A Model for Deployment of Dedicated Connected Autonomous Vehicle Lanes Considering User Fairness

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***Abstract*—The dedicated Connected Autonomous Vehicle (CAV) lanes can avoid the interference of human-driven vehicles and create relatively safe operating conditions for CAVs. Besides, the dedicated CAV lanes can give full advantages of the connectivity and controllability to further improve the capacity of links. However, the consequent problem is unfairness among the traffic network users due to the higher priority right of CAVs in some links. This paper develops a bi-level programming model to design the CAV dedicated lanes deployment scheme considering the user fairness issue. In the lower-level model, we define the road resistance functions under various scenarios by investigating the effect of the dedicated lane on link capacity and construct the traffic assignment model which is solved by the diagonalized Frank-Wolfe method. The upper-level model aims to solve the multi-objective optimization problem that integrates user fairness and total system travel cost. The user fairness problem determines the fairness index using the Wilson entropy model, and the travel cost problem considers different users' travel time value coefficients.**

***Keywords*—user fairness, connected autonomous vehicle, dedicated lane, Wilson entropy model, genetic algorithm**

I. Introduction

Connected Autonomous Vehicles (CAVs) have advantages over conventional Human-Driven Vehicles (HVs) in transportation systems due to their high collaboration, efficiency, and low emissions. But the convergence of CAVs and HVs will cause them to interfere with each other and cause a certain degree of degradation of CAV [1–4]. Deployed dedicated CAV lanes is an effective measure for separating CAV and HV. CAVs can achieve automatic driving with the assistance of communication and roadside facilities on dedicated CAV lanes, which can improve road capacity while minimizing interaction between CAVs and HVs to some extent [5].

Specifically, the program's execution will change right-of-way reallocation in some links, changing the impedance of some links, and so affecting the travel costs of travelers in different Origin and Destination (OD) and the same OD for different modes of travel in the road network. As a result, when establishing dedicated lanes, it is vital to evaluate the influence on the equity of user groups in terms of the logical allocation of transportation resources and public acceptance [6–10]. Among the challenges of deploying dedicated lanes investigated in this study, the main concern is the equity of travel costs for different groups in the transportation network separated by different OD pairs and modes of travel after program adoption [11]. The benefits of lower travel expenses generated by the dedicated lane scenario may be dispersed fairly across OD pairs of traveler groups [12–14].

The contributions of this study are:

- Dividing users into different groups according to OD. Introducing the Wilson entropy model to determine the fairness index of each group.
- Investigating the impact of dedicated lane deployment on lane capacity, deriving the road resistance functions for different scenarios. Deriving the user assignment model from the road resistance function.
- Proposing a multi-objective bi-level programming model for deployment of dedicated CAV lanes considering user fairness. The model can produce multiple sets of Pareto solutions with the same degree of priority for choice.

The rest of this paper is organized as follows: Section II introduces studies on dedicated CAV lanes deployment and traffic equity and identifies the research gaps. The multi-objective bi-level model and solution algorithms are presented in Sections III and IV. Section V shows the numerical experiment, and Section VI concludes the paper and discusses further directions.

II. Literature Review

Most of earlier research on dedicated CAV lane deployment has made choices intending to reduce the overall cost of the transportation system. Chen *et al*. [15] provided a mathematical model with the best location, timing, and number of lanes for CAV lanes to reduce the societal cost. Liu and Song [16] consider a new AV-managed route, an Autonomous Vehicle Toll (AVT) lane. The optimal deployment of dedicated Autonomous Vehicle

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(AV) lanes and AVT lanes in a traffic network with mixed AV and HV flows is also investigated. The attained solution is, without a doubt, ideal. But from a "human-oriented" perspective, the choice about the program's merits should consider transportation equity [17–19].

Hao *et al*. [20] established a two-tier planning model for public transportation networks considering different groups' per capita occupied areas. Litman *et al*. [21] propose the following five principles of equity to be followed in transportation planning or traffic management: treat each person equally; individuals bear their costs; be cumulative in the income dimension; benefit socially disadvantaged groups, and increase the basic accessibility level.

In summary, previous studies on the dedicated CAV lane deployment problem have focused on total system cost as the only optimization objective. In contrast, many scholars emphasize traffic equity issues but rarely consider them in the lane deployment problem [22]. As previously stated, the consideration of traffic fairness has a particular significance and necessity in the issue of dedicated CAV lanes deployment. Therefore, this paper proposes a model for deploying dedicated CAV lanes, considering user fairness.

III. Methodology

A. Basic Assumptions

The following are the basic assumptions made in this article: (1) All vehicles in the traffic network in this study are converted to standard vehicle PCU (passenger car unit), and only two types of vehicles exist, CAV and HV; (2) The Wardrop user equilibrium principle is satisfied; (3) Analyze the case of low CAV penetration and deploy no more than one CAV lane per connection; (4) When dedicated CAV lanes are deployed, all CAVs travel in the dedicated CAV lane.

This paper's essential traffic network components are abstractly expressed as nodes and links. The critical variable notations used hereafter are summarized in Table I to facilitate this presentation.

TABLE I. List of Variables Used in This Paper

Variable	Description
$G(N, A)$	An urban road network G consisting of a set N of nodes and a set A of links
a	A directional link in the road network, $a \in A$
R	The set of all origins
r	A node of origins, $r \in R$
S	The set of all destinations
s	A node of destinations, $s \in S$
M	The set of user travel modes, $M = \{CAV, HV\}$
m	Travel mode, $m \in M$
p_{rs}	A particular path between the origin node r and the destination s;
P	The set of p_{rs}
f_{rs}^{p}	Traffic flow on the path p_{rs}
x_a	Traffic flow on the link a
q_{rs}	Traffic demand of the origin and destination pair (r, s)
$\delta_{a,p}^{rs}$	The link correlation coefficient, which takes 1 if link a is on path p_{rs} between OD pair (r, s) and 0 otherwise

B. Upper-Level Multi-objective Optimization Model

To obtain a dedicated lane deployment scheme that achieves the optimal overall road network travel cost and inter-group traffic equity synergy under specific road network conditions. The proposed multi-objective optimization model is as follows:

$$\min_{y} \begin{pmatrix} Z_f(\boldsymbol{y}) \\ Z_t(\boldsymbol{y}) \end{pmatrix} \tag{1}$$

The variable $\boldsymbol{y}$ in this upper-level model represents a dedicated lane scenario, i.e., a vector of binary decision variables y_a corresponding to implementing all dedicated lane alternative links. The objective function Eq. (1) is a multi-objective optimization that contains the minimum optimization of two different objectives [23].

The cost of deploying CAV dedicated lanes is higher than conventional lanes because it takes the deployment of suitable roadside-related infrastructure and network-linked equipment to realize the network-linked autonomous driving of CAV [24, 25]. The deploying price is:

$$g(\boldsymbol{y}) = \sum_{a \in A} y_a l_a d \tag{2}$$

where y_a is the binary decision variable for deploying dedicated lanes on link a. If $y_a = 1$, dedicated lanes are deploying on link a. If $y_a = 0$, they are not deployed. $\boldsymbol{y}$ is the vector consisting of y_a. d is the construction cost per unit length of CAV lane ($). l_a is the length of the lane (km).

To assess the effect of the dedicated lane deployment scheme on the traffic fairness caused between various OD pairs and groups of different travel modes in the transportation system, the Wilson entropy model is introduced for calculating the fairness evaluation indicators of the transportation system [26]. First, construct the complete evaluation term corresponding to each group as:

$$k_{rs}^{m} = \frac{\beta_{rs} + \frac{G_{rs}^{m}}{a_m s_{rs}^{m}}}{\sum_{m \in M, rs \in W}\left(\beta + \frac{G_{rs}^{m}}{a_m s_{rs}^{m}}\right)} \tag{3}$$

where k_{rs}^{m} is the comprehensive evaluation term of transport mode m on the origin and destination pair (r, s); $\beta_{rs}$is the Group importance coefficient of origin and destination pair (r, s), can be obtained from $\beta_{rs} = \left(\frac{q_{rs}}{\sum_{rs \in W} q_{rs}}\right)^{-\varepsilon_1}$; ε_1 is a parameter reflecting the degree of social awareness of fairness, $\varepsilon_1 \geq 0$; s_{rs}^{m} is the total travel distance of transport mode m on the OD pair (r, s) [km]; G_{rs}^{m} is the total travel time variation for the group of travel modes m in the OD pair (r, s) [min], which can be obtained from $G_{rs}^{m} = \left|t_{rs}^{m} - \widetilde{t_{rs}^{m}}\right|$, where $\widetilde{t_{rs}^{m}}$ denotes the travel time of users with travel modes m in the OD pair (r, s) when the dedicated lane deploying scheme is not implemented; a_m is the coefficient of variation for travel mode m. The coefficient of variation for HV users is 1. The coefficient of variation for CAV users can be obtained from $\alpha_{CAV} = \frac{\eta_{CAV}}{\eta_{HV}}$, where η_m is the value of travel time (VOT) coefficient for travel mode m [$/min]. From this, the fairness index of OD pairs (r, s) in the transportation network can be found as:

$$E_{rs} = 1 - \frac{H_{rs}}{H_{max}} \tag{4}$$

where H_{rs} can be obtained from $H_{rs} = -\sum_{m\in M} k_{rs}^m \ln k_{rs}^m$, H_{max} is the maximum value that can be taken for H_{rs}. According to Eq. (3): $\sum_{m\in M, rs\in W} k_{rs}^m = 1$. When $k = \frac{1}{n}$, we have $H_{max} = \sum_{i=1}^{n} \frac{1}{n} \ln \frac{1}{n} = \ln n$. The value of E_{rs} ranges from 0 to 1. When E_{rs} is equal to 0, it means the most fair ideal state, and the closer E_{rs} is to 1, the more unfair it is.

The model's objective function can be set by taking the most significant value of the fairness index of each OD pair in the road network. This maximum value is minimized, which in turn ensures that the importance of the fairness index of each OD pair is underestimated to achieve the optimal fairness of the whole system [27]. As a result, the optimization objective function $Z_f(\boldsymbol{y})$ can be calculated as follows:

$$\min_{\boldsymbol{y}} Z_f(\boldsymbol{y}) = \min_{\boldsymbol{y}} \max_{rs\in W} E_{rs} \tag{5}$$

On the other hand, reducing the total cost of travel on the road network should also be an optimization goal. Another objective function is:

$$\min_{\boldsymbol{y}} Z_t(\boldsymbol{y}) = \min_{\boldsymbol{y}} \sum_{rs\in W} \sum_{m\in M} t_{rs}^m \eta_m \tag{6}$$

C. Lower-Level Network User Equilibrium Model

The impedance of each networked road segment must be identified before the traffic distribution issue on the road network can be solved. The following describes the BPR function for a classical impedance:

$$t_a = t_a^z \left[1 + \alpha \left(\frac{x_a}{c_a}\right)^{\beta}\right] \tag{7}$$

where t_a^z is the free-flow travel time of link a. x_a is the flow rate of link a. c_a is the capacity of link a. α and β are the calibration parameters of the impedance function, which generally take the values of $a = 0.15$ and $\beta = 4$.

According to Ngoduy *et al.* [28] derivation's procedure, the basic diagram equation may be determined using the steady traffic flow's flow-density-velocity relationship as:

$$q_e = \frac{v_e}{s_e} \begin{cases} \frac{v_z}{s_e}, s_e \geq s_0 + Tv_z \\ \frac{v_e}{s_0 + Tv_e}, s_e < s_0 + Tv_z \end{cases} \tag{8}$$

where v_z is the free-flow speed of the link; s_e is the headway spacing under steady traffic flow; v_e is the steady-state vehicle speed; q_e is the traffic flow rate at steady state; T is a (constant) desired time gap of vehicle; s_0 is the headway when stopping, which can be considered as a fixed value.According to the Eq. (8), the capacity of the road section is:$C_a = \frac{v_z}{s_0 + Tv_z}$.

To investigate whether the dedicated lanes deploying affects the link's ability to resist traffic, the desired time gap of the link must first be established. As indicated in Fig. 1. Car-following modes can be divided into four categories: CAV following CAV, CAV following CAV, HV following CAV, and HV following HV [5]. When the front and rear vehicles are all CAVs, the vehicles can share information among themselves in real-time and form a convoy, and the desired time gap T_{cc} is minimal. When the CAV is following the HV, because it is equipped with intelligent sensing measures, it can get the speed change of the car in front of it faster than the HV and give the corresponding response more quickly, so the desired time gap in this case T_{ch} is relatively small [29, 30]. The time gap relationships for the four car-following types are $T_{cc} < T_{ch} < T_{hc} = T_{hh}$, from this, two ratios θ_1, θ_2 can be defined such that $T_{cc} = \theta_1 T_{hh}$ and $T_{ch} = \theta_2 T_{hh}$, it is clear that $\theta_1 < \theta_2 < 1$.

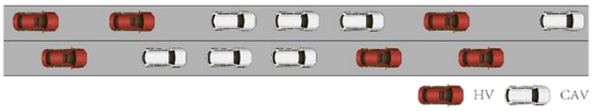

Figure 1. Vehicle following in mixed traffic flow.

Assuming that the proportion of autonomous vehicles in the mixed traffic flow of the link is ρ_c, the probability of generating the four following modes can be obtained as follows: ρ_c^2, $\rho_c(1-\rho_c)$, $(1-\rho_c)\rho_c$ and $(1-\rho_c)^2$, Then the desired time gap when there is no dedicated lane is:

$$T = \rho_c^2 T_{cc} + \rho_c(1-\rho_c)T_{ch} + (1-\rho_c)\rho_c T_{hc} + (1-\rho_c)^2 T_{hh} = (\rho_c^2\theta_1 + \rho_c(1-\rho_c)\theta_2 + (1-\rho_c))T_{hh} \tag{9}$$

In consequence, it is deduced that the capacity of the lane is: $C_a^M = \frac{v_z}{s_0 + (\rho_c^2\theta_1 + \rho_c(1-\rho_c)\theta_2 + (1-\rho_c))T_{hh}v_z}$. Given that link a has k lanes, it is possible to calculate the road resistance function without dedicated lanes as:

$$t_a^M = t_a^z \left[1 + \alpha \left(\frac{x_a}{kC_a^M}\right)^{\beta}\right] \tag{10}$$

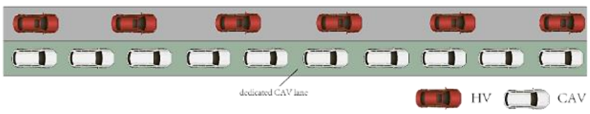

Figure 2. Vehicle following after deploying the dedicated lanes.

When the CAV lane is deployed, as shown in Fig. 2, there are only two following modes in the link, HV following HV in the general lane and CAV following CAV in the CAV lane. The ratio of the two modes is $(1-\rho_c)$ and ρ_c respectively, so the desired time gap of the CAV lane is $T = \rho_c\theta_1 T_{hh}$. The capacity of the CAV lane can be obtained as $C_a^D = \frac{v_z}{s_0 + \rho_c\theta_1 T_{hh} v_z}$ .Similarly, the road resistance function of the CAV dedicated lane can be deduced as follows:

$$t_a^D = t_a^z \left[1 + \alpha \left(\frac{x_a\rho_c}{C_a^D}\right)^{\beta}\right] \tag{11}$$

The desired time gap of the general lane at the time of the dedicated lane is $T = (1-\rho_c)T_{hh}$, so the capacity of the general lane on the link with the dedicated lane is $C_a^N = \frac{v_z}{s_0 + (1-\rho_c)T_{hh}v_z}$. Similarly, when the dedicated lane is deployed, we can calculate the road resistance function of the general lane as follows:

$$t_a^N = t_a^z \left[1 + \alpha \left[\frac{x_a(1-\rho_c)}{(k-1)C_a^N}\right]^\beta\right] \quad (12)$$

The low-level model expresses the user's travel behavior in the bi-level programming model for the dedicated lanes deployment problem. The Wardrop equilibrium principle has been considered to be satisfied by the traffic network under study in this research in the previous model assumptions. Therefore the traditional UE model may be created as follows:

$$\min Z(x) = \sum_{a\in A_M} \int_0^{x_a} t_a^M(x)dx + \sum_{a\in A_D} \int_0^{x_a\rho_c} t_a^N(x)dx + \sum_{a\in A_D} \int_0^{x_a(1-\rho_c)} t_a^D(x)dx) \quad (13)$$

In summary, the following multi-objective programming model for the deployment of dedicated CAV Lanes considering fairness can be constructed as:

$$\min_{\boldsymbol{y}} \begin{pmatrix} Z_f(\boldsymbol{y}) \\ Z_t(\boldsymbol{y}) \end{pmatrix} \quad (14)$$

$$s.t. y_a = \{0,1\}, \forall a \in A \quad (15)$$

$$g(\boldsymbol{y}) \le B \quad (16)$$

$$\min Z(x) = \sum_{a\in A_M} \int_0^{x_a} t_a^M(x)dx + \sum_{a\in A_D} \int_0^{x_a\rho_c} t_a^N(x)dx + \sum_{a\in A_D} \int_0^{x_a(1-\rho_c)} t_a^D(x)dx) \quad (17)$$

$$\text{s.t.} \quad \sum_{p\in P} f_p^{rs} = q_{rs}, \forall r, s \quad (18)$$

$$f_p^{rs} \ge 0, \forall p, r, s \quad (19)$$

$$x_a = \sum_{r\in R} \sum_{s\in S} \sum_{p\in P} f_p^{rs} \delta_{a,p}^{rs}, \forall a \in A \quad (20)$$

The model can be intuitively understood as the decision maker at the upper-level formulates the road network improvement plan $\boldsymbol{y}$ based on the construction investment constraint Eq. (17). The traffic flow on the road network is reallocated under the travel destination selection behavior and the traveler's optimal path selection behavior constraint Eqs. (18), (19) and (20). Then the obtained results, including path flow and OD to travel time allocation, are returned to the upper layer model so that the optimal upper layer objective Eq. (14) is finally achieved through repeated adjustments.

IV. Solution Algorithms

Because the problem to be solved in this paper is a multi-objective problem, the NSGA-II algorithm, based on genetic algorithms, can be used to solve the model in the paper [31]. The algorithm flow is shown in Fig. 3.

For the user equilibrium assignment problem of mixed traffic flow, the diagonalized Frank-Wolfe algorithm is adopted to solve the problem as follows [32]:

Algorithm 1: Diagonalized Frank-Wolfe Algorithm

Input the road network G(N,A), CAV dedicated lane deployment scheme, and Frank-Wolfe algorithm parameters.

According to the given CAV lane deploying scheme, the impedance and other attributes of the corresponding lanes are changed, and the all-or-nothing assignment is executed for users of different travel modes in the changed road network.

Obtain the road network traffic Q_m^n, set the number of iterations n=0, and divide the two types of traffic flows into two subproblems for traffic assignment.

Solve the equilibrium problem for two different types of users with varying modes of travel separately. When solving the equilibrium for a kind of user, first determine the equilibrium traffic of another type of user as the background traffic, and then solve the equilibrium traffic of that type of user with the Frank-Wolfe algorithm, which can obtain the equilibrium traffic vector of the link Q_m^{n+1}.

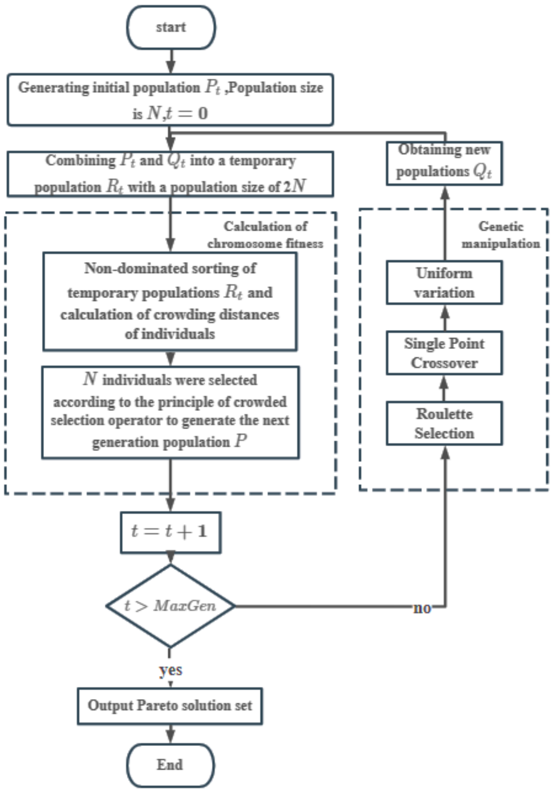

Figure 3. Algorithm flow.

V. Numerical Examples

The suggested model and algorithm are applied to the Nguyen-Dupuis network to validate its viability and efficacy [33]. 13 nodes, 19 links, and 4 OD pairs comprise the network examined in this research, which is shown in Fig. 4. 800, 800, 600, and 600 vehicles/h, respectively, are the travel demands for OD pairings (1,12), (1,13), (3,12), and (3,13), where it is expected that CAV vehicle penetration in all OD pairs is 50%. Table II displays the parameters of the BPR function with the Nguyen-Dupuis network features. This includes the number of lanes, length of the pathL_a (km), and free flow travel time of the lane t_a^z (min).

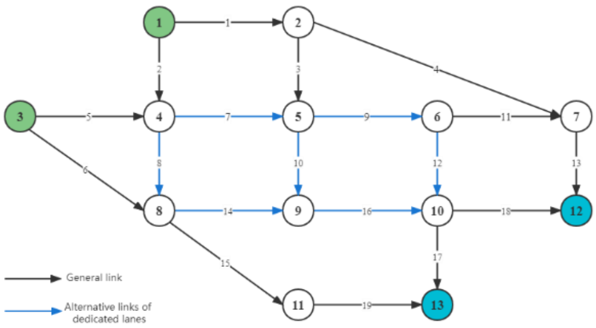

Figure 4. Nguyen-Dupuis Network.

TABLE II. NGUYEN-DUPUIS NETWORK PROPERTIES

Link	t_a^z	lanes	L_a	link	t_a^z	lanes	L_a
1	9	3	5.4	11	2	3	11
2	7	4	4.2	12	9	4	12
3	7	3	4.2	13	9	3	13
4	14	2	8.4	14	10	4	14
5	9	3	5.4	15	9	2	5.4
6	12	3	7.2	16	6	4	3.6
7	3	4	1.8	17	5	3	3
8	9	3	5.4	18	9	4	5.4
9	5	3	3	19	11	3	6.6
10	13	3	7.8				

The values of the parameters in the model and algorithm are given in Table III below.

TABLE III. MODEL AND ALGORITHM PARAMETER VALUES

Parameter Name and Unit	Value
B ($)	3,300,000
d	8760
ε_1	0.2
η_{hv} ($/min)	0.5
η_{cav} ($/min)	0.4
ρ_c	0.5
T_h (s)	2
θ_1	0.3
θ_2	0.6
v_z (km/h)	60
s_0 (m)	7
ε_2	1

The multi-objective optimization problem's Pareto solution set is obtained using the algorithm described in the preceding link, which has nine solutions, with the dedicated lanes deploying scheme corresponding to each Pareto solution shown in Table IV below.

TABLE IV. PARETO SOLUTION SET CORRESPONDING TO THE DEDICATED LANE DEPLOYING THE SCHEME

	Alternative Link dedicated Lanes Deploying						
Solution	**7**	**8**	**9**	**10**	**12**	**14**	**16**
1	0	1	1	1	1	0	1
2	1	1	1	1	1	1	1
3	1	1	0	1	1	0	1
4	0	1	0	1	1	1	1
5	1	1	1	0	1	0	1
6	0	1	0	1	1	1	0
7	0	1	0	1	1	0	1
8	1	1	0	0	1	0	0
9	1	0	0	1	1	0	0

As shown in Fig. 5, the amount of change in the average travel time of each OD pair of HV users generated by the nine scenarios is plotted as a bar graph. The values of the fairness index corresponding to the nine scenarios are plotted as a line graph. It can be noted that the fairness indexes reaching plans with a more significant difference in the change in travel time of each OD pair are similarly higher. They indicate that the fairness indexes generated by the Wilson entropy model may effectively capture the fairness of each OD pair.

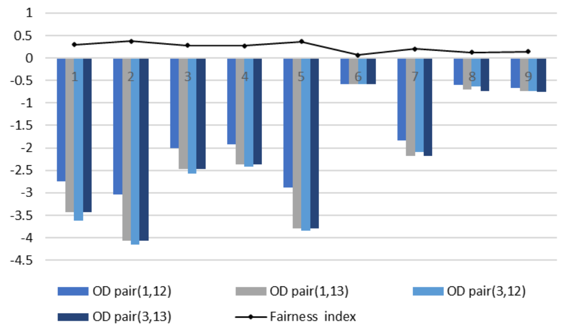

Figure 5. Amount of travel time variation and road network fairness index of OD pairs.

The scatter plot is drawn with the total system travel costs of the road network as the horizontal coordinate, the road network fairness index as the vertical coordinate, and the data in it is fitted to obtain the fitted curve of the quadratic polynomial, as shown in Fig. 6. It can be seen that each Pareto solution have the non-dominated nature. The decision-makers can compare the solutions in the Pareto solution set horizontally based on their focus on different aspects and select a more suitable solution for deploying dedicated lanes under careful consideration of road network performance, traffic fairness, and constructability.

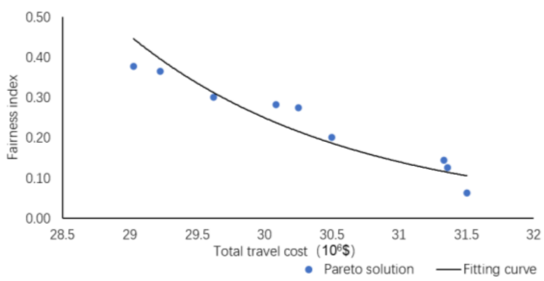

Figure 6. Distribution of Pareto solution set.

The CAV penetration and desired time gap ratios (θ_1) were subjected to a sensitivity analysis.

Since the optimal solution of multi-objective optimization is a solution set, the penetration rate is made to take four values of 10%, 30%, 50%, and 70%, and the remaining parameters are referred to in Table III. As seen in Fig. 7(a), the total travel cost decreases with the increase of CAV penetration, which is because with the rise of CAV penetration the advantage brought by the dedicated lanes deployment will be more obvious. However, the fairness level corresponding to the Pareto solution with the optimal fairness index is no significant correlation with the value of CAV penetration.

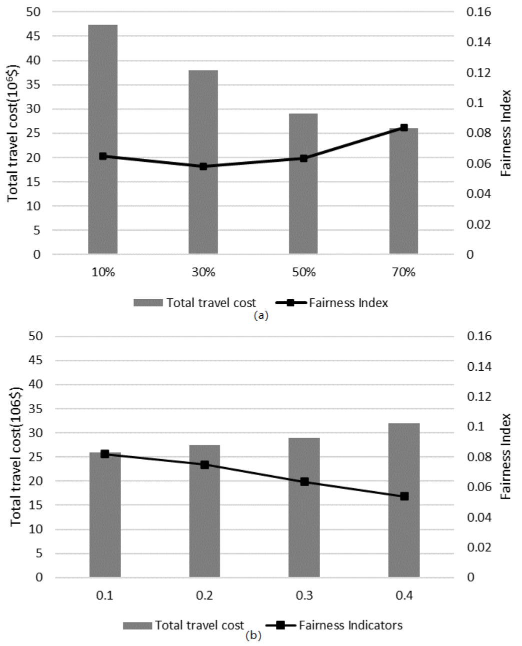

Figure 7. System travel cost and fairness for different CAV penetration rates and desired time gap ratios.

In the analysis of the desired time gap ratios, i.e., the effect of θ_1 on the results, four values of 0.1, 0.2, 0.3, and 0.4 are taken. Fig. 7(b) shows that as the CAV safety headway increases, the travel cost of the road network also increases. This phenomenon is most likely because the Wilson entropy model considers the difference in travel costs between different modes of transportation within the same OD group. The higher the value, the less significant the advantage of CAV over HV, resulting in a more significant minor difference between groups.

VI. Conclusion

In this paper, a genetic algorithm is used to solve a multi-objective bi-level programming model for the dedicated CAV lane deployment problem, which considers the fairness of user groups in the traffic network. The model's Pareto solution set contains several solutions with the exact optimality. Decision-makers can select the appropriate CAV lane solution for road network improvement based on the current situation and focus direction after integrating total travel cost, traffic equity, and construction investment cost. In addition, the research conducts a sensitivity analysis for CAV penetration rate and desired time gap ratios to determine the changing pattern of the two objective functions under different situations.

However, there are limitations in this study. The assumptions in this paper are idealized: All vehicles are converted to standard vehicle PCU, all CAVs travel in the dedicated CAV lane. which is not in line with the actual situation of the road network. Therefore, the feasibility of the model needs to be further verified.

This paper focuses on the selection of dedicated lane deployment options considering fairness. In the subsequent study, the introduction of relative deprivation principle is considered to further explore the conditions of dedicated lane installation. That is, whether to consider the deployment of dedicated lanes under certain conditions of cav market penetration, traffic flow density, etc.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Hongfei Jia and Yunpeng Qi conducted the research; Chao Liu and Ruiyi Wu analyzed the data; Yunpeng Qi and Chao Liu wrote the paper; all authors had approved the final version.

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