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Research Article

Policy Efforts to Promote the Adoption of Autonomous Vehicles: Subsidy and AV Lanes

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Autonomous vehicles (AVs) have the potential to improve safety, traffic capacity, and energy efficiency, but these advantages can only be realized when the AV market penetration is sufficiently high. To promote the adoption of AVs, it would be crucial for the government to take policy measures. This paper develops a two-stage model to explore the effects of subsidy and AV lanes' policies on AV adoption. In the first stage, given the subsidy policy, the vehicle manufacturer sets AV price to pursue maximum profit while anticipating the choice of consumers for AVs or conventional vehicles (CVs), from which the AV market penetration can be accessed. Subsequently, based on the AV market penetration acquired from the first stage model, an optimization model integrating the mixed traffic assignment is developed in the second stage to determine the time-dependent progressive AV lanes' deployment plan. The first and second stage models are solved using the simulation-optimization and genetic-algorithm-based approaches, respectively. Due to the mutual influence of the two models, an iterative optimization approach is applied to solve the whole model. Two numerical experiments are conducted, and the results demonstrate the positive effects of subsidy and AV lane policies on increasing AV market penetration. The analysis provides significant managerial insights for policymakers to promote the development of AVs.

1. Introduction

AVs offer a wide range of advantages in safety, traffic capacity, vehicular emission, and energy consumption. However, these advantages can only be realized when the AV market penetration is sufficiently high [1]. Frustratingly, it will still be many years before AVs become widespread, and heterogeneous traffic flows consisting of CVs and AVs will be inevitability for a long time. To promote AV adoption, a local government could deploy exclusive AV lanes and implement subsidies so that the advantages of AV can be fully exploited [2].

Subsidies are considered an important measure to promote the adoption of emerging vehicles. For example, the German government offers subsidies of up to 6,000 EUR to electric vehicle buyers. And R&D offers subsidies for manufacturers to encourage them to do more in terms of electric vehicle technology innovation. Only with subsidy support can the adoption rate of AV be increased and market expansion accelerated. However, subsidies will inevitably increase financial burden of the government and unreasonable subsidy policies could also lead to market distortions. Therefore, it is necessary to consider the objects, amount, and duration of subsidies in order to establish an effective subsidy policy.

In addition to subsidy policies, road infrastructure construction is another effective measure to promote the adoption of AVs [3]. Deploying dedicated lanes for AVs is a significant way to increase AV market penetration and fully utilize the role of AVs in improving travel efficiency. The aim of installing AV lanes is to separate AVs and CVs, meaning that AVs have the right-of-way on both regular lanes and AV lanes, while CVs can only travel on regular lanes. On the one hand, AV lanes can fully exploit the benefits of AVs, thus improving the travel benefits of the transportation system. On the other hand, converting regular lanes to AV lanes may result in increased travel time for CVs because they lose the accessibility of these AV lanes, which may damage social welfare. Consequently, it is critical to optimize the location of AV lanes to minimize social costs while considering the AV market penetration. Furthermore, since the growth of AV market penetration is a gradual process, AV lanes should also be deployed progressively [3].

There are three major players in the promotion and adoption of AVs: the government, the vehicle manufacturer, and consumers. The government sets the subsidy and AV lanes' policies to achieve the maximum social benefit or minimum cost; the vehicle manufacturer sets AV price to pursue maximum profit depending on the existing subsidy policy; and consumers, with decisions made by the government and manufacturer, choose the vehicle type and travel routes to maximize benefits. Considering the complex interplay of these three in the AV diffusion process, we aim to address the following questions:

(1) How to quantify the impact of subsidy and AV lanes' policies on AV adoption?
(2) How to describe the decision-making behavior and interactions of the government, the vehicle manufacturer, and consumers?
(3) How, when, and where should the AV lanes be deployed?

2. Literature Review

2.1. AV Adoption. Recently, numerous studies have been conducted on AV adoption, mainly involving three aspects: first, obstacles in the way of AV adoption and concerns about AV, including privacy issues [4, 5], security issues [6–8], inadequate infrastructure [9, 10], lack of standards [11, 12], and regulations [13, 14]; second, studies on the influencing factors, such as the willingness to pay of consumers [15, 16], peer effects [17–19], public perception [20–22], affective motivations [23–25], and media commentary [26, 27], of AV adoption; and third, the methods and models for predicting AV market penetration with the theory of planned behavior [28], innovation diffusion approach [29], the scenario analysis [30], and system dynamics [31].

2.2. Subsidy Policy. Since the high price of AVs has hindered their adoption, the subsidy policy also attracted many scholars to study. By the method of a dynamic games approach, Luo et al. [32] considered the uncertainty and information asymmetry and examined an optimal subsidy policy to accelerate the increase in AV market penetration. Zhang et al. [33] discussed the effectiveness of subsidy programs, investigating the effect of providing subsidies to AV users or relevant stakeholders as compensation for their costs or revenues to lead the system to an optimal long-term equilibrium. Chen et al. [34] classified vehicles and used the nested logit model to describe the vehicle selection behavior of users and developed a mixed integer nonlinear programming model to solve the purchase subsidy design problem.

2.3. Deployment of AV Lanes. The dedicated AV lane was first proposed as a management strategy by Chen et al. [3], who developed a time-dependent deployment model considering the AV market penetration. Ghiasi et al. [35] constructed a compact lane management model based on a Markov chain approach to efficiently determine the optimal number of AV lanes to maximize the mixed traffic throughput of multilane highway segments. Liu and Song [36] extended AVT lanes that allow free passage for AVs while paid passage for CVs and investigated the optimal deployment of AV and AVT lanes in a traffic network with mixed AV and CV traffic based on this strategy. Tani et al. [37] determined the pattern of dedicated lanes considering the stochastic traffic demand and the stochastic traffic capacity. Lin et al. [38] considered travel time costs, AV lanes construction costs and emission costs to investigate the optimal deployment of AV lanes that simultaneously consider economic and environmental sustainability.

In summary, most of the existing studies focus on a single policy and pay little attention to its impact on AV penetration. To address these research deficiencies, this paper integrates AV lane and subsidy policies and analyses the effects of single and combined policies on AV penetration. The contributions of our study are threefold.

First, a two-stage model is developed to emulate the effects of subsidy and AV lane policies on the evolution of AV market penetration. This model can characterize the behavior of the government, the vehicle manufacturer, and consumers and capture the interdecision dynamics between them. In addition, it investigates the time-dependent deployment of the optimal AV lane solution based on the predicted AV market penetration.

Second, we develop the simulation-optimization and genetic-algorithm-based approach to solve the proposed two-stage model efficiently. The first stage model is solved using the simulation-optimization approach, and the genetic and diagonalization algorithms solve the second stage model. In addition, an iterative optimization approach is applied to solve the whole model due to the mutual influence of the two models.

Finally, numerical experiments are conducted in the Nguyen–Dupuis network and the Sioux Falls network to demonstrate the proposed model. The results show the effects of the subsidy policy's subsidy objects, subsidy amount, subsidy duration, and AV lanes' policy on AV market penetration and social welfare, as well as the comprehensive effects of the subsidy policy and the AV lanes' policy. Furthermore, numerical results demonstrate how different deployments of AV lanes affect the system performance.

The remainder of this paper is structured as follows: the proposed two-stage model and its solution are described in Sections 3 and 4, respectively. Section 5 gives numerical experiments to verify the effectiveness of the proposed model and solution method. Finally, Section 6 presents a conclusion of this paper and suggests possible future research directions.

3. Two-Stage Model

In this section, we build a two-stage model: (1) the first stage model explores the subsidy effect and characterizes the change in AV market penetration and (2) the second stage model produces the optimal AV lanes' deployment scheme in a transportation network. On the one hand, the output of the first stage model is the result of vehicle type selection for consumers, from which the market penetration of AVs can be obtained as the input of the second stage model. On the other hand, the deployment of AV lanes in the second stage model brings the benefits of AVs in terms of travel time reduction, which will also affect the vehicle type choice of consumers in the first stage model. Hence, these two submodels influence each other. The details of the two-stage model are presented as follows.

3.1. The First Stage Model. Subsidy policies need to be in place to promote the adoption of AVs. There are three main stakeholders in formulating and implementing subsidy policy: the government, the vehicle manufacturer, and consumers. The government makes policy and has complete information on the decision-making of the manufacturer and the choices of consumers; given the subsidy policy, the vehicle manufacturer sets AV price to pursue maximum profit; consumers are the followers who maximize their utility by choosing an AV or CV under the policies of the government and the pricing of the manufacturer.

In our model, the subsidy policy comprises three elements: subsidy objects (vehicle manufacturer or consumers), subsidy amount, and subsidy duration. Furthermore, considering that subsidy policies should not be changed frequently and the government tends to set multiple candidate subsidies, we treat subsidies as scenario variables and discretize them. We will explore how social welfare and AV market penetration change as elements of subsidy policy change, where social welfare is defined as the sum of manufacturer benefits and consumer benefits.

The first stage model is built under a leader-follower game structure, where the AV manufacturer is the leader and consumers are followers. Considering the manufacturing cost of AV and government subsidies, the AV manufacturer prices AV to maximize profits while predicting the consequence of vehicle-type choices for consumers. Consumers consider AV price and other relevant factors for vehicle-type selection to pursue maximum personal benefits. The framework of the first stage model is shown in Figure 1. We will describe the decisions of consumers and the manufacturer in more detail in the following sections.

3.1.1. Agent-Based Vehicle-Type Choice Behavior of Consumers. We employ an agent-based model to account for the vehicle-type choice behavior and interactions of heterogeneous consumers. Concretely speaking, consumers are modeled as agents, and each agent faces a binary decision to buy the AV or CV. Consumer agents differ regarding income level, innovativeness, and commuting distance determined by the home and work address, which may lead to heterogeneous preferences when consumers make purchasing decisions. Innovativeness is the degree to which an individual is relatively earlier in adopting new ideas than the average member of his or her social system [39]. Also, the purchasing decisions of consumers are influenced by social networks. Therefore, the weighted combined benefit of individual preference and social influence is used to assess the final choice behavior of consumers. The relative utility (ΔU) is defined as the benefit obtained by choosing AV over CV, as summarized in the following equation:

$$\Delta U_{i,t} = \alpha_i P_{i,t} + \beta_i S_{i,t}, \quad \forall i \in I, t \in T, \tag{1}$$

where $\Delta U_{i,t}$ is the relative utility obtained by consumer agent i from purchasing AV at year t, $P_{i,t}$ is the preference utility obtained by consumer agent i based on the personal attribute selection at year t, and $S_{i,t}$ is the social network utility of consumer agent i at year t. I is the set of consumer agents, and T is the set of planning years. α_i and β_i are the weight coefficients of preference utility and social utility for consumer agent i, respectively, representing the importance of the two in purchasing decisions. α_i and β_i can vary between 0 and 1, $\alpha_i + \beta_i = 1$, and the values of α_i and β_i vary depending on the attributes of the consumer. Specifically, when α_i is high and β_i is low, agent i is highly innovative and individualistic, that is, he pays more attention to the preference utility and is hardly influenced by his neighbors. However, when α_i is low and β_i is high, agent i is very socially susceptible, and a large part of his utility comes from the influence of his neighbors.

When the relative utility of agent i at year t ($\Delta U_{i,t}$) reaches a given threshold, agent i will adopt AV, otherwise adopt CV. Figure 2 displays a simplified schematic diagram of consumer utility. The preference utility ($P_{i,t}$) and the social network utility ($S_{i,t}$) are discussed as follows.

(1) The Preference Utility. According to the attribute characteristics of consumers and AVs, the preference utility $P_{i,t}$ is modeled as a weighted sum of vehicle cost, safety utility, energy utility, and travel time saving utility perceived by consumer agent i over one year, as presented in the following equation:

$$P_{i,t} = g_i G_t + q_i Q_t + e_i E_{i,t} + l_i L_{i,t}, \quad \forall i \in I, t \in T, \tag{2}$$

where G_t is the annual average cost difference between AV and CV at year t, Q_t is the safety utility of choosing AV at year t, $E_{i,t}$ is the energy utility of agent i choosing AV at year t, and $L_{i,t}$ is the travel time saving utility of agent i choosing AV at year t. And g_i, q_i, e_i, and l_i are the weight coefficients of vehicle cost, safety utility, energy utility, and travel time saving utility of agent i. In this paper, it is assumed that the personal attributes of agent i are fixed and time-invariant, so the perceived weight coefficient of agent i to each utility only depends on the personal attributes and does not change during the diffusion process. However, due to technological

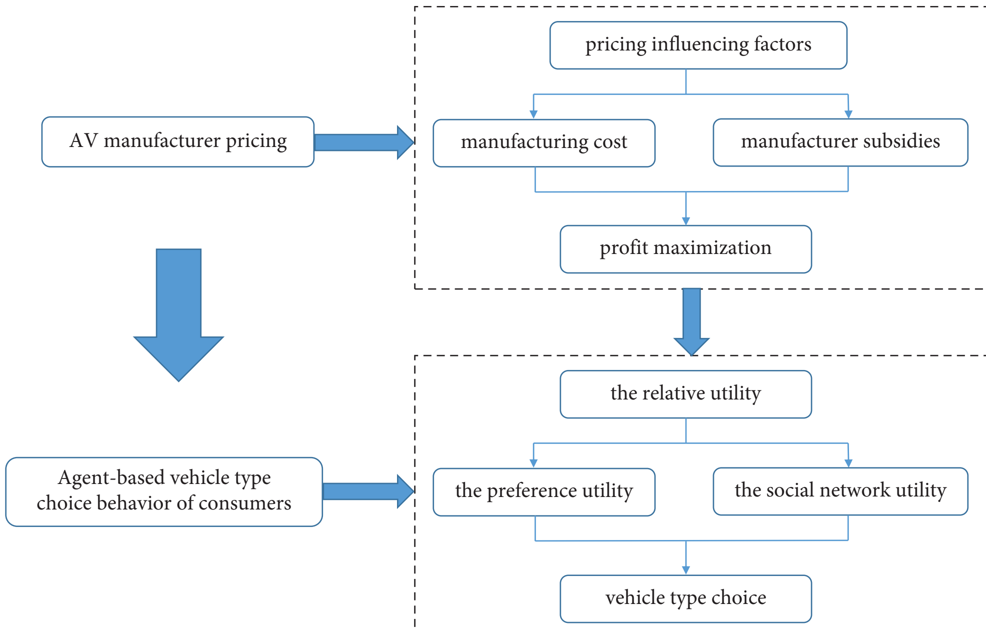


Figure 1: The framework of the first stage model.

progress and changes in AV market penetration, the various utilities of AVs, such as vehicle cost, safety utility, and energy utility, will evolve over time. As a result, perceived preference utility $P_{i,t}$ of agent i fluctuates over time, causing its purchase decision to change. The representation of these utilities is discussed in detail below.

Over 90% of car crashes are caused by driver error [40], so AVs have the potential to reduce crashes dramatically. In order to simulate the safety utility of various market AV penetrations under mixed traffic flows, according to [11], we assume crash rates for CVs are constant and use the Gaussian fitting method to obtain the relationship between the safety utility and the AV market penetration, as shown in the following equation:

$$Q_t = \lambda e^{-\left(N_t - b/c\right)^2}, \tag{3}$$

where λ, b, and c are parameters of the Gaussian fitting curve and N_t is the AV market penetration at year t.

Under the same conditions, AV consumes less energy than CV [41], so energy utility $(E_{i,t})$ is defined as the value of energy savings from using AV compared to CV over one year. The energy utility can be expressed in the following equation:

$$E_{i,t} = \gamma \omega_t L_{i,t}, \tag{4}$$

where γ is the energy consumption factor. ω_t is the energy consumption reduction factor for AV at year t. $L_{i,t}$ is the total commuting mileage of agent i, which is obtained by multiplying the distance of a single commute and the number of commutes in one year. The distance of a single commute is determined by the home and work address of agent i.

We assume that the CV price is known and fixed. In contrast, the AV price is influenced by the AV cost and

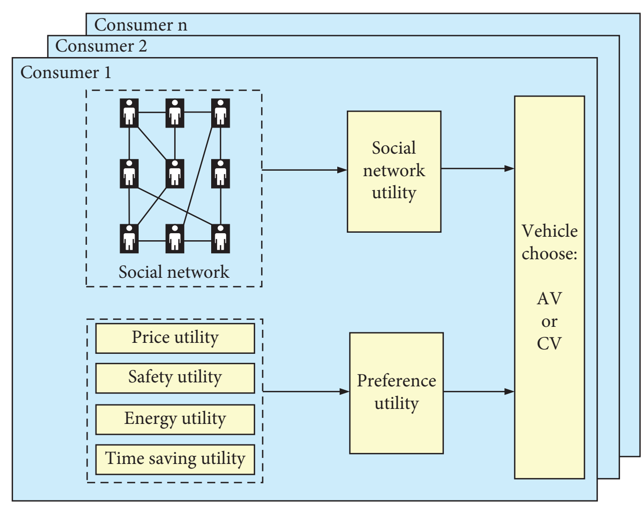


Figure 2: A simplified schematic diagram of consumer utility.

government subsidies to the manufacturer and is obtained by the AV manufacturer through pricing models. Vehicle cost (G_t) is represented by the annual average cost difference between AV and CV obtained from the following equation:

$$G_t = G_t^1 + G_t^2 = \frac{\left(G_{\mathrm{CV}} - G_{\mathrm{AV}}^t + H^t r_c\right) \times \vartheta_1}{\vartheta_2} + \frac{\mathrm{MA}_{\mathrm{CV}} - \mathrm{MA}_{\mathrm{AV}}}{\vartheta_3}, \tag{5}$$

where G_t^1 and G_t^2 are relative purchase cost and relative maintenance cost, respectively. G_{CV} represents the price of the CV. G_{AV}^t represents the price of the AV at year t. r_c is the purchase subsidy given by the government to consumers. H^t is a binary variable with the value of 0 or 1, and $H^t = 1$ represents that the government has implemented purchase subsidies in the t year; otherwise, it means that no subsidies have been implemented. ϑ_1 is the portion of the value lost in the price of the vehicle due to depreciation at the end of the vehicle's lifetime. ϑ_2 is the lifespan of the vehicle. ϑ_3 is the average vehicle occupancy rate. $\mathrm{MA}_{\mathrm{CV}}$ and $\mathrm{MA}_{\mathrm{AV}}$ are the average annual maintenance costs of CV and AV.

Travel time saving utility ($L_{i,t}$) is the benefit of the time saved by the consumers, which is obtained by multiplying the time value of consumers and the travel time saved by using AV in one year. Value of time (VOT) is calculated by personal income. The adoption of AVs will lead to a decrease in the value of VOT, such as 35% [42] and 50% [43]. Travel time will be obtained through the mixed traffic assignment in the second stage model.

(2) Social Network Utility. In this section, we first construct a dynamically weighted small-world network of consumer agents and then use this social network to analyze social influence in AV-CV choices.

The social network is the substrate for AV market diffusion. Several types of social networks have been proposed, mainly regular networks, random networks, small-world networks, scale-free networks, and empirical networks. Empirical networks would be the most realistic social network, but it needs data extracted from social networking sites, which is usually tricky. In contrast, the small-world network proposed by Watts and Strogatz [44] is convenient to build and possible to connect any two nodes through just a few links, which is in line with the characteristics of social networks. For the abovementioned reasons, we employ the small-world network as the base network for AV diffusion.

Despite these advantages, small-world networks are weightless networks that only reflect whether there is an edge between nodes but cannot describe the degree of the close relationship between the nodes, which leads to the limitations of the application of small-world networks. Therefore, the weighted small-world network is chosen to analyze the diffusion. Following the approach of Wolf et al. [45], we form connections between consumer agents based on their degree of similarity. As mentioned before, our model considers the home address, work address, income level, and innovation level of consumer agents. The similarity between two agents is defined as Euclidean distance in 4 dimensions, as seen in equation (6). Based on the similarity, the social relationship weight can be specified as equation (7).

$$\Delta_{ij} = \sqrt{\sum_{s\in S}\left(\frac{F_{si} - F_{sj}}{\max d_s}\right)^2}, \tag{6}$$

$$\delta_{ij} = 1 - \frac{\Delta_{ij}}{\max \Delta}, \tag{7}$$

where Δ_{ij} is the similarity between agents i and j. s is the attribute of the agent, and S is the set of attribute categories, including home address, work address, income level, and innovation level of consumer agents. F_{si} is the attribute value of agent i on the s dimension. The similarity calculations are normalized by the maximum distance d_s along that dimension within the agent population. δ_{ij} is the social relationship weight between agents i and j.

Furthermore, the topology of social networks is often not static, and people always form new social relationships in interpersonal communication over time. However, traditional small-world networks struggle to describe this dynamic change. Therefore, it is necessary to consider the dynamics in social networks to build dynamic social networks. In our model, the dynamics of the social network is reflected in the internal growth of the network, that is, the network evolution caused by the addition of edges to the original nodes while the number of nodes is unchanged. The dynamically weighted small-world network model is constructed as follows:

(1) Construct a nearest-neighbor coupled network of N nodes, where each node is connected to its neighbor $K/2$ nodes, and K is an even number.
(2) Each edge in the network is rewired randomly with probability p.
(3) At each time t, a node is randomly selected, and the weight value of this node and the remaining nodes is calculated. The probability of connection between the selected node and the remaining nodes is presented in the following equation:

$$p_{ij} = \frac{\delta_{ij}}{\sum_{r\epsilon R}\delta_{ir}}, \tag{8}$$

where p_{ij} is the probability of connection between i and j. r is one of the remaining nodes, and R is the set of remaining nodes. Using the roulette method to randomly select a number in the range of 0-1, the nodes are connected if the number is within the node connection probability interval. A group of nodes is newly connected at each time step until the number of new edges reaches the number of nodes or the longest time; the dynamic evolution of the network ends.

As mentioned before, social influence plays a vital role in purchasing decisions of consumers, and we define it as the social network utility ($S_{i,t}$). The social network utility of consumers is determined by the relative utility and weights of the nodes connected to them in the social network, as indicated in the following equation:

$$S_{i,t} = \frac{\sum_{j\in W}\delta_{ij}\Delta U_{j,t}}{\sum_{j\in W}\delta_{ij}}, \tag{9}$$

where W is the set of agents connected to agent i in the social network.

3.1.2. AV Manufacturer Pricing. This section explores the issue of the vehicle manufacturer pricing. Under manufacturer subsidy policy of the government, the vehicle manufacturer maximizes profit by choosing an AV price while predicting the response of consumers. It is assumed that the cost and price of CV in the market are known and constant, while the manufacturing cost of AV will decrease due to technological progress. The profit maximization problem is formulated in the following equation:

$$\max Z_t = \left(G_{AV}^t - C_{AV}^t + R^t r_m\right)\theta_{AV}^t$$
$$\text{subject to:}$$
$$\underset{-}{G}_{AV} \le G_{AV}^t \le \overline{G}_{AV}$$
$$R^t \in \{0,1\}, \tag{10}$$

where Z_t is the profit of the vehicle manufacturer at year t. G_{AV}^t and C_{AV}^t are the price and the manufacturing cost of the AV at year t. θ_{AV}^t is the annual sales of AV at year t, determined by the customer decision model in the previous section. r_m is the single-vehicle AV subsidy given by the government to the vehicle manufacturer. R^t is a binary variable with the value of 0 or 1. $R^t = 1$ represents that the government has implemented manufacturer subsidies in the t year; otherwise, it means that no subsidies have been implemented. $\underset{-}{G}_{AV}$ and $\overline{G}_{AV}$ are the lower and upper bounds of AV price.

3.2. The Second-Stage Model. Compared to the less perceptible safety and energy utility, travel time is often the most critical factor influencing route choice of travelers. Therefore, the second stage model takes the minimum travel time as the optimization objective. Specifically, based on the AV market penetration acquired from the first stage model, we investigate how to optimize the location of AV lanes for minimizing the total travel time. In response to this problem, a leader-follower model is proposed. The government, as the leader at the upper level, decides on the dedicated lane option on the given set of candidate links to minimize the total travel time; the travelers, as the followers at the lower level, choose the travel routes to minimize their travel time under decisions of the government. The lower level is a mixed traffic assignment problem, while the upper level is an optimization problem investigating when and where to deploy AV lanes.

3.2.1. AV-CV Network Description. Let $G(N, A)$ denote a road network, where N and A are the sets of nodes and links in the network, respectively. Let $\widehat{A} \subseteq A$ represent the set of candidate AV links. In order to maintain network connectivity, candidate links must have more than two lanes and at least one regular lane, that is, each candidate AV link is paired with a regular link, which is defined as K. For example, as shown in Figure 3, this is an AV-CV network, where solid lines represent regular links and dashed lines represent candidate AV links. Specifically, in Figure 3, $A = \{1,2,2',3,3',4,5,6,7,7',8,8'\}$, $\widehat{A} = \{2',3',7',8'\}$, and $K = \{(2,2'),(3,3'),(7,7'),(8,8')\}$.

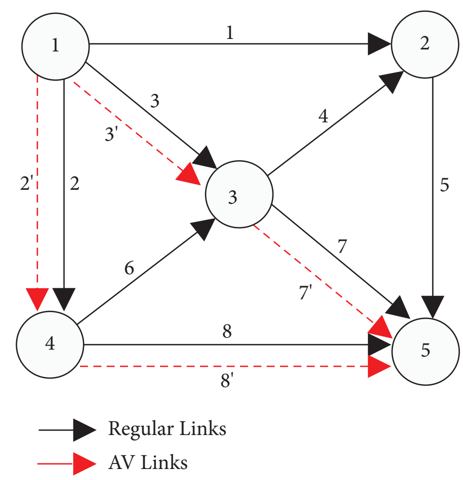


Figure 3: AV-CV network.

We further define links which are represented by $a \in A$ or node pairs (i, j) in the road network, where $i, j \in N$. Let $M = \{1, 2\}$ denote the set of travel modes, where mode 1 represents CV and mode 2 represents AV. $w \in W$ means OD pair w, W is the set of OD pairs, and $o(w)$ and $d(w)$ define the origin and destination of OD pair w. The travel time $(t_{a,\tau}(v_{a,\tau}))$ of link $a \in A$ in planning year $\tau \in \Gamma$ is shown in the following equation:

$$t_{a,\tau}\left(v_{a,\tau}\right) = t_a^0\left[1 + \alpha_a\left(\frac{v_{a,\tau}}{\wedge_{a,\tau}}\right)^{\beta_a}\right], \tag{11}$$

where $v_{a,\tau}$ is the flow of link a at year τ, t_a^0 is the free-flow travel time on link a, α_a and β_a are two parameters, and $\wedge_{a,\tau}$ is the capacity of link a at year τ, which can be calculated by the following equation :

$$\wedge_{a,\tau} = c_{a,\tau}L_a = \frac{3600L_a}{p_{a,\tau}h_{AV} + \left(1 - p_{a,\tau}\right)h_{CV}}, \tag{12}$$

where $c_{a,\tau}$ is the per-lane capacity of link a, L_a is the number of lanes for the link, $p_{a,\tau}$ is the proportion of AVs on link a at year τ, and h_{AV} and h_{CV} are headways of AVs and CVs to a leading vehicle.

3.2.2. The Mixed Traffic Assignment. According to the user equilibrium (UE) principle, the flow distribution of AVs and CVs at year $\tau \in \Gamma$ can be described by the following network equilibrium conditions:

$$\Delta x_\tau^{w,m} = E^{w,m} d_\tau^{w,m}, \quad \forall w \in W, m \in M, \tag{13}$$

$$x_{a,\tau}^{w,1} \ge 0, \quad \forall a \in A \backslash \widehat{A}, w \in W, \tag{14}$$

$$x_{a,\tau}^{w,1} = 0, \quad \forall a \in \widehat{A}, w \in W, \tag{15}$$

$$x_{a,\tau}^{w,2} \geq 0, \quad \forall a \in A, w \in W, \tag{16}$$

$$v_{a,\tau} = \sum_{m\in M}\sum_{w\in W} x_{a,\tau}^{w,m}, \quad \forall a \in A, \tag{17}$$

$$\left(t_{a,\tau}\left(v_{a,\tau}\right) + \rho_{i,\tau}^{w,1} - \rho_{j,\tau}^{w,1}\right)x_{a,\tau}^{w,1} = 0, \quad \forall (i,j) = a \in A\backslash\widehat{A}, w \in W, \tag{18}$$

$$t_{a,\tau}\left(v_{a,\tau}\right) + \rho_{i,\tau}^{w,1} - \rho_{j,\tau}^{w,1} \geq 0, \quad \forall (i,j) = a \in A\backslash\widehat{A}, w \in W, \tag{19}$$

$$\left(t_{a,\tau}\left(v_{a,\tau}\right) + \rho_{i,\tau}^{w,2} - \rho_{j,\tau}^{w,2}\right)x_{a,\tau}^{w,2} = 0, \quad \forall (i,j) = a \in A, w \in W, \tag{20}$$

$$t_{a,\tau}\left(v_{a,\tau}\right) + \rho_{i,\tau}^{w,2} - \rho_{j,\tau}^{w,2} \geq 0, \quad \forall (i,j) = a \in A, w \in W, \tag{21}$$

where Δ is the node-link incidence matrix associated with the network, $x_{\tau}^{w,m}$ is the vector of $\left\{\cdots, x_{a,\tau}^{w,m}, \cdots\right\}$, $E^{w,m}$ is a vector that consists of two nonzero components: one with the value 1 corresponding to the origin $o(w)$ and the other with the value -1 corresponding to the destination $d(w)$, $d_{\tau}^{w,m}$ represents the demand of travel mode m between OD pair w at year τ, $x_{a,\tau}^{w,m}$ is the flow of travel mode m on link a between OD pair w at year τ, and $\rho_{i,\tau}^{w,m}$ and $\rho_{j,\tau}^{w,m}$ are auxiliary variables.

In the abovementioned, constraint (13) ensures flow conservation between each O-D pair, constraints (14) and (16) ensure nonnegativity of link flows, constraint (15) represents that only AVs can use AV links, constraint (17) defines the aggregated link flow as the sum of link flows across all modes and OD pairs, and constraints (18)–(21) ensure that the travel costs on all utilized paths between each OD pair are the same and equal to $\rho_{o(w),\tau}^{w,m} - \rho_{d(w),\tau}^{w,m}$, while the travel costs on those unutilized paths are more than or equal to $\rho_{o(w),\tau}^{w,m} - \rho_{d(w),\tau}^{w,m}$.

In addition, it can be proved by the KKT conditions that when the network reaches equilibrium, the solution to the abovementioned problem is equivalent to the following mathematical problem:

$$\begin{aligned} &\min_{\mathbf{x}} \sum_{\forall a\in A} \int_0^{v_{a,\tau}} \mathrm{t}_{a,\tau}(x)\mathrm{d}x, \\ &\text{subject to:} \\ &\text{Eqs. } (13) - (17). \end{aligned} \tag{22}$$

3.2.3. Optimal AV Lanes' Location. The goal of the location problem is to investigate the optimal time-dependent deployment plan of AV lanes to minimize the total travel time. The deployment plan of AV lanes involves when and where the AV lanes should be deployed. Therefore, based on the mixed traffic assignment, we propose the following program to model the AV lane location problem:

$$\min \sum_{\tau\in\Gamma}\sum_{m\in M}\sum_{w\in W}\sum_{a\in A} t_{a,\tau}\left(v_{a,\tau}\right)x_{a,\tau}^{w,m}, \tag{23}$$

$$\wedge_{a,\tau} = c_{a,\tau}\left(L_a + \sum_{k\in K}\varphi_{a,k}\sum_{j=1}^{\tau} y_j^k\right), \quad \forall a \in A, \tau \in \Gamma, \tag{24}$$

$$y_{\tau}^k \in \{0,1\}, \quad \forall k \in K, \tau \in \Gamma, \tag{25}$$

$$\sum_{\tau\in\Gamma}\sum_{k\in K} y_{\tau}^k L_k u \leq \mathrm{BD}, \tag{26}$$

where y_{τ}^k represents whether an AV candidate link is converted to AV link or not on the k-th pair of links at year τ, L_k is the lane length of the k-th pair of links, and u is the construction cost per unit distance of AV lane; constraint (26) guarantees that the cost cannot exceed the given budget. BD represents the upper limit of the budget. $\varphi_{a,k}$ is a parameter that denotes the pair-link incidence.

$$\varphi_{a,k} = \begin{cases} 1, & \text{if link } a \text{ belongs to the k th link pair and it is an AV link,} \\ -1 & \text{if link } a \text{ belongs to the k th link pair and it is a regular link,} \\ 0, & \text{else.} \end{cases} \tag{27}$$

4. Solution Algorithm

The first stage model employs a simulation-optimization solution approach, in which the manufacturer pricing problem is optimized using the genetic algorithm, and the agent-based simulation solves the vehicle type choice problem of consumers. In the second-stage model, a genetic-algorithm-based approach is proposed, which mainly includes a genetic algorithm to solve the AV lanes' location problem and the mixed traffic assignment problem with a diagonalized Frank–Wolfe algorithm. In addition, since the two models affect each other, an iterative optimization approach is required to solve the model to achieve equilibrium for both stages simultaneously. The schematic diagram of the two-stage model solution is presented in Figure 4.

4.1. The Diagonalized Frank–Wolfe Algorithm. The mixed traffic problem proposed in this paper is a multiuser traffic assignment problem. Specifically, since AV and CV users compete for road space in their trips, there is asymmetric interaction on the corresponding links of the network, thus affecting travel time for each other. Therefore, the diagonalized algorithm is used to solve the traffic assignment problem in our model. The diagonalized algorithm reduces the original problem to a series of interacting subproblems, that is, the multiuser equilibrium problem is converted into several single-user equilibrium subproblems. The basic idea of the solution using the diagonalized algorithm is first to fix the CV traffic flow and use it as the background traffic flow for the equalization of AV traffic flow; then, fix the equalized AV traffic flow and solve for the equalization of CV traffic flow. The two types of traffic flows are iterated repeatedly to achieve equilibrium of them finally. The specific steps of the diagonalized Frank–Wolfe algorithm are as follows:

Step 1. Initialization: Given the network, the deployment plan of AV lanes and algorithm accuracy parameters, set the number of iterations $n = 0$.

Step 2. Given the initial solution. Based on the given AV lanes deployment plan, modify the properties of the network and perform an all-or-nothing assignment to obtain the initial traffic solution.

Step 3. Diagonalization: According to the feasible link-flow vector V_m^n, update the link travel time and convert two types of traffic flows into subproblems.

Step 4. Solve subproblem. Fix the CV traffic flow and solve the equilibrium flow of AV using the traffic assignment algorithm (Frank–Wolfe); then, fix the equalized AV traffic flow and solve for the equalization of CV traffic flow. Obtain the link-flow vector V_m^{n+1}.

Step 5. Judgment of stop condition: If $V_m^n \cong V_m^{n+1}$, the algorithm stops; otherwise, let $n = n + 1$ and return to Step 3.

4.2. The Agent-Based Simulation Module. The agent-based simulation module realizes the simulation of the vehicle-type choices for travelers, and the specific steps are as follows:

Step 1. Initialization: Set the number of agents, the basic properties of each agent, environment properties, and other basic parameters; construct the social network; set the time step to 1 year, and let the time $t = 0$.

Step 2. Calculate the preference utility ($P_{i,t}$) of each agent at the current time t.

Step 3. Update the social network and calculate the social network utility ($S_{i,t}$) of each agent at the current time t.

Step 4. Calculate the relative utility (ΔU) of each agent at the current time t. If $\Delta U \geq \delta$, the agent chooses AV, otherwise chooses CV.

Step 5. Judgment of stop condition: If time t reaches the maximum time $t_{\max}$, the algorithm stops, otherwise let $t = t + 1$ and return to Step 2.

4.3. Genetic Algorithm Module. Due to its strong global search capability, robustness, and good parallelism, the genetic algorithm (GA) has been widely used in road network design and pricing problems. The basic idea of the genetic algorithm is to encode decision variables as chromosomes and obtain optimal individuals through operations such as inheritance, crossover, and mutation. The specific process is as follows:

Step 1. Initialization: Set individual size, population size, crossover and mutation probability, and maximum genetic algebra; encode decision variables; and randomly generate the initial population. Set the number of iterations $n = 0$.

Step 2. Fitness evaluation: Calculate the fitness value of all chromosomes according to the diagonalized Frank–Wolfe algorithm module and the agent-based simulation module and perform the genetic operation of the population based on the fitness.

Step 3. Perform the crossover and mutation operations.

Step 4. Judgment of stop condition: If the number of iterations reaches the maximum number of iterations or the optimal fitness of the population no longer increases, the algorithm stops, otherwise let $n = n + 1$ and return to Step 2.

5. Numerical Studies

In this section, numerical examples are performed based on the Nguyen–Dupuis network and Sioux Falls network to verify the proposed model and solution algorithm. Algorithms and simulation modules are coded in MATLAB R2020b and tested based on a personal computer with Intel Core (TM) i5-10400F, 2.90 GHz CPU, 16 GB RAM.

5.1. The Nguyen–Dupuis Network. The Nguyen–Dupuis network consists of 13 nodes, 19 links, and four OD pairs. In addition, we set up seven links of candidate AV lanes. The structure of the network and the locations of candidate links are depicted in Figure 5. The detailed network properties and demand for OD pairs are reported in Tables 1 and 2, respectively.

The model parameters are set as below. The study period is 30 years, from 2025 to 2055, and the classification of consumers follows the normal population distribution based on the innovation of Valente and Rogers [46]: 2.5%

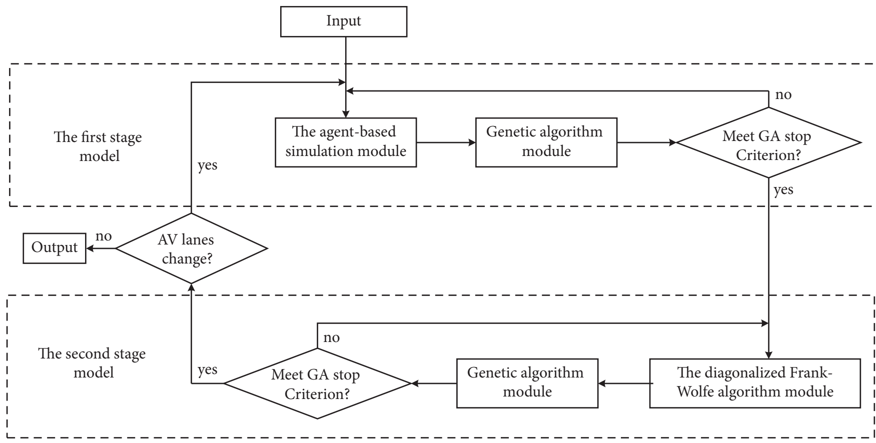


Figure 4: The schematic diagram of the solution.

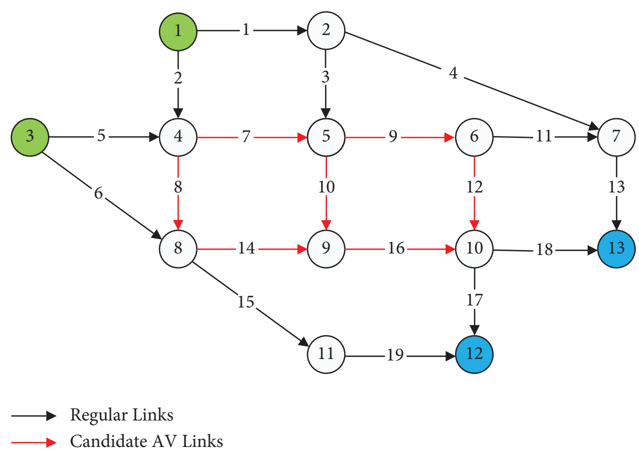


Figure 5: The Nguyen–Dupuis network with candidate AV links.

Table 1: Link characteristics of the Nguyen–Dupuis network.

Link	t_a^0 (min)	Lanes	Capacity (veh/h)
1	9	4	8000
2	7	3	6000
3	7	4	8000
4	14	2	4000
5	9	3	6000
6	12	2	4000
7	3	3	6000
8	9	3	6000
9	5	3	6000
10	13	4	8000
11	5	2	4000
12	9	3	6000
13	9	4	8000
14	10	4	8000
15	9	2	4000
16	6	4	8000
17	8	4	8000
18	7	3	6000
19	11	2	4000

Table 2: Total OD demands of the Nguyen–Dupuis network (veh/h).

O	D	Demand
1	12	12000
1	13	12000
3	12	9000
3	13	9000

innovators, 13.5% early adopters, 34% early majority, 34% late majority, and 16% laggards. The attribute weight value of each type of consumer when choosing a vehicle is fixed, and the weight value changes with the change of the consumer category. The value of N for the social network is considered the same as the OD requirement for the Nguyen–Dupuis network, which is 42,000 with a K of 200 and a reconnection probability of 5%. In addition, we assume the average vehicle lifespan to be ten years, and the cost and price of CV are, respectively, \$18,000 and \$20,000, while the cost of AV is \$30,000 and decreases at a rate of 1.5% per year, and the price ceiling and floor for AV are \$40,000 and \$22,000.

Then, we will analyze from three aspects: subsidy policy, AV lanes deployment, and comprehensive policy.

5.1.1. Subsidy Policy. As mentioned before, our subsidy policy focuses on the impact of three dimensions: subsidy objects (vehicle manufacturer or consumers), the amount of subsidies, and the duration of subsidies.

(1) Subsidy Objects. In order to clearly and intuitively display the differential impact of manufacturer subsidy and consumer subsidy, we investigate the impact on AV market penetration and social welfare when manufacturers and consumers are subsidized \$2,000, \$3,000, and \$4,000 per AV per year, respectively. To prevent the interference of subsidy amount, we further explore the situation of high subsidy amount for \$8,000. Figures 6(a)–6(d) visualize the effects of the four scenarios.

It can be seen that, first, both manufacturer subsidies and consumer subsidies positively affect the growth of AV market penetration and social welfare. Second, consumer subsidies outperform manufacturer subsidies at the same subsidy amount due to the direct effect of the former on AV purchases rather than the indirect effect of the latter.

Furthermore, Figures 7(a)–7(c) illustrate the impact of subsidy objects on manufacturer benefits, consumer benefits, and manufacturer AV pricing for a subsidy amount of \$2,000. Obviously, manufacturer subsidies have a superior effect on manufacturer benefits, although the same amount of consumer subsidies produces a more significant increase in consumer benefits, which lead to the previously described superior effect of consumer subsidies over manufacturer subsidies in improving social welfare. In addition, from the perspective of manufacturer AV pricing, whether it is subsidized to manufacturers or consumers, the trend of AV price changes is basically the same; only the prices differ, which also indicates that consumers are more concerned about the price difference between AV and CV than their prices.

The effect of the simultaneous implementation of manufacturer and consumer subsidies is illustrated in Figure 8. Along the main diagonal direction of Figure 8, the total amount of subsidies to manufacturers and consumers is equal, such as \$8,000 per vehicle in Figure 9. It can be seen that the final AV market penetration tends to decrease as the amount of manufacturer subsidy increases. This indicates that under a fixed total subsidy, the effect of only consumer subsidy is optimal, and both consumer and manufacturer subsidies are the second, and only manufacturer subsidy is the worst.

(2) Subsidy Amount. The subsidy amount is considered to be a key factor affecting subsidy effectiveness. Therefore, consumer subsidies of \$2000, \$4000, \$6000, and \$8000 are set to explore the effect of the subsidy amount on AV market penetration, and the results are illustrated in Figure 10. It can be observed that AV market penetration increases with the amount of subsidy, which is the same as our expectation. However, the increase in subsidy effect seems to be gradually less obvious with augmentation of the amount of subsidy, which may be related to the marginal benefit. To further investigate whether there are marginal benefits in the subsidy amount, we plot the AV market penetration and social welfare in the 30th year for subsidy amounts ranging from \$1,000 to \$8,000. It can be seen in Figure 11 that the subsidy effect increases greatly when the subsidy amount is less than \$5,000, while it increases slightly when the subsidy amount is more than \$5,000. This verifies the existence of marginal benefits and also shows that the \$5,000 consumer subsidy can be considered the optimal subsidy strategy combining subsidy effects and costs.

(3) Subsidy Duration. This section discusses the impact of subsidy duration. We set up four scenarios of consumer subsidies: \$2,000 per AV for 30 years, \$3,000 per AV for 20 years, \$6,000 per AV for 10 years, and \$8,000 per AV for 10 years. Figure 12 describes the evolution of AV market penetration in the four scenarios. Compared to \$3,000 per AV with a 20-year subsidy and \$6,000 per AV with a 10-year subsidy, \$2,000 per AV with a 30-year subsidy works best. This is due to the fact that when the subsidy years are short, the AV market penetration is still at a low level after the subsidy ends, which cannot attract more consumers to choose AV. Only when the subsidy amount is high enough, such as \$8,000, the 10-year subsidy can make the AV market penetration level higher at the end of the subsidy, thus making the final AV market penetration level reach a better result. In summary, long-term subsidies work better; if short-term subsidies are implemented, the amount of subsidy must be high enough so that the AV market penetration reaches a relatively high level by the end of the subsidy to achieve the desired effect.

5.1.2. AV Lanes' Deployment. AV lanes are deployed in a progressive fashion following changes in AV market penetration. But the deployment of AV lanes is not supposed to change too frequently, so we adjust the AV lanes' deployment scheme at five-year intervals. Specifically, the deployment of AV lanes is carried out according to the AV market penetration in the 1st, 6th, 11th, 16th, 21st, and 26th years. The optimal deployment scheme obtained under a subsidy policy of \$4,000 per AV for 30 years is listed in Table 3. The analysis of the table shows that when the AV market penetration is low, it is optimal without deploying AV lanes. And as the AV market penetration gradually increases, the number of candidate links for deploying AV lanes increases until all candidate links are deployed with AV lanes eventually.

To further investigate the effectiveness of the AV lanes' deployment plan, we consider three different AV lanes' deployment plans: (1) no AV lanes will be deployed, (2) AV lanes will be deployed in a progressive fashion as shown in Table 3, and (3) AV lanes will be deployed in all lanes in Table 3 at once in the first year. The evolution of the total travel time under the three plans can be observed in Figure 13: (1) as AV market penetration increases, the total travel time under all three plans tends to decrease, which

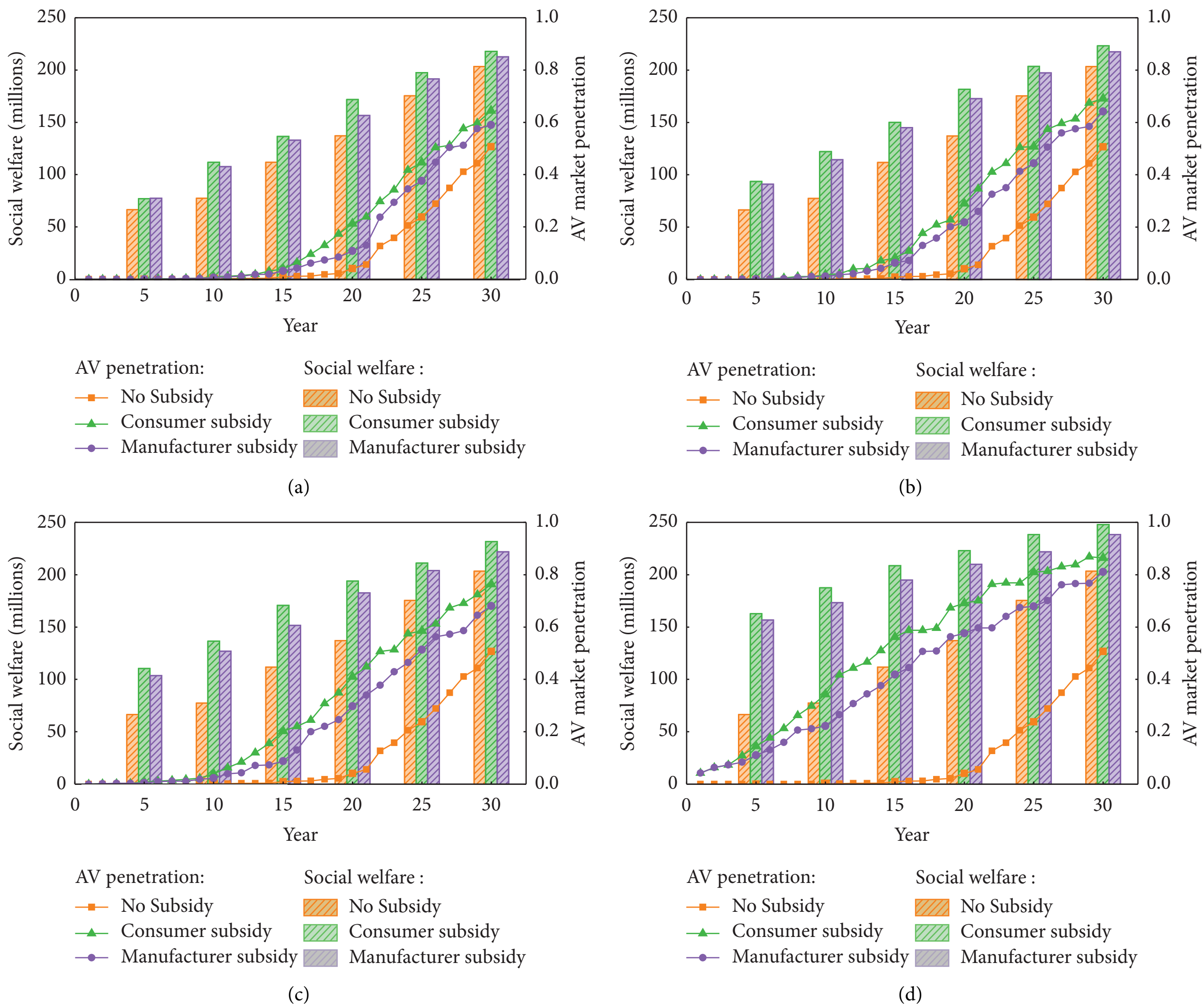


FIGURE 6: Impact of subsidy objects on AV market penetration and social welfare under different subsidy amounts: (a) $2,000 per AV per year, (b) $3,000 per AV per year, (c) $4,000 per AV per year, and (d) $8,000 per AV per year.

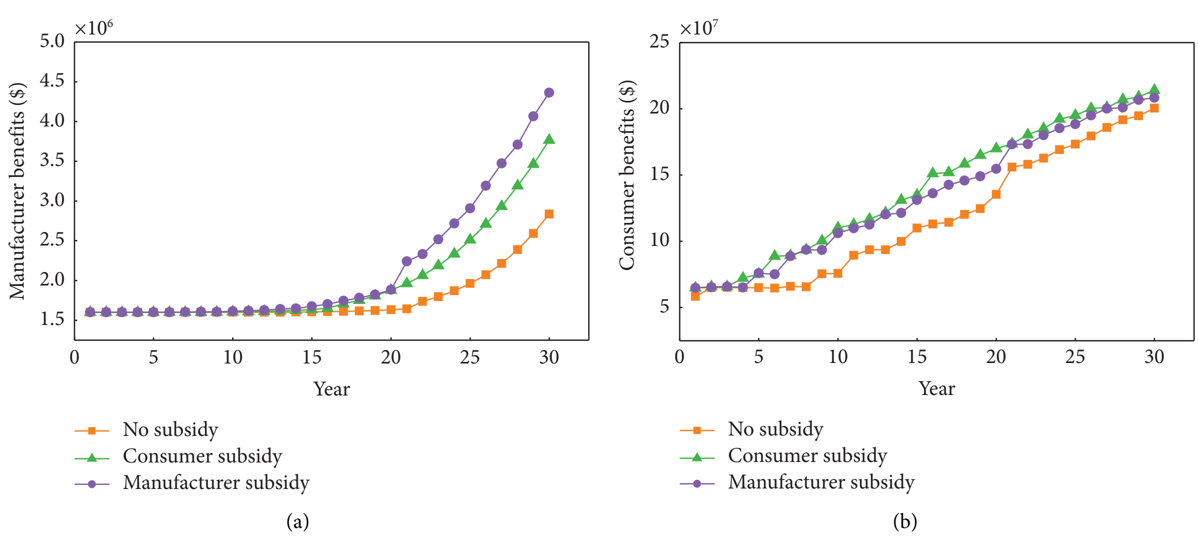
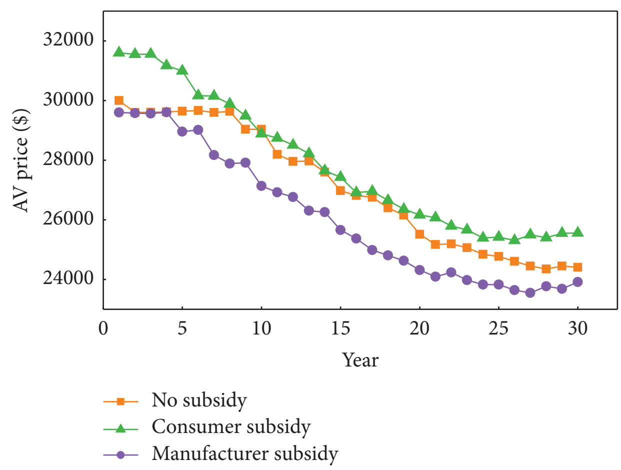


FIGURE 7: Continued.



(c)

FIGURE 7: The impact of subsidy objects: (a) manufacturer benefits, (b) consumer benefits, and (c) AV price.

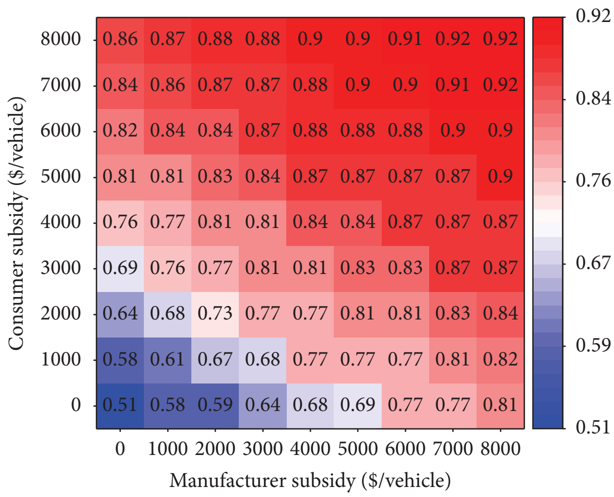


FIGURE 8: Effect of different subsidy objects and amounts.

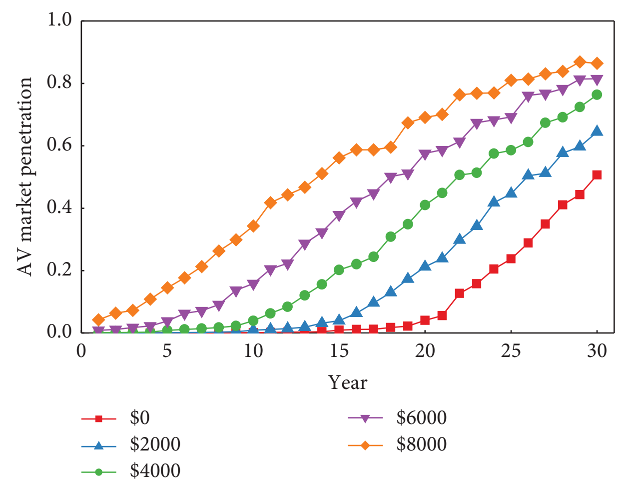


FIGURE 10: Impact of different subsidy amounts on AV market penetration.

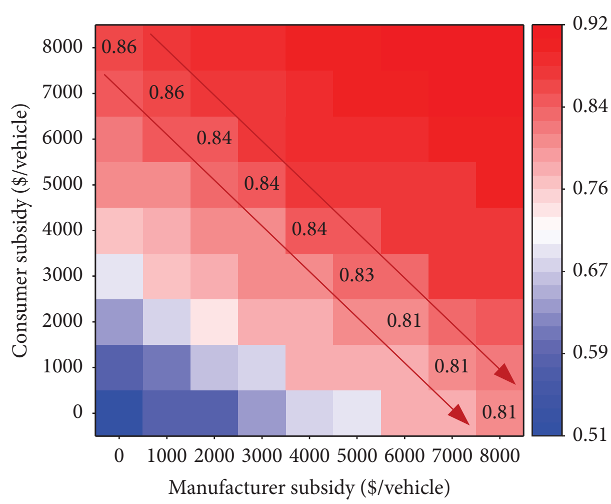


FIGURE 9: Effect of different subsidy for $8000 objects.

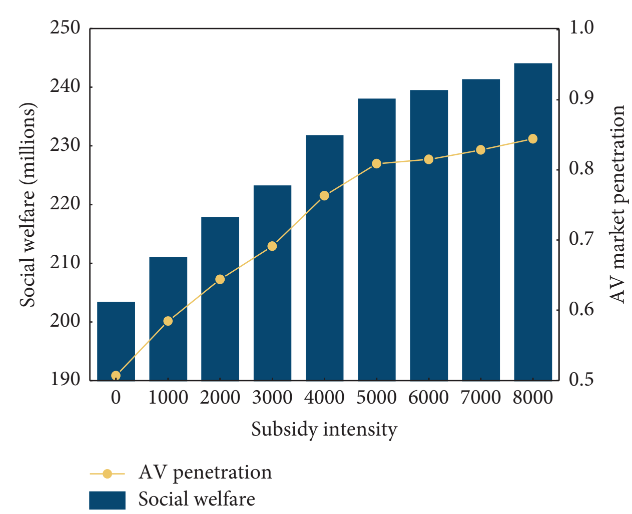


FIGURE 11: AV market penetration and social welfare in the 30th year.

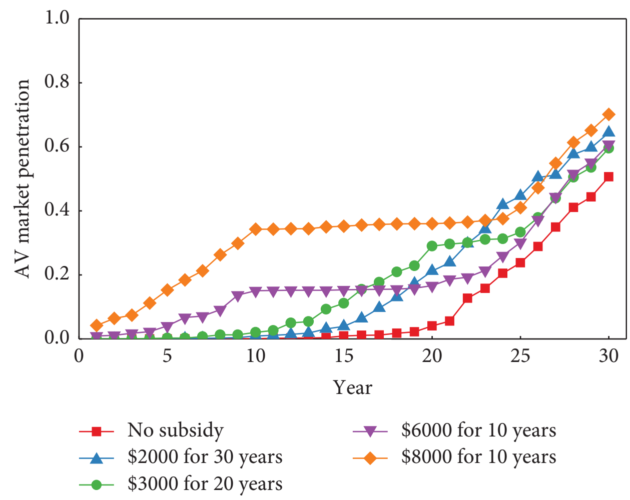


Figure 12: The evolution of AV market penetration in four scenarios.

Table 3: Optimal deployment plan in the Nguyen–Dupuis network.

Year	The AV market penetration (%)	The optimal deployment of AV lanes	Total travel time (min)
1	0.04	No AV lanes	3,198,700
6	1.14	No AV lanes	2,608,133
11	6.30	4-8; 8-9	2,110,618
16	22.09	4-8; 8-9; 4-5; 5-6; 6-10; 9-10	1,518,002
21	44.84	4-8; 8-9; 4-5; 5-6; 6-10; 9-10; 5-9	1,268,821
26	61.23	4-8; 8-9; 4-5; 5-6; 6-10; 9-10; 5-9	1,153,878

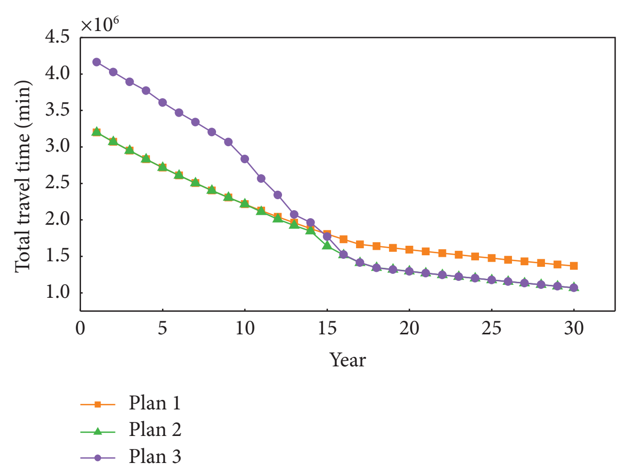


Figure 13: Total travel time under the three plans.

confirms the role of AV in reducing travel time; (2) in the first decade, the total travel time of Plan 3 is much larger than the other two plans; the reason behind is when AV market penetration is low, the deployment of AV lanes will occupy road resources making the travel time of CV users much higher, so the deployment of AV lanes should be implemented after the AV market penetration reached a certain level; and (3) Plan 2, with its deployment in a progressive fashion, performs excellently throughout the program period, significantly reducing total travel time.

(1) Comprehensive Policy. In this section, we further explore the impact of different combinations of subsidy and AV lanes' policies on the evolution of AV market penetration, including (1) no subsidy policy and no AV lanes, (2) AV lanes but no subsidy policy, (3) subsidy policy but no AV lanes, and (4) AV lanes and subsidy policy. The subsidy policy is $4,000 per AV for 30 years, and AV lanes are deployed progressively, as shown in Table 3. The evolution of AV market penetration in the four scenarios is plotted in Figure 14.

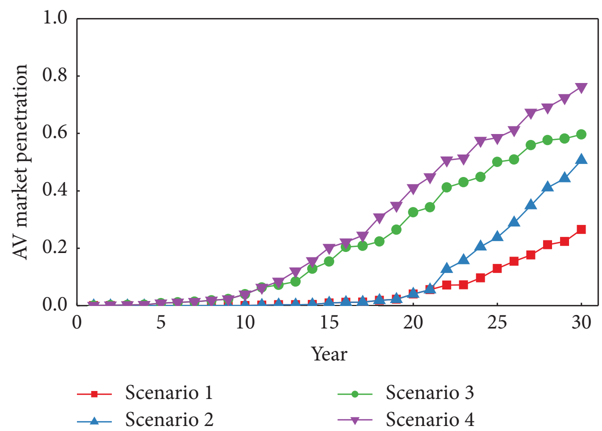


FIGURE 14: AV market penetration in four scenarios.

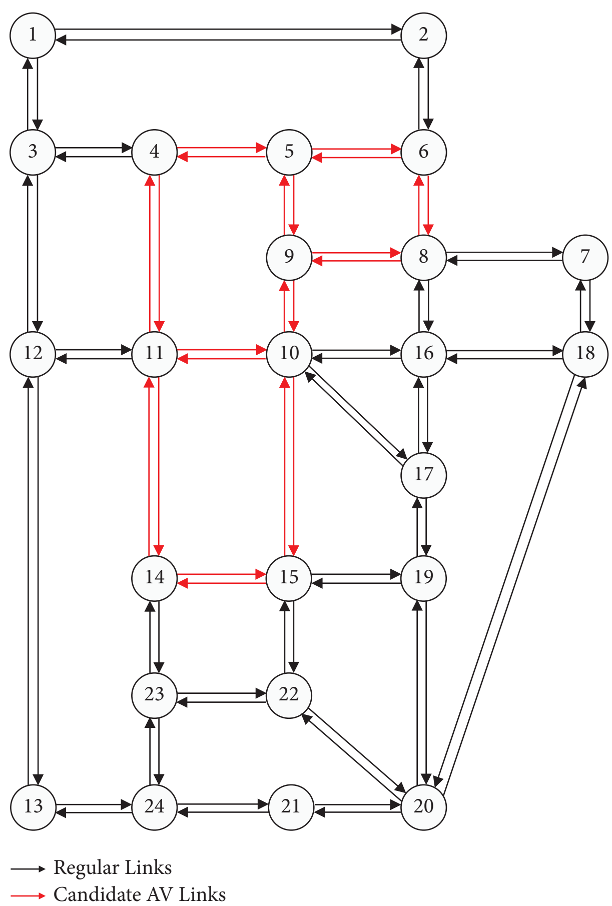


FIGURE 15: Sioux Falls network with candidate AV links.

It can be seen that both the subsidy policy and the deployment of AV lanes have a positive impact on the increase of AV market penetration, and the effect is optimal when the two are implemented simultaneously. As far as a single policy is concerned, the effect of the subsidy policy is better than the deployment of AV lanes. When there is no subsidy policy, AV market penetration grows slowly and AV lanes are not deployed until year 21, while when there is a subsidy policy, AV lanes start to be deployed in the 11th year. Subsidy policy has a more noticeable effect on the early adoption of AV, while the deployment of AV lanes will be effective only after AV penetration reaches a certain level in the middle and late stages. Therefore, the government should determine the subsidy policy and AV lanes' deployment as a whole and implement the corresponding policy at the right time, which can both increase the AV market penetration and achieve a reasonable allocation of government resources.

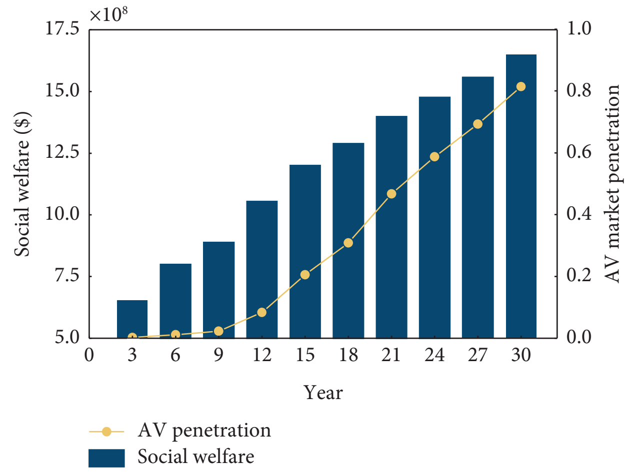


FIGURE 16: AV market penetration and social welfare over time.

TABLE 4: Optimal deployment plan in the Sioux Falls network.

Year	The AV market penetration (%)	The optimal deployment of AV lanes	Total travel time (min)
1	0.04	No AV lanes	24,097,088
6	1.14	9-10; 10-11 10-9; 11-10	19,648,109
11	6.92	9-10; 10-11; 8-9 10-9; 11-10; 9-8	16,356,995
16	23.05	9-10; 10-11; 8-9; 4-5; 14-15; 6-8 10-9; 11-10; 9-8; 5-4; 15-14; 8-6	13,406,660
21	46.70	9-10; 10-11; 8-9; 4-5; 14-15; 6-8; 5-9; 5-6 10-9; 11-10; 9-8; 5-4; 15-14; 8-6; 9-5; 6-5	11,513,047
26	67.09	9-10; 10-11; 8-9; 4-5; 14-15; 6-8; 5-9; 5-6 10-9; 11-10; 9-8; 5-4; 15-14; 8-6; 9-5; 6-5	9,387,386

5.2. Sioux Falls Network. To further test the proposed model and solution algorithm, we implement the model in the network of Sioux Falls—the biggest city in South Dakota. The network consists of 24 nodes, 76 regular links, and 22 candidate AV links, as shown in Figure 15. Detailed data of links and OD demands are shown in Tables 1 and 2 in the Appendix. We set the N value of the social network to 196,000 and the K value to 200. Other parameters are the same as were adopted in the Nguyen–Dupuis network.

Under the conditions of $4,000 per AV subsidy for 30 years and the deployment of AV lanes in a progressive fashion, the AV market penetration and social welfare over time are revealed in Figure 16, and the optimal deployment of AV lanes is given in Table 4.

6. Conclusions

In this paper, we propose a two-stage model to explore the effects of subsidy and AV lanes' policies on AV adoption. The first stage model captures the pricing behavior of the vehicle manufacturer and the vehicle-type choice behavior of consumers, from which AV market penetration and the effect of the subsidy policy on it can be accessed. Based on the AV market penetration acquired from the first stage model, the second stage model identifies the optimal time-dependent progressive AV lanes deployment with the mixed traffic assignment. The first and second stage models are solved using the simulation-optimization and genetic-algorithm-based approaches, respectively. An iterative optimization approach is required to solve the whole model because the two models affect each other. Finally, two numerical experiments are presented to validate the proposed model. The results show that (1) both subsidy and AV lanes' policies play a positive role in AV adoption and work better when implemented simultaneously; (2) in terms of subsidy policy, first, there are differential effects between consumer subsidies and manufacturer subsidies, with the former being more effective in improving social welfare and AV market penetration, while the latter is more beneficial to the manufacturer; second, the effect of subsidy policy increases with the amount of subsidy but there are marginal benefits; third, the effect of the subsidy is closely related to the duration of the subsidy and can only be exerted if the AV market penetration reaches a certain level at the end of the subsidy, which should be taken into account when the subsidy duration is set. In conclusion, in the formulation of subsidy policy, the government should reasonably determine the subsidy objects, subsidy amount, and subsidy duration according to the requirements; (3) premature deployment of AV lanes will not only fail to reduce travel time but will play a negative role, so AV lanes should be deployed when the AV market penetration reaches a certain level and should be deployed in a progressive fashion.

In future research, the following three aspects can be expanded. First, the correlation model of travel demand variation can be developed by considering elastic or time-varying travel demand. Second, considering the uncertainties in the policy implementation and AV market, it is also worthwhile to investigate the establishment of stochastic programming models. Finally, a large-scale SP survey of consumers to understand their preferences for AV is an effective way to further improve the accuracy of the model.

Data Availability

The data used to support the findings of this study are available from the corresponding author on request. The data are not publicly available due to privacy.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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Supplementary Materials

Table 1 in Appendix describes link characteristics of the Sioux Falls network. Table 2 in Appendix describes total OD demands of the Sioux Falls network. (*Supplementary Materials*)

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