, 0.45, 0.6, 0.4, 80, and 40, respectively). The results of these three types of transit route network solutions are denoted as Solution-b, Solution-c, and Solution-d in Table 3, respectively. The comparison shows that the numbers of direct travelers, transfers, and unsatisfied demand are almost equal in the three different solutions, but the numbers of direct travelers and average travel time ratios between LMIs to the GP in Solution-b are the largest in the three different solutions, followed by Solution-c, and then by Solution-d. These findings reveal that the proposed weights in this paper (i.e., the tendency for LMIs) applied on the TRND problem promote the transit travel environment of LMIs better than the other two types of weights.

Table 3: Results of original and ACA–GA transit route networks.

	Groups	Original	Solution-a	Solution-b	Solution-c	Solution-d	Solution-e	Solution-f
N_{DT} (person)	GP	1830	3694	3952	3922	4204	4062	3724
	LMIs	3396	8734	9536	9202	9478	8098	7625
AR_{DT}		0.54	0.42	0.41	0.43	0.44	0.50	0.49
N_T (person)	GP	520	810	1254	1216	1030	550	1020
	LMIs	1330	1808	1676	1898	1694	1402	2266
AR_T		1.59	1.01	1.17	1.07	1.12	0.91	0.91
N_{UD} (person)	GP	6650	4510	3816	3911	3789	4388	4256
	LMIs	23729	17940	17279	17428	17319	18955	18564
V_{OF} (min)		1195194	900512	857763	718191	562194	940501	922784

5.2.3. Evolution Analysis from ACA to GA. The evolution process from ACA to GA, including the major tuning (from original to ACO) and fine tuning (from ACO to GA), was analyzed from two aspects: transit route and network points.

(1) *Transit Route Point*. As shown in Figure 4, route 2 produces larger-scale adjustments in the stop configuration during the major tuning, which causes an increase of 252 persons in the transit travel demand from original to ACO. Then, the stop configuration change of route 2 during fine tuning only produces subtle variations, which agrees with the expected change degree. Generally, such a change should not result in a significant transit travel demand change on route 2. However, the transit travel demand on route 2 is increased by 274 persons from ACO to GA. The main reason is that the headway of route 2 was reduced from 10 to 7.5 min during fine tuning. Likewise, the evolution analyses of routes 6, 7, 9, 10, 11, and 12 are similar to that of route 2. Note that the evolution analysis of route 1 is similar to that of route 2 from original to ACO, but route 1 has no stop configuration change from ACO to GA.

(2) *Transit Network Point.* The results of the ACO transit route network (Solution-a) are listed in Table 3. Comparing the original with the ACO transit route network, we see the evolution process of the major tuning: more direct travelers and transfers are realized by the ACO transit route network, but the optimal tendency (i.e., the direct traveler and transfer ratios between LMIs to GP) from original to ACO is almost equal for LMIs and GP. Furthermore, the evolution from ACO to GA can be analyzed by comparing the results of the ACO and ACA–GA transit route networks. We see that more direct travelers and transfers are accommodated by the transit route network and the average travel time ratio between LMI to GP direct travelers is increased from ACO to GA. The explanations for the transit route points are also applicable here.

5.2.4. Comparison to Other Approaches. In this section, the proposed approach (ACA–GA), the ACA approach of Yang and Yu [17] and the GA approach of Nayeem et al. [21], are compared.

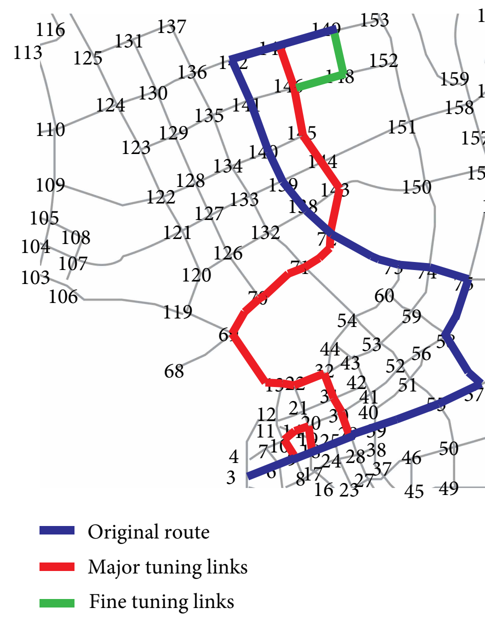


Figure 4: Stop evolution of route 2 from ACA to GA.

As the objective function does not have any practical interpretation for LMIs, we performed the optimization processes for the ACA and GA applied on the TRNDLMI problem with the same travel demands, respectively. Table 3 also presents the results of the transit route network optimization using the ACA (Solution-e) and GA (Solution-f), respectively. Compared to the results of ACA–GA (Solution-b), the optimal solution of the ACA achieves the same number of direct travelers and fewer transfers, and the ratio between direct LMI travelers to GP travelers remains virtually unchanged. The optimal solution of the GA gives fewer direct travelers and more transfers, and the ratio between direct LMI travelers to GP travelers also remains virtually unchanged, while the values of the objective function of the ACA and GA are both inferior to that of ACA–GA. Hence, the ACA–GA applied on TRNDLMI problem obtains a better optimal solution for LMIs than both ACA and GA.

As shown in Figure 5, comparative results were obtained by executing the optimization processes ten times for the three approaches (ACA–GA, ACA and GA) applied on the TRNDLMI problem with the same travel demands,

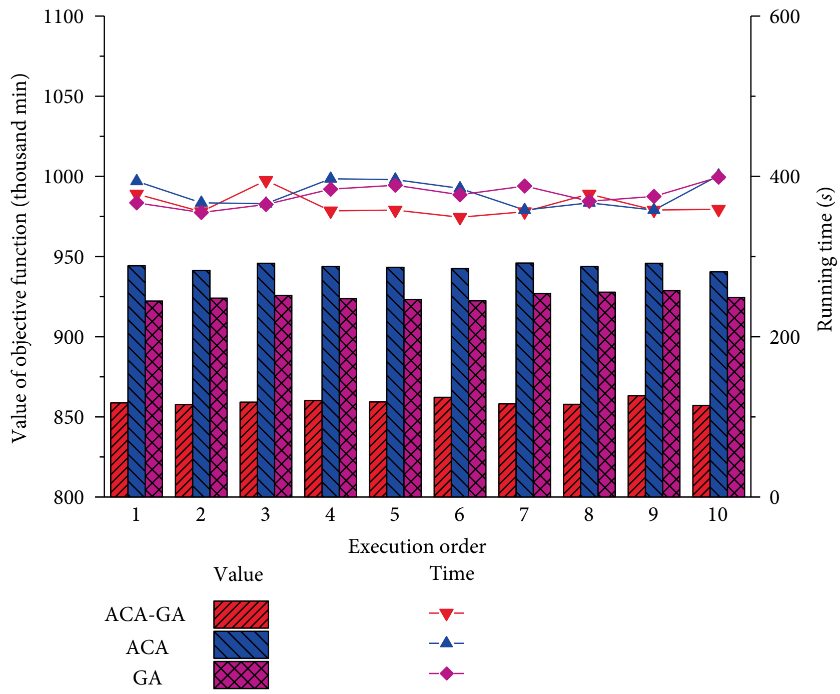


Figure 5: Comparisons of different approaches.

respectively. As expected, the results of ACA–GA are the best among the three approaches. Furthermore, we see that the three approaches have almost the same runtime with reasonable iterations. The ACA–GA reduces the search scope in the major tuning and fine tuning processes. However, the ACA–GA contains one more optimization process than both ACA and GA. This result is consistent with the results of Kuan et al. [26], who found that ACA and GA have similar runtimes when solving the feeder bus network design problems. Therefore, when the ACA–GA is applied on the TRNDLMI problem, it increases search efficiency without influencing the total runtime.

6. Conclusion

This paper puts forward the research of transit route network optimization for LMIs following the authors' previous effort, and proposes a suitable solution algorithm by integrating ACA and GA to solve the TRNDLMI problem.

In the model, a multi-objective function is presented to minimize the weighted sum of different user class costs (direct traveler, transfer, and unsatisfied demand), and considers the relationship between three transit travel demands of LMIs and GP further. Then, the values of weight parameters related to the interaction between different user classes and trade-offs between LMIs and GP are determined according to the existing analysis results and our optimization goal.

In the solution methodology, a hybrid metaheuristic approach (ACA–GA), including the major tuning and fine tuning, is presented to solve the TRNDLMI problem according to the optimization requirement (different existing routes need to produce different degrees of configuration adjustments). The major tuning uses the ACA to instigate large changes in the configuration of some routes, whereby increasing transit travel demands equitably for LMIs and GP. The minor tuning, based on GA, produces subtle variations in the configuration oftransit routes and changes in the headway, whereby meeting more transit travel demands, particularly those of LMIs.

A real world case study is presented in four of the paper's results sections. Section 5.2.1 (Comparison between original and optimal solutions) shows that the ACA–GA transit route network solution is better than the original transit route network. Section 5.2.2 (Sensitivity analysis of different weights) shows that the proposed weight set (i.e., tendency for LMIs) promotes the transit travel environment of LMIs better than two other types of weight sets (i.e., tendency for LMIs, and equitableness for LMIs and GP). The results of these two sections indicate that the proposed model obtains a better transit route network and attains the goal of improving the transit travel environment of LMIs. Section 5.2.3 (Evolution analysis from ACA to GA) suggests that the ACA–GA applied on the TRNDLMI problem can meet three degrees of configuration adjustments and better satisfies the transit demands of LMIs. Section 5.2.4 (Comparison to other approaches) points out that the ACA–GA applied on the TRNDLMI problem produces a better optimal solution for LMIs than both ACA and GA without influencing the total runtime. The results of these two latter sections indicates that the proposed hybrid metaheuristic approach applied on the TRNDLMI problem not only satisfies our optimization requirement and goal but also improves the convergence rate and precision of the algorithm.

In future work, we will further our research from four aspects: (a) how to improve runtime to improve the searching efficiency of the ACA–GA; (b) how to build new TRND models considering transit trips of distinct LMI groups (including older adults, low-income individuals, and individuals with disabilities), respectively; (c) how to study the localization of transit vehicles for LMIs based on relevant research [34–36]; (d) how to apply the proposed model based on the ACA–GA approach to more cities so as to calibrate related parameters and enhance the practical application value.

Data Availability

In this study, the data of travel demands are presented in the previous article of authors [4], other data used are contained within the article.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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