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Multiobjective-Based Decision-Making for the Optimization of an Urban Passenger Traffic System Structure

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Abstract: Urbanization has aggravated the conflict between continuously increasing urban travel demands and limited supply. Moreover, the inability to expand urban roads due to previous land planning and utilization has resulted in significant traffic congestion, traffic safety issues, and environmental problems. To address these problems, this work attempted to develop a multiobjective model to optimize the passenger traffic system while considering carbon emissions, transport costs, and resource utilization. In addition, the ideal point method and entropy weight method were combined to obtain the optimal solution. Based on the operational data on traffic modes and travel data on passengers in Harbin, the northern capital of China, the proposed method was used to solve the case in Harbin. The results show that the proportion of buses increased by 1.05%, that of subways increased by 36.60%, that of taxis decreased by 11.86%, and that of private cars decreased by 25.78% after optimization. Furthermore, the analyses of the results show that the optimized passenger traffic system structure can promote the sustainable development of urban transport and demonstrate the practicality of the proposed method for solving multiobjective optimization problems. Relative to the ideal point method and genetic algorithm, the proposed method is more applicable for optimizing the passenger traffic structure in Harbin. In addition, this study explored the sensitivity of the optimization goals to the four motorized modes. The results show that subways and private cars are the key areas to prioritize in adjusting the urban passenger traffic system structure. Based on the analysis results, recommendations for the development of transportation in Harbin are given. This study provides a reference for decision-makers to formulate policies for the urban sustainable development of Harbin as well as for transportation development in other cities.

Keywords: urban traffic; passenger traffic structure; multiobjective optimization; ideal point method; entropy weight method; sensitivity analysis

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1. Introduction

Urban transformation toward sustainability is vital to global sustainable development as humans increasingly become city dwellers [1]. A reasonable urban traffic structure plays a significant role in the sustainable development of the whole society, helping to reduce energy consumption, air pollution, and other related environmental problems [2]. In China, the use of motorized modes of transport, such as private cars, has significantly increased in recent decades. The conflict between travel demand and limited road resources is intensifying, resulting in traffic congestion, exhaust pollution, energy shortages, and other problems in traffic operation [3]. On the one hand, people are seeking more convenient, comfortable, and efficient travel modes. On the other hand, city managers must solve the pressing problems of carbon emissions and road resource occupation to meet the travel demands of residents [4]. Establishing a more reasonable urban passenger traffic system structure by studying the direction of sustainable urban transportation development can improve the environmental quality of urban transportation and enhance the effectiveness of the road system. Furthermore, an appropriate traffic structure can fully utilize the carrying capacity of the current urban road network and reduce ecological and environmental pressure.

The innovation of this paper is reflected in two aspects: first, multiobjective optimization model building not only considers travel times, travel costs, and other such traditional objectives but also considers the comfort of residents traveling and the adverse impact of traffic modes on the environment. Second, the solution method uses the entropy weight method to compensate for the shortcomings of the ideal point method, which has the disadvantage of being relatively subjective in determining the weight coefficients.

This paper has three main contributions: (1) A multiobjective optimization model was developed to solve the urban traffic structure optimization problem by considering five aspects: traffic carbon emissions, traffic utility, travel costs, resource occupation costs, and energy consumption. The results show that the model has applicability. (2) The model was solved using the ideal point method, the genetic algorithm, and the proposed method. The solution results show that the proposed method yields a better urban passenger traffic structure and demonstrates strong practicality. (3) The sensitivity analysis of the objective function was carried out by changing the index weights of the four modes of transport in the five objective functions. First, the passenger turnover of one traffic mode was changed at a time. Then, the passenger turnovers of two traffic modes were changed simultaneously. Based on the results of the sensitivity analysis, this study provides policy suggestions for the optimization of the urban passenger traffic system structure.

The remainder of this paper is organized as follows. In Section 2, the related studies are briefly discussed. In Section 3, this paper builds a multiobjective optimization model and introduces the research methodology. In Section 4, the multiobjective optimization model of the urban passenger traffic system structure is solved, and the related analysis in Harbin is performed. Finally, this study concludes and puts forward suggestions for urban traffic development in Section 5.

2. Literature Review

2.1. Optimization of Urban Passenger Traffic Structure

Reasonable urban passenger traffic and a low-carbon urban traffic travel structure are the conditions that ensure sustainable urban development [5,6]. Optimizing an urban passenger traffic structure significantly relieves road traffic congestion, saves energy, and reduces emissions in cities [7]. Existing studies related to urban passenger traffic optimization are shown in Table 1. The research on passenger traffic optimization is relatively comprehensive. In addition to studies on single modes of traffic such as buses, subways, and vehicles, there are also studies on road networks and the overall optimization of the traffic structure. Optimization goals focus on travel times, costs, and energy consumption. Some scholars have transformed multiobjective optimization problems into single-objective problems, while other authors have used heuristic algorithms to solve multiobjective problems directly.

Table 1. Studies on urban passenger traffic optimization.

Objective	Study Area	Goal	Method	Data	Source
Bus	Zhaoyuan, China	Passenger volume and travel time	Simulated annealing and ant colony optimization	Survey data	[8]
	Beijing, China	Waiting time, travel time, and energy consumption	Genetic algorithm	Survey data	[9]
	Beijing, China	Travel cost and operating cost	Capacity restraint incremental assignment algorithm	Projected data	[10]
	Beijing, China	Guidance speed	Lagrange multiplier method	-	[11]
Subway	Guangzhou, China	Travel cost	Genetic-based algorithm	Projected data	[12]

Table 1. *Cont.*

Objective	Study Area	Goal	Method	Data	Source
Public transit	Boston, USA	Fare and travel time	Round-based public transit optimized router algorithm	Statistical data	[13]
Vehicle	Chengdu, China	Revenue	Reinforcement learning	Survey data	[14]
	Berlin, Germany	Fuel consumption, cost, and mass	Particle swarm optimization	Statistical data	[15]
	China	Passenger revenue and battery depletion	Adaptive learning rate firefly algorithm	Survey data	[16]
Traffic structure	Beijing, China	Ecological impact, utility, and cost	Ideal point, linear weighting, and hierarchical sequence method	Statistical data	[2]
	Harbin, China	Energy consumption	Artificial fish swarm algorithm	Statistical data	[17]
Road network	Tianjin, China	Noise cost	Line sound source noise emission model	Survey data	[18]
	Tianjin, China	Operation cost	Deep belief network mode	Survey data	[19]
	-	Travel cost and traffic flow	User equilibrium model and Frank–Wolfe algorithm	-	[20]
	-	Transit time	Genetic algorithm	-	[21]
	-	Travel time and cost	Epsilon-constraint algorithm	-	[22]

In recent years, researchers have focused on constructing urban traffic structure optimization models and exploring sustainable urban traffic structures. Awasthi et al. [23] presented a hybrid approach based on the analytical hierarchy process (AHP) for evaluating urban traffic structures and estimated the city's sustainability state using a transport sustainability index (TSI). Vos [24] studied the likelihood of travelers choosing different modes of travel through their preference for and satisfaction with different modes of travel. Conway et al. [13] modeled transportation planning considering both transportation costs and travel times and found Pareto solution sets that minimize both fares and travel times. Wang et al. [8] proposed a hybrid optimization model for the urban bus transit route network design problem (TRNDP). The results showed that the total travel time using the proposed method was significantly lower than that using the competing method. Wang et al. [18] constructed a multivariate planning road network optimization model based on traffic flow, road structure, road location, and length. The scholars' goal was to minimize the cost of traffic noise from the point of view of improving the road traffic structure. Yang et al. [19] analyzed the processing center's economic indexes and optimized the dynamic transportation network assignment based on a continuous big IoT input database. Liu et al. [9] developed a multitype bus operation organization model based on energy consumption to minimize vehicle energy consumption, passenger waiting times, and travel times. Ding et al. [20] proposed a complex-network-based integrated multilayer urban growth and optimization model. They generated more efficient transportation network layouts based on different land use, population density, and travel speed scenarios.

Scholars have focused on the optimization path for urban passenger traffic system structures to determine the development goals for traffic travel structures. Li et al. [25] conducted research on residents' travel behavior characteristics and travel preferences. Under multimodal transportation conditions, they addressed the urban road congestion problem for the sustainable development of modern cities. Gan et al. [26] investigated private car ownership in China, concluding that limiting private car sales and controlling the growth of car ownership may be an effective strategy to reduce energy consumption and greenhouse gas emissions. Szłapka et al. [27] emphasized that the active cooperation of all stakeholders, including local governments, people, businesses, unions, and associations, is a prerequisite for sustainable urban development. Li et al. [28] found that private car ownership's contribution to carbon emissions increases with the increase in private car ownership and concluded that the development of environmentally friendly transportation modes such as new energy vehicles should be accelerated. In general, many scholars consider strengthening urban transportation demand management, prioritizing public transportation, limiting private car travel, and forming diversified transportation modes as paths to optimize the transportation travel structure.

2.2. The Ideal Point Method

In the real world, many problems can be described as multiobjective optimization problems, where multiple objectives conflict with each other [29,30]. Each objective has to compromise in optimization and, finally, generate a set of balanced solutions, called the Pareto optimal set [31,32]. Generally, the ideal method provides a broader principle of compromise for solving multiobjective problems. It is a decision analysis method that transforms the objectives of a multiobjective problem into fewer objectives [33]. Okpoti et al. [34] developed a solution to guide decision-makers to find the Pareto optimum using the ideal point method. First, the ideal points for every single goal are identified and a compromise solution is then searched for, starting from a single ideal point. Peng et al. [35] objectively selected the best compromise Pareto solution from a repository with the ideal point decision method (IPDM), which achieves the best trade-off between different objectives. Wang et al. [36] established a multiobjective decision model for module configuration optimization. The optimal configuration scheme is selected according to the comprehensive distance between the feasible configuration schemes and the ideal outranking cardinal point. The ideal point method is also applied to traffic planning problems. Li et al. [2] used the ideal point method, linear weighting method, and hierarchical sequence to solve and compare multiobjective optimization models. It was concluded that the ideal point method is more suitable to optimize the traffic structure of Beijing. The characteristics of these methods for solving multiobjective optimization problems are summarized and compared in Table 2.

Table 2. Characteristics of solving methods.

Methods	Advantages	Disadvantage
Ideal point, linear weighting, and hierarchical sequence method	Calculation simplicity and high reliability	Subjective
Other heuristic algorithms mentioned in Section 2.1	Fast solution speed and high precision	Local optimization

In summary, scholars have achieved outstanding research on the optimization of urban passenger traffic structures. Optimization models based on single or double targets have been employed for urban passenger traffic structures, but the objective functions have not been considered comprehensively enough. Some scholars do not distinguish between the importance of objective functions when solving an optimization model using the ideal point method, considering the weights of the objective functions to be the same. Hence, this paper built a multiobjective urban passenger traffic system structure optimization model based on traffic carbon emissions, traffic utility, travel costs, resource occupation costs, and energy consumption. Moreover, a superior method that combines the entropy weight method with the ideal point method is proposed. The entropy weight method, as an objective weight assignment method, enables us to select the most desirable solution result based on the weight [37].

3. Methodology

3.1. Model Assumptions

In this section, a multiobjective optimization conceptual model combining the optimization ideas proposed above is constructed. Considering the macroscopic characteristics of general government decision-making while ensuring scientific and rigorous research, the optimization model established in this paper is based on the following three prerequisites [38]:

(1) To fix the total amount of intracity traffic, urban traffic is treated as a closed system. This study excludes the flow of resources between the study city and the surrounding cities, ignoring the population flow and trips between the study area and the surrounding area.

(2) The parameters in this model are taken as the average parameters obtained at the macro level. This study does not consider the changes in individual traveler parameters and the impacts of unexpected or major events on the urban passenger transport system.

(3) The model is limited to the road traffic in the urban passenger transportation system. Because this paper aimed to optimize the urban passenger transport structure from the perspectives of carbon emissions, energy consumption, and land resource occupation, the four motorized modes, i.e., bus, subway, taxi, and private car, were selected for the analysis. Nonmotorized modes of travel, such as walking and bicycles, were not considered.

3.2. Optimization Model Construction

3.2.1. Optimization Goals

(1) Minimize traffic carbon emissions.

Traffic carbon emissions are treated as a separate target, and this paper refers to the CO_2 emissions generated by passenger traffic behaviors in a specific city. With the global climate problem becoming more and more prominent, the sustainable development strategies of saving energy and reducing emissions have become the core direction of urban transportation construction [39]. The formula is as follows:

$$minC = \sum_{i=1}^{n} c_i \cdot x_i \tag{1}$$

where x_i is the variable of the passenger turnover of the i-th traffic mode (unit: 10^4 p·km). The specific meaning of each variable is shown in Table 3.

Table 3. List of variables.

Variable	Traffic Mode
x_1	Bus
x_2	Subway
x_3	Taxi
x_4	Private car

(2) Maximize traffic utility.

Traffic utility can be calculated by the contributions of the four modes of passenger transport to the improvement of urban transportation efficiency [40]. A traffic network that is operating efficiently not only meets the city's traffic demands to the maximum extent but also fully utilizes traffic facilities and avoids wasting resources. The formula is as follows:

$$maxU = \sum_{i=1}^{n} u_i \cdot x_i \tag{2}$$

(3) Minimize travel costs.

Travel costs are based on the perspective of the traveler, including time costs, expense costs, and comfort costs [41,42]. Time costs refer to the value generated by the time consumed by a traveler during a trip. Expense costs are the costs paid in the process of using transportation, including the fare paid by a public transportation traveler and the fuel cost and maintenance cost paid by a private transportation traveler. Comfort costs are defined according to the comfort level of the mode of passenger transport. The more comfortable the passenger mode is, the higher the comfort cost that will be paid. The formula is as follows:

$$minT = T_t + T_e + T_c = \sum_{i=1}^{n}\left(\frac{1}{v_i} \cdot vot \cdot \alpha_i \cdot x_i\right) + \sum_{i=1}^{n}\beta_i \cdot \frac{x_i}{l_i} + \sum_{i=1}^{n}\gamma_i \cdot x_i \tag{3}$$

(4) Minimize resource occupancy costs.

Resource occupancy costs mainly refer to the expenses that occupy transportation resources without producing any actual transportation benefits, including the maintenance and treatment costs caused by traffic accidents and the land resource occupation costs caused by land use. Severe traffic accidents destroy traffic facilities and the normal order of traffic, and the handling of accidents requires the intervention of relevant personnel agencies. Personal medical expenses, public property damage, and public expenditure costs for services provided by the relevant authorities are caused [43]. Land resource occupation costs take into account the costs of occupying road space, parking lots, gas stations, and other facilities based on land price. The formula is as follows:

$$minR = R_a + R_l = \sum_{i=1}^{n}\frac{\delta_i}{l_i \cdot p_i} \cdot x_i + \sum_{i=1}^{n}\frac{\varepsilon_i}{l_i \cdot p_i} \cdot x_i \tag{4}$$

(5) Minimize energy consumption.

In terms of energy consumption, the operation of most motor vehicles requires the consumption of nonrenewable energy. This study measures the degree of its impact on the ecological environment by the amount of energy consumed by different modes of transportation. The formula is as follows:

$$minE = \sum_{i=1}^{n} e_i \cdot x_i \tag{5}$$

3.2.2. Constraints

(1) Travel demand constraint.

The optimization of an urban passenger traffic structure should satisfy the travel demands, i.e., the sum of the traffic supply should exceed the traffic demands of the residents in the planning year. The formula is as follows:

$$\sum_{i=1}^{n} x_i \geq P \cdot D \cdot L \cdot \sqrt{\frac{FA}{NA}} \tag{6}$$

(2) Road resource capacity constraint.

To achieve sustainable urban development, the road resource capacity constraint is one of the conditions for the optimization of an urban passenger traffic structure [44,45]. The dynamic floor space of different modes of passenger transport must meet the road land requirements in the planning year. The formula is as follows:

$$\sum_{i=1}^{n} s_i \cdot x_i \leq P \cdot D \cdot L \cdot S \tag{7}$$

(3) Tolerable time constraint.

Currently, travelers are more concerned with travel times. The maximum travel time that residents can tolerate with high levels of development in a city reflects their pursuit of mobility and accessibility [46]. The formula is as follows:

$$\sum_{i=1}^{n} t_i \cdot x_i \leq P \cdot D \cdot L \cdot t_d \tag{8}$$

(4) Traffic mode scale constraint.

The development scales of traffic modes are bounded according to the characteristics of the traffic modes, capital investment, the environmental carrying capacity, and the current development levels of the traffic modes. The lower limit of constraint reflects that the supply capacity of the traffic modes should not be idle, and the upper limit of constraint reflects the scale of each traffic mode allowed by the level of urban development. The formula is as follows:

$$0 < x_{imin} \leq x_i \leq x_{imax} \tag{9}$$

The meanings of the abbreviations and traffic parameters in Equations (1)–(9) are shown in Tables 4 and 5.

Table 4. List of abbreviations.

Abbreviation	Meaning	Unit
C	Traffic carbon emissions	ton
U	Traffic utility	10^6 p·km
T	Travel costs	million CNY
T_t	Time costs	million CNY
T_e	Expense costs	million CNY
T_c	Comfort costs	million CNY
R	Resource occupancy costs	million CNY
R_a	Traffic accident costs	million CNY
R_l	Land resource occupation costs	million CNY
E	Energy consumption	MJ
P	Population number in the planning year	person
D	Average number of urban residents' trips per day	time
L	Average distance of a single trip for urban residents	km
FA	Scale of urban land in the planning year	km^2
NA	Scale of urban land in the current year	km^2
S	Occupied road area per capita in the planning year	m^2/person

Table 5. List of traffic parameters.

Parameter	Meaning	Unit
c_i	Carbon emissions factor of the *i*-th mode	g/p·km
u_i	Contribution weight of the *i*-th mode	-
v_i	Average operating speed of the *i*-th traffic mode	km/h
vot	Time value per urban resident	CNY/h
α_i	Time value coefficient of the traveler who chooses *i*-th traffic mode	-
β_i	Average cost of a trip for *i*-th traffic mode	CNY
l_i	Average operation distance of *i*-th traffic mode	km
γ_i	Comfort value of *i*-th traffic mode	CNY/km
δ_i	Average cost per incident of *i*-th traffic mode	CNY
p_i	Average number of passengers carried by *i*-th traffic mode	person
ε_i	Land resource occupation costs per day of *i*-th traffic mode	CNY
e_i	Energy consumption per unit of turnover of *i*-th traffic mode	MJ/p·km
s_i	Dynamically occupied road area per capita of *i*-th traffic mode	m^2/person
t_i	Average travel time for residents choosing the *i*-th traffic mode	minute
t_d	Residents' tolerable time for a trip	minute
x_{imin}	Lower limit of the scale of the *i*-th traffic mode	10^4 p·km
x_{imax}	Upper limit of the scale of the *i*-th traffic mode	10^4 p·km

3.3. Solution

3.3.1. Ideal Point Method

The ideal point method involves multiobjective decision-making. It transforms a multiobjective problem into a single-objective problem for numerical optimization. By constructing the distance function, the value of each objective function is made to be as close to the optimal value as possible. It provides a balance among the objective functions and effectively solves the difficulty of finding the optimal solution for multiobjective problems. Compared with other methods for solving multiobjective problems, this method does not require a complicated computational process, and the operation process is simple. Meanwhile, the computational results obtained are very scientific and effective [47].

- Min–max normalization.

The coefficients of the variables of the model's objective function represent different physical meanings, while there are differences in the order of magnitude. Therefore, the initial values of each variable coefficient need to be normalized before solving the model. The dimensional restrictions of the data are removed and transformed into dimensionless relative values, enabling comparisons and operations between coefficients of different magnitudes or units [48]. The values of the variable coefficients after the min–max normalization process fall in the interval [0, 1]. The coefficient matrix of the objective functions is in m rows and n columns. For a particular objective function, it has n coefficients. The process of normalizing the variable coefficients is as follows:

$$\overline{a_{ij}} = \frac{a_{ij} - min\{a_{1j}, \ldots, a_{nj}\}}{max\{a_{1j}, \ldots, a_{nj}\} - min\{a_{1j}, \ldots, a_{nj}\}} \tag{10}$$

where a_{ij} is the *i*-th variable coefficient in the *j*-th objective function.

- The optimal solution of each objective function is solved.

The new expressions of the objective functions are obtained after normalization. The ideal point method first solves the optimal solution of every single-objective function under the constraints of Equations (6)–(9). For example, F_1^0 is the unique optimal solution of the first objective function subject to the constraints. The set $F^0 = \left(F_1^0, F_2^0, \ldots, F_m^0\right)$, consisting of the optimal solutions F_j^0 of multiple single-objective optimization problems, is viewed as the ideal point.

- The optimal solution for the multiobjective optimization problem is solved.

The purpose of the ideal point method is to obtain an optimization result as close to the ideal point F^0 as possible [49]. The closest $F(X)$ to the ideal point is considered the optimal solution that can be achieved under the constraints. This study introduces the distance function $d\left[F(X), F^0\right]$ for $F(X)$ and F^0 into the function space. Consider the distance function as the objective function and solve for $F(X)$ under the constraints of Equations (6)–(9). The distance function should be as small as possible, as specified in Equation (11):

$$\begin{aligned} & mind\left[F(X), F^0\right] = \sqrt{\sum_{j=1}^{m}\left[F_j(X) - F_j^0\right]^2} \\ & s.t.\begin{cases} \sum_{i=1}^{n} x_i \geq P \cdot D \cdot L \cdot \sqrt{\frac{FA}{NA}} \\ \sum_{i=1}^{n} s_i \cdot x_i \leq P \cdot D \cdot L \cdot S \\ \sum_{i=1}^{n} t_i \cdot x_i \leq P \cdot D \cdot L \cdot t_d \\ 0 < x_{imin} \leq x_i \leq x_{imax} \end{cases} \end{aligned} \tag{11}$$

where $X = (x_1, x_2, \ldots, x_n)$. The optimal solution X is the unique optimal solution of the multiobjective optimization problem.

3.3.2. Combination of Entropy Weight Method and Ideal Point Method

The distance function Equation (11) is used to minimize the sum of squares of the differences between the optimal solution and the ideal point, without distinguishing the differences in the importance of the objective functions. This paper further assigns different weights to the objective functions depending on the degree of importance of the objectives.

The entropy weight method is used to assign weights to each objective function. The greater the dispersion of the objective function, the greater the variability of the objective function and the higher the weight that should be given to assign it a larger role. The main steps in the proposed method are presented in Figure 1.

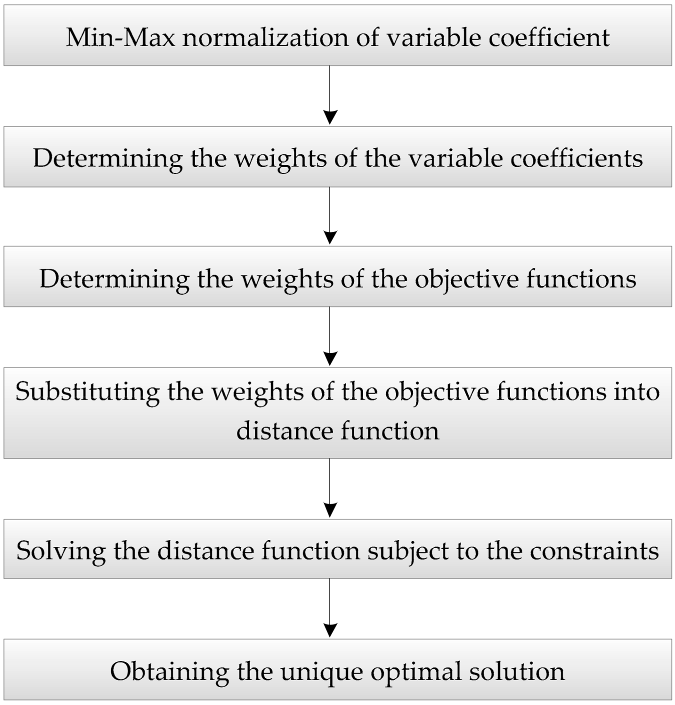

Figure 1. The solution procedure of the proposed method.

The specific steps are as follows:

- The weight of the variable coefficient $\overline{a_{ij}}$ is determined.

As with the ideal point method, the entropy weight method in this paper first requires min–max normalization to obtain $\overline{a_{ij}}$. Then, p_{ij} is calculated:

$$p_{ij} = \frac{\overline{a_{ij}}}{\sum_{i=1}^{n} \overline{a_{ij}}}, i = 1, \ldots, n; j = 1, \ldots, m \tag{12}$$

where p_{ij} is the weight of the i-th variable coefficient value of all the variable coefficient values in the j-th objective function.

- The entropy of the j-th objective function is calculated:

$$g_j = -k\sum_{i=1}^{n} p_{ij} ln\left(p_{ij}\right), j = 1, \ldots, m \tag{13}$$

where g_j is the entropy of the j-th objective function, and $k = \frac{1}{ln(n)}$>0, satisfying $g_j \geq 0$.

- The weight of the j-th objective function is calculated:

$$w_j = \frac{1 - g_j}{\sum_{j=1}^{m} \left(1 - g_j\right)} \tag{14}$$

where w_j is the weight of the j-th objective function. $W = (w_1, w_2, \ldots, w_m)^T$. The sum of the weights of each objective function is 1.

After obtaining the weights of different objective functions with the entropy weight method, the optimal-solution-solving ideal point method needs to be improved. The weights of different objective functions are added to the distance function, solving the improved distance function subject to the constraints of Equations (6)–(9), as specified in Equation (15):

$$
\begin{aligned}
& mind\left[F(X'),F^0\right] = \sqrt{\sum_{j=1}^{m} w_j \cdot \left[F_j(X') - F_j^0\right]^2} \\
& s.t.\begin{cases}
\sum\limits_{i=1}^{n} x_i \geq P \cdot D \cdot L \cdot \sqrt{\frac{FA}{NA}} \\
\sum\limits_{i=1}^{n} s_i \cdot x_i \leq P \cdot D \cdot L \cdot S \\
\sum\limits_{i=1}^{n} t_i \cdot x_i \leq P \cdot D \cdot L \cdot t_d \\
0 < x_{imin} \leq x_i \leq x_{imax}
\end{cases}
\end{aligned}
\tag{15}
$$

where $X' = (x_1, x_2, \ldots, x_n)$ is the unique optimal solution of the proposed method.

4. Case Study

4.1. The Optimization Model of Harbin Passenger Traffic System Structure

To verify the operability of the model, this paper took Harbin as the research object to optimize its passenger traffic system structure, taking 2020 as the current year and 2035 as the planning year. Four modes of urban passenger transport—bus, subway, taxi, and private car—are discussed herein.

The data for the traffic parameters were obtained from the Urban Road Traffic Planning and Design Code, the Guidelines for Heilongjiang Province Comprehensive Grade Separation Traffic Network, Harbin Statistical Yearbook 2020, The Sixth Population Census of Heilongjiang Province, Harbin Urban Master Planning, the Harbin Economic and Social Development of the 14th Five-Year Plan and 2035 Visionary Goals Outline, the Heilongjiang Province Comprehensive Transportation System Development Plan of the 14th Five-Year, and the China Urban Rail Transit Association 2020 Annual Statistics and Analysis Report and Literature [17]. See Appendix A for the specific traffic parameter data.

The above basic data were sorted and substituted into Equations (1)–(9). After standardizing the variable coefficients according to Equation (10), the multiobjective optimization model of the urban passenger traffic system structure was obtained as follows:

$$
\begin{aligned}
& \begin{cases}
minC = 0.09269x_1 + x_3 + 0.82442x_4 \\
maxU = 0.38051x_1 + x_2 + 0.12417x_4 \\
minT = 0.18276x_1 + x_3 + 0.31229x_4 \\
minR = 0.06440x_1 + x_3 + 0.52518x_4 \\
minE = 0.01242x_1 + x_3 + 0.77640x_4
\end{cases} \\
& s.\,t.\begin{cases}
x_1 + x_2 + x_3 + x_4 \geq 16045 \\
2.23x_1 + 37.57x_3 + 34.39x_4 \leq 20666 \\
46x_1 + 14x_2 + 31x_3 + 32x_4 \leq 459242 \\
3008 \leq x_1 \leq 6685 \\
882 \leq x_2 \leq 7515 \\
565 \leq x_3 \leq 2261 \\
3329 \leq x_4 \leq 6658
\end{cases}
\end{aligned}
\tag{16}
$$

Heuristic algorithms are frequently used to solve multiobjective optimization problems. In this paper, the genetic algorithm was considered as a comparison method to verify the advancement of the proposed method. The population size was 50, the elite count was 2.5, the crossover fraction was 0.8, and the generations number was 400. MATLAB R2018b software was used to implement the programming of the ideal point method and the proposed method. The running platform was a computer with an Intel (R) Core (TM) i7-7700HQ CPU @ 2.80 GHz and 8 GB RAM.

4.2. Result Analysis

Equation (16) was the first to be solved with the ideal point method. The optimal solution of each objective function under the seven constraints was solved separately, and the optimal solution $X = (x_1, x_2, x_3, x_4)$ of Equation (16) was then determined with the distance function of Equation (11). The optimal solution obtained was $X = (4153, 6210, 565, 5117)$.

In this paper, a new method combining the entropy weight method and the ideal point method was proposed. The weights of the objective functions were obtained according to Equations (12)–(14), which were $W = (0.18563, 0.19384, 0.18418, 0.20687, 0.22948)^T$. The weights of the objective functions were substituted into Equation (15) to obtain $X' = (x_1, x_2, x_3, x_4)$. The result was calculated as $X' = (4545, 6515, 565, 4420)$.

The genetic algorithm solving Equation (16) resulted in $X'' = (4177, 6644, 1201, 4106)$.

The obtained X, X', and X'' are the optimized urban passenger traffic structures in 2035, and the passenger turnover proportions of the four modes are shown in Table 6.

Table 6. Optimal passenger traffic structure obtained using three methods.

Traffic Mode	Bus	Subway	Taxi	Private Car
Ideal point method	25.88%	38.70%	3.52%	31.89%
Genetic algorithm	25.90%	41.20%	7.45%	25.46%
Proposed method	28.33%	40.60%	3.52%	27.55%
Before optimization	27.28%	4.00%	15.38%	53.33%

It is assumed that the proportions of the passenger volumes before optimization in Table 6 are the same as those for the current year. As can be seen from the results, the proportion of public transport before optimization accounts for 31.28%, approximately one-third, of the residents' travel activities. Due to the late construction of the subway in Harbin, the proportion of subways is low, and buses account for a large proportion of public transport. The proportion of private cars reaches 53.33%, which is the highest among all modes of passenger transport. The results show that the ideal point method, the genetic algorithm, and the proposed method can all optimize the urban passenger transport structure. In addition, the passenger traffic structure obtained using the proposed method is more conducive to the city's sustainable development. After optimization, the proportion of low-carbon public transport was increased to 68.93%, with the proportion of subways being raised to 40.60% compared with before. Although the proposed method obtained a slightly lower percentage of subways than the genetic algorithm, the proposed method outperforms the genetic algorithm regarding the percentage of low-carbon public transport. The proportion of private cars was reduced to 27.55%, and the proportion of taxis was reduced to 3.52%. Considering the actual situation, although taxis and private cars have high accessibility, their characteristics of high energy consumption and high carbon emissions cannot meet the needs of sustainable development. After the coverage of the bus line network and subway stations reaches a certain scale, residents will gradually shift their trips from cars to public transport.

According to the average distance of a single trip for urban residents and the development trend of passenger volumes in Harbin in previous years, the urban passenger turnover in 2035 was predicted and substituted into Equation (16). The values of the five objective functions were solved by substituting X, X', and X'' into Equation (16), and the solution results are shown in Figure 2. The four colored areas indicate the objective function values of the ideal point method, the genetic algorithm, the proposed method, and before optimization.

Figure 2 shows that the ideal point method, the genetic algorithm, and the proposed method effectively optimize some objective function values relative to before optimization. The proposed method optimizes significantly more than the ideal point method and the genetic algorithm. The proposed method yields the lowest carbon emissions, the greatest traffic utility, the lowest travel costs, the lowest resource occupation costs, and the lowest energy consumption. Detailed data are required to further analyze the optimization capabilities of the ideal point method, the genetic algorithm, and the proposed method. The values of the objective functions obtained using the three methods are listed in Table 7.

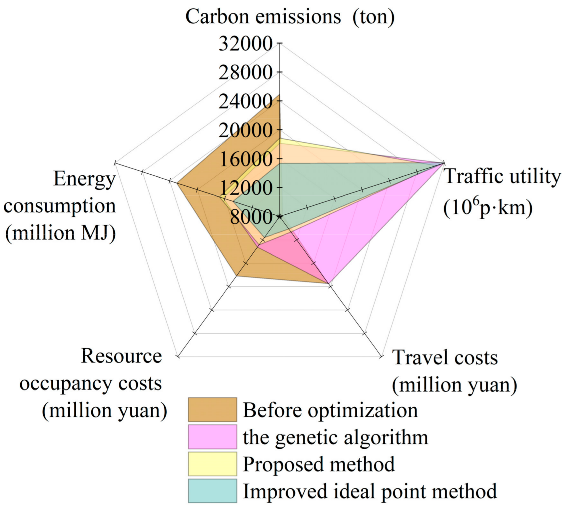

Figure 2. Objective function values obtained using three methods.

Table 7. Comparison of the objective function values obtained using three methods.

Optimization Objective	Carbon Emissions (ton)	Traffic Utility (10^6 p·km)	Travel Cost (million CNY)	Resource Occupancy Cost (million CNY)	Energy Consumption (million MJ)
Ideal point method	18,857	30,783	10,665	12,844	16,751
Genetic algorithm	18,152	31,913	19,526	13,236	16,209
Proposed method	15,356	32,095	10,132	11,600	14,794
Before optimization	24,906	8452	19,471	18,171	22,994

The optimization degrees of the three methods can be seen in Table 7. The genetic algorithm obtained better objective values in carbon emissions, traffic utility, and energy consumption than the ideal point method, while the two objective values obtained for costs were worse than those of the ideal point method. It is difficult to say which of the two methods solves better. The carbon emissions of the proposed method were 3501 tons and 2796 tons less than those of the ideal point method and the genetic algorithm, which corresponds to a reduction of 18.57% and 16.39%. Similarly, the traffic utility was increased by 4.26% and 0.57%, the travel costs were reduced by 5.00% and 48.11%, the resource occupancy costs were reduced by 9.69% and 14.10%, and the energy consumption was reduced by 11.68% and 8.73%. The proposed method demonstrates superior performance in optimization, fully indicating it is more suitable for this study.

The optimization model from [2] was solved using the method proposed in this paper, aiming to again verify the validity of the method. The obtained efficiency, carbon emissions, and cost were 2040 thousand people km, 27,544 ton, and 71,354 thousand CNY, respectively. In addition, the values of the objective functions obtained in the original paper were 2052 thousand people km, 28,690 ton, and 72,739 thousand CNY, respectively. Thus, in terms of the efficiency goal, the solution results of the proposed method in this paper and the original method are similar. In terms of carbon emissions and cost, the proposed method solves much better. Therefore, the effectiveness of the proposed method is illustrated to some extent in this example.

The proposed method was used for subsequent analysis. The optimization degree of the proposed method compared with before optimization is depicted in Table 8, which includes the five objective function values and the urban passenger traffic structure.

Table 8. Optimization degree of the proposed method.

Optimization Objective	Carbon Emissions	Traffic Utility	Travel Cost	Resource Occupancy Cost	Energy Consumption
Rate of change	−38.34%	279.73%	−47.96%	−36.16%	−35.66%
Traffic mode	Bus	Subway	Taxi	Private car	
Rate of change	1.05%	36.60%	−11.86%	−25.78%	

The optimized traffic carbon emissions decreased by 38.34% and energy consumption decreased by 35.66%, indicating that the optimized traffic structure meets the energy saving and emissions reduction requirements. The traffic utility was improved by 279.73%, indicating that the optimized scheme greatly satisfies the city's traffic demand. The travel costs were reduced by 47.96%, and the resource occupancy costs were reduced by 36.16%. The necessary transportation costs were effectively reduced for both residents and city managers, contributing to the sustainable development of the passenger traffic structure. The proportion of buses increased by 1.05% compared with before optimization, indicating that buses now occupied a reasonable proportion of the traffic structure and that maintaining the current development pattern would meet the requirements of sustainable urban development. The optimal proportion of subways was 36.60% higher than before optimization, which shows that subways play an important role in building low-carbon urban traffic. The key direction of urban passenger traffic structure optimization was to shift the travel demand toward subways by increasing the proportion of subway trips. The proportions of taxis and private cars decreased by 11.86% and 25.78%, respectively, showing that the inherent characteristics of taxis and private cars violate the principle of the sustainable development of urban transportation. In future, the focus should be on controlling the growth in the number of taxis and private cars and developing reasonable and effective measures to reduce car travel.

Next, the sensitivity of the five objective functions to the four modes of passenger transport was explored by varying the passenger turnover of the four modes. In this paper, four changes in passenger turnover were performed. Based on the passenger turnovers of the four modes obtained using the proposed method, the turnover was reduced by 10%, reduced by 5%, increased by 5%, and increased by 10%, respectively.

First, the passenger turnover of only one mode was changed at a time. According to the expression of the objective function in Equation (16), each objective function was affected by three passenger modes. This paper assumed that the passenger turnovers of the other two traffic modes had reached the optimal ratio. For example, for the objective function of carbon emissions, the proportions of buses, taxis, and private cars were changed. The value of the changed passenger turnover was inserted into Equation (16) to calculate the values of the five objective functions, so the sensitivity of each objective function to each traffic mode was calculated. The sensitivity analysis of each traffic mode is shown in Figure 3. Four different colors are used to represent the four travel modes that affect the objective function. Each objective function is influenced by different travel modes. The slope in the figure represents the change in the value of the objective function caused by the percentage change in the passenger turnover of each traffic mode. The larger the absolute value of the slope, the stronger the sensitivity of the objective function to the corresponding traffic mode.

Figure 3a illustrates that urban carbon emissions are most sensitive to changes in the passenger turnover of private cars. The difference in slope between the three travel modes is substantial. When the passenger turnover of private cars was reduced by 10%, urban carbon emissions decreased by 8.16%, and while the passenger turnover of buses was reduced by 10%, carbon emissions decreased by only 0.74%, indicating that reducing private car travel is the most effective way to reduce carbon emissions. Figure 3b shows that traffic utility is most sensitive to changes in the passenger turnover of the subway. The traffic utility increased by 7.37% when the passenger turnover of the subway increased by 10%, while the traffic utility increased by only 0.75% when the passenger turnover of private cars increased by 10%, indicating that increasing the proportion of subways produces the most significant increase in traffic utility. Similarly, in Figure 3c–e, travel costs, resource occupancy costs, and energy consumption are the most sensitive to changes in the passenger turnover of private cars. When the passenger turnover of private cars decreased by 10%, travel costs, resource occupancy costs, and energy consumption decreased by 5.47%, 7.63%, and 8.66%, respectively. In general, subway travel and private car travel have the greatest impact on urban traffic and should be the focal point in the adjustment of the urban traffic structure.

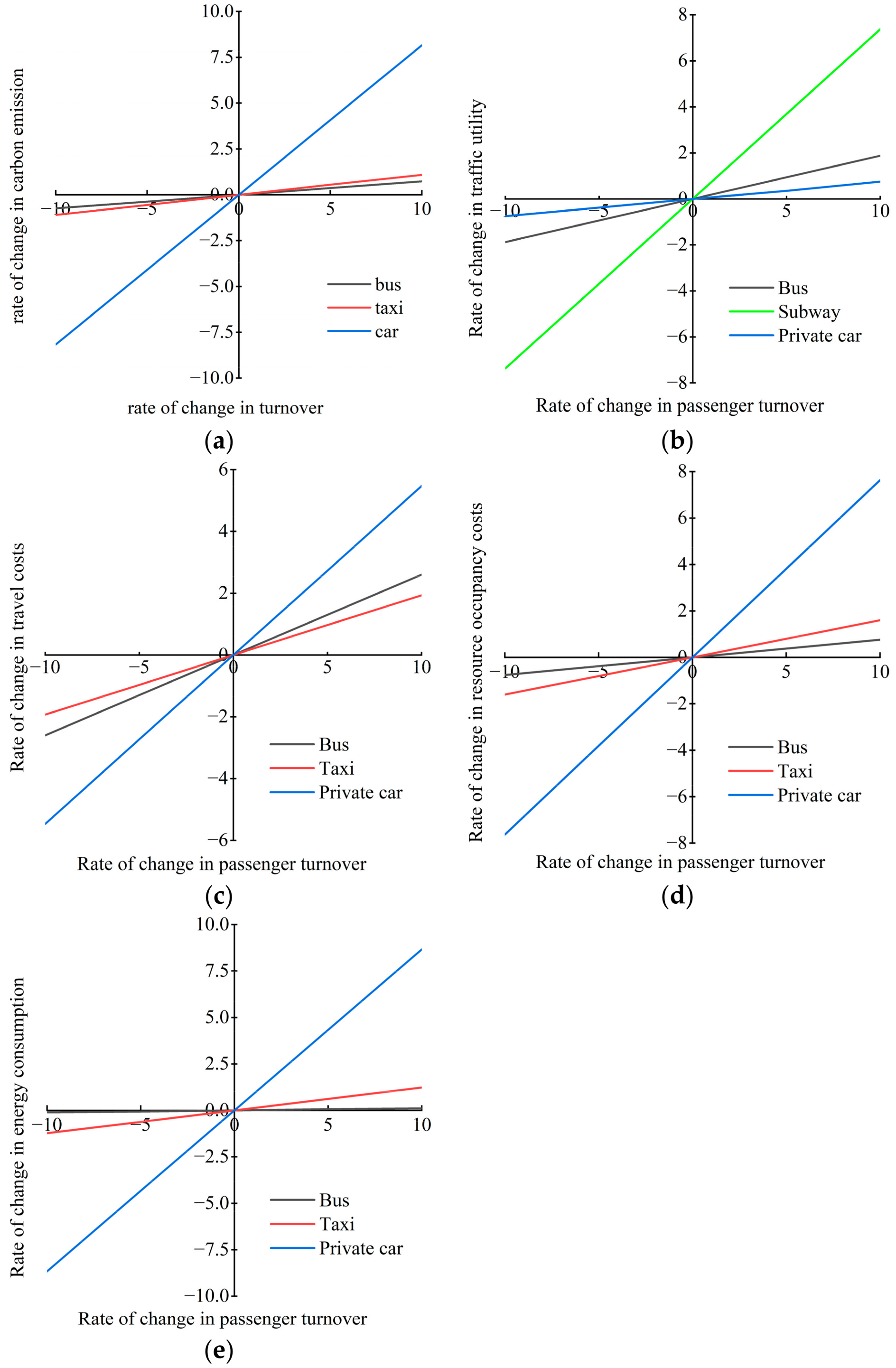

Figure 3. The sensitivity of the five objective functions to each passenger traffic mode. (**a**) Sensitivity of carbon emissions. (**b**) Sensitivity of traffic utility. (**c**) Sensitivity of travel costs. (**d**) Sensitivity of resource occupancy costs. (**e**) Sensitivity of energy consumption.

In the following, the passenger turnovers of two traffic modes were changed simultaneously. The passenger turnover was changed a further four times. Based on Table 6 and Figure 3, buses now occupied a reasonable proportion of the urban traffic structure. The changes in the passenger turnover of buses had little effect on the objective functions. Therefore, for each objective function, the passenger turnovers of the remaining two traffic modes were changed, as shown in the objective function expressed in Equation (16). For example, for carbon emissions, the passenger turnovers of taxis and private cars were changed to analyze the sensitivity (see Figure 4 for details).

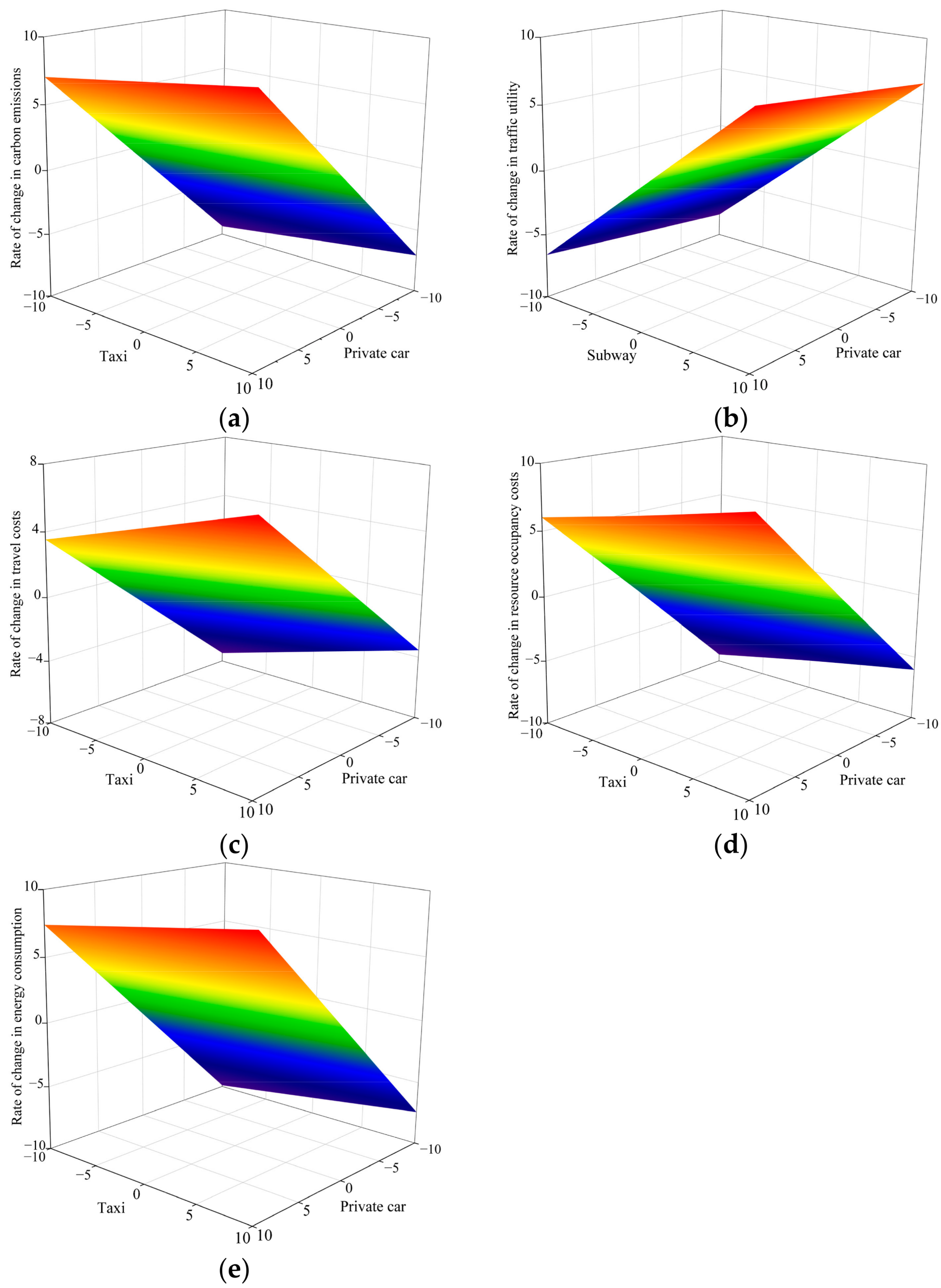

Figure 4. The sensitivities of the five objective functions to two passenger traffic modes simultaneously. (**a**) Sensitivity of carbon emissions to taxis and private cars. (**b**) Sensitivity of traffic utility to subways and private cars. (**c**) Sensitivity of travel costs to taxis and private cars. (**d**) Sensitivity of resource occupancy costs to taxis and private cars. (**e**) Sensitivity of energy consumption to taxis and private cars.

As can be seen in Figure 4a, the colors from blue to red indicate the rate of change in carbon emissions from small to large. The redder the area, the closer the rate of change is to 10%. The bluer the area, the closer the rate of change is closer to −10%. When the passenger turnover of taxis decreased by 10% or increased by 10%, the rate of change in carbon emissions was not significant. When the passenger turnover of private cars decreased by 10%, the color of the corresponding area in the figure is blue, which indicates that the carbon emissions decreased significantly. When the passenger turnover of private cars increased by 10%, the color of the corresponding area in the figure is red, which indicates that the carbon emissions increased considerably. This corresponds to what is shown in Figure 3a.

In terms of the joint role of taxis and private cars (Figure 4a,c–e), carbon emissions and energy consumption are sensitive to both increases and decreases in the passenger turnovers of the two traffic modes. In contrast, travel costs and resource occupancy costs are more sensitive to increases and less sensitive to decreases in the passenger turnovers of taxis and private cars. In other words, reducing the turnover of both taxis and private cars can effectively reduce traffic carbon emissions and energy consumption, while the reduction in travel costs and resource occupancy costs is relatively small. In terms of the joint effect of subways and private cars (Figure 4b), traffic utility is more sensitive to decreases but less sensitive to increases in the passenger turnovers of subways and private cars. In general, optimizing the urban passenger traffic structure can significantly reduce traffic carbon emissions and energy consumption and minimally decrease travel costs and resource occupancy costs.

5. Conclusions and Recommendations

This paper developed a multiobjective urban passenger traffic system structure optimization model and solved it with the ideal point method, the genetic algorithm, and the proposed method. By comparing the results with the urban passenger traffic structure before optimization, the following conclusions are drawn:

(1) The optimized passenger traffic structure and the objective function values showed that the proposed method's performance was superior to the ideal point method's and genetic algorithm's. This proved that the proposed method is more conducive to the city's sustainable development.

(2) In Harbin's optimized passenger traffic system structure, the proportion of subways rose to 40.60%, which was significantly higher than the 4.00% before optimization; the proportion of private cars fell to 27.55%, which was significantly lower than the 53.33% before optimization; the proportion of taxis was reduced to 3.52%, which was much lower than the 15.38% before optimization; and the proportion of buses rose to 28.33%, which was almost unchanged from the 27.28% before optimization. Based on the sensitivity analysis, this paper found that the proportions of subways and private cars had the greatest impact on the sustainable development of urban passenger traffic. Optimizing the passenger traffic structure significantly reduced traffic carbon emissions and energy consumption and was slightly less effective in decreasing travel costs and resource occupancy costs. Therefore, the development of a subway-led travel mode should be the future direction of urban traffic structure, while the government should take measures to control car travel.

(3) In the optimization results, the optimization model designed in this paper satisfied the travel demand and improved the ecological environment while reducing transportation costs for residents and city managers. This indicates that the model has an application value. However, the model in this paper only considers four modes of passenger transport, which may have some limitations. The inclusion of nonmotorized modes of travel could be considered in subsequent studies.

Based on the second conclusion, this paper proposes the following relevant policy recommendations:

(1) Public transport's proportion should be improved, and the urban passenger traffic structure should be tilted toward public transportation modes. The subway has great

development potential, and the government should increase investment in its construction. Moreover, the connection between buses and subways should be strengthened, and city planners need to increase the density of the bus network and the coverage of bus stations. At the same time, preferential public transport policies could be introduced to increase the attractiveness of public transport and encourage the public to adopt green travel modes.

(2) The development of private cars should be limited. Relevant agencies could formulate policies to set the quota amount for residents to purchase cars and adopt purchase restrictions. Thus, they could regulate private car ownership and control it to a level that maximizes social welfare. At the same time, private car owners should be charged taxes and fees to travel, and macro policies such as an odd–even car ban could be conducted to reduce the proportion of car travel.

(3) New energy vehicles should be promoted. The government ought to accelerate the construction of urban charging facilities and carry out new energy vehicle purchase subsidies, tax breaks, and other policies. The use of new energy in buses, taxis, and private cars is expected to be promoted systematically.

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Appendix A

According to the "Urban Road Traffic Planning and Design Code", the occupied road area per capita in the planning year is 13.5 m^2/person. According to the "Guidelines for Heilongjiang Province Comprehensive Grade Separation Traffic Network", the average number of urban residents' trips per day is 2.14. Based on the population, GDP, travel distance, and travel time provided in the "Harbin Statistical Yearbook 2020" and "The Sixth Population Census of Heilongjiang Province", the time value per urban resident is calculated to be 20.08 CNY/h, the average distance of a single trip for urban residents is 6.562 km, and the residents' tolerable time for a trip is 30 min. According to the "Harbin Urban Master Planning", the scale of urban land in the current year is 582.74 km^2, and in the planning year is 640.21 km^2. Concerning the current situation of transportation in developed countries and the "Harbin Economic and Social Development of the 14th Five-Year Plan and 2035 Visionary Goals Outline" and the "Heilongjiang Province Comprehensive Transportation System Development Plan of the 14th Five-Year" constrains the scales of the four traffic modes. The specific scales of the traffic modes and other traffic parameters are shown in Table A1.

Table A1. Traffic parameters of Harbin.

Traffic Mode	Bus	Subway	Taxi	Private Car
c_i	19.8	7.5	140.2	116.9
u_i	0.0429	0.0893	0.0144	0.0237
v_i	12.12	49.81	21.02	21.19
α_i	0.81	1.00	1.07	1.27
β_i	1.00	2.67	20.63	6.22
l_i	7.05	11.62	5.32	11.30
γ_i	0.10	0.12	0.40	0.42
δ_i	98,500	-	98,450	98,460
p_i	34.00	389.78	2.90	2.60
ε_i	0.32	-	0.16	0.62
e_i	0.23	0.21	1.82	1.46
s_i	2.23	0	37.57	34.39
t_i	46	14	31	32
x_{imax}	6685	6515	2261	6658
x_{imin}	3008	882	565	3329

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