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Research Article

Bilevel Programming Model of Urban Public Transport Network under Fairness Constraints

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In this paper, the bilevel programming model of the public transport network considering factors such as the per capita occupancy area and travel cost of different groups was established, to alleviate the urban transportation equity and optimize the urban public transport network under fairness constraints. The upper layer minimized the travel cost deprivation coefficient and the road area Gini coefficient as the objective function, to solve the optimization scheme of public transport network considering fairness constraints; the lower layer was a stochastic equilibrium traffic assignment model of multimode and multiuser, used to describe the complex selection behavior of different groups for different traffic modes in the bus optimization scheme given by the upper layer. The model in addition utilised the noninferior sorting genetic algorithm II to validate the model via a simple network. The results showed that (1) the travel cost deprivation coefficient of the three groups declined from 33.42 to 26.51, with a decrease of 20.68%; the Gini coefficient of the road area declined from 0.248 to 0.030, with a decrease of 87.76%; it could be seen that the transportation equity feeling of low-income groups and objective resource allocation improved significantly; (2) before the optimization of public transport network, the sharing rate of cars, buses, and bicycles was 42%, 47%, and 11%, respectively; after the optimization, the sharing rate of each mode was 7%, 82%, and 11%, respectively. Some of the high and middle income users who owned the car were transferred to the public transportation. It could be seen that the overall travel time of the optimized public transport network reduced, enhancing the attraction of the public transport network to various travel groups. The model improves the fairness of the urban public transport system effectively while ensuring the travel demand of the residents. It provides theoretical basis and model foundation for the optimization of public transit network, and it is a new attempt to improve the fairness of the traffic planning scheme.

1. Introduction

Equity is a topic of concern to the whole society. The promotion of equity is more important than the increase of wealth to a great extent. Although the issue of equity has aroused great concern in society, the transportation equity has not received enough attention. At present, urban traffic planning theory attaches importance to traffic efficiency and neglects transportation equity, making it more difficult to be guaranteed.

In recent years, certain scholars have begun to explore the scheme of transportation equity. For instance, Litman [1] analyzed the manifestation of transportation equity and its interaction with urban planning, traffic planning, and traffic development strategies systematically. Vasconcellos [2] studied the negative externalities of different social groups due to travel by using disaggregate model and pointed out that low-income groups only obtain lower levels of mobility when they spend more on transportation costs in a selected case of São Paulo. Preston et al. [3] investigated the social exclusion phenomenon related to transportation from the perspective of accessibility and mobility and constructed a social-spatial model that caused social exclusion. Ahmed et al. [4] conducted a comparative analysis of Beijing and

Karachi cities as examples and illustrated the development trend of transportation equity in the urbanization from a macrolevel; Nuworsoo et al. [5] analyzed the impact of different public transport charging schemes on transportation equity through resident surveys and assessed the actual impact on low-income groups specifically; Brocker et al. [6] studied the actual impact of transportation infrastructure investment and construction on regional transportation equity and established a spatial equilibrium model to evaluate the transportation infrastructure investment policy; Ying et al. [7] used the Logit model to describe the competition and development of different traffic modes in urban traffic networks and evaluated the fairness of road resource allocation under various scenarios via the Lotka-Volterra model.

The improvement of transportation equity has also attracted the attention of researchers. Farrington et al. [8] analyzed the impact mechanism of accessibility and transportation system on social exclusion in suburban and rural areas and discussed policy design to improve accessibility from the perspective of social equity; Olvera et al. [9] provided policy recommendations for enhancing residents' travel environment and social equity based on the analysis of trends in different household transportation expenditures. Duvarcia et al. [10] discussed the suppressed travel demand of traffic vulnerable groups and their equality with ordinary groups and put forward corresponding suggestions from the technical aspects of urban traffic policy and traffic planning; Lucas [11] took South Africa as an example to analyze the typical social exclusion phenomenon in urban transportation systems in developing countries and proposed specific suggestions for improving the traffic environment of low-income groups from the perspective of traffic policy; Ferguson et al. [12] exemplified the important impact of the accessibility of public transport services on the employment opportunities for low-income groups and tried to embed the evaluation indicators of transportation equity into the evaluation process of the public transport system.

It is not difficult to find that the current research focuses on equity assessment, mainly on the equity analysis of travel expenses, road resource allocation, and congestion charging policies, and proposes specific countermeasures from the aspects of public participation, traffic demand analysis, and operational design. The fairness of public transport system means that, through the public transit network optimization, more road traffic resources can be provided for bus travel groups. However, little attention is paid to the lack of fairness in urban transportation planning practice, especially in the case of relatively fixed resource elements including urban spatial layout, land use form, and road network structure, which planning pattern can be used to maximize the fairness and efficiency.

As the leading travel mode in urban transportation system, public transport and the optimization of its network guarantees basic accessibility for low-income groups effectively, which directly affects urban transportation equity. Thus, the public transport system is of great significance to improve transportation equity. Its service level is related to the transportation rights of most residents, and it is also the adjustment lever of transportation equity among different social groups. It thereby improves the overall accessibility of the public transport system and shortens the gap between the bus travel groups and other travel groups. Finally, the bus travel groups and other travel groups have the same opportunities to participate in social activities. Obviously, it is helpful to meet the travel needs of different social groups by improving the fairness of public transport system. In particular, it is of great significance for the improvement of the travel environment of vulnerable groups. However, the traditional public transport network optimization schemes are mostly optimized with the minimum passenger travel time, the highest passenger flow rate, the lowest line overlap factor, and the largest bus economic benefit [13–20], excluding the transportation equity. Therefore, in view of uneven urban transportation resources and differentiated spatial accessibility, this paper intends to use the Gini coefficient of road area and relative deprivation coefficient of travel cost to evaluate the utility of public transit network optimization scheme. The bilevel optimization model of public transport network considering transportation equity constraints is established, and NSGA-II algorithm is designed to solve the problem. The main work in this paper is as follows:

(i) The complex travel behavior of urban residents is analyzed systematically by constructing multimode and multiuser traffic network.

(ii) The travel cost relative deprivation coefficient and the road area Gini coefficient are proposed to characterize the fairness of the public transport system, based on travel perception and resource allocation.

(iii) Under the fairness constraint, the bilevel planning model of urban public transport network is constructed. Moreover, the algorithm is designed, and the validity of the model is verified by examples.

The structure of the paper is arranged as follows: (1) construct multimode and multiuser traffic network and analyze the complex travel behavior of urban residents; (2) construct the bilevel planning model of public transport network considering fairness constraints, and give algorithm for solving the model; (3) design an example to verify the actual calculation and validity of the model; (4) give the main conclusions of this paper.

2. Urban Traffic Network of Multimode and Multiuser

In order to facilitate the modeling and analysis of this paper, three travel modes, car, bus and bicycle, are considered in the traffic network, and the travelers are classified into three travel groups, high, medium, and low, according to income levels. A simple transportation network is constructed as shown in Figure 1. It consists of 2 traffic zones, 16 nodes and 24 road segments, where O and D indicate the origin and destination zones, respectively.

After each travel group chooses the traffic modes, the mapping to urban transportation network presents different subnetwork structure, that is, the above networks are divided

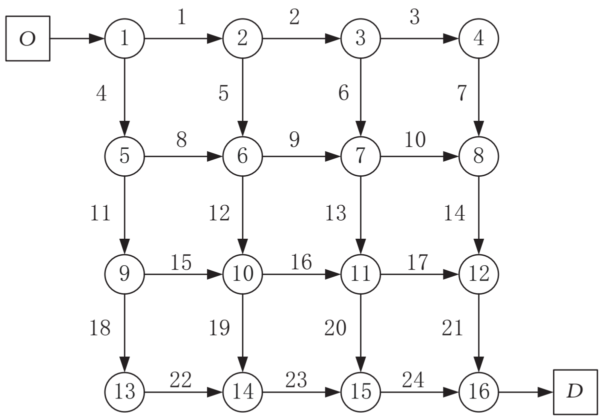


Figure 1: Sample of transportation network.

into high income group travel subnets, medium income group travel subnets, and low-income group travel subnets. Also, according to the traffic mode, different groups of travel subnets are subdivided into car subnets, bus subnets, and bicycle subnets. In this study, the initial public transport network among different groups is all the same. There are structural differences between the car and the bicycle subnet, and these differences do not change with the adjustment of the public transit network. Therefore, it can be considered that the multimode and multiuser traffic network mentioned above is composed of nine layers of subnets. Each subnet consists of a single group and a single travel mode. Moreover, G_{ik} represents the network formed by the i-th group choosing the k-th traffic mode. Among them, i =1, 2, 3 represents three groups of high, medium and low income; k =1, 2, 3 represents three travel modes of car, bus and bicycle.

Assuming that the travel demand of the multimode and multiuser transportation network is known and invariant, the travel demand of different traffic modes should meet the following constraints:

$$\sum_i q_i^w = q^w \quad \forall i, w \tag{1}$$

$$\sum_k q_{i,k}^w = q_i^w \quad \forall i, k, w \tag{2}$$

where q^w denotes the total travel amount of OD pair w; q_i^w denotes the travel demand of the i-th group OD pair w; $q_{i,k}^w$ denotes the travel demand of the i-th group choosing the traffic mode k on OD pair w.

The traveler's choice of transportation is affected by many factors. This paper only considers factors such as transportation cost and travel time. Combining the car ownership ratios of different groups, the Logit model is used to deal with traffic mode choice. After determining the mode, the traveler makes a route selection for the traffic mode subnet. For each type of traveler, the travel demands of the road segment and the route have the following relationship:

$$x_{i,k}^a = \sum_w \sum_r f_{i,k}^{w,r} \delta_{i,k}^{w,r,a} \quad \forall w, a \tag{3}$$

$$\sum_r f_{i,k}^{w,r} = q_{i,k}^w \quad \forall w, a \tag{4}$$

where $x_{i,k}^a$ denotes the travel demand on the segment a in the subnet G_{ik}; $f_{i,k}^{w,r}$ denotes the travel demand of the OD pair w on the route r in the subnet G_{ik}; $\delta_{i,k}^{w,r,a}$ denotes the Boolean variable associated with routes and segments. If the segment a is on the route r that between OD pair w, its value is 1; otherwise it is 0.

Considering the difference in the average passenger capacity of each traffic mode, the travel demand of different traffic modes needs to be converted into a unified road flow. The conversion formula is

$$v_{i,k}^a = x_{i,k}^a \frac{E_k}{N_k} \quad \forall k, a \tag{5}$$

where $v_{i,k}^a$ denotes the road segment traffic on the segment a in the subnet G_{ik}; E_k denotes the equivalent car conversion coefficient of the traffic mode k; N_k denotes the average number of passengers in the traffic mode k. In the subnet G_{ik}, $h_{i,k}^{w,r}$ denotes the road traffic on the route r and satisfies the following path-segment relationship:

$$v_{i,k}^a = \sum_w \sum_r h_{i,k}^{w,r} \delta_{i,k}^{w,r,a} \quad \forall w, a \tag{6}$$

$$h_{i,k}^{w,r} \geq 0 \tag{7}$$

Since the standard BPR function does not consider the interaction of different traffic modes, it is not suitable for multimode traffic networks. Thus, this paper uses the following improvements:

$$t_{i,k}^a = t_{i,k}^{a(0)} \prod_k \left[1 + 0.15 \left(\frac{\sum_{i=1} v_{i,k}^a}{C_k^a} \right)^4 \right] \quad \forall k, a \tag{8}$$

where $t_{i,k}^a$ represents the travel time on the segment a in the subnet G_{ik}; $t_{i,k}^{a(0)}$ represents the free flow time on the segment a in the subnet G_{ik}; C_k^a represents the travel capacity of the k-th travel mode for all groups on the segment a. In the subnet G_{ik}, the route travel time and the segment travel time satisfy the following relationship:

$$d_{i,k}^{w,\mathrm{r}} = \sum_\alpha t_{i,k}^a \delta_{i,k}^{w,r,a} \quad \forall w, a \tag{9}$$

where $d_{i,k}^{w,\mathrm{r}}$ represents the travel time on the route r in the subnet G_{ik}.

In the multimode and multiuser traffic network, assuming that the three types of travel groups select routes according to the Logit mode, the probability that the i-th travel group selects the path r in the subnetwork G_{ik} is

$$P_{i,k}^{w,r} = \frac{\exp\left(-\theta^i \cdot d_{i,k}^{w,r}\right)}{\sum_l \exp\left(-\theta^i \cdot d_{i,k}^{w,l}\right)} \quad r \neq l \tag{10}$$

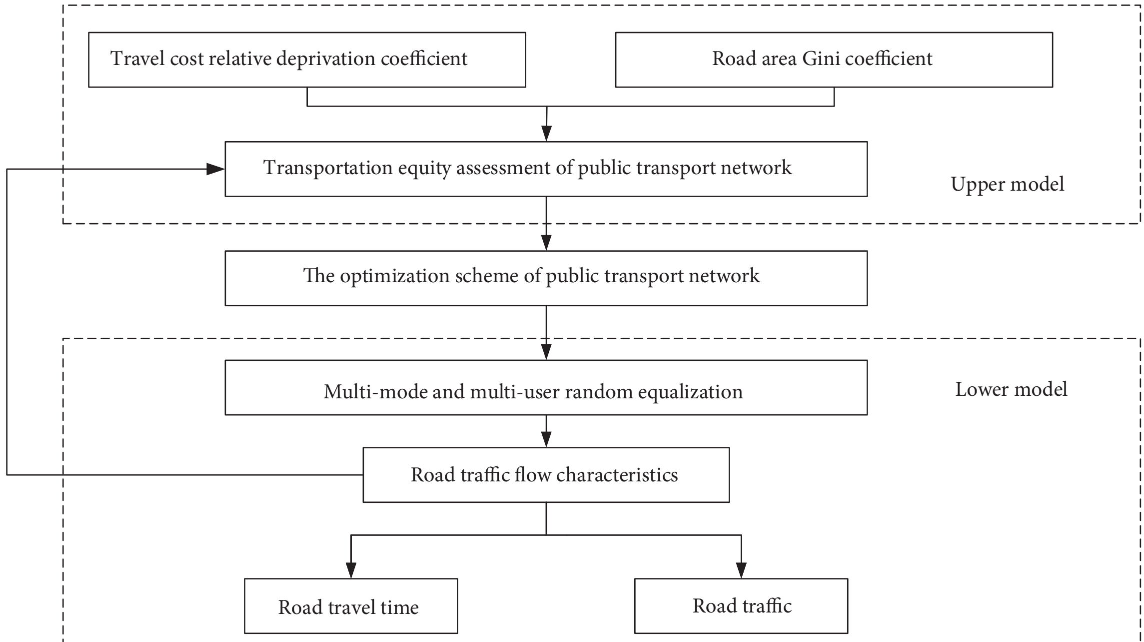


Figure 2: Model structure.

where $P_{i,k}^{w,r}$ represents the probability that the i-th travel group chooses the route r in the subnet G_{ik}; θ^i reflects the familiarity of different travel groups with the road network.

3. Model Construction and Solution

The optimization of public transport network considering transportation equity constraint is a special network optimization problem. The optimization of the public transport network leads to the redistribution of traffic resources inevitably, resulting in changes in the traffic mode sharing rate and general travel cost of various travel groups. Moreover, the distribution of bus travel demand of different groups is also affected, which leads to differences in residents' travel costs and per capita road occupancy area. The bilevel optimization model of public transport network considering transportation equity in this paper is an effective improvement on the existing bilevel optimization model of public transport network. In the bilevel optimization model of public transport network, the planners first propose the optimization scheme for the original one, and the lower layer model completes the multimode and multiuser traffic allocation according to the optimization scheme. The two objective functions of the upper model are calculated by the traffic and travel time of each traffic mode to evaluate the adaptability and fairness of the optimization scheme. The model structure is shown in Figure 2.

3.1. Upper Model. The assessment of transportation equity is mainly based on the subjective feelings of residents and the allocation of objective resources. The generalized travel cost and the possession of road resources determine the choice of residents' travel modes and routes. Hence, the objective function of the upper model mainly includes the travel cost relative deprivation coefficient and the road area Gini coefficient. The travel cost relative deprivation coefficient is used to express the subjective feelings of residents, and the road area Gini coefficient is used to express the allocation of objective resources.

3.1.1. Travel Cost Relative Deprivation Coefficient. Travel cost relative deprivation coefficient refers to certain travelers who measure the cost of completing their travel behavior and other groups by comparing the generalized travel costs between different groups to reflect the coefficient of deprivation of a certain travel group.

$$\min \quad y_1 = \sum_k \sum_{i,j} \left| H_{j,k}^w - H_{i,k}^w \right| \quad i \neq j \tag{11}$$

$$s.t. \quad H_{i,k}^w = \tau_i \cdot T_{i,k}^w + L_k \quad \forall w, i, j \tag{12}$$

where y_1 denotes the relative deprivation of travel costs incurred by all travelers in the multimode transportation network, and the smaller the y_1, the lower the relative deprivation of all travelers; $H_{i,k}^w$ denotes the travel cost of selecting the k-th way for the OD pair w in the subnet G_{ik} to the i-th resident group; $H_{j,k}^w$ denotes the travel cost of selecting the k-th way for the OD pair w in the subnet G_{jk} to the j-th group of residents; $T_{i,k}^w$ denotes the travel time of the k-th mode in the subnet G_{ik} to the i-th resident group for the OD pair w, and its value can be expressed by the travel time in the subnetwork balance state; τ_i denotes the time value of the i-th resident group; L_k denotes the cost of vehicle use for selecting the k-th traffic mode, such as car fuel consumption, bus fare.

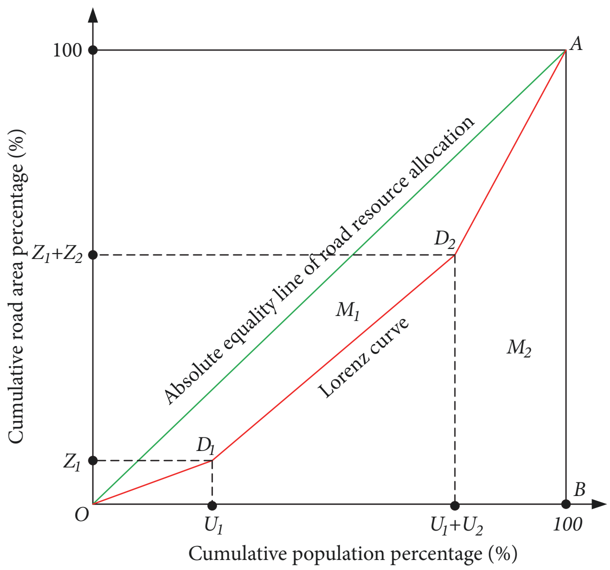


FIGURE 3: Lorenz curve for transport resource allocation.

According to the above discussion, the Logit model was used to describe the random traffic behavior of different traffic modes between the OD pairs based on the principle of the minimum travel cost. The formula is as follows:

$$Q_{i,k}^{w} = \frac{\exp\left(-\lambda \cdot H_{i,k}^{w}\right)}{\sum_{\pi} \exp\left(-\lambda \cdot H_{i,\pi}^{w}\right)} \quad \forall k, \pi, \ k \neq \pi \tag{13}$$

where $Q_{i,k}^{w}$ denotes the probability that the i-th group selects the traffic mode k on OD pair w; λ denotes the correction parameter.

3.1.2. Road Area Gini Coefficient. In order to quantify the difference of road occupation area per capita among different groups, the Lorentz curve and Gini coefficient were used to measure the fairness of road resource allocation. As shown in Figure 3, the Lorenz curve is OD_1D_2A, and the absolute fair line for road resource allocation is OA. The fairness of distribution is determined by the distance between the Lorenz curve and the absolute fair line. That is, the smaller the area enclosed by the Lorenz curve and the absolute fair line, the smaller the Gini coefficient, and the more equitable the actual distribution of traffic resources.

The radians of Lorentz curve are mainly determined by three groups of numerical values: the ratio of low-income group U_1 and the ratio of road resources occupied by the group Z_1, the ratio of medium income group U_2 and the ratio of road resources occupied by the group Z_2, and the ratio of high income group U_3 and the ratio of road resources occupied by the group Z_3. The proportion of road resources occupied by different groups can be expressed as

$$Z_i = \frac{\sum_k \left(q_{i,k}^{w} \cdot S_k / N_k\right)}{\sum_j \sum_k \left(q_{j,k}^{w} \cdot S_k / N_k\right)} \quad \forall i, j, k \tag{14}$$

where S_k denotes the road area occupied by the single vehicle of the k-th travel mode; N_k denotes the standard passenger number of the single vehicle of the k-th travel mode.

Therefore, it can be determined that the area M_2 enclosed by the line of points O, D_1, D_2, A, B is

$$M_2 = \frac{1}{2}\left[Z_1\left(U_1 + 2U_2 + U_3\right) + Z_2\left(U_2 + U_3\right) + U_3\right] \tag{15}$$

Then the Gini coefficient evaluation equation is

$$\min \quad y_2 = \frac{M_1}{M_1 + M_2} = 1 - 2M_2 \tag{16}$$

$$s.t. \quad \text{equation } (14), (15) \tag{17}$$

where y_2 represents the Gini coefficient of the road area; M_1 represents the area enclosed by the Lorenz curve and the absolute equality line.

3.2. Lower Model. Considering that it is impossible for travelers to master the traffic state of the road network completely, the route selection should be a stochastic process. Therefore, the stochastic user equilibrium assignment model was adopted to characterize the route choice behavior for travelers, of which the travel mode of each group was determined first. Further, the traffic assignment results which solved by the optimal target of minimum travel time in terms of the process of users' route choice behavior were put into the upper model. The optimization objective function of the lower model is minimizing the sum of the travel time of each subnet, and the specific model is as follows:

$$\begin{aligned} \min \quad & y_3 \\ & = \frac{1}{\theta^i} \sum_i \sum_k \sum_w \sum_r h_{i,k}^{w,r} \ln h_{i,k}^{w,r} \\ & \quad + \sum_i \sum_k \sum_\alpha \int_0^{v_{i,k}^{\alpha}} t_{i,k}^{\alpha}(x)\, dx \end{aligned} \tag{18}$$

$$s.t. \quad \text{equation } (1) - (4), (6), (7) \tag{19}$$

where y_3 is the sum of travel time.

3.3. Model Solution. Due to the conflict of the objective functions, the travel cost relative deprivation coefficient and the road area Gini coefficient in the upper optimization only obtain multiple sets of noninferior solutions or suboptimal solutions, and it is impossible to obtain the optimal solution simultaneously. Hence, the decision maker chooses a set of noninferior solutions based on the degree of preference. The traditional multiobjective optimization method uses weighted method and transforms multiple targets into single-objective function to solve the problem. The disadvantage of this method is that the weights of each objective are subjective and there is no alternative. The best method is noninferior sorting genetic algorithm II, which gets multiple Pareto optimal solutions after one program runs. With the advantages of speediness, diversity, and uniformity, it has

Table 1: Relevant data of the sample of public transport network.

Segment	1	2	3	4	5	6	7	8	9	10	11	12
$t_{i,2}^{a(0)}/h$	0.196	0.186	—	—	0.165	0.164	—	—	—	—	—	0.157
$C_2^a(veh{\cdot}h^{-1})$	900	600	—	—	800	700	—	—	—	—	—	700
Segment	13	14	15	16	17	18	19	20	21	22	23	24
$t_{i,2}^{a(0)}/h$	0.196	—	—	—	—	—	0.195	0.206	—	—	0.197	0.187
$C_2^a(veh{\cdot}h^{-1})$	900	—	—	—	—	—	600	700	—	—	900	700

Table 2: Relevant data of different travel groups.

Travel Groups	Percentage of total travel	Car ownership ratio	Time value τ_i $(yuan/h)$
High income group	25%	90%	25
Medium income group	40%	45%	16
Low income group	35%	5%	6

been considered as the most suitable simulation algorithm for solving multiobjective problems [21]. The specific steps of the algorithm are as follows.

Step 1. Algorithm parameters such as population size PopSize and evolutionary algebra GenMax were set; the car and bicycle subnet data were initialized; the initial public transport network population was generated randomly by 0-1 coding; the length of bit strings was determined by the number of bus lines searched by depth-first algorithm; for example: 001010001 means that there were 9 bus lines between origin and destination, and the lines 3, 5, and 9 were selected to form the public transport network.

Step 2. The users with cars in the three groups were divided into three travel modes, and the users without cars were divided into bus and bicycle travel modes by Logit model.

Step 3. For each individual in each generation (public transport network) and other mode subnets to achieve SUE traffic allocation, the MSA algorithm was used to solve 9 mode subnets at the same time. In addition, the upper objective function was calculated by using the distribution result, and the fitness function was the objective function itself.

Step 4 (NSGA-II algorithm core operation). (1) The number of individuals was selected via the tournament strategy to determine the tournament population; (2) the cross-operation was performed by the OX-like method, and the exchange operation was performed on two variation points in the individual by the exchange method; (3) the upper objective function value of each individual in the new population was calculated after the merging of parent and child populations; (4) the fast undominated sort was made based on the value of the objective function, and the crowding distance of the individual in the population is calculated; (5) the former PopSize individuals were selected to generate a new generation population, according to the frontier order value and the crowding distance of each individual.

Step 5 (the termination condition was determined). If the maximum number of iterations is reached, the algorithm terminates, producing a Pareto optimal solution set. Otherwise, turn to Step 2.

4. Example Analysis

Taking the simple road network shown in Figure 1 as an example, the optimization model and algorithm of public transport network are verified. Due to space constraints, this paper lists certain initial data of the public transport network, as shown in Table 1. It is assumed that the road network between origin and destination has sufficient capacity to allow multiple travel lines in the network without considering the transfer mode and the interests of the operators. In this paper, the existing two bus lines are optimized, and direct bus lines are rearranged between origin and destination, in order to improve the fairness of the public traffic line network scheme.

Take q^w =8000 $people{\cdot}h^{-1}$, λ=0.1, θ^1=1, θ^2=2, θ^3=5. The relevant data of different travel groups are shown in Table 2, and the relevant data of traffic modes are shown in Table 3.

In the NSGA-II algorithm, the population size is 100, the crossover rate is 0.8, the mutation rate is 0.1, and the evolutionary algebra is 500. The distributions of the Pareto optimal solution set and other solution set are shown in Figure 4. Table 4 lists the six groups of noninferior solutions obtained by NSGA-II algorithm. Each group of noninferior solution corresponds to the optimization scheme of public transport network under traffic fairness constraints. The decision makers select the best scheme among these six noninferior solutions, considering the construction and operation cost, the service level, and other factors of bus lines. The optimization calculation results are shown in Figures 5 and 6. Through the analysis of six groups of data related to optimization scheme, the following conclusions are drawn:

For the three travel groups, the travel cost relative deprivation coefficient is 33.42, and the road area Gini coefficient is 0.248 before the optimization of the public

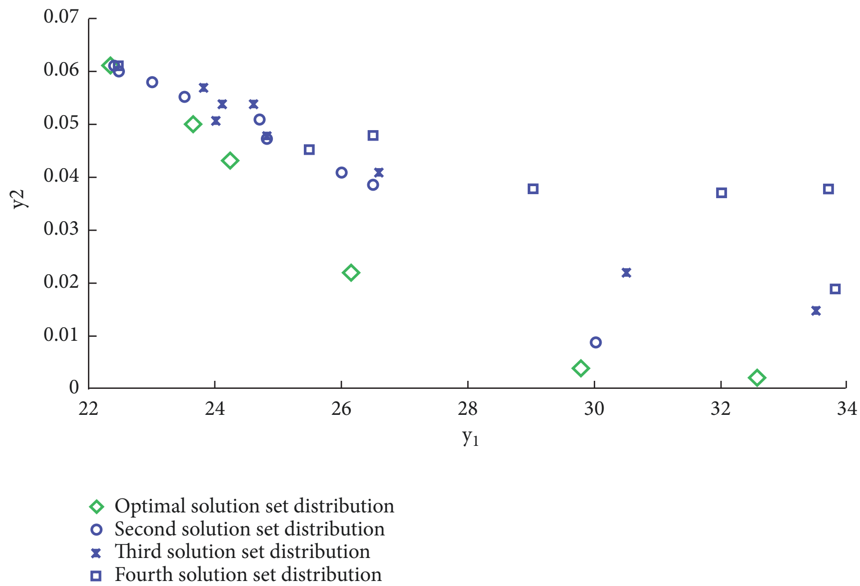


FIGURE 4: Distribution of Pareto optimal solutions and other solutions.

TABLE 3: Relevant data of different traffic modes.

Traffic Modes	Car unit conversion factor E_k	Average number of passengers per vehicle N_k (*person / vehicle*)	Vehicle usage fee L_k (*yuan*)	Road area occupied by vehicle S_k (m^2)
Car	1.00	2	12	30
Bus	1.50	30	2	45
Bicycle	0.25	1	0	7.5

Note: due to the particularity of the network structure in the example, the lengths of all travel routes between origin and destination are equal, and the transportation cost of the car is set as a fixed value.

transport network; after optimization, as shown in Table 4, the travel cost relative deprivation coefficient of the six optimized schemes averages 26.51, which is 20.68% lower than that before optimization; the Gini coefficient of road area averages 0.030, which is 87.76% lower than before. Thus, the model optimized the public transit network effectively. While meeting the travel needs of residents, it shortened the difference in travel costs between different groups and improved the fairness of transportation resource allocation.

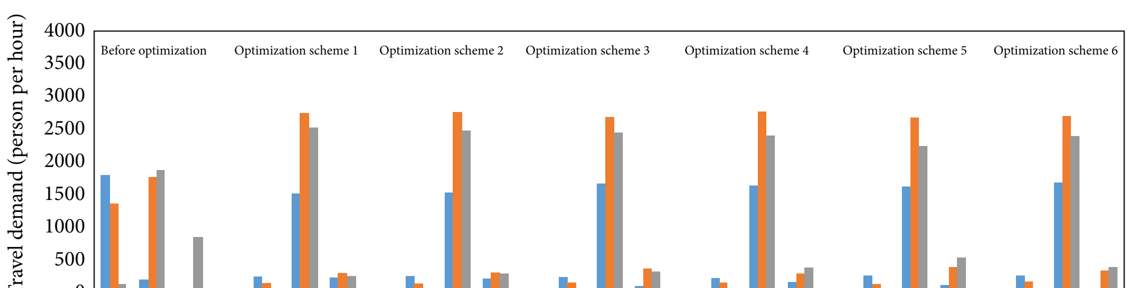
Before the public transit network optimization, a large number of transportation resources were occupied by high income groups to meet the needs of private car travel. In contrast, low-income groups without car purchasing power only chose buses with less comfort, convenience, and accessibility. After optimization, the preferences of the three groups changed significantly. As can be seen from Figure 5, certain high and medium income groups who used to travel by car begin to choose bus and bicycle modes, while the low-income group choose a higher rate of public transportation. Besides, both car and bicycle usage rates are declining. This trend indicates that the optimized public transport network has significantly increased the attraction for each group. The reason is known from Figure 6. It is mainly because the travel time of all groups by car has increased, the travel time by bicycle is basically the same, and the travel time by bus has decreased, after the public transit network optimization. The change of travel time not only restrains the demand of each group to choose cars, but also improves the convenience and accessibility of public transportation, which makes more travelers willing to choose bus travel.

5. Conclusions

(1) The relative deprivation coefficient of travel cost described the influence of the generalized travel cost difference of different groups on transportation equity, while the Gini coefficient of road area reflected the equilibrium of traffic resources distribution among different groups. In this paper, the bilevel optimization model of public transport network was established under the condition of traffic fairness constraint, and the relationship between the public transit network optimization and travel opportunities of different groups was discussed. The upper level optimization aimed at minimizing the travel cost relative deprivation coefficient and the road area Gini coefficient, and the lower level

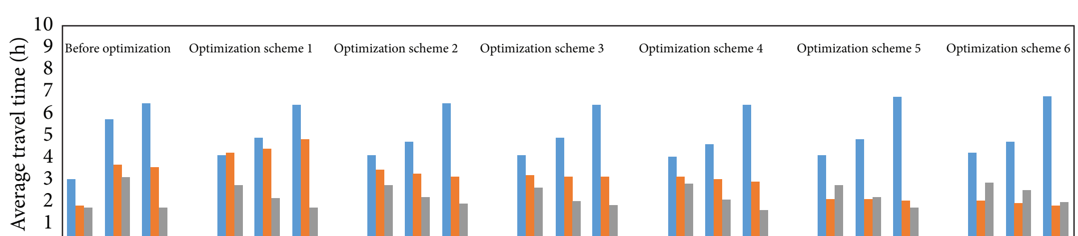
Table 4: Calculation results.

Optimization	Bus lines	Target value y_1	Target value y_2	Optimization	Bus lines	Target value y_1	Target value y_2
1	1⟶2⟶3⟶4⟶8⟶12⟶16 1⟶2⟶6⟶10⟶11⟶15⟶16 1⟶5⟶9⟶10⟶14⟶15⟶16 1⟶5⟶9⟶13⟶14⟶15⟶16	22.35	0.061	4	1⟶2⟶6⟶7⟶11⟶15⟶16 1⟶5⟶6⟶7⟶8⟶12⟶16 1⟶5⟶6⟶7⟶11⟶12⟶16	26.13	0.022
2	1⟶2⟶6⟶7⟶11⟶15⟶16 1⟶5⟶6⟶10⟶11⟶12⟶16 1⟶5⟶9⟶10⟶14⟶15⟶16	23.64	0.050	5	1⟶2⟶6⟶7⟶8⟶12⟶16 1⟶5⟶6⟶7⟶11⟶12⟶16 1⟶5⟶6⟶10⟶11⟶15⟶16 1⟶5⟶9⟶13⟶14⟶15⟶16	29.78	0.004
3	1⟶2⟶6⟶7⟶11⟶12⟶16 1⟶5⟶6⟶7⟶8⟶12⟶16 1⟶5⟶6⟶10⟶11⟶12⟶16 1⟶5⟶9⟶10⟶11⟶15⟶16 1⟶5⟶9⟶13⟶14⟶15⟶16	24.24	0.043	6	1⟶5⟶6⟶10⟶11⟶12⟶16 1⟶2⟶3⟶4⟶8⟶12⟶16 1⟶5⟶9⟶13⟶14⟶15⟶16	32.70	0.003



	Car	Bus	Bicycle	Car	Bus	Bicycle	Car	Bus	Bicycle	Car	Bus	Bicycle	Car	Bus	Bicycle	Car	Bus	Bicycle	Car	Bus	Bicycle
High income group	1800	200	0	246	1516	238	258	1526	216	239	1663	98	226	1624	150	265	1612	123	269	1679	52
Medium income group	1435	1765	0	153	2735	312	149	2746	305	159	2667	374	156	2762	282	138	2667	395	175	2685	340
Low income group	140	1870	853	32	2512	256	36	2468	296	26	2442	332	23	2393	384	23	2235	542	19	2382	399

Figure 5: Compared the different traffic mode ridership.



	Car	Bus	Bicycle	Car	Bus	Bicycle	Car	Bus	Bicycle	Car	Bus	Bicycle	Car	Bus	Bicycle	Car	Bus	Bicycle	Car	Bus	Bicycle
High income group	3	5.7	6.5	4.1	4.9	6.4	4.1	4.7	6.5	4.1	4.9	6.4	4	4.6	6.4	4.1	4.8	6.8	4.2	4.7	6.8
Medium income group	1.8	3.7	3.6	4.2	4.4	4.8	3.4	3.2	3.1	3.2	3.1	3.1	3.1	3	2.9	2.1	2.1	2	2	1.9	1.8
Low income group	1.7	3.1	1.7	2.7	2.1	1.7	2.7	2.2	1.9	2.6	2	1.8	2.8	2.1	1.6	2.7	2.2	1.7	2.8	2.5	1.9

Figure 6: Compared the different traffic mode travel time.

optimization was a stochastic equilibrium traffic assignment model of multimode and multiuser. Furthermore, the complex selection behaviors of different groups to different travel modes were analyzed.

(2) The example analysis showed that the public transport network model considering the traffic fairness constraints shortened the travel cost difference among different groups effectively and distribute road resources more equitably on one hand; it guided all travel groups to choose more bus trips, improve the fairness of the public transit network optimization schemes, and reduced the chances of high income groups choosing cars on the other hand.

Variables

See Table 5.

Table 5: Variable list description.

Symbol	Symbolic Meaning	Subscript and Superscript Meaning
	1 Urban traffic network of multi-mode and multi-user	
G_{ik}	the network formed by the i-th group choosing the k-th traffic mode	the i-th group; traffic mode k
q^w	the total travel amount of OD pair w	Any OD pair w
q_i^w	the travel demand of the i-th group OD to w	the i-th group
$q_{i,k}^w$	the travel demand of the i-th group on OD pair w choosing the traffic mode k	traffic mode k
$x_{i,k}^a$	the travel demand on the segment a in the subnet G_{ik}	segment a; the i-th group; traffic mode k
$f_{i,k}^{w,r}$	the travel demand of the OD pair w on the route r in the subnet G_{ik}	OD pair w; route r; the i-th group; traffic mode k
$\delta_{i,k}^{w,r,a}$	Boolean variables associated with routes and segments	OD pair w; route r; segment a; the i-th group; traffic mode k
$v_{i,k}^a$	the road segment traffic on the segment a in the subnet G_{ik}	segment a; the i-th group; traffic mode k
E_k	the equivalent car conversion coefficient of the traffic mode k	traffic mode k
N_k	the average number of passengers in the traffic mode k	traffic mode k
$h_{i,k}^{w,r}$	the road traffic on the route r	OD pair w; route r; the i-th group; traffic mode k
$t_{i,k}^a$	the travel time on the segment a in the subnet G_{ik}	segment a; the i-th group; traffic mode k
$t_{i,k}^{a(0)}$	the free flow time on the segment a in the subnet G_{ik}	segment a; the i-th group; traffic mode k
C_k^a	the travel capacity of the k-th travel mode for all groups on the segment a	segment a; traffic mode k
$d_{i,k}^{w,\mathrm{r}}$	the travel time on the route r in the subnet G_{ik}	OD pair w; route r; the i-th group; traffic mode k
$P_{i,k}^{w,r}$	the probability that the i-th travel group chooses the route r in the subnet G_{ik}	OD pair w; route r; the i-th group; traffic mode k
θ^i	the familiarity of different travel groups with the road network	the i-th group
	2 Model Construction and Solution	
y_1	the relative deprivation of travel costs incurred by all travelers in the multi-mode transportation network	Serial number
$H_{i,k}^w$	the travel cost of selecting the k-th way for the i-th resident group on the OD pair w in the subnet G_{ik}	OD pair w; the i-th group; traffic mode k
$H_{j,k}^w$	the travel cost of selecting the k-th way in the subnet G_{ik} of the i-th resident group on the OD pair w	OD pair w; the j-th group; traffic mode k
$T_{i,k}^{\mathrm{w}}$	the travel time of the k-th mode in the sub-$\mathrm{G_{ik}}$ of the i-th resident group on the OD pair w	OD pair w; the i-th group; traffic mode k
τ_i	the time value of the i-th resident group	the i-th group
L_k	the cost of vehicle use for selecting the k-th traffic mode	traffic mode k
$Q_{i,k}^w$	the probability that the i-th group selects the traffic mode on OD pair w	OD pair w; the i-th group; traffic mode k
λ	the correction parameter	
U_1	the ratio of low income group	Serial number
U_2	the ratio of medium income group	Serial number
U_3	the ratio of high income group	Serial number
Z_1	the ratio of road resources occupied by the low income group	Serial number
Z_2	the ratio of road resources occupied by the medium income group	Serial number
Z_3	the ratio of road resources occupied by the high income group	Serial number
S_k	the road area occupied by the single vehicle of the k-th travel mode	traffic mode k
N_k	the standard passenger number of the single vehicle of the k-th travel mode	traffic mode k
M_2	the area M_2 enclosed by the line of points O, $\mathrm{D_1}$, $\mathrm{D_2}$, A, B	Serial number
M_1	the area enclosed by the Lorenz curve and the absolute equality line	Serial number
y_2	the road area Gini coefficient	Serial number
y_3	The sum of travel time	Serial number

Data Availability

The example data used to support the finding of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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