Research Article

Exhaust Emission Assessment with Energy Structural Evolution in Transportation Network

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Electric vehicles have become a ubiquitous form of transportation in the transition period from the petroleum era to the electricity era. The development of electric vehicles is of great interest to researchers, policy-makers, consumers, and industries. However, the dynamic environmental impact assessment along with energy structural evolution in transportation network is still wondering as the vehicular exhaust emissions are highly dependent on their market shares and working conditions. In this paper, a Markov chain model is formulated to represent the transition process between traditional internal combustion engine vehicles (ICEVs), plug-in electric vehicles (PEVs), and hybrid electric vehicles (HEVs), with which the dynamic market penetration level of three vehicle types can be predicted. Therefore, the amount of pollutants can be figured out based on their market penetration level and network traffic conditions. For a given transportation network, system equilibrium is proposed to calculate network traffic conditions. It is a four-step sequential model with feedback which can be solved by method of successive averages (MSA) with decreasing weights effectively. A simulation experiment using Nguyen–Dupuis network demonstrates the effect of the proposed method. It is found that the proposed method is effective to assess the dynamics of environmental impacts as the penetration of electric vehicles into transportation system. The method is particularly operable for policy designs stimulating the development of electric vehicles.

1. Introduction

Plug-in electric vehicles (PEVs) are being introduced into transportation system rapidly in the ongoing transition period from the petroleum era to the electricity era. They consume energy in a way that is fundamentally different from traditional internal combustion engine vehicles (ICEVs). In addition, hybrid electric vehicles (HEVs) are a type of hybrid vehicle that combines a conventional ICEV mode with a PEV mode. It is no doubt that electric vehicles can abate environmental pollution substantially. Therefore, the development of electric vehicles is of great interest to researchers, policy-makers, consumers, and industries. However, the dynamic environmental impact assessment along with energy structural evolution in transportation network is still wondering as the vehicular exhaust emissions are highly dependent on their market shares and working conditions. The emission rates tested in laboratory cannot represent the real situations. Therefore, the exhaust emissions with energy structural evolution must be studied in transportation network.

Although vehicular emissions of conventional ICEVs have been studied extensively in transportation networks, their dynamics are few explored as the penetration of PEVs and HEVs. As electric vehicles become a ubiquitous form of transport, Duell et al. [1] incorporated PEVs energy consumption into network design decisions. They developed a multi-objective optimization model to minimize both system-level energy consumption and total system travel time. Gardner et al. [2] developed a bi-level decision framework to evaluate the role of PEVs in terms of environmental pollution and energy consumption under travel demand variability in transportation network. Jiang and Xie [3] presented a convex optimization model for a mixed network equilibrium problem that accommodated both gasoline and electric vehicles. The two vehicle types were distinguished in
terms of driving range and travel cost composition. He et al. [4] demonstrated that the route choice behaviors of PEV drivers are different from that of conventional ICEV drivers as the limited driving ranges, the scarcity of recharging stations, and potentially long battery recharging or swapping time. Papargyri et al. [5] analyzed the potential contribution of electric vehicles in GHG emission reduction over the next decade using a simulation procedure. Different market penetration scenarios of electric vehicles were introduced and compared to the base case scenario. Mitropoulos and Prevedouros [6] demonstrated that the introduction of PEVs was likely to change the traditional transportation planning process because their different characteristics need to be taken into account. Ma et al. [7] showed the environmental benefits of introducing electric vehicles into transportation networks and revealed the relationship between the quantity of electric vehicles and the environmental costs of the overall transportation network. Xu et al. [8] and Xu et al. [9] devoted to the development of full system simulation tools to support the large transportation network projections of EV operations and energy consumptions, integrating a variety of EV market share scenarios. Hensher et al. [10] investigated the energy rebound effect of the EV introduction in Australia. As the significantly lower usage costs of EVs compared to ICEVs, we would expect a level of demand uptake that could impact on the performance of the road network (increased congestion and crash risk). Zhong et al. [11] and Xi et al. [12] proposed road pricing schemes for environmental externality in transport network mixed with EVs and ICEVs, which is beneficial for the penetration of EV.

In summary, there are at least two problems existed in previous research efforts that deserve our study here. Firstly, environmental impact assessment as the penetration of electronic vehicles in transportation network is not investigated yet. However, the market shares of electric vehicles need to be explicitly incorporated into transportation network analysis. Secondly, the vehicular emission rates are highly dependent on network traffic conditions in reality, which is few explored. Therefore, a four-step sequential model with feedback is developed to achieve the transportation system equilibrium that can adequately capture network traffic conditions.

The structure of the paper is organized as follows. Section 2 describes the environmental impact assessment methods for ICEV, PEV, and HEV, respectively. Section 3 is the energy structural evolution method that is a Markov chain model. Section 4 describes the detailed method for transportation system equilibrium, and Section 5 is the solution method. In order to demonstrate the effectiveness of the model formulation and solution algorithm, a simulation study using Nguyen–Dupuis network is conducted in Section 6. Section 7 concludes the paper.

2. Environmental Impact Assessment

This analysis requires emissions rates for ICEV, PEV, and HEV. The ICEV emissions are related to many factors including the transport mode, engine type, driving habit, and vehicle speed. Many researchers studied the relationship between emissions and the average vehicle speed since other factors are diverse and difficult to be measured. Here, emissions-speed relationships are extracted from MOVES2010a (Motor Vehicle Emissions Simulator). The emission rates produced per mile by each vehicle in g/mi are usually fitted as a power function of average travel speed $s_a$ on link a. Please note that the emission rates decrease as the speed increases. They are represented as follows [2]:

$$\text{CO}_2^{\text{ICEV}} (s_a) = 3158 \cdot s_a^{-0.56}$$

$$\text{VOC}^{\text{ICEV}} (s_a) = 1.3647 \cdot s_a^{-0.679}$$

$$\text{NO}_x^{\text{ICEV}} (s_a) = 2.5376 \cdot s_a^{-0.42}$$

In addition, the average speed $s_a$ on link a is defined as the distance covered per unit of time. In equation form, that is

$$s_a = \frac{I_a}{t_a(v_a)}$$

where $I_a$ is the length of link a in miles and $t_a(v_a)$ is the link travel time in hours that is a function of link traffic flow $v_a$ in pcu/h to account for congestion effect. Therefore, the emissions produced by each ICEV in grams on link a can be represented as a function of link traffic flow $v_a$ as follows:

$$\text{CO}_2^{\text{ICEV}} (v_a) = 3158 \cdot \left(\frac{I_a}{t_a(v_a)}\right)^{-0.56} \cdot I_a$$

$$\text{VOC}^{\text{ICEV}} (v_a) = 1.3647 \cdot \left(\frac{I_a}{t_a(v_a)}\right)^{-0.679} \cdot I_a$$

$$\text{NO}_x^{\text{ICEV}} (v_a) = 2.5376 \cdot \left(\frac{I_a}{t_a(v_a)}\right)^{-0.42} \cdot I_a$$

While PEVs do not produce tailpipe emissions directly, they are still responsible for emissions indirectly via power stations that have a notorious reputation for polluting the atmosphere, particularly coal-fired stations. To account for the environmental impact of PEVs, the total energy consumed by the vehicles is multiplied by average power station emission rates in g/kWh. The result is the total emissions produced by generating the amount of electricity consumed by the electric vehicles. The energy consumption rate per mile for each PEV in kWh/mi is fitted as a polynomial function of the average travel speed on link a, $s_a$, using data obtained from Tesla Motors [2]:

$$EC_{\text{PEV}} (s_a) = 1.79e - 8s_a^4 - 4.073e - 6s_a^3 + 3.654e - 4s_a^2 - 0.0109s_a + 0.2372$$

Again the link average speed $s_a$ can be substituted by equation (2) to account for congestion effect. Therefore, the energy consumption by each PEV in kWh on link a can be represented as a function of link traffic flow $v_a$ as follows:
The average emission rates for CO$_2$, NO$_x$, and SO$_2$, published in an analysis by the Commission for Environmental Cooperation of North America, are used in this study, which are 893 g/kWh, 1.66 g/kWh, and 3.79 g/kWh, respectively [2]. Finally, the emissions produced by each PEV in grams on link $a$ can be represented as a function of link traffic flow $v_a$ as follows:

$$\begin{align*}
CO_2^{PEV}(v_a) &= 893 \cdot EC_{PEV}(v_a) \\
NO_x^{PEV}(v_a) &= 1.66 \cdot EC_{PEV}(v_a) \\
SO_2^{PEV}(v_a) &= 3.79 \cdot EC_{PEV}(v_a).
\end{align*}$$

HEV is a type of hybrid vehicle that combines a conventional ICEV mode with a PEV mode. Modern HEV makes use of efficiency-improving technologies so that it produces fewer emissions than a comparably sized ICEV. As HEV is a combination of ICEV and PEV, a factor $\alpha$ is used to integrate their emissions for simplicity. Therefore, the emissions produced by each HEV in grams on link $a$ can also be represented as a function of link traffic flow $v_a$ as follows:

$$\begin{align*}
CO_2^{HEV}(v_a) &= \alpha \cdot [CO_2^{ICEV}(v_a) + CO_2^{PEV}(v_a)] \\
NO_x^{HEV}(v_a) &= \alpha \cdot [NO_x^{ICEV}(v_a) + NO_x^{PEV}(v_a)] \\
VOC^{HEV}(v_a) &= \alpha \cdot VOC^{ICEV}(v_a) \\
SO_2^{HEV}(v_a) &= \alpha \cdot SO_2^{PEV}(v_a).
\end{align*}$$

It should be noted that the expressions and parameters used here are a common case for demonstration. They could vary from city to city. Although the major production of electricity is achieved through thermal power plants, the penetration of renewable energies (wind power, hydroelectric power, photovoltaic power, nuclear power, etc.) is growing. Therefore, the parameters here may not be always reasonable and they should be adjusted according to the power source. However, the methods here are still meaningful without loss of generality.

## 3. Energy Structural Evolution

The drivers can replace vehicle type from one to another. The market penetration level of three vehicle types can be formulated with a Markov chain model. It is a stochastic process theory that studies the states of things and their evolution. It is to determine the trend of the states by studying the initial probability of different states and the transition probability between states, so as to achieve the purpose of predicting the future.

Considering a set of states, $S = \{s_1, s_2, \ldots, s_r\}$, the evolution process starts in one of these states and moves successively from one state to another. Each move is called a step. If the chain is currently in state $s_i$, then it moves to state $s_j$ at the next step with a transition probability denoted by $p_{ij}$, and this probability does not depend upon which states the chain was in before the current state that is known as Markov property. The process can also remain in the state it is in, and this occurs with probability $p_{ii}$. Let $P = [p_{ij}]$ be the transition matrix of a Markov chain. The $ij$th entry $p_{ij}^n$ of the matrix $P^n$ gives the probability that the Markov chain, starting in state $s_i$, will be in state $s_j$ after $n$ steps. Note that each row vector of $P^n$ has non-negative entries and sum to one. Let $u$ be the probability vector which represents the starting distribution. Then, the probability that the chain is in state $s_i$ after $n$ steps is the $ith$ entry in the vector $u^{(n)} = uP^n$.

A Markov chain is called an ergodic chain if it is possible to go from every state to every state (not necessarily in one move). Ergodic Markov chains are also called irreducible. In addition, a Markov chain is called a regular chain if some power of the transition matrix has only positive elements. However, it is possible for a regular Markov chain to have a transition matrix that has zeros. Let $P$ be the transition matrix for a regular chain. Then, as $n \to \infty$, the power $P^n$ approaches a limiting matrix $W$ with all rows the same vector $\omega$ that is a strictly positive probability vector (i.e., the components are all positive and they sum to one). Then, $uP = \omega$, and $u$ is called a fixed row vector for $P$. Regardless of the probability vector of starting states, the probability of being in the various states after $n$ steps is given by $\omega$ and is stationary. Let $A_n$ be the matrix defined by

$$A_n = \frac{I + P + P^2 + \ldots + P^n}{n+1}.\quad (9)$$

Then, $A_n \to W$, where $W$ is a matrix all of whose rows are equal to the unique fixed probability vector for $P$.

## 4. Transportation System Equilibrium

The travel behaviors of PEV drivers are usually different from that of conventional ICEV drivers as the limited driving ranges and the scarcity of recharging stations. In this paper, both PEV and HEV travelers are assumed to behave in the same manner as conventional ICEV travelers such as destination choice and route choice. They are not distinguished from ICEV travelers because it is in the context of urban transportation rather than long-distance intercity transportation. Besides with the development of battery technologies and the wide availability of recharging stations, the behaviors of HEV and PEV travelers are expected to be same with those of ICEV travelers in the near future. However, the three vehicle types, ICEV, PEV, and HEV, are
distinguished by their respective emission rates. The transportation system equilibrium returns link traffic volumes and link travel times. A single average speed is then associated with each link. From link speeds and volumes at the equilibrium state, the environmental impact of three vehicle types can be assessed.

Given a network structure, transportation system equilibrium is implemented to determine link-level flow patterns. The transportation system equilibrium is a combined trip generation, trip distribution, modal split, and trip assignment model system. The four-step sequential model widely used in transportation planning is well known to be inconsistent in travel times. That is, the travel times used in trip distribution and modal split are inconsistent with those generated in trip assignment. In fact, travel times are endogenously determined rather than exogenously inputted. Generally speaking, there are two ways to solve the inconsistency problems to achieve transportation system equilibrium in literature. One is to combine two or more steps into an equivalent single mathematical programming formulation, which ensures a well-converged and consistent result [13, 14]. The other is to iteratively feed back the sequential model until it meets the consistency requirement [15–23]. Although the former is widely used in literature, it is not operation-friendly as the nonlinear mathematical programming is usually a tough problem and even quite restrictive as it cannot adequately capture traveler decision behaviors. For example, gravity model is used for trip distribution. However, it is well recognized that a number of key variables in destination choices that have a significant explanatory power are not included such as traveler preferences and income. Therefore, the sequential model with feedback is adopted here.

After the transportation network is given, trip generation, trip distribution, modal split, and trip assignment are followed. Trip generations in origin nodes are assumed to be fixed here. Trip distribution is the aggregated result of individual’s destination choice decisions. Random utility theory has become the most widely used paradigm for modeling the destination choices. This theory has largely substituted the spatial interaction models, i.e., gravity analogous models, which offered a smaller behavioral base, although as various researches have shown, both approaches can produce equivalent results under specific suppositions [24]. The multinomial logit model is the simplest and most popular practical random utility model used for destination choices which can accommodate not only destination-specific attributes but also individual-specific attributes. Only private cars are used for simplicity so that there is no mode choice at the moment. Therefore, after trip distribution matrix is identified, travel demands are assigned to the transportation network by user equilibrium to calculate mobility indicators including link flows, link travel times, and O-D path travel times. Then, these path travel times are fed back to the destination choice model in order to update the trip distribution matrix. The iterative process continues until the trip distribution matrix does not change to an extent. To be more specific, the feedback process is shown in Figure 1. The notations are consistent with the aforementioned, in addition,

\[ O_i: \text{the travel demand in origin node } i \]
\[ q_{ij}: \text{the travel demand between origin } i \text{ and destination } j \]
\[ \beta_j: \text{the representative traveler preference for destination } j \text{ which can be also regarded as the intrinsic attractiveness of destination } j \]
\[ t_{ij}: \text{the shortest path travel time between OD pair } ij \]
\[ emp_j: \text{the number of employees in destination } j \]
paths between an traffic arranges itself in congested networks such that all used “Wardrop equilibrium,” under equilibrium conditions path choice, also known as “user equilibrium” or just can be figured out. According to Wardrop’s first principle of problem where the travel flows and travel times on each link can be figured out. According to Wardrop’s first principle of path choice, also known as “user equilibrium” or just “Wardrop equilibrium,” under equilibrium conditions traffic arranges itself in congested networks such that all used paths between an O-D pair have equal and minimum costs, while all unused paths have greater or equal costs. Therefore, the shortest path travel time between origin i and destination j, namely, tij, which can be achieved by the Dijkstra algorithm now, can be used to represent travel cost between O-D pair ij. They are fed back to the trip distribution model to update the trip distribution matrix. The iterative process continues until the trip distribution matrix does not change anymore which is known as a transportation system equilibrium state. As a result, the environmental impacts of the three vehicle types can be assessed based on the network traffic conditions and the market penetration level.

5. Solution Algorithm

The transportation system equilibrium is to solve the four-step sequential procedure with feedback. There could be various feedback loops as the complex feedback relationships. In this paper, trip generation is predetermined and only private cars are used so that there is only feedback between trip distribution and assignment which is the most common one. Boyce et al. [16] summarized that there generally are three alternative feedback solution procedures: (a) naive or direct feedback (no averaging of trip distribution matrices or link flows), (b) MSA with constant weights, and (c) MSA with decreasing weights that usually are the reciprocals of the iteration numbers. The convergence of the feedback procedures is generally measured by comparing the results as follows: total misplaced flow (or trip distribution matrices), relative gap (path-based user equilibrium traffic assignments), and root squared error (travel cost matrices).

Although there are some successful applications of MSA with constant weights, the convergence of trip distribution matrices is not always guaranteed. Therefore, MSA with decreasing weights is adopted to achieve transportation system equilibrium here [25]. The algorithm flowchart is shown in Figure 2.

The detailed algorithm procedure is specified in steps as follows:

Step 1. Input transportation network including network structure, link length, and link capacity.

Step 2. Initialize trip distribution matrix q^n_0 by even distribution. Set n = 0, which denotes the number of iterations.

Step 3. Initialize trip assignment. Trip distribution matrix is assigned to a transportation network based on user equilibrium principle by the Frank–Wolfe algorithm to compute travel flows and travel times on each link a. Afterward, the shortest travel time between origin i and destination j, namely, t^n_i,j, can be calibrated by Dijkstra algorithm.

Step 4. Trip distribution. Based on τ^n−1, destination choice model is adopted to update trip distribution matrix q^n_0:

\[
q^n_0 = O_i \frac{\exp(\beta_j + \beta_1 t^n_{ij}) + \beta_{emp}}{\sum_j \exp(\beta_j + \beta_1 t^n_{ij}) + \beta_{emp}}
\]

Step 5. Average trip matrices q^n−1 and q^n using MSA with decreasing weight

\[
q^{n+1}_{ij} = q^n_{ij} + \frac{(1}{n})(q^n_{ij} - q^{n−1}_{ij}).
\]

Step 6. Check convergence of trip matrix using relative root squared error (RRSE)

\[
\frac{\sqrt{\sum_{ij}(q^{n+1}_{ij} - q^n_{ij})^2}}{\sum_{ij}q^n_{ij}} < \epsilon.
\]

If the convergence condition is satisfied, turn to Step 8; otherwise turn to Step 7.

Step 7. Trip assignment. Trip distribution matrix q^{n+1}_{ij} is assigned to the transportation network based on user equilibrium by Frank–Wolfe algorithm to compute travel flows and travel times on each link a. Afterward, the shortest travel time between origin i and destination j, namely, τ^n_{ij}, can be computed by Dijkstra’s algorithm which is fed back to Step 4.

Step 8. Output system performance. Output trip distribution matrix q^n−1 as well as traffic volume v_a on link a and travel times t^n_{ij} between origin i and destination j. The network performance in terms of environmental impact can be finally determined with vehicular market shares.

6. Experimental Study

Travel demand is generated and is transformed into link traffic flow under the given traffic network by the following
classic transportation planning method: trip generation, trip distribution, modal split, and traffic assignment. The Nguyen–Dupuis transportation network as shown in Figure 3 is widely used in transportation research to verify kinds of methods. The link parameters including free flow travel time, link capacity, and link length are shown in Table 1.

There are two origin nodes 1 and 4 and two destination nodes 2 and 3 in the Nguyen–Dupuis network. Assume the trip generations on origin nodes 1 and 4 in peaking hour are 1800 pcu/h and 1200 pcu/h, respectively. That is, \( O_1 = 1800 \) pcu/h and \( O_4 = 1200 \) pcu/h. In the trip distribution step, it is well known that a number of key variables that have a significant explanatory power cannot be included in the conventional gravity model. The most influential one is traveler destination preference. For example, travelers usually favor traditional destination rather than a newly developed area. Therefore, the multinomial logit model with traveler preferences is adopted for destination choices here. As a result, the destination choice model in the feedback process is formulated as

![Algorithm flowchart for transportation system equilibrium.](image-url)
\[ q_{ij}^n = O_j \frac{\exp(\beta_j + \beta_t t_{ij}^{n-1})}{\sum_{j \in J(i)} \exp(\beta_j + \beta_t t_{ij}^{n-1})}. \]  

(14)

where \( \beta_j \) is traveler preference on destination \( j \) and \( \beta_t \) is coefficient of path travel time between \( O-D \) pair \( ij \). The values of \( \beta_j \) and \( \beta_t \) can be calibrated using empirical data. Here, we set \( \beta_2 = 0, \beta_3 = 1, \) and \( \beta_t = -0.1 \). That is, the traveler preference on destination node 2 is 0 and on destination node 3 is 1 which means that the travelers traditionally prefer destination 3. The coefficient of travel time is \(-0.1\) which means that the travel time is a negative utility.

In the trip assignment step, this study employs the classic user equilibrium method which incorporates a link impedance function to an equilibrium state. A commonly used link impedance function, developed by the former Bureau of Public Roads (BPR) of USA, is formulated as follows:

\[ t_a(v_a) = t_f^0 \left[ 1 + \alpha \left( \frac{v_a}{c_a} \right)^{0.15} \right]. \]  

(15)

where \( t_a(v_a) \) is the impedance function of a given link \( a \) with traffic volume \( v_a \); \( c_a \) is the link capacity; \( t_f^0 \) is the free flow

### Table 1: Link parameters of the Nguyen–Dupuis network.

<table>
<thead>
<tr>
<th>Link</th>
<th>Free flow time (min)</th>
<th>Link capacity (pcu/h)</th>
<th>Link length (mile)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7.0</td>
<td>900</td>
<td>4.00</td>
</tr>
<tr>
<td>2</td>
<td>9.0</td>
<td>700</td>
<td>4.00</td>
</tr>
<tr>
<td>3</td>
<td>9.0</td>
<td>700</td>
<td>4.00</td>
</tr>
<tr>
<td>4</td>
<td>12.0</td>
<td>900</td>
<td>7.00</td>
</tr>
<tr>
<td>5</td>
<td>3.0</td>
<td>800</td>
<td>2.00</td>
</tr>
<tr>
<td>6</td>
<td>9.0</td>
<td>600</td>
<td>4.00</td>
</tr>
<tr>
<td>7</td>
<td>5.0</td>
<td>900</td>
<td>4.00</td>
</tr>
<tr>
<td>8</td>
<td>13.0</td>
<td>500</td>
<td>8.00</td>
</tr>
<tr>
<td>9</td>
<td>5.0</td>
<td>300</td>
<td>4.00</td>
</tr>
<tr>
<td>10</td>
<td>9.0</td>
<td>400</td>
<td>5.00</td>
</tr>
<tr>
<td>11</td>
<td>9.0</td>
<td>700</td>
<td>5.00</td>
</tr>
<tr>
<td>12</td>
<td>10.0</td>
<td>700</td>
<td>6.00</td>
</tr>
<tr>
<td>13</td>
<td>9.0</td>
<td>600</td>
<td>5.00</td>
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<tr>
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<td>700</td>
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<td>7.0</td>
<td>300</td>
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<td>14.0</td>
<td>700</td>
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</tr>
<tr>
<td>19</td>
<td>11.0</td>
<td>700</td>
<td>6.00</td>
</tr>
</tbody>
</table>

### Table 2: The link performances under the given transportation network.

<table>
<thead>
<tr>
<th>Link</th>
<th>Traffic volume (pcu/h)</th>
<th>Travel time (min)</th>
<th>Level of service ( (v_a/c_a) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1097</td>
<td>9.32</td>
<td>1.22</td>
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<tr>
<td>2</td>
<td>703</td>
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<tr>
<td>3</td>
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</tr>
<tr>
<td>4</td>
<td>969</td>
<td>14.42</td>
<td>1.08</td>
</tr>
<tr>
<td>5</td>
<td>1205</td>
<td>5.32</td>
<td>1.51</td>
</tr>
<tr>
<td>6</td>
<td>122</td>
<td>9.00</td>
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<tr>
<td>7</td>
<td>883</td>
<td>5.70</td>
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</tr>
<tr>
<td>8</td>
<td>367</td>
<td>13.57</td>
<td>0.73</td>
</tr>
<tr>
<td>9</td>
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<td>5.98</td>
<td>1.07</td>
</tr>
<tr>
<td>10</td>
<td>562</td>
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<td>6.53</td>
<td>0.88</td>
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<td>0.28</td>
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<td>982</td>
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<td>15.65</td>
<td>0.94</td>
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<tr>
<td>19</td>
<td>845</td>
<td>14.51</td>
<td>1.21</td>
</tr>
</tbody>
</table>

Figure 3: The Nguyen–Dupuis network.
impedance of link \( a \); and \( \alpha \) and \( \beta \) are volume/delay coefficients which can be calibrated empirically. The traditional BPR values for \( \alpha \) and \( \beta \) are 0.15 and 4.0, respectively, which are also used in our simulation study. Therefore, we can get the link traffic volume \( v_a \) through Frank–Wolfe algorithm.

The convergence criteria RRSE is set as 0.01, namely, \( \varepsilon = 0.01 \). A single and stable solution with consistent travel times and trip distribution matrix can be achieved by using the aforementioned parameters. Moreover, the shortest path travel time between \( i \) and \( j \) can be calculated using the Dijkstra algorithm. The link traffic conditions under the given transportation network are shown in Table 2.

The market penetration level of three vehicle types is dynamic which evolves yearly. The car owners can keep on using one type of vehicle or move to one of the other types. The transition process can be represented by a Markov chain model. The transition probabilities can be affected by transport policies such as regulations and subsidies for electric vehicles. Assume the transition matrix \( P \) is

\[
P = \begin{pmatrix}
0.8259 & 0.0810 & 0.0931 \\
0.0954 & 0.8147 & 0.0899 \\
0.0000 & 0.1625 & 0.8375
\end{pmatrix}
\]

for ICEV, HEV, and PEV in order. It means that 82.59% ICEV users will adhere to ICEV next year, 8.10% ICEV will transfer to HEV, and 9.31% to PEV; 9.54% HEV users will transfer to ICEV next year, 81.47% HEV users will adhere to HEV, and the others will transfer to PEV; none of PEV users will transfer to ICEV, 16.25% will transfer to HEV, and 83.75% will adhere to PEV. In addition, assuming the present market share is \( \mu = (0.7, 0.2, 0.1) \), which means that the ICEV accounts for the majority of vehicle fleet at present.

The dynamics of market penetration level in the future ten years are shown in Figure 4 according to equation (8).

Note that both HEV and PEV travelers are assumed to behave in the same manner as conventional ICEV travelers. They are not distinguished from ICEV travelers in a behavioral context at present. They behave identically to travelers of conventional vehicles with regard to destination choice, route choice, etc. Therefore, the vehicle fleet composition is assumed to be consistent with their market penetration level on each link. However, the three vehicle types, ICEV, PEV, and HEV, are distinguished by their respective emission rates as defined previously. Although it is reported that HEV can reduce air emissions of smog-forming pollutants by up to 90% and cut carbon dioxide emissions in half, the factor \( \alpha \) is set to be 0.6 here. Moreover, the transportation system equilibrium returns link traffic volumes and link travel times. As a result, the dynamic

\[
\text{Figure 4: The dynamics of market penetration level in the future.}
\]

\[
\text{Table 3: The dynamic environmental impact along with energy structural evolution.}
\]

<table>
<thead>
<tr>
<th>Year</th>
<th>( \text{CO}_2 ) (kg)</th>
<th>( \text{NO}_x ) (kg)</th>
<th>VOC (kg)</th>
<th>( \text{SO}_2 ) (kg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>25.269</td>
<td>33.08</td>
<td>6.92</td>
<td>6.95</td>
</tr>
<tr>
<td>2</td>
<td>23.585</td>
<td>31.32</td>
<td>6.24</td>
<td>9.74</td>
</tr>
<tr>
<td>3</td>
<td>22.298</td>
<td>29.99</td>
<td>5.71</td>
<td>11.91</td>
</tr>
<tr>
<td>4</td>
<td>21.316</td>
<td>28.98</td>
<td>5.31</td>
<td>13.59</td>
</tr>
<tr>
<td>5</td>
<td>20.568</td>
<td>28.20</td>
<td>5.00</td>
<td>14.90</td>
</tr>
<tr>
<td>6</td>
<td>19.999</td>
<td>27.62</td>
<td>4.76</td>
<td>15.90</td>
</tr>
<tr>
<td>7</td>
<td>19.566</td>
<td>27.18</td>
<td>4.58</td>
<td>16.67</td>
</tr>
<tr>
<td>8</td>
<td>19.237</td>
<td>26.84</td>
<td>4.44</td>
<td>17.27</td>
</tr>
<tr>
<td>9</td>
<td>18.988</td>
<td>26.59</td>
<td>4.34</td>
<td>17.72</td>
</tr>
<tr>
<td>10</td>
<td>18.800</td>
<td>26.40</td>
<td>4.26</td>
<td>18.07</td>
</tr>
<tr>
<td>11</td>
<td>18.657</td>
<td>26.25</td>
<td>4.20</td>
<td>18.34</td>
</tr>
</tbody>
</table>
environmental impact can be assessed along with energy structural evolution of vehicle fleet in transportation network, which is shown in Table 3.

It is obvious that the amounts of CO$_2$, NO$_x$, and VOC keep on decreasing as the conventional ICEVs are abandoned gradually. Their amounts in the tenth year account for 73.8%, 79.4%, and 60.7% of that in the base year, respectively. However, the amount of SO$_2$ is increasing as the prevailing of HEVs and PEVs. The amount of SO$_2$ in the tenth year is 2.64 times that in the base year. Although there are dramatic changes in the first few years, the changes in environmental impacts begin to be stable in the last few years that is called stationary. Finally, the environmental impacts will not change further.

7. Conclusions

This paper proposed a method to estimate the dynamic environmental impact as the introduction of electric vehicles. The method depends on market penetration level of three vehicle types and their working conditions in transportation network. The transition process between three vehicle types is represented by a Markov chain model in which the market shares can be predicted yearly. The network traffic conditions are predicted by a transportation system equilibrium for a given road network. It is a four-step sequential model with feedback where MSA with decreasing weights is adopted to solve the model. Specifically, the multinomial logit model is used for trip distribution instead of conventional gravity model, which can adequately capture traveler decision behaviors. It is demonstrated that a number of key variables in destination choices that have a significant explanatory power are not included in the gravity model.

A simulation study using Nguyen–Dupuis network verified the effectiveness of the proposed method. As the penetration of PEVs and HEVs, the emissions of CO$_2$, NO$_x$, and VOC begin to decrease while the emission of SO$_2$ begins to increase. This is caused by the thermal power plants. In fact, the emissions of electric vehicles highly depend on power source. The introduction of electric vehicles is still promising as the renewable power is growing. The parameters used for emission rates can be adjusted according to the reality. The proposed method is still useful without loss of generality. The results are certainly encouraging in terms of future application to other real-world large-scale transportation networks.

This research can be improved in several directions. First, real-life cases can be adopted to obtain more convincing results. Since we could not find a more realistic case with available data, a simulation experiment is conducted to show how our method can be applied. Second, the transportation system equilibrium model can be improved in two ways. One is to use elastic travel demand rather than fixed travel demand. The other is to incorporate other powerful explanatory factors for destination choices. Last but not least, different policies affecting transition probabilities between ICEV, PEV, and HEV can be tested. It will be very helpful for policy-makers to assess the environmental benefits of kinds of policies.

Data Availability

The data used to support the experimental study are included within the article.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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