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Research Article

Characteristics Analysis and Equilibrium Optimization of Mixed Traffic Flow considering Connected Automated and Human-Driven Vehicles

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Considering the impact of informatization condition, vehicles on the road network are divided into connected automated vehicles (CAVs) and human-driven vehicles (HDVs), which follow the principle of system optimization and stochastic user equilibrium, respectively. Taking the road network reserve capacity maximization model under the condition of road capacity constraint as the upper-level programming and the traffic assignment model under heterogeneous flow environment as the lower level programming, then a bilevel programming model is constructed. Among them, the nonuniform demand growth multiplier is adopted for each OD pair to reflect the inconsistency of traffic demand structure growth, and the calculation of link capacity is related to the market penetration of CAVs. The incremental method, method of successive averages, and simulated annealing algorithm are used to solve the model, and the effects of different market penetration on road network capacity, travel time, and saturation are analyzed through a numerical example. The relevant data under different weights are normalized and the optimal deployment scheme of CAVs and HDVs in different periods is obtained by comprehensive evaluation. Meanwhile, the mixed equilibrium flow state is explored under the premise of given market penetration to verify the feasibility of the model and algorithm.

1. Introduction

In the background of increasing traffic pressure and continuous progress of science and technology, the intelligent transportation system emerges at the historic moment and has achieved unprecedented progress in the field of transportation. High-end chips, 5G communication, and other new generations of information technology have been booming. The prospect of unmanned driving is so promising that it is bound to be an upcoming travel necessity. In recent years, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) technologies have matured [1] and connected automated vehicle (CAV) technology has witnessed unprecedented development. There is an emerging trend of CAVs related studies. Milakis et al. [2] did a comprehensive review to explore the potential effects of automated driving on policy and society. Noruzoliaee et al. [3] determined the optimal purchase price of autonomous vehicles from the perspective of the manufacturer, considering vehicle type and route choice behavior.

Compared with human-driven vehicles (HDVs), CAVs can obtain extensive benefits in traffic capacity [4], travel safety [5], energy consumption [6], and exhaust emission. However, before HDVs are completely eliminated, the traffic flow in the road network will still be heterogeneous traffic flow composed of HDVs and CAVs. It is necessary to analyze how to make traffic flow reach equilibrium under the mutual influence. The concept of mixed traffic equilibrium has been mentioned in earlier literature. Haurie and Marcotte [7] illustrated the coexistence of competitive and cooperative traffic flows. Wang et al. [8] formulated two bilevel programs to study the network reserve capacity with the SUE principle and resolved it via sensitivity analysis. Ryu et al. [9] launched traffic assignment under capacity constraints in combination with stochastic utility theory and settled the model by combining the equilibrium iteration method and column generation method. Huang et al. [10] established a stochastic assignment model for travelers' path selection on the basis of the disequilibrium theory, which was verified by model simulation. Bagloee et al. [11] established a mixed equilibrium model in which connected vehicles and other vehicles adhere to the system optimal principle and the user equilibrium principle, respectively, while the practical features, for instance, road capacity, elastic demand, and travel time are explicitly considered.

The concept of mixed traffic equilibrium is not new in the literature, scholars have conducted extensive and in-depth research on mixed traffic flow, and different types of vehicles follow corresponding principles to select paths and achieve equilibrium under mutual influence. However, most studies only consider two types of vehicles (CAVs and HDVs). In fact, for the existing HDVs, travelers can obtain comprehensive, efficient, and real-time traffic information via advanced traveler information systems (ATIS) devices and assist travelers in choosing travel time and route. With the emergence of ATIS, scholars have researched its impact on traffic flow. Vuren and Watling [12] upheld that the system optimum (SO) principle can be realized through ATIS route guidance. Yang and Meng [13] proposed a modified logistic growth model to investigate the adoption rate of ATIS. Yin and Yang [14] categorized travelers according to with or without ATIS, selected paths in conformity with stochastic user equilibrium (SUE), and analyzed market penetration rate and compliance rate. Bifulco et al. [15] constructed an assignment model for ATIS to analyze the stability of traffic equilibrium. Dell'Orco et al. [16] proposed the dynamic model of driver's information compliance to represent the dynamic selection behavior of the driver in ATIS. The above studies are only for HDVs, the adoption rate of ATIS devices is analyzed, and the traffic assignment model is constructed.

Under the background of the intelligent network, a well-designed planning and operation strategy for CAVs based on estimated network flows is of crucial importance during the coexistence period of CAVs and HDVs, so as to realize maximum operation efficiency. Relevant research is mainly focused on topics such as road network capacity, market penetration, and lane management. First, traffic congestion, primarily caused by the mismatch between traffic demand and supply [17], has become a thorny problem in metropolises around the world [18]. Traffic congestion can be alleviated from the level of traffic supply. As one of the important basic data of traffic supply, road network capacity is a key index of traffic planning and management. It could be regarded as the maximum sum of throughput of all OD pairs under the constraint of link capacities [19]. Modeling and analysis of road network capacity can predict the maximum number of trips that the road network can be satisfied and evaluate the network performance of the road system. Based on this, scholars regard road network capacity as a key indicator to measure the performance of traffic system under CAV environment. Levin and Boyles [20] presented a multiclass traffic assignment model by considering the influence of the proportion of CAVs on road capacity. Van den Berg and Verhoef [21] adopt a dynamic equilibrium model to investigate the effect of CAVs on congestion and confirm that CAVs can improve road capacity and reduce bottleneck externality. Noruzoliaee et al. [3] presented that CAVs can reduce the value of travel time by making in-vehicle time more efficiently and increase road capacity through smaller headway. Second, despite the rapid technological development, there is still a long time to go before the CAVs dominate the full market. In this context, considering the market penetration, heterogeneous traffic flow consisting of CAVs and HDVs is more plausible for the foreseeable future. As a critical factor affecting the road network capacity in the mixed traffic, many scholars have conducted researches based on the market penetration. Lavasani et al. [22] constructed a market penetration model for CAVs based on existing technologies and conducted sensitivity analysis from two aspects of scale and price. Li et al. [23] deliberated the nonlinear change in road capacity with increasing penetration rate of autonomous vehicles to investigate the impacts of mixed flow conditions. Chen et al. [24] proposed formulations for the capacity of mixed traffic in equilibrium state that takes autonomous vehicle market penetration rate into account. Furthermore, several researches also pointed out that through lane management, the operation efficiency of CAV can be better improved by transforming traditional lanes into CAV dedicated lanes. Ghiasi et al. [25] developed a compact lane management model to efficiently determine the optimal number of CAV exclusive lanes to maximize the HDVs and CAVs mixed flow. Chen et al. [26] presented a framework for the optimal design of CAV zones to adapt to and further promote the deployment of CAV technology. Amirgholy et al. [27] designed the optimal lane management strategy for the heterogeneous traffic condition to reduce the experienced delay.

To sum up, scholars have explored the mixed traffic flow of CAVs and HDVs, followed the principles of SO, UE, or SUE, and discussed the optimization design under the mixed equilibrium state. However, few scholars further subdivided HDVs according to the presence of ATIS devices. Meanwhile, most of the literature shows that the application of CAVs will affect road capacity but usually only analyze the increasing effect of CAVs on lane capacity, without considering the impact on the entire road network capacity. Some scholars have revealed the change process of road network capacity, but generally all OD pairs adopt the uniform demand growth multiplier, and the impact of each OD pair with different demand growth multiplier on the road network reserve capacity is rarely studied. Therefore, it is necessary to fully research the road network capacity under different traffic demands and market penetration rates.

On the basis of the above work, the vehicles on the road network in this paper are divided into CAVs and HDVs, which assumed that the two types of vehicles follow the principles of SO and SUE, respectively. Among them, HDVs are further subdivided considering whether the ATIS device is available, where HDVs-I and HDVs-II represent HDVs with ATIS devices and HDVs without ATIS devices, respectively. A bilevel programming model of mixed traffic flow with nonuniform demand growth multiplier is constructed to maximize the reserve capacity of road network under the condition of the link capacity constraints. The Nguyen-Dupuis network is adopted to explore the influence of diverse market penetration on road network capacity, travel time, and saturation. The optimal deployment scheme of CAVs and HDVs is formulated by analyzing the characteristics of road network, and the mixed equilibrium state of road network is verified.

The remainder of this paper is organized as follows. Section 2 formulates a bilevel model to maximize the travel demand considering link capacity with equilibrium constraints. Section 3 describes the solution procedures for the bilevel programming model. In Section 4, a numerical example is used to discuss the influence of market penetration on transportation equilibrium assignment and illustrate the effectiveness of the proposed model. Section 5 summarizes the finding in this paper and points out the potential future work.

2. The Bilevel Planning Model

2.1. Notation. In Table 1, we summarize the notations commonly used in this paper, and other notations are explained when they are used.

2.2. The Upper Level Model. The upper-level optimization objective is to maximize the traffic travel volume of the road network, different OD pairs adopt nonuniform demand growth multiplier, and the constraint condition is the link capacity, predicting the maximum demand that the road network can accommodate.

$$\begin{aligned} &\max \sum_{w\in W} \mu_w q_w, \\ &\text{s.t. } x_a(\boldsymbol{\mu}\mathbf{q}) \le C_a, \quad \forall a \in A. \end{aligned} \tag{1}$$

2.3. The Lower Level Model

2.3.1. Traffic Assignment Model of Connected Automated Vehicles. The planning model of CAVs is constructed according to the SO assignment model, and the system optimization can be achieved when the marginal travel time function is adopted to carry out the user optimal flow assignment. The specific planning model is as follows:

$$\min Z_1(X_1) = \sum_{a\in A} x_{a,1} t_a(x_{a,1}) = \sum_{a\in A} \int_0^{x_{a,1}} \bar{t}_a(\omega)\mathrm{d}\omega, \tag{2}$$

$$\text{s. t. } q_{w,1} = \alpha\mu_w q_w, \tag{3}$$

$$\sum_k f_k^{w,1} = q_{w,1}, \quad \forall w \in W, \tag{4}$$

$$x_{a,1} = \sum_w \sum_k f_k^{w,1}\delta_{a,k}^w, \quad \forall a \in A, \tag{5}$$

$$f_k^{w,1} \ge 0, \quad \forall w \in W, k \in K. \tag{6}$$

2.3.2. Traffic Assignment Model of Human-Driven Vehicles. The planning model of HDVs is constructed according to the SUE assignment model, and considering whether the ATIS device is available, the corresponding information quality level is different. The specific planning model is as follows:

$$\begin{aligned} \min Z_2(X_2) = &\sum_{a\in A} \int_0^{x_{a,2}} t_a(\omega)\mathrm{d}\omega + \frac{1}{\theta_1}\sum_w\sum_k f_k^{w,3}\ln f_k^{w,3} \\ &+ \frac{1}{\theta_2}\sum_w\sum_k f_k^{w,4}\ln f_k^{w,4}, \end{aligned} \tag{7}$$

$$\begin{aligned} \text{s.t. } & q_{w,2} = (1-\alpha)\mu_w q_w, \\ & q_{w,3} = \beta q_{w,2}, \\ & q_{w,4} = (1-\beta) q_{w,2}, \end{aligned} \tag{8}$$

$$\begin{aligned} &\sum_k f_k^{w,2} = q_{w,2}, \\ &\sum_k f_k^{w,3} = q_{w,3}, \\ &\sum_k f_k^{w,4} = q_{w,4}, \quad \forall w \in W, \end{aligned} \tag{9}$$

$$x_{a,2} = \sum_w \sum_k f_k^{w,2}\delta_{a,k}^w, \quad \forall a \in A. \tag{10}$$

$$\begin{aligned} & f_k^{w,2} \ge 0, \\ & f_k^{w,3} \ge 0, \\ & f_k^{w,4} \ge 0, \\ & \forall w \in W, \\ & k \in K, \end{aligned} \tag{11}$$

where θ_1 represents the quality level of travel information received by drivers with ATIS device, and θ_2 represents the familiarity of drivers without ATIS device to road networks. In general, θ_1 is greater than θ_2.

Table 1: Notation summarization.

Notations	Definitions
Sets	
N	Set of nodes
A	Set of links
K	Set of paths
T	Set of vehicle types: type 1 denotes CAVs, type 2 denotes HDVs, type 3 denotes HDVs-I, type 4 denotes HDVs-II
W	Set of origin-destination (OD) pairs
R	Set of origin nodes and $R \subset N$
S	Set of destination nodes and $S \subset N$
Parameters	
a	Index of link, $a \in A$
k	Index of path, $k \in K$
τ	Index of vehicle types, $\tau \in T$
w	Index of OD pairs, $w \in W$
$\delta_{a,k}^{w}$	Link–path incidence that equals 1 if link a belongs to path k between OD pair $w \in W$ and 0 otherwise.
C_a	Capacity of link a
L_a	Length of link a
α	Market penetration of CAVs among all vehicles
β	Market penetration of ATIS vehicles among human-driven vehicles
Variables	
μ_w	Multiplier of travel demand growth between OD pair $w \in W$
q_w	Basic travel demand between OD pair $w \in W$
$q_{w,\tau}$	Basic travel demand of vehicle types $\tau \in T$ between OD pair $w \in W$
x_a	Traffic flow on link a
$x_{a,\tau}$	Traffic flow of vehicle types $\tau \in T$ on link $a \in A$
f_k^w	Traffic flow on path k between OD pair $w \in W$
$f_k^{w,\tau}$	Traffic flow of vehicle types $\tau \in T$ on path k between OD pair $w \in W$
$t_a(x_a)$	Travel time on link a
c_k^w	Actual travel time on path k between OD pair $w \in W$, i.e. $c_k^w = \sum_{a\in A} t_a(x_a)\delta_{a,k}^w$
$\bar{t}_a(x_a)$	Marginal travel time on link a

2.3.3. Traffic Assignment Model of Mixed Equilibrium. CAVs and HDVs are mixed in the road network according to different path selection principles. Among them, the former follows the principle of system optimization, and the flow of HDVs is taken as the background flow, while the latter follows the principle of stochastic user equilibrium and the flow of HDVs is regarded as the background flow. Considering the influence of information conditions, the SO-SUE mixed equilibrium traffic assignment model is constructed as follows:

$$\begin{aligned} \min Z(X) = {} & \sum_{a\in A} \int_0^{x_{a,1}} \bar{t}_a\left(x_{a,2}+\omega\right)\mathrm{d}\omega \\ & + \sum_{a\in A} \int_0^{x_{a,2}} t_a\left(x_{a,1}+\omega\right)\mathrm{d}\omega \\ & + \frac{1}{\theta_1}\sum_w \sum_k f_k^{w,3} \ln f_k^{w,3} \\ & + \frac{1}{\theta_2}\sum_w \sum_k f_k^{w,4} \ln f_k^{w,4}, \end{aligned} \tag{12}$$

s.t., (3)–(6) and (8)–(11).

3. Solution Algorithm of the Programming Model

Different demand growth multipliers are adopted in each OD pair and the upper model is a nonconvex function. It is difficult to obtain the optimal solution by conventional numerical optimization methods. The incremental method, method of successive averages (MSA), and simulated annealing algorithm (SAA) are adopted to solve the established bilevel programming model. The concept of SAA is based on the principle of solid annealing. Under the action of high temperature, the particles move relatively freely and disorderly, and the probability of accepting the inferior solution is large. With the continuous decrease of temperature, an ordered state is gradually formed, the probability of receiving a poor solution is reduced, and the global optimal solution of the objective function is randomly searched. The temperature is an important factor affecting the global search performance of SAA. The initial temperature should be set sufficiently large to ensure a wide search range of the algorithm, and the minimum temperature usually takes a small decimal. The temperature change rate is mainly used to control the annealing speed. In practical applications, it is generally taken as 0.95~0.99. In addition, the Metropolis criterion accepts the nonoptimal solution with a certain probability, which is the key for SAA to jump out of the local optimality and converge to the global optimality. The specific steps of the algorithm are as follows.

Step 1. Set the initial temperature T_0, minimum temperature $T_{\min}$, temperature change rate ΔT, let the current temperature $T = T_0$, take the initial travel demand growth multiplier as the initial solution **S**, and take the total initial travel demand as the objective function $F(\mathbf{S})$, the vector of nonuniform demand growth multiplier step is set as $\Delta\mu$, the number of iterations $k = 1$.

Step 2. Randomly select the value in vector $\Delta\mu$ as the demand growth multiplier step for each OD pair $\Delta\mu_w$, then generate a new solution S'.

Step 3. According to the known road network information, the basic travel demand of OD pair $w \in W$ is given as q_w, the nonuniform demand growth multiplier step is set as $\Delta\mu_w$, and initialize μ_w, i.e. $\mu_w(1) = \mu_0$, $n = 1$.

Step 4. In accordance with the given $\mu_w(n)$, the lower mixed equilibrium traffic assignment model is solved, and the link flow $x_a(n)$ is obtained.

(4.1) The travel flow is divided according to the market penetration of different vehicles, and the travel flow of CAVs, HDVs, HDVs-I, and HDVs-II can be obtained as $q_{w,1} = \alpha\mu_w q_w$, $q_{w,2} = (1-\alpha)\mu_w q_w$, $q_{w,3} = \beta q_{w,2} = (1-\alpha)\beta\mu_w q_w$, $q_{w,4} = (1-\beta)q_{w,2} = (1-\alpha)(1-\beta)\mu_w q_w$, $\forall w \in W$, respectively.

(4.2) Let the flow on each link be zero, and the free flow travel time of each link is obtained as $t_a^{(0)} = t_a(0)$. The all or nothing traffic flow assignment is carried out on $q_{w,1}$, and the stochastic traffic flow assignment is carried out on $q_{w,3}$ and $q_{w,4}$. Then the flow of CAVs, HDVs-I and HDVs-II can be, respectively, obtained as $x_{a,1}^{(m)}$, $x_{a,3}^{(m)}$ and $x_{a,4}^{(m)}$, respectively, so as to obtain the link flow $x_a^{(m)} = x_{a,1}^{(m)} + x_{a,2}^{(m)} = x_{a,1}^{(m)} + x_{a,3}^{(m)} + x_{a,4}^{(m)}$, and let the iteration number $m = 1$.

(4.3) The new actual travel time of the link is calculated according to the link flow, i.e. $t_a^{(m)} = t_a(x_a^{(m)})$, $\forall a \in A$.

(4.4) According to the marginal cost function and in combination with the link travel time calculated in step 2.3, the marginal travel time of the link is calculated as $\bar{t}_a^{(m)} = t_a^{(m)} + x_{a,1}^{(m)}(\mathrm{d}t_a^{(m)}/\mathrm{d}x_{a,1}^{(m)})$. The all or nothing traffic flow assignment is carried out on $q_{w,1}$, the additional traffic flow of each link $y_{a,1}^{(m)}$ is obtained, and then the search direction $d_{a,1}^{(m)} = y_{a,1}^{(m)} - x_{a,1}^{(m)}$ is determined. The weighted average method is adopted to update the link traffic flow, i.e. $x_{a,1}^{(m+1)} = x_{a,1}^{(m)} + 1/m(y_{a,1}^{(m)} - x_{a,1}^{(m)})$.

(4.5) The stochastic traffic flow assignment is carried out on $q_{w,3}$ and $q_{w,4}$ in accordance with the link travel time calculated in step 2.3, the additional traffic flow of each link $y_{a,3}^{(m)}$ and $y_{a,4}^{(m)}$ are obtained. The search direction is determined as $d_{a,3}^{(m)} = y_{a,3}^{(m)} - x_{a,3}^{(m)}$ and $d_{a,4}^{(m)} = y_{a,4}^{(m)} - x_{a,4}^{(m)}$, respectively. The weighted average method is adopted to update the link traffic flow, i.e., $x_{a,3}^{(m+1)} = x_{a,3}^{(m)} + 1/m(y_{a,3}^{(m)} - x_{a,3}^{(m)})$ and $x_{a,4}^{(m+1)} = x_{a,4}^{(m)} + 1/m(y_{a,4}^{(m)} - x_{a,4}^{(m)})$.

(4.6) The total link flow is calculated based on the link flow of CAVs and HDVs, i.e., $x_a^{(m+1)} = x_{a,1}^{(m+1)} + x_{a,2}^{(m+1)} = x_{a,1}^{(m+1)} + x_{a,3}^{(m+1)} + x_{a,4}^{(m+1)}$.

(4.7) The convergence test is performed by the predetermined iteration accuracy ε, and if $\sqrt{\sum_a (x_a^{(m+1)} - x_a^{(m)})^2}/\sum_a x_a^{(m)} \le \varepsilon$, then terminate the circulation; Otherwise, let $m = m + 1$ and return to step 2.3 and continue the iterative calculation.

Step 5. If $\forall a \in A$, $x_a(\mu_w(n)) \le C_a$, then let $\mu_w(n+1) = \mu_w(n) + \Delta\mu_w$, $n = n + 1$, and return to step 4. Otherwise, calculate the maximum reserve capacity of road network as the objective function $F(S') = \sum_{w\in W}[\mu_w(n) - \Delta\mu_w]q_w$.

Step 6. Calculate the difference in objective function $\Delta F = F(S') - F(\mathbf{S})$, and judge whether to accept the new solution S' based on the metropolis criterion. If $\Delta F > 0$, S' is accepted as the new current solution **S**; otherwise, the acceptance probability of the new solution is calculated, i.e. $P = \exp(-\Delta F/T)$, and a random number R uniformly distributed in the interval $(0,1)$ is randomly generated, S' is accepted as the new current solution **S** while $P > R$.

Step 7. If the termination condition is satisfied, the current solution **S** is output, which is the optimal travel demand growth multiplier for each OD pair, and the algorithm is terminated; otherwise, the annealing process is performed according to the attenuation function, i.e. $T = T \times \Delta T$, return to step 2 after the temperature is reduced, and let $k = k + 1$. The termination condition is usually set as the temperature T reaches the minimum temperature $T_{\min}$ or several consecutive new solutions are not accepted.

4. Numerical Example Analysis

4.1. Basic Information of Road Network. The test road network includes 13 nodes, 19 links, and 4 OD pairs, as shown in Figure 1. The OD initial travel demand is given in Table 2. Assuming initial temperature $T_0 = 1000$, minimum temperature $T_{\min} = 1 \times 10^{-3}$, temperature change rate $\Delta T = 0.98$, and the termination condition is set as the temperature T reaches the minimum temperature $T_{\min}$ or fifty consecutive identical solutions are accepted. The vector of nonuniform demand growth multiplier step is set as $\Delta\mu = [0.01, 0.02, 0.03, 0.04]$, and the value can be randomly selected from this interval vector as the increasing factor of an OD pair. The initial traffic demand growth multiplier μ_0 is assumed to be 1. The iteration accuracy ε is assumed to be 1×10^{-4}. The multiplier θ_1 and θ_2 are assumed to be 10 and

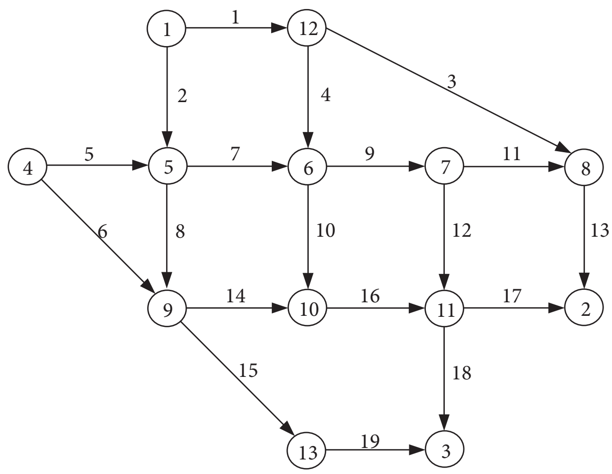


Figure 1: Test road network.

Table 2: Initial travel demand of OD pair.

OD pair number	Origin number	Destination number	Demand (veh/h)
1	1	2	400
2	1	3	800
3	4	2	600
4	4	3	200

0.5, respectively. The Bureau of Public Roads (BPR) function is applied as the link impedance function.

$$t_a(x_a) = t_a^0\left[1 + 0.15\left(\frac{x_{a,1} + x_{a,2}}{C_a}\right)^4\right], \quad (13)$$

where t_a^0 is the free flow travel time on link a, C_a is the capacity of the link a. In this study, C_a is a function of the proportion of CAVs, which can be formulated as follows:

$$C_a = \frac{1}{\left(x_{a,1}/x_a\right)\cdot\left(1/C_{a,1}\right) + \left(1 - \left(x_{a,1}/x_a\right)\right)\cdot\left(1/C_{a,2}\right)}, \quad (14)$$

where $C_{a,1}$ and $C_{a,2}$ are the link capacity for pure CAV flow and pure HDV flow, respectively.

Compared with HDVs, CAVs have shorter reaction times and can respond faster when encountering problems during driving. CAVs can follow the vehicle ahead more closely than HDVs, leading to increased link capacity. Therefore, it is assumed that the link capacity of pure CAV flow is twice than that of pure HDV flow. The characteristic parameters of each link, including free travel time, capacity, and length, are shown in Table 3. The paths and corresponding links contained in each OD pair are shown in Table 4.

4.2. Market Penetration Analysis. The flow of different types of vehicles is determined according to the market penetration of CAVs among all vehicles and ATIS vehicles among HDVs. The impact of different market penetration on road network capacity, travel time, and saturation is analyzed.

4.2.1. Impact on Road Network Capacity. Table 5 demonstrates the road network reserve capacity of different market penetration rates under a nonuniform mode. Note that the market penetration of HDVs-I here is based on human-driven vehicles, not all vehicles in the road network. It can be concluded on the basis of the relevant data that:

(1) The reserve capacity of the road network and the market penetration of CAVs change in the same direction. When the market penetration of CAVs $\alpha < 0.3$, network reserve capacity shows a trend of slow growth before it booms and then shows a trend of rapid growth. When all the vehicles on the road network are CAVs, i.e., $\alpha = 1$, the road network reserve capacity is maximum, up to 9436 veh/h. The car-following capacity of CAVs is better than HDVs, such as the safety distance and headway, thereby significantly increasing the reserve capacity of the road network when α is large enough.

(2) There is basically a reverse change relationship between the road network reserve capacity and the market penetration of HDVs-I, but the change is small. There is a slight increase when the market penetration of CAVs and HDVs-I is very small. When the market penetration of CAVs is large enough, it is almost unaffected by HDVs-I. The road network reserve capacity is a minimum of 2682 veh/h when all vehicles on the road network are HDVs-I.

(3) Compared with HDVs, the market penetration of CAVs has a greater impact on the road network reserve capacity, indicating that the market penetration of CAVs is a more sensitive factor. Especially when the proportion of CAVs becomes larger, the road network reserve capacity is almost unaffected by the market penetration of HDVs-I.

Table 6 and Figure 2 show the travel demand growth multiplier of each OD pair and the distribution of road network capacity under different market penetrations. Each OD pair adopts different travel demand growth multiplier steps to maximize road network reserve capacity under the constraint of link capacity. It can be seen that affected by the market penetration of different types of vehicles, the change trend of the travel demand multiplier for each OD pair is different. However, on the whole, when all vehicles in the road network are human-driven vehicles, with the increase of HDVs-I market penetration, the road network capacity first increases and then decreases, but the change is small. The emergence of CAVs has improved the road network capacity, especially when the market penetration of CAVs reaches a certain value. The improvement effect is more obvious.

4.2.2. The Impact on Travel Time. Considering that the total travel time increases with the increase of road network flow, the average travel time is adopted as the evaluation index. The change of average travel time under different market penetration is shown in Table 7. According to the relevant data, it can be obtained that

Table 3: Characteristic parameters of road network link.

Links	Free travel time (min)	Capacity of HDVs (veh/h)	Capacity of CAVs (veh/h)	Link length (km)
1	8	1400	2800	2.3
2	7	1800	3600	2.5
3	15	1400	2800	4.9
4	7	1000	2000	1.8
5	9	1400	2800	2.6
6	14	1800	3600	4.5
7	5	1600	3200	1.7
8	9	1200	2400	2.4
9	5	1800	3600	1.9
10	13	1000	2000	2.7
11	5	1000	2000	1
12	9	1200	2400	2.3
13	10	1400	2800	2.8
14	10	1400	2800	3
15	9	1200	2400	2
16	8	1400	2800	2.3
17	9	1400	2800	2.6
18	8	1400	2800	2.5
19	11	1400	2800	3.2

Table 4: The index of road network path.

OD pair number	Path number	Included links
1	1	1, 3, 13
	2	1, 4, 9, 11, 13
	3	1, 4, 9, 12, 17
	4	1, 4, 10, 16, 17
	5	2, 7, 9, 11, 13
	6	2, 7, 9, 12, 17
	7	2, 7, 10, 16, 17
	8	2, 8, 14, 16, 17
2	9	1, 4, 9, 12, 18
	10	1, 4, 10, 16, 18
	11	2, 7, 9, 12, 18
	12	2, 7, 10, 16, 18
	13	2, 8, 14, 16, 18
	14	2, 8, 15, 19
3	15	5, 7, 9, 11, 13
	16	5, 7, 9, 12, 17
	17	5, 7, 10, 16, 17
	18	5, 8, 14, 16, 17
	19	6, 14, 16, 17
4	20	5, 7, 9, 12, 18
	21	5, 7, 10, 16, 18
	22	5, 8, 14, 16, 18
	23	5, 8 ,15, 19
	24	6, 14, 16, 18
	25	6, 15, 19

(1) With the increase of the market penetration of CAVs, more and more traffic flow is distributed on the link, the driving time of the link is prolonged, and the average travel time will rise, showing a trend from slow to fast and then to stable.

(2) With the increase of the market penetration of HDVs-I, limited by the link capacity, the traffic flow on the link will gradually decrease, the link travel time will shorten, and the average travel time will decline, but with a small overall decline range.

(3) When all vehicles on the road network are HDVs-I, i.e., $\alpha = 0\beta = 1$, the average travel time at this time is a minimum of 35.54 min; when the market penetration of CAVs and HDVs-I is 0.9 and 0.2, respectively, the average travel time at this moment is a maximum of 38.78 min.

4.2.3. The Impact on Saturation. Saturation is an important index to evaluate the service level of the road network and reflects the matching of traffic supply and demand. Based on various market penetration, the flow distribution and corresponding saturation of each link are obtained, and the average saturation ratio $\overline{S}$ is determined. The calculation formula is as follows:

$$\overline{S} = \frac{\sum_{a\in A} S_a L_a}{\sum_{a\in A} L_a} = \frac{\sum_{a\in A} x_a L_a}{\sum_{a\in A} C_a L_a}. \quad (15)$$

Table 8 shows the changes of average saturation at different market penetration. It can be seen that

(1) When all vehicles are HDVs-I, and the average saturation is a minimum of 0.401 at this time. The average saturation is a maximum of 0.734 when all vehicles are CAVs.

(2) On the one hand, the average saturation increases with the market penetration of CAVs and presents a growth from slow to fast and then gentle. On the other hand, the average saturation presents a small decrease with the increase in the market penetration of HDVs-I.

(3) The value of average saturation should be moderate. When the average saturation is small, it indicates that the road congestion degree is low, the road traffic is smooth, and the driving comfort degree is high, but

Table 5: Road network reserve capacity under different market penetration (veh/h).

β	α										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0	3156	3178	3196	3218	3120	3064	2986	2900	2840	2760	2682
0.1	3368	3406	3408	3400	3344	3260	3188	3120	3058	2992	2930
0.2	3672	3710	3674	3632	3568	3496	3426	3380	3334	3248	3196
0.3	4014	3980	3980	3914	3848	3794	3728	3656	3584	3536	3458
0.4	4618	4622	4484	4450	4300	4160	4070	4016	3976	3924	3872
0.5	5220	5230	5240	5348	5186	5168	5220	5120	4970	4964	4340
0.6	6000	6074	6032	5990	5906	5840	5828	5808	5774	5712	5720
0.7	6740	6740	6680	6620	6680	6662	6588	6514	6482	6424	6488
0.8	7624	7550	7500	7476	7502	7500	7434	7390	7328	7328	7254
0.9	8480	8480	8468	8468	8468	8468	8468	8468	8468	8468	8468
1.0	9436	9436	9436	9436	9436	9436	9436	9436	9436	9436	9436

Table 6: Distribution of demand growth multiplier under different market penetration.

Vehicle type	OD pair number	The market penetration									
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
CAVs and HDVs-II	1	2.44	2.76	3.12	3.31	3.80	4.00	4.16	4.04	4.60	3.86
	2	1.36	1.44	1.53	1.77	2.40	3.00	3.37	4.04	4.60	5.29
	3	1.36	1.44	1.53	1.77	1.70	2.00	2.58	3.28	3.70	5.29
	4	2.44	2.76	3.12	4.08	3.80	4.00	4.16	4.04	3.70	2.43
CAVs and HDVs-I	1	1.44	1.60	2.04	2.08	2.44	2.56	2.86	3.04	3.84	3.94
	2	1.44	1.60	1.52	1.81	2.08	1.78	3.48	3.72	3.84	4.92
	3	1.11	1.15	1.26	1.27	1.36	1.78	2.24	3.04	3.13	3.94
	4	1.44	1.60	2.04	2.08	2.08	4.12	2.24	2.36	3.84	2.96
HDVs-I and HDVs-II	1	2.02	2.24	2.04	1.84	1.80	1.76	1.68	1.60	1.56	1.80
	2	1.34	1.31	1.52	1.84	1.80	1.76	1.68	1.60	1.56	1.20
	3	1.34	1.31	1.26	1.21	1.20	1.19	1.17	1.15	1.14	1.20
	4	2.36	2.24	2.04	1.42	1.20	1.19	1.34	1.45	1.42	1.80

the road network resources are not fully utilized, and the road benefit is low. When the average saturation is large, the utilization rate of road resources is high, and the roads benefit more, but the overall congestion of the road network is high, and the service level is low.

4.2.4. Comprehensive Evaluation. Due to different dimensions of road network reserve capacity, the average travel time, and the average saturation ratios, a simple direct addition of indexes of different properties cannot correctly reflect the comprehensive results. In order to solve the comparability between data indexes, data have to be processed by the Method of Normalization, rendering each index normalized in the same order of magnitude for a better comprehensive analysis. In this thesis, deviation standardization is adopted to make the result value map between [0, 1] through linear processing of original data, and the conversion function is as follows:

$$x_{ij}' = \frac{x_{ij} - \min\{x_{ij}\}}{\max\{x_{ij}\} - \min\{x_{ij}\}}. \tag{16}$$

The average travel time is a backward indicator and the smaller, the better. Render it positive through $y_{ij} = -x_{ij}$. The average saturation is a moderate index, and its value should be neither too large nor too small. Through the forward transformation of the index by $y_{ij} = -|x_{ij} - k|$, where the moderate value k is the mean of saturation, i.e., $k = \sum_i\sum_j x_{ij}/n$, the normalized processing results of road network reserve capacity, average travel time, and average saturation are shown in Tables 9–11, respectively.

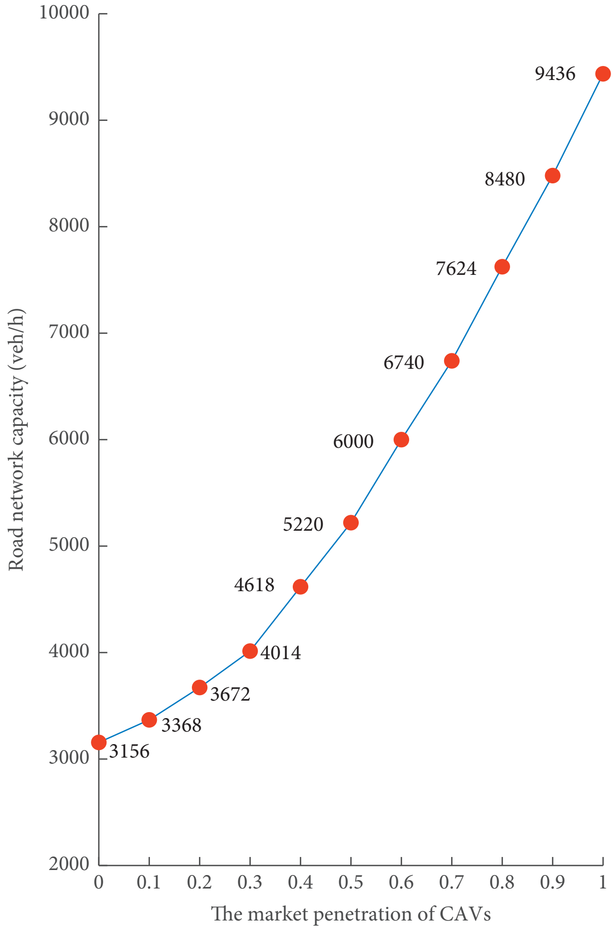
By normalizing the data of three indicators, the comprehensive score value D can be calculated as follows:

$$D = \lambda_1 C^* + \lambda_2 T^* + \lambda_3 S^*, \tag{17}$$

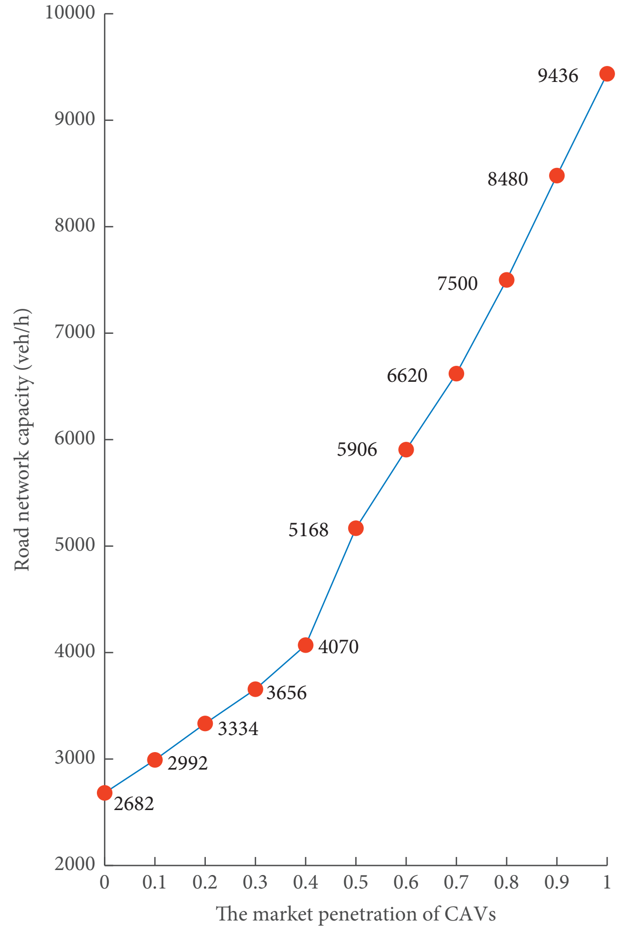
where C^*, T^* and S^* are the normalized matrix of road network reserve capacity, average travel time, and average saturation, respectively. λ_1, λ_2 and λ_3 are the weight of road network reserve capacity, average travel time, and average saturation, respectively.

Among them, the index weight can be determined according to the road network, traffic demand, road utilization degree, etc. The value range of the index weight is [0, 1], and the sum of the weights is 1.

The corresponding comprehensive score values are calculated according to the weights of different indicators, and the location distribution of the maximum comprehensive score values in different weights is shown in Figure 3. The numbers in Figure 3 are position numbers, indicating the market penetration distribution of CAVs and HDVs-I, numbered in order from top to bottom and

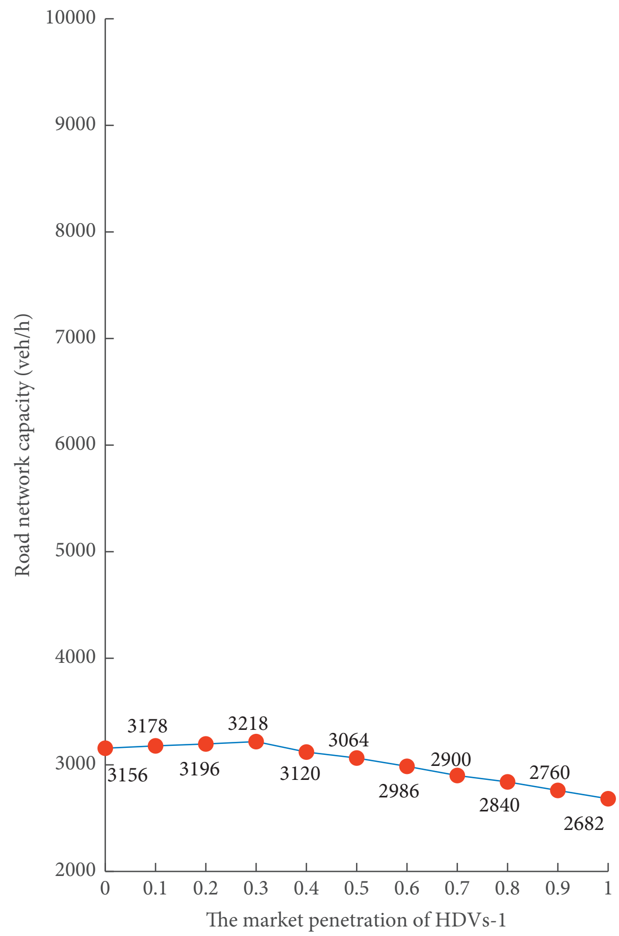


(a)



(b)

Figure 2: Continued.



(c)

Figure 2: Changing diagram of road network capacity under different market penetration. (a) CAVs and HDVs-II. (b) CAVs and HDVs-I. (c) HDVs-I and HDVs-II.

Table 7: Average travel time under different market penetration (min).

β	α										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0	36.61	36.58	36.57	36.70	36.53	36.38	36.17	35.96	35.84	35.74	35.54
0.1	36.55	36.55	36.58	36.70	36.56	36.28	36.06	36.08	35.83	35.71	35.60
0.2	36.59	36.60	36.59	36.67	36.56	36.25	36.06	35.98	35.91	35.81	35.73
0.3	36.64	36.66	36.63	36.70	36.62	36.21	36.35	36.00	36.12	36.04	35.71
0.4	36.88	36.95	36.75	36.96	36.72	36.60	36.15	36.35	36.11	36.03	35.95
0.5	37.20	37.43	37.42	37.57	37.30	37.68	37.62	37.45	37.44	37.52	35.97
0.6	37.76	37.79	37.71	37.64	37.50	37.88	37.77	37.67	37.60	37.90	37.80
0.7	38.01	38.00	37.91	38.09	38.09	38.01	37.91	37.80	37.78	37.66	38.00
0.8	38.46	38.36	38.19	38.24	38.15	38.16	38.07	38.01	38.17	38.03	37.93
0.9	38.56	38.56	38.78	38.77	38.77	38.76	38.76	38.76	38.76	38.76	38.75
1.0	38.67	38.67	38.67	38.67	38.67	38.67	38.67	38.67	38.67	38.67	38.67

left to right, as shown in Table 12. Through analysis and calculation, the reasonable market penetration of different types of vehicles under different characteristic requirements can be obtained so as to determine the optimal deployment scheme of CAVs and HDVs in different periods.

(1) When the weight of road network reserve capacity is larger, the optimal position number of the comprehensive score value is 11, and the market penetration of CAVs is 1. It can be seen that if the priority is to increase the reserve capacity of the road network, the putting into use of CAVs should be

Table 8: Average saturation under different market penetration.

β	α										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0	0.475	0.478	0.481	0.484	0.469	0.460	0.448	0.434	0.425	0.411	0.401
0.1	0.483	0.488	0.489	0.488	0.480	0.467	0.455	0.446	0.434	0.425	0.414
0.2	0.501	0.506	0.502	0.497	0.488	0.475	0.464	0.456	0.448	0.436	0.422
0.3	0.519	0.517	0.516	0.510	0.501	0.489	0.481	0.466	0.457	0.446	0.433
0.4	0.548	0.547	0.529	0.524	0.507	0.501	0.493	0.484	0.478	0.465	0.437
0.5	0.583	0.582	0.581	0.592	0.571	0.562	0.566	0.551	0.529	0.521	0.451
0.6	0.634	0.642	0.636	0.631	0.620	0.605	0.602	0.597	0.590	0.578	0.562
0.7	0.672	0.672	0.665	0.656	0.661	0.657	0.648	0.638	0.632	0.621	0.615
0.8	0.700	0.693	0.698	0.686	0.695	0.693	0.685	0.679	0.677	0.670	0.651
0.9	0.721	0.720	0.717	0.717	0.717	0.716	0.716	0.715	0.715	0.714	0.714
1.0	0.734	0.734	0.734	0.734	0.734	0.734	0.734	0.734	0.734	0.734	0.734

Table 9: Normalization of road network reserve capacity.

β	α										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0	0.070	0.073	0.076	0.079	0.065	0.057	0.045	0.032	0.023	0.012	0.000
0.1	0.102	0.107	0.107	0.106	0.098	0.086	0.075	0.065	0.056	0.046	0.037
0.2	0.147	0.152	0.147	0.141	0.131	0.121	0.110	0.103	0.097	0.084	0.076
0.3	0.197	0.192	0.192	0.182	0.173	0.165	0.155	0.144	0.134	0.126	0.115
0.4	0.287	0.287	0.267	0.262	0.240	0.219	0.206	0.198	0.192	0.184	0.176
0.5	0.376	0.377	0.379	0.395	0.371	0.368	0.376	0.361	0.339	0.338	0.245
0.6	0.491	0.502	0.496	0.490	0.477	0.468	0.466	0.463	0.458	0.449	0.450
0.7	0.601	0.601	0.592	0.583	0.592	0.589	0.578	0.567	0.563	0.554	0.564
0.8	0.732	0.721	0.713	0.710	0.714	0.713	0.704	0.697	0.688	0.688	0.677
0.9	0.858	0.858	0.857	0.857	0.857	0.857	0.857	0.857	0.857	0.857	0.857
1.0	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 10: Normalization of average travel time.

β	α										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0	0.670	0.679	0.682	0.642	0.694	0.741	0.806	0.870	0.907	0.938	1.000
0.1	0.688	0.688	0.679	0.642	0.685	0.772	0.840	0.833	0.910	0.948	0.981
0.2	0.676	0.673	0.676	0.651	0.685	0.781	0.840	0.864	0.886	0.917	0.941
0.3	0.660	0.654	0.664	0.642	0.667	0.793	0.750	0.858	0.821	0.846	0.948
0.4	0.586	0.565	0.627	0.562	0.636	0.673	0.812	0.750	0.824	0.849	0.873
0.5	0.488	0.417	0.420	0.373	0.457	0.340	0.358	0.410	0.414	0.389	0.867
0.6	0.315	0.306	0.330	0.352	0.395	0.278	0.312	0.343	0.364	0.272	0.302
0.7	0.238	0.241	0.269	0.213	0.213	0.238	0.269	0.302	0.309	0.346	0.241
0.8	0.099	0.130	0.182	0.167	0.194	0.191	0.219	0.238	0.188	0.231	0.262
0.9	0.068	0.068	0.000	0.003	0.003	0.006	0.006	0.006	0.006	0.006	0.009
1.0	0.034	0.034	0.034	0.034	0.034	0.034	0.034	0.034	0.034	0.034	0.034

vigorously promoted, and the market penetration of CAVs should be improved as much as possible.

(2) When the weight of average travel time is larger, the best position number of the comprehensive score value is 111. At this time, the market penetration of CAVs and HDVs-I is 0 and 1, respectively. It can be seen that if the travel time of travelers is to be reduced as much as possible, the market penetration of HDVs-I should be increased, and more travelers can travel in the shortest path through ATIS devices.

(3) When the weight of average saturation is larger, the best position numbers of the comprehensive score value are 50. At this time, the market penetration of CAVs and HDVs-I is 0.5 and 0.4, respectively. Therefore, the market penetration of CAVs and HDVs-I should be increased to a certain level at the same time if the traffic load of the road network is considered to ensure that the appropriate traffic flow is relatively smooth to drive in the road network.

(4) When the weight of the three indicators is moderate, the best position is different according to the focus of

Table 11: Normalization of average saturation.

β	α										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0	0.435	0.453	0.471	0.488	0.400	0.347	0.276	0.194	0.141	0.059	0.000
0.1	0.482	0.512	0.518	0.512	0.465	0.388	0.318	0.265	0.194	0.141	0.076
0.2	0.588	0.618	0.594	0.565	0.512	0.435	0.371	0.324	0.276	0.206	0.124
0.3	0.694	0.682	0.676	0.641	0.588	0.518	0.471	0.382	0.329	0.265	0.188
0.4	0.865	0.859	0.753	0.724	0.624	0.588	0.541	0.488	0.453	0.376	0.212
0.5	0.968	0.974	0.979	0.915	1.000	0.947	0.971	0.882	0.753	0.706	0.294
0.6	0.668	0.621	0.656	0.685	0.750	0.838	0.856	0.885	0.926	0.997	0.947
0.7	0.444	0.444	0.485	0.538	0.509	0.532	0.585	0.644	0.679	0.744	0.779
0.8	0.279	0.321	0.291	0.362	0.309	0.321	0.368	0.403	0.415	0.456	0.568
0.9	0.156	0.162	0.179	0.179	0.179	0.185	0.185	0.191	0.191	0.197	0.197
1.0	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079

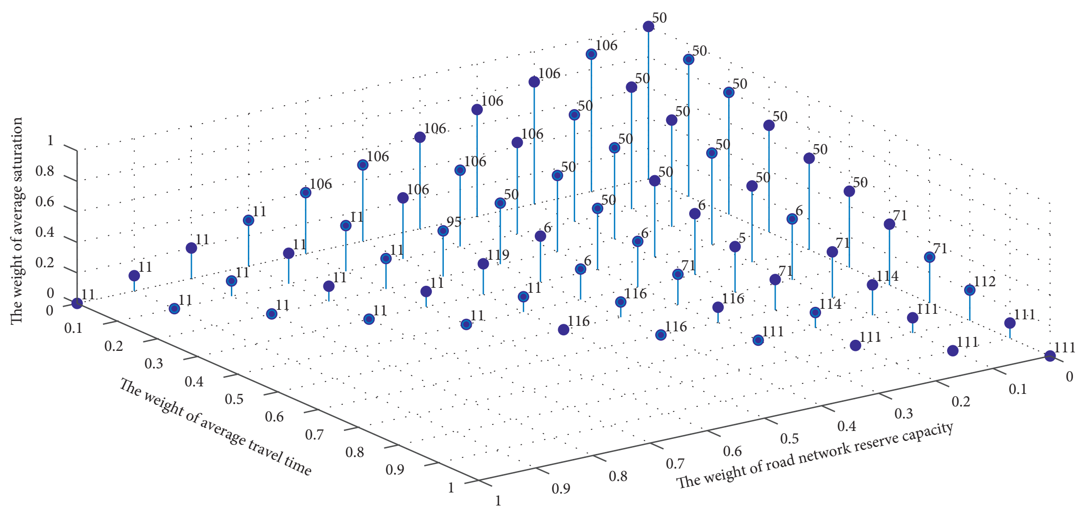


Figure 3: The optimal location distribution of comprehensive score values under different index weights.

Table 12: Position numbers corresponding to different market penetration.

β	α										
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0	1	12	23	34	45	56	67	78	89	100	111
0.1	2	13	24	35	46	57	68	79	90	101	112
0.2	3	14	25	36	47	58	69	80	91	102	113
0.3	4	15	26	37	48	59	70	81	92	103	114
0.4	5	16	27	38	49	60	71	82	93	104	115
0.5	6	17	28	39	50	61	72	83	94	105	116
0.6	7	18	29	40	51	62	73	84	95	106	117
0.7	8	19	30	41	52	63	74	85	96	107	118
0.8	9	20	31	42	53	64	75	86	97	108	119
0.9	10	21	32	43	54	65	76	87	98	109	120
1.0	11	22	33	44	55	66	77	88	99	110	121

Table 13: Travel demand of OD pair.

OD pair number	Demand growth multiplier	Travel demand (veh/h)
1	3.36	1344
2	2.77	2216
3	1.59	954
4	3.36	672

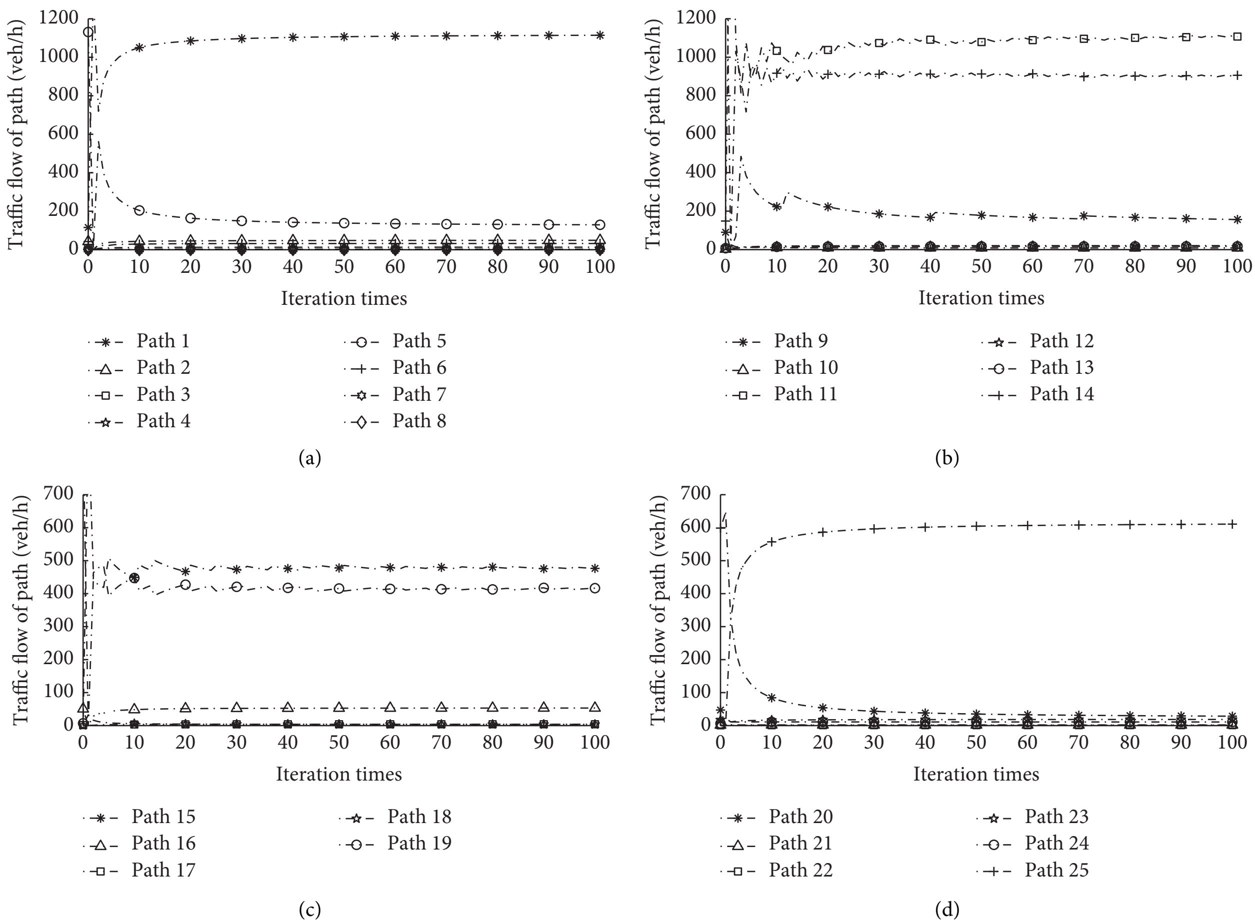


Figure 4: Evolution of path flow with iterations. (a) OD pair 1. (b) OD pair 2. (c) OD pair 3. (d) OD pair 4.

Table 14: Path data of OD pair 2 in equilibrium state.

Path number	Traffic flow of CAVs (veh/h)	Traffic flow of HDVs-I (veh/h)	Traffic flow of HDVs-II (veh/h)	Total traffic flow (veh/h)	Average travel time (min)
9	37	0	113	150	39.65
10	0	0	9	9	44.79
11	430	419	271	1120	37.90
12	0	0	21	21	43.04
13	0	0	17	17	43.39
14	641	24	234	899	38.19

attention but mainly concentrated in 50. At this time, without the excessive pursuit of the comprehensive popularization of CAVs, different types of vehicles reach a certain proportion, orderly mixed in the road network.

4.3. Analysis of the Bilevel Programming Model. The previous section has given the optimal comprehensive score value under different weights and the corresponding market penetration. Among them, position number 50 has the largest proportion. Meanwhile, considering that CAVs cannot be fully popularized for a long time in the future, different types of vehicles will be mixed in the road network. This section assumes that the market penetration of CAV and HDVs-I are 0.5 and 0.4, respectively. The demand growth multiplier and travel demand of each OD pair can be obtained as shown in Table 13. According to the bilevel programming model established in this thesis, the mixed traffic flow is analyzed, and the test road network can rapidly converge to the equilibrium state, as shown in Figure 4. When it gets into the equilibrium state, the road network reserve capacity is 5186 veh/h, the total travel time is 193426 min, the average travel time is 37.30 min, and the average saturation is 0.571. For the OD pair 1, more than 83.4% of the traffic flow is concentrated in path 1, where the flow of this path is 1121 veh/h, and the path travel time is the smallest, which is 34.99 min. The flow of OD pair 2 is mainly distributed in paths 11 and 14, of which 50.5% is distributed in paths 11, up to 1120 veh/h, and the travel time of this path is 37.90 min, while the flow of path 14 is 899 veh/h and the travel time is 38.19 min. The flow of OD pair 3 is mainly concentrated in paths 15 and 19, with selection probabilities of 50.1% and 43.5%, respectively. The travel time of path 15 is 37.02 min and the flow is 478 veh/h, while the travel time of path 19 is 41.05 min and the flow is 415 veh/h. In addition, the traveling time of path 16 is 39.64 min, which is smaller than that of path 19. However, link 7 contained in path 16 is saturated, and the flow allocated by path 16 is relatively small due to the constraints of the capacity of links. For OD pair 4, more than 91.7% of the traffic flow selects path 25, and the travel time is 35.34 min.

OD pair 2 is selected to analyze the path selection of different types of vehicles in the equilibrium state to verify the traffic assignment model. The relevant data are shown in Table 14. The traffic flow of CAVs is distributed on paths 9, 11, and 14, of which path 14 is not the shortest path but has the most distributed traffic flow, indicating that CAVs follow the SO principle to select paths to minimize the total travel time of the system, and the traffic flow is not concentrated on the shortest path. The traffic flow of HDVs is allocated according to the SUE principle. On the one hand, HDVs-I has a high level of information quality, and the traffic is only distributed on paths 11 and 14. Among them, path 11 is the shortest path and has the most distributed traffic, but some traffic is also distributed in the second shortest path. If the level of information quality is further improved, users can fully grasp the road information, the traffic flow can be concentrated on the shortest path, and ultimately realize user optimization. On the other hand, the traffic flow of HDVs-II is distributed on all paths, indicating that HDVs-II has certain randomness in selecting the path, and the smaller the travel time, the greater the probability of being selected.

5. Conclusion

Note that smart and unintelligent vehicles unavoidably converge on the road network with the development of increasingly maturing autonomous driving technology. This study focuses on the development of a model and algorithm for traffic assignment problems under link capacity constraints, which aims to formulate a reasonable CAVs deployment scheme by analyzing the impact of market penetration of different types of vehicles on road network performance so as to facilitate the promotion and application of CAVs.

In this paper, SO-SUE mixed equilibrium traffic assignment model is constructed, which maximizes the road network reserve capacity for the sake of the link capacity constraint. The effects of different market penetration on road network reserve capacity, average travel time, and average saturation are analyzed using the Nguyen-Dupuis network. On the one hand, the three indicators all increase with the market penetration of CAVs and present a trend from slow to fast; On the other hand, all indicators generally decrease with the increase of the market penetration of HDVs-I, and the decreased amplitude is small. There is a slight increase when the market penetration of CAVs and HDVs-I is very small. Through the normalization of three index data, the optimal comprehensive score and the corresponding market penetration in different index weights are analyzed herein. Thus, the optimal deployment scheme of CAVs and HDVs can be determined according to different planning objectives. The bilevel programming model is solved by a numerical example to analyze the equilibrium state of mixed traffic flow, and the convergence of the model and algorithm is verified. It is worth noting that the non-uniform demand growth multiplier adopted by each OD pair in this paper not only improves the reserve capacity of the road network but also reflects the inconsistency of traffic demand structure growth, which is more in line with the characteristics of actual travel demand. Considering that CAVs have small headway, the link capacity is not a fixed value, and its size depends on the market penetration of CAVs. In addition, SAA is innovatively proposed to solve the model to obtain the global optimal solution.

Beyond the above research, there are several directions for further study. First, there are some research theories about the dedicated area of CAVs, and it is necessary to study the impact of the dedicated area setting on road network capacity. Second, the next step can consider that the travelers in the road network follow the system optimal, user optimal, and stochastic user optimal to select the path and analyze the influence of mixed traffic flow characteristics on the mixed equilibrium traffic assignment mechanism, which will be more in line with the actual situation. In addition, from the perspective of comfort, the influence of turning times, service level, number of signal lights, and other factors on path selection will be considered, and the model will be improved so as to satisfy the actual travel demand and describe the distribution pattern of road network traffic flow more realistically.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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