

Research Article

Congestion Control for Mixed-Mode Traffic with Emission Cost

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This paper presents two models to investigate the traffic assignment problem. In the two models, the emission cost for gasoline vehicles (GVs) is considered. The credit schemes are considered in the constraint of the models. The operation costs for battery electric vehicles (BEVs) and GVs are also studied. Particularly, the constraints related to the credit schemes can be utilized to adjust the number of GVs and to promote growth of the number of BEVs, which is a novel idea that was not studied. Preliminary numerical experiments demonstrate that the models are effective and the extended distance limit of BEVs can raise the volume of BEVs under the condition that the unit traffic cost of BEVs is lower than GVs. Therefore, it is feasible to control the quantity of GVs by adjusting the total credit schemes, and it is viable to reduce the emission by enlarging the number of BEVs' users.

1. Introduction

In recent years, in order to decrease petroleum consumption, various organizations are pushing to utilize various electric vehicles (e.g., [1–5]). It is predicted that electric vehicles will take up a significant market share in the near future as a result of the maturity of electric vehicle technologies and increasing public acceptance [6]. In light of engine technologies, the electric vehicles can be divided into two classes: plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs). The main difference between them is that the former is equipped with both gasoline engine and electric motor, while the latter is only equipped with electric motor. Bradley and Brank [7] stated that PHEVs do not fully mitigate environmental consequences since they still require gasoline. On the contrary, Lin and Greene [8] presented that, due to the characteristic of utilizing electricity entirely, BEVs may provide a definitive solution for electrification of personal transportation.

PHEVs and gasoline vehicles (GVs) can be substituted for BEVs to realize the goal of declining petroleum consumption, enhancing energy security, and improving

environmental sustainability. However, similarly as stated by He et al. [3] and Nie and Ghamami [9], the users of BEVs may bump into a different kind of problems such as the cost caused by the limited driving range of BEVs, long charging time, scarce availability of charging stations, and limitation of battery technologies. These problems lead the BEVs not to be universally accepted by users who also have to bear the worry of being stranded when battery runs out of charge, which is normally referred to as range anxiety in the literature (e.g., [10]). It is still unrealistic to eliminate range anxiety in the near future, although more and more public charging stations have been deployed and many other strategies to deal with range anxiety have emerged (e.g., [3]).

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be universally accepted by users who also have to bear the worry of being stranded when battery runs out of charge, which is normally referred to as range anxiety in the literature (e.g., [10, 11]). It is still unrealistic to eliminate range anxiety in the near future, although more and more public charging stations have been deployed and many other strategies to deal with range anxiety have emerged (e.g., [3]).

On the other hand, the fact that the idea of tradable credit schemes was employed to decrease emissions and/or to reduce traffic congestion in urban was investigated in the latest decade. Yang and Wang [12] suggested a tradable credit plan to assuage jam which may eliminate unfairness of traditional jam pricing and analyze more reasonable pikes strategies. Three steps can be adopted as follows: initial credit allocations, credit charges, and credit transactions. Compared with traditional jam pikes plan, the financial transfer from users to governments is not contained. Afterward, transportation investigators have extensively concentrated on the tradable credit schemes. The effects of transaction costs on auction market and negotiated market for tradable credits were investigated by [13], whose investigation demonstrated that the initial allocation of credits may influence the equilibrium state. Under some proper conditions, the auction market can reach the equilibrium allocation of credits under appropriate conditions and, in the negotiated market, the transaction costs can divert the system from the desired equilibrium. The tradable credit plan for heterogeneous users with discrete value of time (VOT) was introduced by Wang et al. [14], who formulated adequate tradable credit plans and confirmed that these schemes could distribute optimal or Pareto-improving optimal traffic flow patterns to users. Moreover, the existence of optimal tradable credit scheme was proved by Xiao et al. [15], who eradicated the bottleneck queue. The price of tradable credits was studied by Shirmohammadi et al. [16], in which the aim of the study was to reduce congestion in urban by adjusting the price of tradable credits. A multiclass traffic network equilibrium issue under a given tradable credit plan with VOT decentralization was studied by Zhu et al. [17]. In addition, a novel jam decrease approach for optimizing tradable credit schemes on general traffic network was presented by Wang et al. [18]. On the other hand, a stochastic user equilibrium model containing tradable credit plan was studied by Han and Cheng [19], in which the maximization of volume of the traffic network capacity was the goal of the study. A public-private hybrid transportation network with tradable credits was scouted by Wang and Zhang [20] and Wang et al. [21], who solved the problem by equilibrium theory. For managing private financing and mobility, Bao et al. [22] proposed bilevel programming to study the problem, of which the tradable credits plan was considered. In view of the application of the tradable credits for operating the trip of car, a review paper was proposed by Dogterom et al. [23], which focused on the investigation of empiricism and the pertinent behavioral methods. In order to lessen the emission of vehicles, multiperiod tradable credit scheme methods were proposed by Miralinaghi and Peeta [24, 25]. In order to manage the queue length of vehicles at bottleneck, tradable credit plan was employed by

Shirmohammadi and Yin [26]. Lahlou and Wynter [27] investigated a binary transport game containing tradable credit plans and introduced a Nash equilibrium model to solve the problem. In view of tradable credit scheme idea, tradable bottleneck permits were firstly introduced by Akamatsu and Wada [28], which was utilized to operate the transportation demand. In the design of the discrete traffic network, the noncontinuous credit pricing policy was scrutinized by Wang et al. [29]. Dogterom et al. [30] studied the adjustment actions at the trip level, in which the tradable credit plan was contained. Guo et al. [31] studied the tradable credit scheme based on the system optimum of the evolutionary traffic flows and evaluated the convergence of the system. The fact that the system optimum theory was utilized to investigate the tradable credit arrangement was introduced by Lv et al. [32]. Based on experimental economics method, Tian et al. [33] analyzed the tradable mobility credit plan with the influence factors of behavior. The experimental results demonstrate that the stated tradable mobility credit plan in their study was well-organized and economically maintainable. A novel model for tradable credit arrangement was stated by Lian et al. [34] and it was formulated based on driving-day under the congestion situation in urban. The existence of the unique equilibrium of dynamic jam noninternality with tradable credit policies was investigated by Bao et al. [35]. Gao et al. [36] studied the incremental-cost pricing of the tradable credits and utilized Cobweb model to explore the constancy of the credit price. The fact that the cyclic tradable credits were employed to improve the social justice was stated by [37]. In the same year, assuming that the nonhomogeneity of the demands and the commuters were conservative, Miralinaghi et al. [38] investigated the tradable credit scheme problem under the morning traffic congestion. The zero-emission vehicles were studied by Miralinaghi and Peeta [39]. The robust multiperiod tradable credit plan was employed to promote drivers to choose zero-emission vehicles and the target was to lessen the emission. For decreasing emission, the allocation efficiency of the method of tradable permit schemes was scrutinized by De Palma and Lindsey [40]. By their investigation, the good performance of the method was verified. The tradable credit scheme in a bimodal transportation network based on uncertain behaviors of traveler was reconnoitered by Han et al. [41], who formulated the issue to a variational equality model and proposed a heuristic approach to solve the model. Miralinaghi and Peeta [42] presented a bilevel model to optimize the multiperiod tradable credit scheme. The goal of the study was to diminish the emission and alleviate congestion.

However, how to distribute the preliminary credits is a significant and complicated procedure and it contains how to recognize the eligibility of travelers and allocate credits to competent travelers. Nie and Yin [43] suggested a bottleneck model that contains the allocation of credit without considering the initial distribution of credits to the avoidance of these difficulties. Liu and Huang [44] stated a model without initial credit distributions for general traffic network and gained a credit toll. They formulated the problem as mathematical programming with equilibrium constraints

and gained a credit charging mechanism under some conditions. Zhu et al. [45] presented a biobjective model without initial credit distribution to optimize jam and emissions and stated a system containing linear equalities and linear inequalities to solve the model.

Furthermore, the models mentioned above ignored the association between congestion and emission. Yin and Lawphongpanich [46] introduced a counterexample for social cost pricing and a nonnegative first-best emissions pricing strategy to the system optimum pricing issue for congestion and emissions. They provided methods to calculate the trade-off between conflicting objectives and alleviating congestion versus reducing traffic emissions. Chen and Yang [47] stated a biobjective optimization model to study the relationship between congestion and emissions on traffic networks. Abdul Aziz and Ukkusuri [48] also proposed a biobjective model to study the trade-off between travel time and emissions. In addition, Grant-Muller and Xu [49] scrutinized the tradable credit plan to operate a traffic jam and the behavior of the model choice, of which the goal was to decrease the total miles of vehicles. Furthermore, Li et al. [50] proposed a model for dynamic carbon credit plan to operate traffic network mobility and emissions. In the study, a bilevel model was constructed and a projection search approach was introduced to deal with the model.

In this paper, we consider a mixed traffic network in which travelers can select GVs or BEVs and the goal is to minimize the sum of traffic cost and emission cost of GVs with the constraints of credit schemes. In fact, some people may have GVs only, which makes the network optimization problem similar to the basic traffic assignment problem; some people may have BEVs only, which has already been studied by Jiang et al. [51]; others may own both GVs and BEVs, which is similar to the study conducted by Jiang and Xie [52]. In addition, a network user equilibrium problem for BEVs and GVs was studied by Hu et al. (2017), in which the BEVs and GVs were embraced in the study and the battery exchanging centers and road grade constraints also were included. Furthermore, two new impedance functions for the traffic time on the road of EVs and GVs were proposed by Lin et al. [53] and Zou et al. [54]. On the other hand, the problem that EVs and GVs were contained in ride-sourcing market was investigated by Ke et al. [55]. In the study, recharging schedules of EV drivers were considered in a time-expanded traffic network. Jensen et al. [56] stated an investigation of the real path problem, in which BEVs and internal combustion engine vehicles were contained in the study and the behavior of drivers was considered.

Based on the above discussions, the studies can be summarized as several types: some researchers investigated the traffic congestion with tradable credit scheme, some scholars studied the emissions with tradable credit plan of traditional fuel vehicles (GVs), and some investigators scrutinized the traffic assignment problem of EVs and GVs. Compared with the existing works, our main contributions can be stated as follows:

- (i) Two novel models are presented in this paper, which contain BEVs and GVs. Particularly, the former

model can be employed to expand the usage of BEVs and control the number of GVs in the traffic network.

- (ii) In the models, the constraints of credit schemes have two cases: constraints containing both BEVs and GVs and constraints containing GVs only. The latter case can be regarded as a promotion of the travelers choosing BEVs with adjusting the total of credits displayed in our third experiment. That is, on the one hand, credit scheme can be utilized to adjust the traffic congestion. On the other hand, it can be employed to promote utilization of BEVs, which is an interesting perspective that was not investigated.
- (iii) Particularly, the study of Miralinaghi and Peeta [39] must be noticed. The zero-emission vehicles were considered in the study. In the experiments of the investigation, the credits were distribution between internal combustion engine vehicles and zero-emission vehicles. Furthermore, in our study, it needs to be emphasized that the credits only for GVs are studied in the experiment and model (3.6)-(3.13) is investigated.

This paper is organized as follows: In Section 2, we introduce a new link travel time function and demonstrate its advantages. The models are constructed in Section 3, and numerical experiments are displayed in Section 4. The conclusions are drawn in Section 5.

2. Link Time Functions

As is known to us, the transportation optimization models are generally in the forms of

$$\begin{aligned} \min \quad & pt \sum_{a \in A} t_a(v_a(\rho)), \\ \text{or} \quad & \min \quad pt \sum_{a \in A} t_a(x_a), \end{aligned} \quad (1)$$

$$\begin{aligned} \min \quad & pt \sum_{a \in A} pt_a(v_a(\rho)) + c(x_a), \\ \text{or} \quad & \min \quad pt \sum_{a \in A} pt_a(x_a) + c(x_a), \end{aligned} \quad (2)$$

subject to link constraints, path constraints, and some other related constraints. Here, A is the set of all links in the network, ρ denotes traffic density per mile, x_a denotes traffic flow on link $a \in A$, v_a denotes a speed-density impedance function, t_a denotes a time-speed or time-flow impedance function, p is the price of unit time, and c stands for other costs associated with vehicles such as energy cost.

The objective functions (1) and (2) require traffic network to minimize total travel costs and main difference between them is that (2) also minimizes other related costs. Model (2.1) was firstly applied to describe network equilibrium by Jiang et al. [51], while (2) was firstly considered by Jiang and Xie [52]. The GVs and BEVs were embraced in the two studies. Both are reasonable from their own perspectives. In this paper, we introduce two models different from the objective functions (1) and (2).

The impedance function t_a , which reveals the relationship between travel costs and traffic conditions on the road reflecting the crowded effect of traffic network, plays a significant role in (1) and (2). The most popular impedance function is the Bureau of Public Roads (BPR) function defined by

$$t_a^{\text{BPR}}(x_a) = t_a^0 \left(1 + \alpha \left(\frac{x_a}{C_a} \right)^\beta \right), \quad (3)$$

where x_a , t_a^0 , and C_a denote the traffic flow, free travel time, and capacity on link a , respectively, and $\alpha > 0$ and $\beta > 0$ are specified parameters. This function is gained through regression method based on investigating lots of road section by the Bureau of Public Roads in 1964.

In this paper, in view of the link travel time function given by [53], we define a new time impedance function:

$$t_a(x_a, b_a) = \begin{cases} t_a^0, & b_a \leq x_a + b_a \leq C_a, \\ t_a^0 \left(1 + \alpha \left(\frac{x_a + b_a - C_a}{Z_a - C_a} \right)^\beta \right), & C_a < x_a + b_a \leq Z_a, \\ t_a^0 \left(1 + \alpha \left(\frac{\epsilon}{Z_a - x_a - b_a + \epsilon} \right)^\beta \right), & Z_a < x_a + b_a < Z_a + \epsilon. \end{cases} \quad (4)$$

Here, the meanings of $\{x_a, t_a^0, \alpha, \beta, C_a\}$ are the same as above, Z_a is a critical value over which there will be a traffic jam on link a , $b_a \geq 0$ is the number of the buses on link a , and $\epsilon > 0$ is a small constant. This impedance function, which is depicted in Figure 1, has the following properties.

Comparing with the BPR function and the time function of [53], the number of the buses is contained on link a in equation (4), which is more in line with the actual traffic conditions in urban. On the other hand, since the bus travel route is fixed, there is no need to assign the routing. Thus, we ignore the factor in the study.

Theorem 1. Suppose that $\alpha > 0$, $\beta > 1$, $b_a \geq 0$, and $\epsilon \leq Z_a - C_a - b_a$. Then, one has the following statements:

- (1) The function $t_a(x_a, b_a)$ is continuous over $[0, Z_a + \epsilon)$

- (2) The function $t_a(x_a, b_a)$ is differentiable everywhere over $[0, Z_a + \epsilon)$ except the point Z_a
- (3) The functions $t_a(x_a, b_a)$ and $t_a(x_a, b_a) \cdot x_a$ are both convex over $[0, Z_a + \epsilon)$

Proof. The proof of theorem (1) is analogous to [53].

Comparing with the BPR function and the time function of [53], the advantages of this link travel time function can be stated as follows:

- (1) When the number of vehicles is no more than the capacity allowing to travel freely, travel time is stable in general.
- (2) When the number of vehicles is more than the capacity, travel time begins to change sharply when approaching the threshold value.
- (3) When congestion happens, few vehicles can travel into the network. In this case, we may think that the number of vehicles is a constant but travel time still increases. \square

3. Models

The notations in the considered traffic network are as follows: K denotes the set of O-D pairs; $k \in K$ means a single O-D; $k_g \in K$ and $k_e \in K$ mean feasible paths of GVs and BEVs of O-D pair k , respectively; ω_{k_g} and ω_{k_e} stand for the traffic flows of GVs and BEVs between O-D pairs k , respectively; $\omega_{k_g}^a$ and $\omega_{k_e}^a$ stand for the traffic flows of GVs and BEVs on link a between O-D pairs k , respectively; A is the set of all links in traffic network; $a \in A$ denotes a single link in the traffic network; $a_g \in A$ and $a_e \in A$, respectively, are feasible links of GVs and BEVs for $a \in A$; x_{a_g} and x_{a_e} denote the total traffic flows of GVs and BEVs on link a , respectively; d_{k_g} and d_{k_e} denote the original outflows or terminal inflows of GVs and BEVs between O-D pairs k , respectively.

3.1. Constraints. The set of feasible path flow patterns is defined by

$$\Gamma_\omega = \left\{ \left(\omega_{k_e}, \omega_{k_g} \right) \mid \omega_{k_e} \geq 0, \omega_{k_g} \geq 0, \sum_k \omega_{k_e} = d_{k_e}, \sum_k \omega_{k_g} = d_{k_g}, k_e \in k, k_g \in k, k \in K \right\}, \quad (5)$$

and the set of feasible link flow patterns is defined by

$$\Gamma_x = \left\{ \left(x_{a_e}, x_{a_g} \right) \mid x_{a_e} = \sum_{k_e \in K} \omega_{k_e}^a, x_{a_g} = \sum_{k_g \in K} \omega_{k_g}^a, x_{a_g} + x_{a_e} + b_a \leq Z_a, a_g \in a, a_e \in a, a \in A \right\}. \quad (6)$$

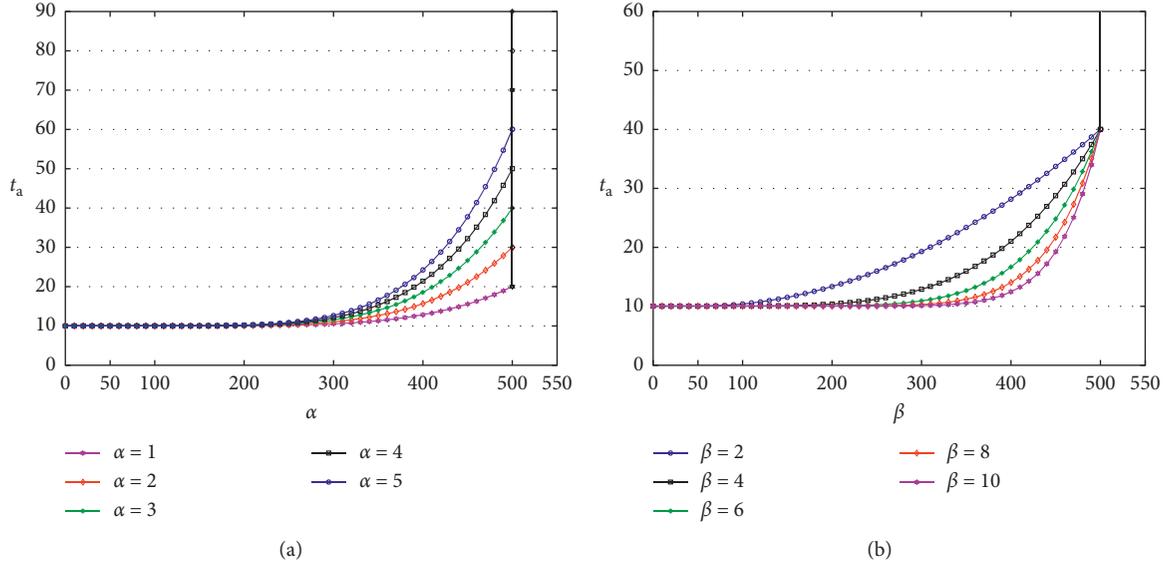


FIGURE 1: The impedance function $t_a(x_a)$. (a) Different value of α . (b) Different value of β .

In addition, let Q be an upper bound of the total amount of credits, with which the traffic management department intends to control the total of the vehicles in the traffic network [43, 45]. In other words, in general, the total demand for the credits may be more than the supply. Thus, in order to adjust the traffic situation, the traffic management department can adjust the upper bound of the total amount of credits in the traffic network.

3.2. Travel Cost Function. In a traffic network, the traffic costs consist of several parts: the traffic time cost, operating cost, and depreciation charge of vehicles. Here, we consider a mixed traffic network with GVs and BEVs, which is distinguished by two factors: driving distance limit and travel cost. The operating cost contains the cost of consumption of energy and depreciation charge. For simplicity, since the routes of buses need not be assigned, thus, let $c_{a_e}(x_{a_e} + x_{a_g}, l_a)$ and $c_{a_g}(x_{a_g} + x_{a_e}, l_a)$ denote the total operating costs functions of BEVs and GVs, respectively; let c_{a_e} and c_{a_g} be the unit price of the BEVs and GVs on link a , respectively; let p_a be the price of unit time on link a ; and l_a denotes the length of link a . Then, we can establish the system cost function for the mixed traffic network by

$$F = \sum_{a \in A} \left(p_a t_a(x_{a_e} + x_{a_g}, b_a)(x_{a_e} + x_{a_g}) + c_{a_e}(x_{a_e} + x_{a_g}, l_a) + c_{a_g}(x_{a_e} + x_{a_g}, l_a) \right). \quad (7)$$

Note that the objective function is similar to [51, 57]. However, the time function of equation (7) is different from that in papers [51, 57]. Thus, (7) is more reasonable.

3.3. Emissions Function from Vehicles. The emission engendered by gasoline vehicles on link a is a detachable

function $r_a(x_a)$ of link flow and speed. Yin and Lawphongpanich [46] investigated the first-best nonnegative emission tolls for minimization emission problem and proved that a first-best nonnegative emission toll exists when the emission function $r_a(x_a)$ is increasing with respect to link $a \in A$ in a transportation network, which is expressed as

$$R_a = r_a(x_a)x_a, \quad (8)$$

where $x_{a_g} = \sum_{k \in K} \omega_{k_g}^a$ is the sum of the traffic flow of GVs on link a and $R(x_a)$ denotes the sum of the emissions of the traffic network.

The relationship between emission and traffic flow on link a has been investigated in recent years (e.g., [45–47, 58]), which is formulated as

$$r_a(x_a) = 0.2038 t_a(x_a) \exp\left(\frac{0.7962 l_a}{t_a(x_a)}\right), \quad \forall a \in A, \quad (9)$$

where l_a denotes the length for link $a \in A$.

In this paper, we only consider the emissions of GVs. Then, the emissions function R_a on link a can be formulated as

$$R_a = r_a(x_{a_g} + x_{a_e})x_{a_g} = 0.2038 t_a(x_{a_g} + x_{a_e}) \cdot \exp\left(\frac{0.7962 l_a}{t_a(x_{a_g} + x_{a_e})}\right) x_{a_g}, \quad (10)$$

where $t_a(x_a)$ is defined as (4).

3.4. Optimization Models. In this subsection, we state two models to optimize the flow assignment problem and emissions of GVs in urban traffic network. The first model is to minimize the sum of travel time cost and operating cost of

BEVs and GVs, the anxiety cost of BEVs, and the emissions cost of GVs; that is,

$$\min_{\omega_{k_e}, \omega_{k_g}} \alpha_1 \sum_{a \in A} \left(p_a t_a (x_{a_e} + x_{a_g}) (x_{a_e} + x_{a_g}) + c_{a_e} (x_{a_e} + x_{a_g}, l_a) + c_{a_g} (x_{a_e} + x_{a_g}, l_a) \right) + \alpha_2 \sum_{a \in A} r_a (x_{a_g} + x_{a_e}) x_{a_g}, \quad (11)$$

$$\text{s.t. } E_{k_g} \omega_{k_g} = d_{k_g} i_{k_g}, \quad \forall k_g \in K, \quad (12)$$

$$E_{k_e} \omega_{k_e} = d_{k_e} i_{k_e}, \quad \forall k_e \in K, \quad (13)$$

$$x_{a_g} = \sum_{k \in K} \omega_{k_g}^a, \quad \forall a \in A, \quad (14)$$

$$x_{a_e} = \sum_{k \in K} \omega_{k_e}^a, \quad \forall a \in A, \quad (15)$$

$$x_{a_g} + x_{a_e} \leq Z_a, \quad \forall a \in A, \quad (16)$$

$$\sum_a \kappa_a x_{a_g} \leq Q, \quad \forall a \in A, \quad (17)$$

$$\omega_{k_g} \geq 0,$$

$$\omega_{k_e} \geq 0,$$

$$\forall k_g \in K,$$

$$k_e \in K. \quad (18)$$

Here, $\alpha_1 \geq 0$ and $\alpha_2 \geq 0$ are weight factors, and λ_a is the unit price of emissions. The first two equalities follow from the fact that each column of the matrix E_{k_g} has only two nonzero elements $\{1, -1\}$ and so is the matrix E_{k_e} . The vectors $i_{k_g} = (1, 0, \dots, 0, -1)^T$ and $i_{k_e} = (1, 0, \dots, 0, -1)^T$ are with suitable dimensions, where the element 1 corresponds to the original of k_g or k_e and the element -1 corresponds to the terminal of k_g or k_e . Conditions (12) and (13) are flow balance constraints of GVs and BEVs; that is, the flows at middle nodes are equal to zero and the flows at origins or terminals are equal to d_k . Conditions (14)–(16) mean that the total traffic flow on each feasible link is no more than its threshold value. Condition (17) is the sum of credits that is no more than the given number of the traffic managements.

In addition, constraint (17) is only for the GVs; that is, BEVs are not constrained by the credit schemes, which can be regarded as a new method to expand the usage of BEVs in the traffic network.

If the link flow of BEVs is not considered in constraint (17), we use

$$\sum_a \kappa_a (x_{a_e} + x_{a_g}) \leq Q, \quad \forall a \in A, \quad (19)$$

to replace (17). That means that GVs and BEVs are constrained by the credit schemes and (17) can be utilized to adjust the volume of GVs and BEVs in the traffic network. Then, model (11)–(18) can be transferred as another model:

$$\min_{\omega_{k_e}, \omega_{k_g}} \alpha_1 \sum_{a \in A} \left(p_a t_a (x_{a_e} + x_{a_g}) (x_{a_e} + x_{a_g}) + c_{a_e} (x_{a_e} + x_{a_g}, l_a) + c_{a_g} (x_{a_e} + x_{a_g}, l_a) \right) + \alpha_2 \sum_{a \in A} r_a (x_{a_g} + x_{a_e}) x_{a_g}, \quad (20)$$

$$\text{s.t. } (12) - (16), (18), (19). \quad (21)$$

Models (11)–(18) and (20) and (21) are not studied in the former studies. Particularly, the constraint of the credits schemes is utilized to control the GVs number and to promote the usage of BEVs in the traffic network.

Remark 1. As the study of [57], the distance constraint of BEV is ignored in models (11)–(18) and (20) and (21). It is considered in algorithm in the next section.

Proposition 1. *In model (11)–(18), if $Q = 0$, there are no GVs in the traffic network and so the emission of GVs is 0; that is, all users choose BEVs.*

Proof. Since $Q = 0$, according to (17), (14), and (18), we have $x_{a_g} = 0$ and $R(\omega_{k_g}) = 0$. This completes the proof.

Based on model (11)–(18), we know that reducing the number of credits of GVs can promote the utilization of BEVs in the traffic network.

On the other hand, note that the Lagrangian function of model (11)–(18) can be expressed as

$$\begin{aligned}
L(\omega_{a_e}, \omega_{a_g}, \gamma, \mu) &= \alpha_1 \sum_{a \in A} \left(p_a t_a(x_{a_e} + x_{a_g}) (x_{a_e} + x_{a_g}) \right. \\
&\quad \left. + c_{a_e}(x_{a_e} + x_{a_g}, l_a) + c_{a_g}(x_{a_e} + x_{a_g}, l_a) \right) \\
&\quad + \alpha_2 \sum_{a \in A} r_a(x_{a_e} + x_{a_g}) x_{a_g} \\
&\quad + \sum_{k_g \in K} \gamma_{k_g}^T (E_{k_g} \omega_{k_g} - d_{k_g} i_{k_g}) \\
&\quad + \sum_{k_e \in K} \gamma_{k_e}^T (E_{k_e} \omega_{k_e} - d_{k_e} i_{k_e}) \\
&\quad + \sum_{a \in A} \mu_a (x_{a_g} + x_{a_e} - Z_a) \\
&\quad + \mu_c \left(\sum_a \kappa_a x_{a_g} - Q \right) \\
&\quad - \sum_{k_g \in K} \mu_{k_g}^T \omega_{k_g} - \sum_{k_e \in K} \mu_{k_e}^T \omega_{k_e},
\end{aligned} \tag{22}$$

where the Lagrangian multipliers $\mu_{k_g}^T$ and $\mu_{k_e}^T$ are the vectors of $\mu_{k_g}^a$ and $\mu_{k_e}^a$ for $a \in A$, respectively. One has

$$\begin{aligned}
x_{a_g} &= \sum_{k_g \in K} \omega_{k_g}^a, \\
x_{a_e} &= \sum_{k_e \in K} \omega_{k_e}^a, \\
\forall a \in A.
\end{aligned} \tag{23}$$

Then, the optimality conditions for model (11)–(18) can be written as

$$\begin{aligned}
\frac{\partial L}{\partial \omega_{k_g}^a} &= \alpha_1 \left(p_a t_a'(x_{a_e} + x_{a_g}) \cdot (x_{a_e} + x_{a_g}) \right. \\
&\quad \left. + p t_a(x_{a_e} + x_{a_g}) + c_{a_e}'(x_{a_e} + x_{a_g}, l_a) \right. \\
&\quad \left. + c_{a_g}'(x_{a_e} + x_{a_g}, l_a) \right) \\
&\quad + \alpha_2 \left(r_a'(x_{a_e} + x_{a_g}) x_{a_g} + r_a(x_{a_e} + x_{a_g}) \right) \\
&\quad + \left(\gamma_{k_g}^{a_i} - \mu_{k_g}^{a_j} \right) + \mu_a + \mu_c - \mu_{k_g}^a = 0, \\
\frac{\partial L}{\partial \omega_{k_e}^a} &= \alpha_1 \left(p_a t_a'(x_{a_e} + x_{a_g}) \cdot (x_{a_e} + x_{a_g}) \right. \\
&\quad \left. + p t_a(x_{a_e} + x_{a_g}) + c_{a_e}'(x_{a_e} + x_{a_g}, l_a) \right) \\
&\quad + c_{a_g}'(x_{a_e} + x_{a_g}, l_a) + \alpha_2 r_a'(x_{a_e} + x_{a_g}) x_{a_g} \\
&\quad + \left(\gamma_{k_e}^{a_i} - \mu_{k_e}^{a_j} \right) + \mu_a - \mu_{k_e}^a = 0, \\
x_{a_g} + x_{a_e} - Z_a &\leq 0, \\
\mu_a &\geq 0, \\
\mu_a (x_{a_g} + x_{a_e} - Z_a) &= 0, \\
\sum_a \kappa_a x_{a_g} - Q &\leq 0, \\
\mu_c &\geq 0, \\
\mu_c \left(\sum_a \kappa_a x_{a_g} - Q \right) &= 0, \\
x_{a_g} &= \sum_{k_g \in K} \omega_{k_g}^a, \\
x_{a_e} &= \sum_{k_e \in K} \omega_{k_e}^a, \\
\forall k_g \in K, k_e \in K, a = (a_i, a_j) \in A.
\end{aligned} \tag{24}$$

We then have the following results. \square

Proposition 2. *The Lagrangian multipliers of $\gamma_{k_g}^{a_i}, \mu_{k_g}^{a_j}, \mu_{k_g}^a, \gamma_{k_e}^{a_i}, \mu_{k_e}^{a_j}, \mu_a$, and $\mu_{k_e}^a$ satisfy the equation*

$$\begin{aligned} & \left(\mu_{k_g}^{a_j} + \gamma_{k_e}^{a_i} \right) - \left(\gamma_{k_g}^{a_i} + \mu_{k_e}^{a_j} \right) + \left(\mu_{k_g}^a - \mu_{k_e}^a \right) + \mu_a \\ & = \alpha_2 r_a \left(x_{a_e} + x_{a_g} \right). \end{aligned} \quad (25)$$

Proof. Since $\partial L / \partial \omega_{k_g}^a = \partial L / \partial \omega_{k_e}^a = 0$, the conclusion can be proved immediately.

From Proposition 2, we have an interesting property that the Lagrangian multipliers only relate to the emission cost and the weight factor α_2 for every a . In addition, in model (11)–(18), the definitions of the operating function do not impact the values of the Lagrangian multipliers. Furthermore, the emissions are only affected by the shadow prices, while the model reaches optimality. \square

Proposition 3. *If there are no waiting users in the traffic network, then the Lagrangian multiplier μ_a is equal to zero for all a in A .*

Proof. According to the definition of Z_a and the assumption of this proposition, we have $x_{a_g} + x_{a_e} < Z_a$. It follows that $\mu_a = 0$ on all links in the traffic network.

It means that constraint equation (16) is noneffective. That is, the situation of traffic does not attain the critical value over which there will be a traffic jam. \square

Proposition 4. *If the total credits are more than the demand in the traffic network, then the Lagrangian multiplier μ_c is equal to zero.*

It means that constraint equation (17) is noneffective. That is, decreasing emission by setting the total credits is invalid. In addition, two properties can be obtained as follows:

- (1) If $\alpha_1 > 0$ and $\alpha_2 = 0$, the objective functions of models (11)–(18) and (20) and (21) do not involve the emission factor. That is, in this situation, models (11)–(18) and (20) and (21) only study the credit schemes problem by minimizing the sum of the time cost and operating cost of BEVs and GVs. The model is only employed to reduce traffic congestion by choosing proper traffic paths. Of course, if the traffic is smooth, the emission also is declined.
- (2) If $\alpha_1 = 0$ and $\alpha_2 > 0$, the models only consider the emission of the traffic network with the credit schemes. That is, the goals of models (11)–(18) and (20) and (21) are utilized to lessen the emission by assigning proper paths.

4. Algorithm and Numerical Experiments

In our numerical tests, we use a Windows 8.1-based PC equipped with a Core (TM) 2 CPU i5-4210M processor running at 2.60 GHz as the computing platform and

algorithm is coded in Matlab2010b. In addition, the numerical experiments contained two main steps: find feasible path of GVs and BEVs; choose proper algorithm to solve the optimization models.

In particular, the emission function is chosen as (10) and the time function $t_a(x_{a_e} + x_{a_g})$ is defined as (4).

4.1. Algorithm Frame. In this subsection, we give an algorithm frame (see Table 1) to solve the models.

In view of Table 1, the algorithm can be summarized as two stages: find the feasible paths with distance limit $\$D\$$ of BEVs and feasible paths of GVs and solve model (11)–(18).

4.2. Numerical Experiments. In our tests, we had four aims: (1) checking the effect of changing distance limit of BEVs for choice of users in model (11)–(18); (2) testing the influence of changing unit operation cost of BEVs and GVs for pick of users in model (11)–(18); (3) verifying the impact of varying total credits for pick of users in model (11)–(18); (4) testing the influence of variation of λ_a in $R_a = r_a(x_a)x_a = \lambda_a x_{a_g} l_a$ for selection of users in model (20) and (21).

Nguyen–Dupuis’ network contains 13 nodes and 19 links (see Figure 2). More information about this network can be found in [59]. All feasible paths, O-D pairs, route compositions, and length of every path are shown in Table 2 [53, 54]. The travel demand of each O-D pair was set to be 400 and $\alpha_1 = \alpha_2 = 1$, $\alpha = 0.15$, $\beta = 100$, $\rho = 1$, and $p = 10$ in all experiments.

In the first experiment, for simplicity, in model (11)–(18), let the unit price p of travel time be equal to 10. Let the operating cost functions of BEVs and GVs on link a be expressed as $c_{a_e} = 0.3l_a(x_{a_e} + x_{a_g})$ and $c_{a_g} = l_a(x_{a_e} + x_{a_g})$, respectively. Furthermore, let emissions cost $r_a(x_a)$ be equivalent to $x_{a_g}l_a$ and the upper bound of the credits Q be set to 50000. In addition, the distance limit of BEVs was from 30 to 45.

Numerical results in Figures 3 and 4 reveal that the number of BEVs’ users increases as the distance limit is getting longer. In more details, when the distance limit is 30, there is no BEV in the traffic network since no feasible path of BEVs exists. On the other hand, when the distance limit is 39, all users choose BEVs in the traffic network since the unit cost of BEVs is lower than the unit cost of GVs and there is no emission of BEVs in the network. When the distance limit is 31, on path 4, all users give up using GVs but other paths are not because only the O-D pair (1, 2) has a feasible path for BEVs; see Figure 4(a) and Table 2. Since the shortest path of the O-D (4, 2) is index 15, the users of the O-D pair (4, 2) select BEVs when the distance limit of BEVs is no less than 35. From this experiment, promoting the BEVs is utilized by expending the longest traveling distance of BEVs. This means that increasing the number of BEVs by technological progress is feasible.

In the second experiment, let the distance limit of BEVs be equal to 45. Let the operating cost functions of BEVs and GVs on link a be expressed as $c_{a_e}(x_{a_e} + x_{a_g}) = 0.005 + \beta_e(x_{a_e} + x_{a_g})^2$ and $c_{a_g}(x_{a_e} + x_{a_g}) = 1$, respectively. Furthermore, let $\beta_e = 0.00001, 0.0001, 0.001, 0.01, 0.1, 1$ in model

TABLE 1: Algorithm frame.

- Step 1. Initialization x_0 , tolerances ϵ_{\min} , and maximum iterations k_{\max} .
- Step 2. Find the feasible paths with distance limit D of BEVs and feasible paths of GV's.
- Step 3. Input $A, b, A_{eq}, beq, lb, ub, nonlcon$, and the constraints.
- Step 4. Set $\omega_0 = \left\{ \omega_{k_g,0}^a, \omega_{k_c,0}^a : k_g \in K, k_c \in K, a \in A \right\}$ such that the strict inequalities in (16)–(18) hold. Let \mathbf{H}_0 be the unit matrix.
- Step 5. Solve the approximation quadratic programming problem
- $$\begin{aligned} \min \quad & 1/2d^T \mathbf{H}_n d + \nabla g(\omega_n)^T d \\ \text{s.t.} \quad & (16)–(18) \end{aligned}$$
- to get Lagrange multiplier λ_n and the search direction $d_{(n)} = \omega_{(n+1)} - \omega_{(n)}$. Here, $g(\omega_n)$ is the objective function in model (11)–(18).
- Step 6. Calculate the new iteration point $\omega_{n+1} = \omega_n + \alpha_n d_{(n)}$, where α_n is a stepsize calculated by one-dimensional search.
- Step 7. If $\|\omega_{n+1} - \omega_n\| \leq \epsilon$, stop. Otherwise, go to step 8.
- Step 8. Update the Hessian matrix \mathbf{H}_n by BFGS algorithm, let $n = n + 1$, and go to Step 4.

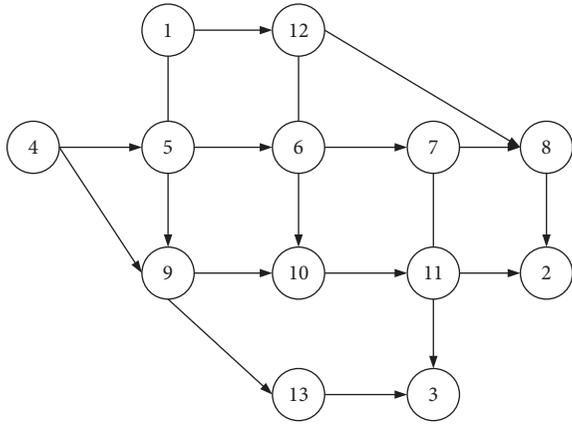


FIGURE 2: Nguyen-Dupuis' network.

TABLE 2: Analysis results for Nguyen-Dupuis' network.

O-D	Route	Node sequence	Length
	1	1-5-6-7-8-2	33
	2	1-5-6-7-11-2	38
	3	1-5-6-10-11-2	43
(1, 2)	4	1-12-8-2	31
	5	1-5-9-10-11-2	48
	6	1-12-6-7-8-2	46
	7	1-12-6-7-11-2	51
	8	1-12-6-10-11-2	56
	9	1-5-6-7-11-3	39
	10	1-5-6-10-11-3	44
(1, 3)	11	1-5-9-13-3	39
	12	1-5-9-10-11-3	49
	13	1-12-6-7-11-3	52
	14	1-12-6-10-11-3	57
	15	4-5-6-7-8-2	35
	16	4-5-6-7-11-2	40
(4, 2)	17	4-5-6-10-11-2	45
	18	4-9-10-11-2	45
	19	4-5-9-10-11-2	50
	20	4-5-6-7-11-3	41
	21	4-5-9-13-3	41
(4, 3)	22	4-9-13-3	36
	23	4-5-6-10-11-3	46
	24	4-5-9-10-11-3	51
	25	4-9-10-11-3	46

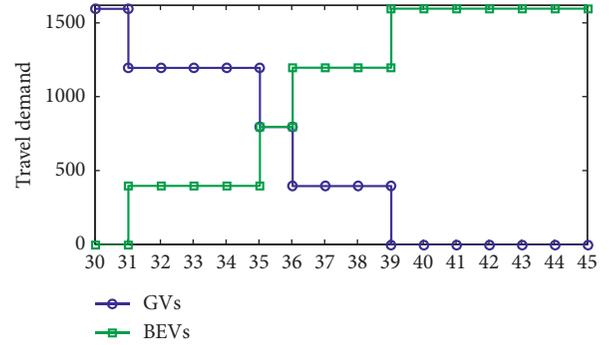


FIGURE 3: Changing distance limit of BEVs of all O-D pairs in Nguyen-Dupuis' network.

(11)–(18). The results displayed in Figures 5 and 6(a) indicate that the number of BEVs' users reduces with β increasing. In detail, the first reduction is the O-D pair (4, 2) with $\beta = 0.001$. When $\beta_e = 0.1$, all users choose GV's; that is, there are no BEVs in the traffic network. This experiment demonstrates that we can increase the number of BEVs' users by reducing the operating cost such as cutting down the price of BEVs or increasing subsidies for BEVs.

In the third experiment, let the distance limit of BEVs be also equal to 45. Let the operating cost functions of BEVs and GV's on link a be expressed as $c_{a_e} = 1$ and $c_{a_g}(x_{a_e} + x_{a_g}) = 0.005 + \beta_g(x_{a_e} + x_{a_g})^2$, respectively. Furthermore, let $\beta_g = 0.00001, 0.0001, 0.001, 0.01, 0.1, 1$ in model (11)–(18). The traffic flows of BEVs and GV's on each optimization feasible path for each O-D pair are displayed in Figure 7. The total traffic flow of all O-D pairs is exhibited in Figure 6(b). The results show that the amount of BEVs' users is increasing with β_g increasing. In particular, when $\beta_g = 0.001$, the number of GV's' users reduces in all feasible paths of all O-D pairs. In the first experiment, the quantity of users is changing only between the O-D pairs (4, 2) when $\beta_e = 0.001$. The reason for this difference may be that the emission contains GV's only.

In the fourth experiment, model (11)–(18) was considered. In the model, the upper bound of total credit schemes \$Q\$ is set to be 0, 100, 500, 1000, 5000, 10000, 30000, 50000, 100000, and 500000 and there is no distance limit of BEVs.

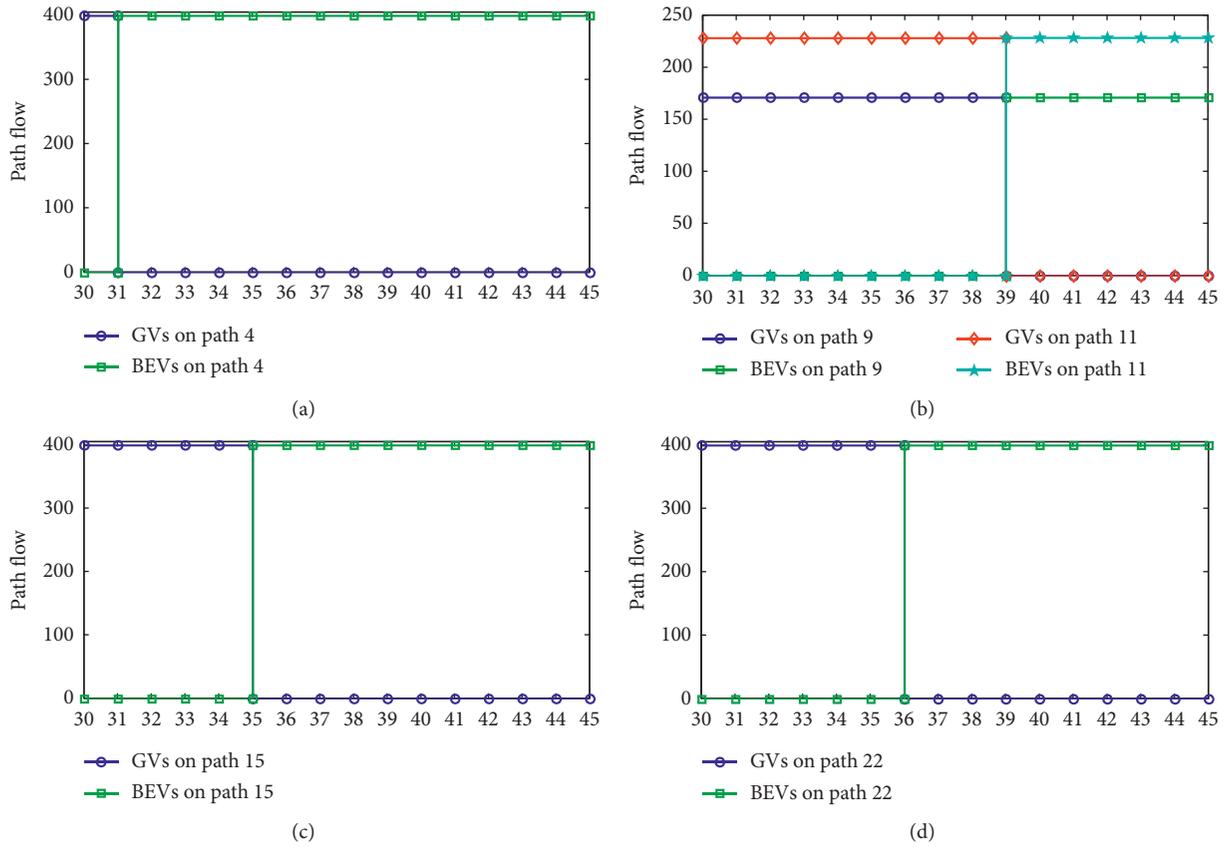


FIGURE 4: Changing distance limit of BEVs of each O-D pair in Nguyen-Dupuis' network. (a) O-D pair (1, 2). (b) O-D pair (1, 3). (c) O-D pair (4, 2). (d) O-D pair (4, 3).

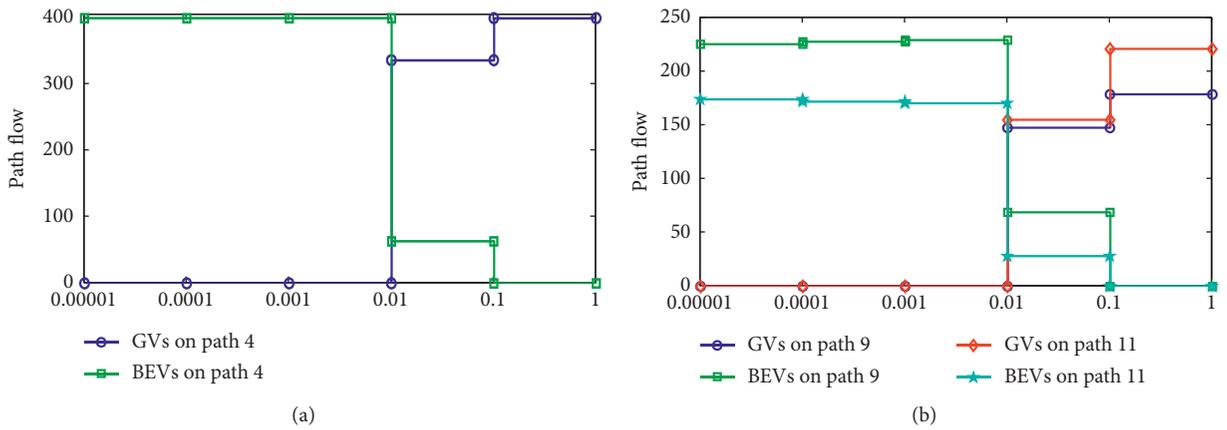


FIGURE 5: Continued.

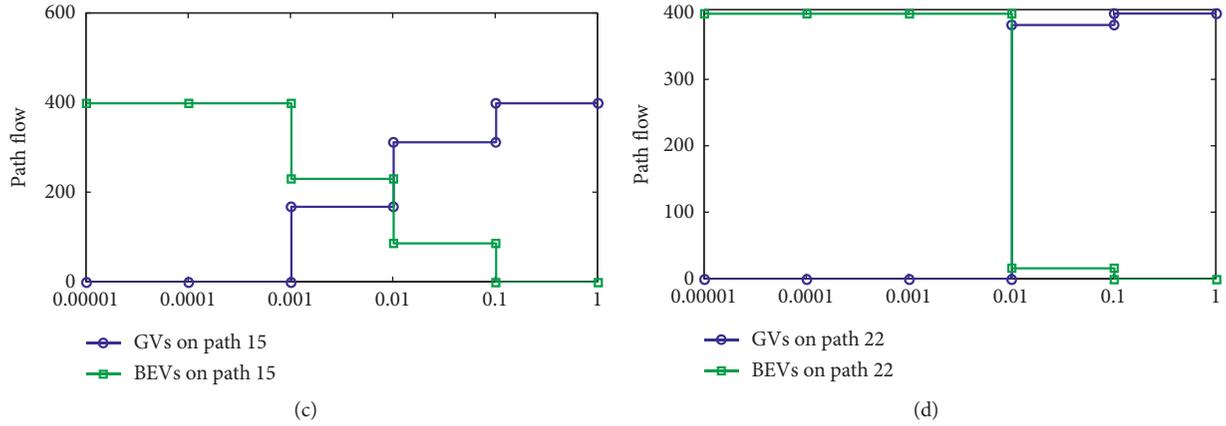


FIGURE 5: Changing unit operating cost of BEVs of each O-D pair in Nguyen–Dupuis’ network. (a) O-D pair (1, 2). (b) O-D pair (1, 3). (c) O-D pair (4, 2). (d) O-D pair (4, 3).

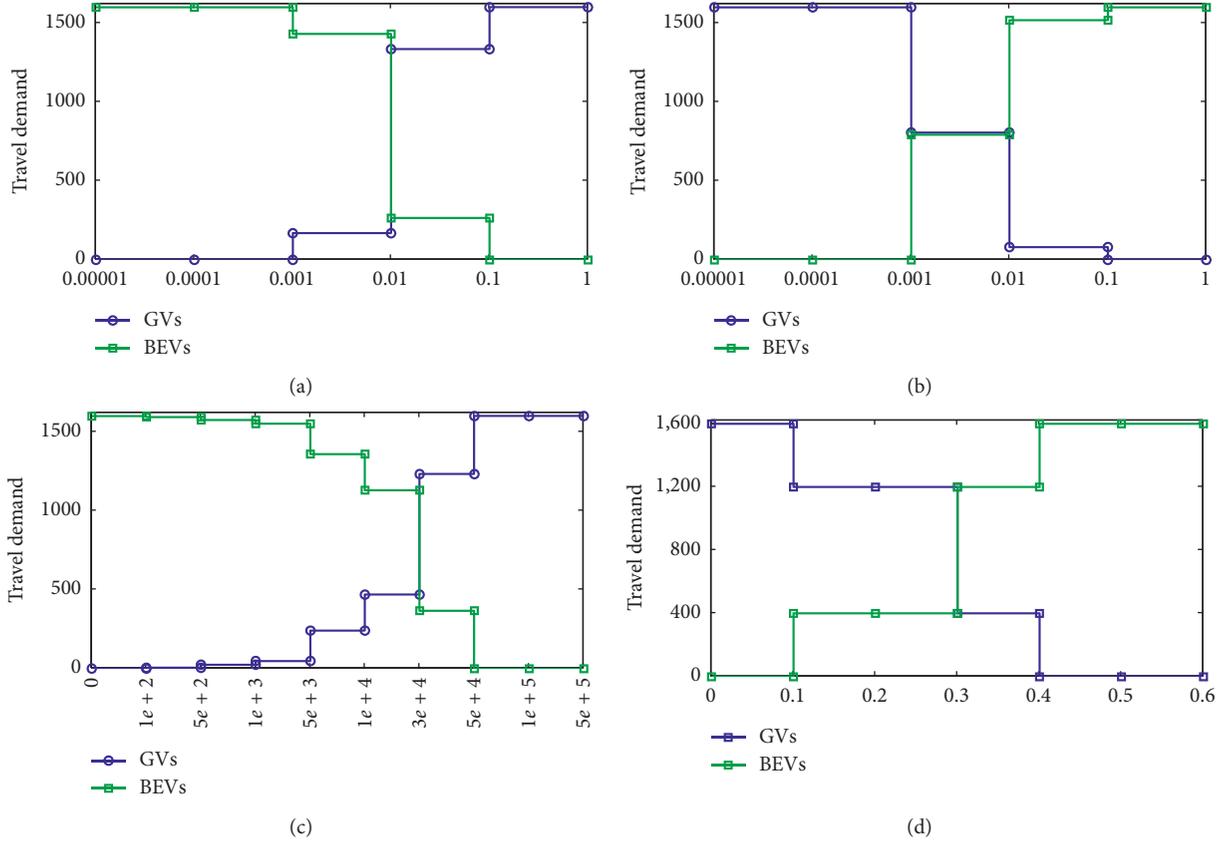


FIGURE 6: Total traffic flow. (a) Unit operating cost of EVs. (b) Unit operating cost of GVs. (c) Unit credit cost of GVs. (d) Unit price λ_a of GVs.

The operation cost functions of BEVs and GVs were expressed as $c_{a_e} = 2l_a(x_{a_e} + x_{a_g})$ and $c_{a_g} = l_a(x_{a_e} + x_{a_g})$. The results stated in Figures 8 and 6(c) show that $Q = 0$, which means that the traffic network only includes BEVs of all O-D pairs. This experiment indicates that the volume of GVs’

users increases with the upper bound of total credits enlarging in a proper range. In detail, when Q is a large number such as $Q = 50000, 100000, 500000$, the traffic network only embodies GVs in Figures 5 and 6(b). In addition, from Figures 8 and 6(c), the number of GVs in the traffic network

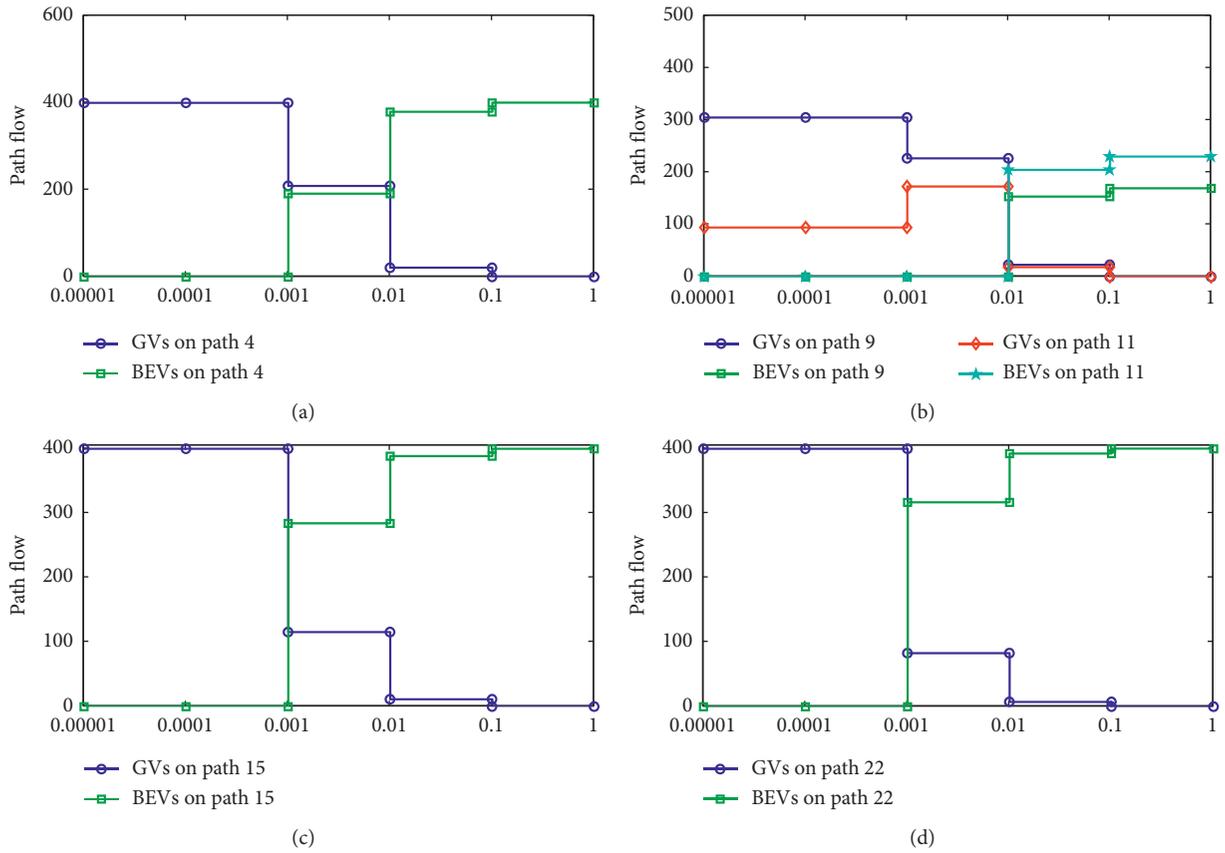


FIGURE 7: Changing unit operating cost of GV in Nguyen-Dupuis' network. (a) O-D pair (1, 2). (b) O-D pair (1, 3). (c) O-D pair (4, 2). (d) O-D pair (4, 3).

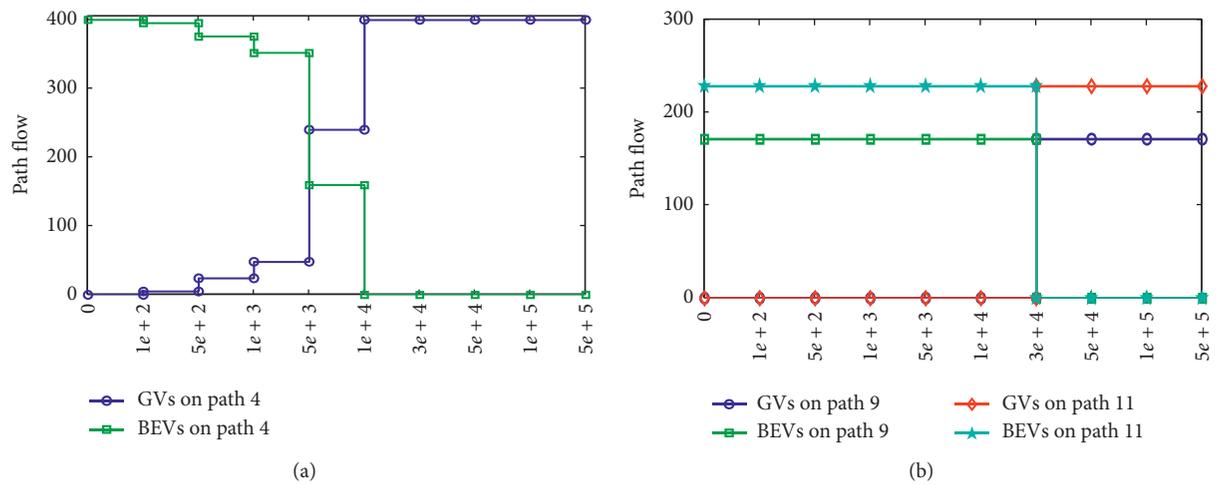


FIGURE 8: Continued.

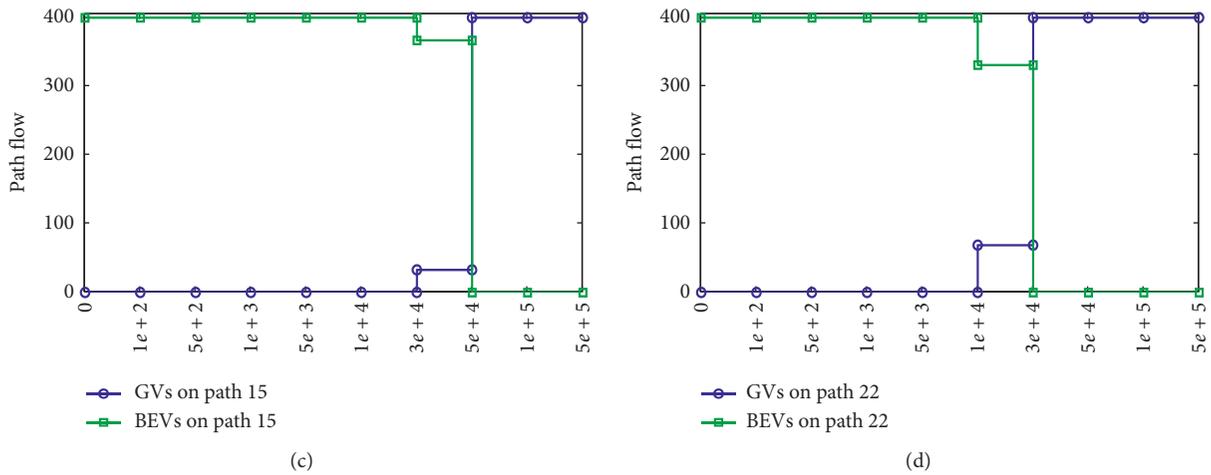


FIGURE 8: Changing total credits of GV in Nguyen–Dupuis’ network. (a) O-D pair (1, 2). (b) O-D pair (1, 3). (c) O-D pair (4, 2). (d) O-D pair (4, 3).

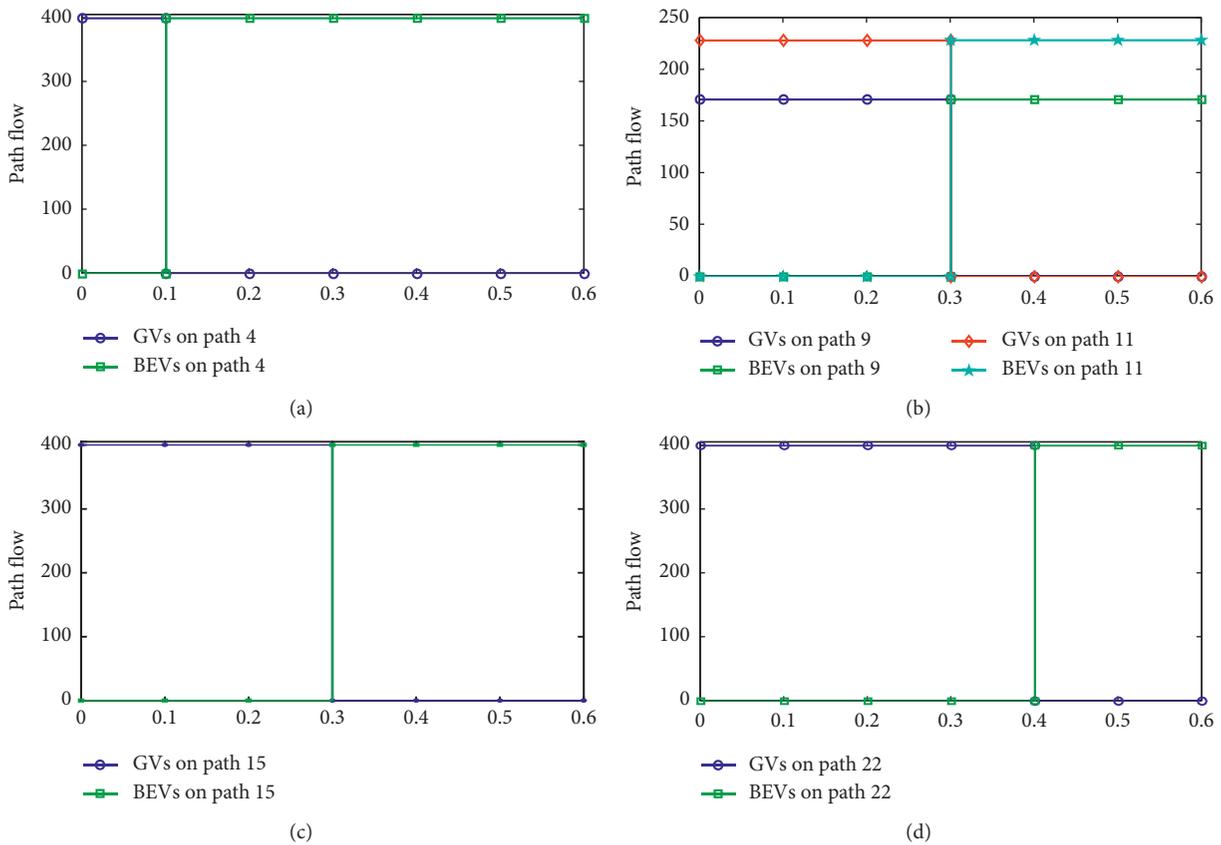


FIGURE 9: Changing λ_a of GV in Nguyen–Dupuis’ network. (a) O-D pair (1, 2). (b) O-D pair (1, 3). (c) O-D pair (4, 2). (d) O-D pair (4, 3).

can be adjusted by modifying total credits for optimization model (11)–(18). This is an interesting approach to promote the number of BEVs.

In the last experiment, the unit price λ_a of emissions of GV was tested. The operation cost functions of BEVs and GV were formulated as $c_{a_e} = 0.5l_a(x_{a_e} + x_{a_g})$ and $c_{a_g} = 0.25l_a(x_{a_e} + x_{a_g})$. The distance limit of BEVs was set to

be 45. The upper bound of credits was equal to 500000. The unit price λ_a of emissions of GV was set to be 0, 0.1, 0.2, 0.3, 0.4, 0.5, and 0.6. The results are given in Figures 6(d) and 9. This experiment manifests that the volume of GV’s users decreases with the unit price of emissions rising. Thus, for accelerating the utilization of BEVs, raising the unit price of emissions may be employed.

5. Conclusions

We studied two types of vehicles (BEVs and GVs) in urban road network. We presented two models for the traffic flow assignment and emissions problems with the credits constraint. One of them is to minimize the sum of traffic cost and emissions cost by adjusting the total credits for BEVs and GVs in the traffic network. Another tries to adjust the volume of BEVs in the traffic network by changing the upper bound of total credits for GVs. Furthermore, we gave a simple algorithm to solve the models.

In our experiments, we first checked the influence of distance limits of BEVs and observed that expanding the distance limit of BEVs may promote the utilization of BEVs by technical progress. Then, we investigated the effect of changing unit operating cost of BEVs and GVs. It was observed that reducing the unit operating cost of BEVs may promote the utilization of BEVs and the total GVs in the traffic network may be controlled by changing the upper bound of total credits of GVs in model (11)–(18); that is, we may give a smaller upper bound of the volume of credits of GVs to promote the employment of BEVs in the traffic network. Finally, the unit price of emissions of GVs was also investigated and it was observed that the number of GVs is reducing with increasing the unit price of emission of GVs; in other words, diminishing the amount of GVs in the traffic network may be realized by raising the unit price of emissions of GVs.

As a future research direction, dynamic cases may be considered. The cases that some uncertainties (weather, traffic accidents, etc.) occur in the network may also be considered. Biobjective models or bilevel optimization models will be studied and the two-way street traffic network will also be considered. In addition, we will study more details about the anxiety cost function. The multiple charges of BEVs will also be considered in the future.

Data Availability

The datasets are described in the experiments section of the paper.

Conflicts of Interest

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

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