ROUTING ASPECTS OF ELECTRIC VEHICLE USERS AND 
THEIR EFFECTS ON NETWORK PERFORMANCE

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ABSTRACT

This study investigates the routing aspects of electric vehicle (EV) users and their effects on the overall traffic network performance. EVs are classified as battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). This study focuses on BEVs. BEVs have some unique characteristics such as long battery recharging time, and recuperation of energy lost during the deceleration phase if equipped with regenerative braking systems. This raises two interesting questions: (i) whether the energy recuperation characteristics of BEVs will lead to different route selection compared to conventional internal combustion engine vehicles (ICEVs), and (ii) whether such route selection implications of BEVs will affect the network performance. With the increasing market penetration of BEVs, these questions are becoming increasingly important.

The study formulates a multi-class dynamic user equilibrium (DUE) model to determine the equilibrium flows for a traffic system consisting of a mix of BEVs and ICEVs. A simulation-based framework is used to obtain the solution of the DUE problem. Results from computational experiments on a test network illustrate that the dominantly selected routes by BEV drivers are different from ICEV drivers as BEV drivers may select congested routes to recuperate battery charge while ICEV drivers focus on routes minimizing their travel time. Hence, BEV drivers may select routes with more congestion characteristics so that the start-and-stop phenomena associated with such routes can recuperate the energy at a better rate, implying increased energy efficiency for the chosen route. This has implications for the overall network performance, in that it can synergistically move the traffic system towards optimal performance as the congestion and energy imperatives of ICEVs and BEVs, respectively, are traded off.
INTRODUCTION

An electric vehicle (EV) uses a battery-powered electric motor for propulsion unlike gasoline-powered internal combustion engine vehicles (ICEVs). EVs have received much attention in the last few years with the promise of achieving reduced petroleum dependency, enhanced energy efficiency, and improved environmental sustainability. The U.S. Department of Energy (USDOE) (1) determined that only about 17–21% of the energy stored in the gas tank of an ICEV is converted to power at the wheels. The combustion engine alone loses 62.4% of the energy from fuel as heat (2). By contrast, EVs convert about 59–62% of the electrical energy from the grid to power at the wheels (1). Therefore, an EV performs more efficiently than an ICEV. The commonly used metrics for fuel economy (electricity consumption) of EVs are miles per gallon of gasoline equivalent (mpge) and kilowatt-hours (kWh) per 100 miles. As per USDOE estimates, a fuel economy higher than 100 mpge can be achieved for light-duty EVs as compared to 32 mpg for ICEVs.

In the current market, there are two types of EVs: plug-in hybrid electric vehicle (PHEV) and battery electric vehicle (BEV). PHEVs are equipped with both gasoline ICE and electric motor, and BEVs are equipped with the electric motor only. As PHEV requires two drive-trains, typically the operating cost of a PHEV is higher than the BEV that requires single drive-train. Although BEVs achieve significant overall lower cost and are more energy efficient, there are unique characteristics associated with BEVs including limited battery capacity and long recharging time that can be limiting for travel compared to ICEVs. Given the current battery technologies, a BEV typically has a range of around 100 miles with a full charge, depending on the vehicle type and battery size. However, some vehicles have a higher range of about 250 miles and with the advancement of battery technology it is expected to improve further. As for the recharging time, a BEV usually spends 6 - 8 hours (slow charging) to get fully charged, depending on the electricity charging equipment, charging schemes, and battery capacity (3). Therefore, BEV drivers currently and in the near future are expected to charge their vehicles through home-based overnight charging or workplace-based charging mechanisms most of the time. Fast charging technology is available, with ten-minute charging for a range of 100 miles. However, it requires special equipment and infrastructure, which are sparsely deployed in the public domain.

With the improvement in battery and automobile technologies, it is anticipated that EVs will capture a significant market share in future years because of the low cost, energy efficiency, infrastructure availability, and increasing public acceptance. The market share of EVs, including BEV and PHEV, has increased from 0.8% in 2012 to 1.3% in 2013 in US (4). Recent studies predicted that EV could comprise 24% of the light-vehicle fleet in USA by 2030 (5).

The increase in the market penetration of BEVs can impact the traffic stream, which may imply new driving and route choice imperatives. BEVs (as well as PHEVs) can be equipped with regenerative braking systems (RBS) that can recuperate a part of the kinetic energy lost during the deceleration phase to recharge the battery. This is where braking energy that would otherwise be dissipated as heat is captured and stored in batteries. This can increase the driving range of a BEV. Studies show that in typical urban areas, the recuperation could increase range by about 20%, and often more in hilly areas (6). Due to the long battery recharging time, en-route recharging is usually not an attractive option for BEVs currently, and thus energy-efficient driving and driving range improvement are important factors for BEV drivers. This raises two interesting questions: (i) whether the incentive in terms of range improvement can lead to
different route selection by BEV drivers as compared to the ICEV drivers, and (ii) whether this
difference in route selection by BEV drivers can lead to changes in network performance in
terms of system travel time. The past studies have focused on energy efficient routing decision
and the static user equilibrium assignment under range constraint (7) or under restricted path set
with consideration of battery-charging stations. However, to the best of authors’ knowledge, the
above two aspects related to BEVs have not been investigated in the past. This study endeavors
to bridge this gap in the literature, and can potentially have positive implications in that as the
congestion and energy imperatives of ICEVs and BEVs, respectively, are synergistically traded
off, the traffic system performance can be enhanced beyond that of a traffic stream with only
ICEVs, at least up to certain BEV market penetration levels.

This study proposes a heterogeneous dynamic user equilibrium (DUE) formulation to
investigate the equilibrium flows under a mix of BEVs and ICEVs. The change in network
performance with change in market penetration of BEV is also investigated. The network
performance analysis can provide valuable insights to: (i) traffic system operators in terms of
devising effective operational management strategies in traffic streams with a mix of BEVs and
ICEVs, and (ii) decision-makers for effective policy-making such as electricity pricing and
charging station facility location.

The remainder of the paper is organized as follows. The next section reviews the relevant
literature in this domain. This is followed by the model formulation and the solution procedure.
Next, numerical experiments are presented for a synthetic network and its insights are
summarized. Finally, concluding comments are presented along with some directions for future
research.

LITERATURE REVIEW

The past studies related to EVs in the transportation domain can be broadly classified into three
groups: energy-efficient routing, EV traffic assignment and facility location of charging stations.

Related to the energy-efficient routing, Sachenbacher et al. (8) introduced the problem of finding
the most energy-efficient path for BEVs with recuperation in a graph-theoretical context.
Artmeier et al. (6) and Storandt (9) proposed revised shortest-path algorithms to address the
energy-optimal routing. They formulated energy-efficient routing in the presence of rechargeable
batteries as a special case of the constrained shortest path problem and presented an adaptation of
a shortest path algorithm. Adler et al. (10) studied the EV shortest-walk problem to determine the
route from an origin to a destination with minimum detouring; this route may include cycles for
detouring to recharge batteries.

In terms of the EV traffic assignment, Jiang et al. (7) formulated the problem as a path-
constraint traffic assignment problem. Arguing that the range limit inevitably changes BEV
drivers’ travel behavior, Jiang and Xie (11) further addressed the traffic assignment problem with
mode and route choice for BEVs. Jiang et al. (12) extended their equilibrium model to both
ICEVs and BEVs assuming different travel cost functions and studied the combined destination,
route and parking choices subject to the driving range limit associated with BEVs. He et al. (13)
studied the single class BEV traffic equilibrium on a set of usable paths with and without
considering en-route battery-charging time. They considered travel time minimization as the
single decision criterion for route choice neglecting the energy consumption factor in the cost
function. However, energy consumption is used to compute the set of usable paths. The
aforementioned assignment models focus on static traffic equilibrium rather than DUE. Related
to a dynamic context, Schneider et al. (14) investigated the EV routing problem with custom
time windows and battery-charging stations. They considered the travel time to be independent
of flow in the routing model.

Several studies have investigated the facility location problem of charging stations (15-18)
and battery-swapping stations (19) at which depleted batteries can be exchanged for
recharged ones in the middle of long trips. By considering a fast battery-charging option during
the mid-tour, the vehicle routing problem is reformulated where vehicles with limited range are
allowed to recharge their battery at charging stations (20, 21).

The market penetration of the EVs is projected to rise due to multiple factors such as
government subsidies, advancement in battery technology and public acceptance for EVs.
Shepherd et al. (22) investigate the effect of multiple factors such as subsidy, average vehicle life
and emission rates on the market penetration of BEVs. Yu et al. (23) suggested that range
anxiety of drivers that the vehicle will run out of charge before reaching the destination, is a
major hindrance for the market penetration of EVs.

METHODOLOGY

This study assumes that the route choices of BEV and ICEV users are governed by the DUE
principle with respect to the generalized cost. That is, BEV and ICEV users seek the individual
minimum time-dependent generalized cost in their route selection. The generalized cost accounts
for both travel time and range improvement for the BEV, and considers only the travel time for
the ICEV. The analytical single class DUE has been extensively studied in the literature using
mathematical programming, optimal control, and variational inequality (24). Different from
those studies, our problem is a multi-class DUE formulation with two vehicle classes (BEVs and
ICEVs). This study extends the DUE formulation proposed by Ban et al. (25) as a
complementarity problem from a single user class to multiple user classes.

Notation

Let G(N,A) denote a traffic network as a fully connected and directed graph, where N is the set
of nodes and A is the set of directed links. Let the time horizon of interest be divided into T
discrete time intervals. The time-dependent fixed travel demand from node i ∈ N to
destination s ∈ S ⊆ N, where S is the set of destination nodes, for each vehicle class m ∈ M ≡
\{E, I\} at time period t ∈ (0, T) is denoted by d_{is}^m(t), where E represents the BEV class and I
represents the ICEV class. A(i) and B(i) are the set of outbound and inbound links of node i,
respectively.

Multi-Class DUE Formulation

The single class static user equilibrium principle of route choice states that “the journey times in
all routes actually used are equal and less than those which would be experienced by a single
vehicle on any unused route” (26). Its extension to the multiple vehicle-class dynamic user
equilibrium assignment would be that “the generalized travel costs of all utilized time-dependent
routes with the same departure time are equal and are less than those of the unutilized routes for
each vehicle class”. Mathematically, this multi-class DUE principle can be formulated as a
complementarity problem for each vehicle class m by Equation (1), where u_{nis}^m(t) is the inflow
rate to link $a$ with respect to destination $s$ for vehicle class $m$ at time $t$, $C^m_a(t)$ is the generalized travel cost for vehicle class $m$ on link $a$ at time $t$, $\pi^m_{ha}(t)$ and $\pi^m_{la}(t)$ are the minimum generalized travel costs, respectively, from the head-node $h_a$ and the tail-node $l_a$ of link $a$ to destination $s$ for vehicle class $m$ at time $t$, and $\tau_a(t)$ is the link travel time at time $t$. The mathematical operator $p \perp q$ used in (1) means $p$ is perpendicular to $q$, i.e. $p^Tq = 0$.

$$0 \leq u^m_{as}(t) \perp \{C^m_a(t) + \pi^m_{ha}(t + \tau_a(t)) - \pi^m_{la}(t)\} \geq 0 \quad \forall m, a, s, t \quad (1)$$

**Generalized cost functions**

The generalized travel cost on link $a$ at time $t$ for vehicle class $m \in M$ includes the link travel time $\tau_a(t)$ and $\gamma^m_a(t)$ which represents other possible factors such as fuel cost, battery consumption, and driving range.

$$C^m_a(t) = \tau_a(t) + \gamma^m_a(t) \quad \forall m, a, t \quad (2)$$

**Mass balance constraints**

Mass balance constraints ensure that vehicles are not entering or exiting the network in between the link, i.e. the rate of change of link flow $x^m_{as}(t)$ is the difference between inflow rate $u^m_{as}(t)$ and exit flow rate $v^m_{as}(t)$ is for each vehicle class. This constraint is expressed in Equation (3).

$$\frac{dx^m_{as}(t)}{dt} = u^m_{as}(t) - v^m_{as}(t) \quad \forall m, a, t \quad (3)$$

**Flow conservation constraints**

These constraints ensure that the flow is conserved on each node at each time instant with respect to destination $s$ for vehicle class $m$, i.e. the total outbound flows are equal to the demand plus the total inbound flows for each node $i$.

$$\sum_{a \in A(i)} u^m_{as}(t) = d^m_{is}(t) + \sum_{a \in B(i)} v^m_{as}(t) \quad \forall m, i, s, t \quad (4)$$

**FIFO constraints**

The first-in first-out (FIFO) principle states that vehicles departing later cannot exit a link earlier, that is, vehicles must exit later than the vehicles that entered the same link earlier than them. Although FIFO may not always hold in reality as vehicles can overtake, but on average this constraint is satisfied. FIFO constraints can be represented as:

$$t_1 + \tau_a(t_1) \leq t_2 + \tau_a(t_2) \quad \forall t_1 < t_2 \quad (5)$$

**Flow propagation constraints**

Flow propagation constraints describe the spatial and temporal traffic flow dynamics at the macroscopic level (27). Note that traffic flows interact as a whole regardless of their vehicle class and hence, these constraints hold only if the driving characteristics, such as maximum speed and acceleration, of all vehicle classes are similar.
\[
\sum_{m \in M} v_{as}^m(t + \tau_a(t)) = \frac{\sum_{m \in M} u_{as}^m(t)}{1 + d \tau_a(t)/dt} \quad \forall a, s, t (6)
\]

**Definitional constraints**

Equation (7) represents inflow rate and exit flow rate for a link aggregated over all destinations for each vehicle class for all time intervals. Equation (8) represents the flows on each link aggregated over all destinations for each vehicle class for all time intervals. Equations (9) and (10) represent the non-negativity constraint for flow and cost variables.

\[
u_a^m(t) = \sum_{s \in S} u_{as}^m(t), \quad \forall m, a, t (7)
\]

\[
v_a^m(t) = \sum_{s \in S} v_{as}^m(t), \quad \forall m, a, t (8)
\]

\[
\pi_{ta}^m(t) \geq 0, \quad \pi_{sa}^m(t) \geq 0, \quad \forall m, a, s, t \quad (9)
\]

\[
\pi_{la}^m(t) \geq 0, \quad \pi_{ha}^m(t) \geq 0, \quad \forall m, a, s, t \quad (10)
\]

**Path-feasibility constraints**

Path-feasibility constraints are required to circumvent the possibility of circulation of flow that may arise due to negative link costs. For BEVs, link costs can be negative as they have a negative cost component in the form of recuperation of battery charge. Under multiple start-and-stop phenomena, this negative component can be higher than the travel time component leading to negative link cost for BEVs. The path-feasibility constraint implies that a path is feasible only if it is a simple path that does not visit the same node twice. A path is a candidate for the shortest path only if it is a feasible path. In other words, these constraints restrict the shortest paths in the feasible path set. Path feasibility constraints can be represented by Equation (11), where \(Z_{ha,s}^m(t)\) is the binary vector of size \(N\) having elements equal to 1 if the node is in the shortest path from \(h_a\) to \(s\) at time \(t\), 0 otherwise. \(\psi_a\) is the binary vector of size \(N\) having elements equal to 1 if the node is same as the tail node \(l_a\), 0 otherwise.

\[
[Z_{ha,s}^m(t)]^T \cdot \psi_a = 0 \quad \forall m, a, s, t (11)
\]

Equations (1) – (11) constitute the multi-class DUE model in the complementarity formulation. There are two vehicle classes in this model formulation, BEV and ICEV. Each vehicle class follows the DUE principle, but the flow propagation constraint addresses the flow dynamics produced by total flows obtained by combining the two classes. Next, we present a solution procedure to solve the complementarity formulation.

**Solution Procedure**

Various methods have been proposed in the literature to solve the complementarity problem \((13, 25)\). The complexity of the complementarity problem proposed in this study is similar to the DUE formulation proposed by Ban et al. \((25)\) and hence a similar solution strategy can be used to solve the problem analytically given that the generalized cost function has a closed form.
As discussed heretofore, the generalized travel cost function of BEVs in this study consists of travel time and range improvement due to energy recuperation (or percentage of battery consumed). The percentage of battery consumed and its regeneration due to RBS for the path depend on the microscopic driving characteristics such as speed and acceleration. These microscopic details are not available a priori and hence, percentage of battery consumed and its regeneration cannot be expressed as a closed form function using macroscopic parameters. This hinders this study from using an analytical approach to solve the proposed DUE formulation. Hence, a microscopic simulation-based method is employed to compute the generalized travel cost. The overall solution procedure is an iterative process as shown in Figure 1.

The DUE solution procedure is initialized with All-or-Nothing (AON) assignment on the time-dependent shortest path for each time interval. A microscopic traffic simulator AIMSUN is used to generate microscopic driving parameters such as speed and acceleration/deceleration profiles of vehicles by simulating path flows (28, 29). A vehicle simulator namely, Advanced Vehicle Simulator (ADVISOR), is used to compute the series of battery state-of-charge (SOC) at each unit instant of time (30-32). ADVISOR is an analysis tool developed by the National Renewable Energy Laboratory (NREL) designed to analyze vehicle performance and fuel economy. It uses basic physics and model component performance to replicate the vehicle drive-train process. The ADVISOR module is highly parameterized and hence its components can be varied to simulate the drive-train of new vehicle types using the baseline scenarios. The limitation of ADVISOR is that it cannot be used with very small time scales. In this study, the SOC is computed by ADVISOR by utilizing the drive cycle generated by AIMSUN. A drive cycle constitutes a series of vehicle speeds as a function of time. The generalized travel costs for both vehicle classes for every link at each time interval are computed by aggregating vehicle-based SOC data and travel time data at the link level. The decreasing order of time (DOT) algorithm (33) is used to compute the set of time-dependent shortest paths (TDSP). TDSP is used to update the path set for each user class at each time interval for each origin-destination (O-D) pair. Then Smith’s algorithm (34) is used to update the path flow vectors for each vehicle class for each time interval for all O-D pairs simultaneously. These path flows are simulated with AIMSUN to generate the drive cycles of vehicles. The process continues until the algorithm achieves convergence. The convergence is assumed to be achieved when the average difference between the generalized path travel costs of the O-D pair are less than a threshold value, taken in this study as 5% of the lowest generalized path travel cost of the O-D pair.
FIGURE 1 Solution Procedure.
NUMERICAL EXPERIMENTS

Figure 2 illustrates a synthetic network used to analyze the proposed model. It consists of 43 nodes, 92 links, 7 origins/destinations, and 42 O-D pairs with non-zero demand. Origins and destinations are marked through A - F. The network has 4 types of links: freeway, two-lane arterial, one-lane arterial, and ramps. Numbers next to the link in Figure 2 represent their link IDs. The arterials are connected to the freeway through 12 ramps at three locations.

In this study, the experimental setup is designed to run for a time horizon of one hour. The time horizon is divided into 12 time intervals of 5 minutes. The base demand for the complete time horizon is presented in Table 1. The congestion level based on this demand is moderate to high. The temporal distribution factors for the demand are shown in Figure 3. The demand for a time interval is determined by multiplying the base demand with the corresponding temporal distribution factor. Further, the demand for each vehicle class is determined by factoring its market penetration.

<table>
<thead>
<tr>
<th>O/D</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
<td>1500</td>
<td>300</td>
<td>500</td>
<td>100</td>
<td>200</td>
<td>300</td>
</tr>
<tr>
<td>B</td>
<td>1500</td>
<td>0</td>
<td>500</td>
<td>300</td>
<td>100</td>
<td>75</td>
<td>400</td>
</tr>
<tr>
<td>C</td>
<td>150</td>
<td>300</td>
<td>0</td>
<td>200</td>
<td>25</td>
<td>100</td>
<td>75</td>
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<tr>
<td>D</td>
<td>250</td>
<td>75</td>
<td>150</td>
<td>0</td>
<td>50</td>
<td>25</td>
<td>200</td>
</tr>
<tr>
<td>E</td>
<td>50</td>
<td>100</td>
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<td>50</td>
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<tr>
<td>F</td>
<td>100</td>
<td>50</td>
<td>50</td>
<td>25</td>
<td>50</td>
<td>0</td>
<td>50</td>
</tr>
<tr>
<td>G</td>
<td>150</td>
<td>300</td>
<td>75</td>
<td>150</td>
<td>50</td>
<td>50</td>
<td>0</td>
</tr>
</tbody>
</table>
The second component, $\gamma^m_a(t)$, of the generalized travel cost function presented in Equation 2 is defined for both vehicle classes $I, E \in M$. For ICEV, this component is assumed to be zero. For BEV, this component is assumed to be a function of the percentage of battery consumed, as shown in Equation (13), where $\rho_a(t)$ is the percentage of battery consumed on link $a$ at time $t$ and $\beta$ is the coefficient that represents the relative importance of the battery state-of-charge with respect to travel time in minutes.

$$
\gamma^m_a(t) = 0
$$

$$
\gamma^E_a(t) = \beta \rho_a(t)
$$

The parameter $\beta$ needs to be calibrated using field data. In the absence of field data in this study, the numerical experiments are carried out assuming a base $\beta = 0.09$. Further, sensitivity analysis is performed by varying $\beta$ to investigate its effect on the route selection by the BEV drivers.

**FIGURE 3** Temporal Distribution Factors of Traffic Demand.

**FIGURE 4** Route Flows of ICEVs and BEVs for O-D Pair (D-G).
Figure 4 illustrates the paths taken by ICEVs and BEVs for O-D pair D-G in the second time interval for $\beta$ equal to 0.09 and at BEV market penetration of 10%. The corresponding route flows of BEVs and ICEVs along with their travel time and percentage of battery consumed are summarized in Table 2 equal to 0.09. It shows that a majority of the ICEVs (88.31% of the demand) travel on the route having a major portion along the freeway, and with the lowest travel time. However, the BEVs do not travel on the freeway route even though it has the lowest travel time due to disincentive of high battery consumption as shown in Table 2. About 58% of the BEVs travel on the arterial routes (routes 2 - 4) with higher travel time but with much lesser battery consumption. Other routes are not shown in the Figure 4 for better visualization. Multiple other routes similar to the routes presented in Figure 4 for BEV (arterial routes) are available that carry 42% of the remaining BEV flow.

![Graph](image-url)

**FIGURE 5 System Travel Time for Different Values of $\beta$.**

<table>
<thead>
<tr>
<th>Route ID</th>
<th>Flow (% class demand $d^m$)</th>
<th>Travel Time (min)</th>
<th>Battery Consumed (% Battery Capacity)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BEV</td>
<td>ICEV</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>88.31</td>
<td>7.43</td>
</tr>
<tr>
<td>2</td>
<td>29.53</td>
<td>1.99</td>
<td>8.36</td>
</tr>
<tr>
<td>3</td>
<td>17.18</td>
<td>5.87</td>
<td>8.59</td>
</tr>
<tr>
<td>4</td>
<td>11.29</td>
<td>0.92</td>
<td>8.45</td>
</tr>
<tr>
<td>Others</td>
<td>42</td>
<td>2.92</td>
<td></td>
</tr>
</tbody>
</table>
TABLE 3 Sensitivity Analysis of Flow Proportions with the Parameter $\beta$

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>0.05</th>
<th>0.08</th>
<th>0.09</th>
<th>0.10</th>
<th>0.15</th>
</tr>
</thead>
<tbody>
<tr>
<td>Route No.</td>
<td>TT (min)</td>
<td>ICEV-Flow</td>
<td>BEV-Flow</td>
<td>TT (min)</td>
<td>ICEV-Flow</td>
</tr>
<tr>
<td>1</td>
<td>8.48</td>
<td>39.55</td>
<td>0.04</td>
<td>8.11</td>
<td>82.50</td>
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<tr>
<td>3</td>
<td>8.59</td>
<td>10.46</td>
<td>20.95</td>
<td>9.46</td>
<td>0.92</td>
</tr>
<tr>
<td>4</td>
<td>8.43</td>
<td>8.08</td>
<td>19.78</td>
<td>9.19</td>
<td>2.84</td>
</tr>
<tr>
<td>5</td>
<td>8.44</td>
<td>8.88</td>
<td>4.32</td>
<td>8.85</td>
<td>4.3</td>
</tr>
<tr>
<td>6</td>
<td>8.72</td>
<td>5.08</td>
<td>5.56</td>
<td>8.95</td>
<td>2.37</td>
</tr>
<tr>
<td>7</td>
<td>8.83</td>
<td>3.72</td>
<td>12.56</td>
<td>9.95</td>
<td>0.68</td>
</tr>
<tr>
<td>8</td>
<td>8.46</td>
<td>7.61</td>
<td>3.05</td>
<td>8.89</td>
<td>1.98</td>
</tr>
<tr>
<td>Other Routes</td>
<td>6.27</td>
<td>8.17</td>
<td>2.13</td>
<td>15.92</td>
<td>0.50</td>
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</tbody>
</table>
The sensitivity of path flows of the two vehicle classes with respect to the parameter $\beta$ is performed to determine the importance of this parameter on the observed route flows. The results of the sensitivity analysis are presented in Table 3. They indicate that with increase in the value of $\beta$, the paths that are sub-optimal from a travel time perspective, and which were not used by the BEV drivers due to higher travel times become attractive as the relative weight of battery consumption increases in the generalized travel cost. In addition, the network performance in terms of the total system travel time was also evaluated at different levels of the parameter value $\beta$, including at $\beta$ equal to zero, as illustrated in Figure 5. At $\beta$ equals to zero, the generalized cost function for BEV drivers is the same as that of ICEV drivers, and implies a zero market penetration of BEVs. This acts as the reference level to evaluate the network performance in terms of system travel time at different levels of $\beta$. As seen in Figure 5, the total system travel time decreases initially with the increase in the value of $\beta$ but becomes nearly constant afterwards. There is a clear tradeoff involved in the path selection process by BEV drivers who weigh travel time and battery consumption simultaneously. With the increase in $\beta$, the difference in terms of the path travel time is more than compensated by the difference in the percentage of battery consumed on those paths. Thereby, BEV drivers may be more willing to take congested paths, usually with higher travel time but lesser battery consumption, which drives the system towards system optimality in terms of total system travel time. Hence, the presence of BEVs may synergistically improve the system performance in terms of travel time, especially if the drive range of the BEVs is limited relative to the typical range desirable in an urban area. Also, while only two market penetration levels are considered in the numerical example, Figure 5 illustrates that the system travel time gains can be significant when BEVs are present in the traffic mix, if range limitations of BEVs lead to route choice decisions that seek to minimize the generalized travel cost rather than the travel time only.

CONCLUSIONS

This study investigates the effect of battery consumption and regeneration on the route selection by BEV drivers. A heterogeneous dynamic user equilibrium formulation for multi-user class is proposed to assign traffic of BEVs and ICEVs according to the minimum generalized travel cost. The generalized cost of BEVs includes travel time and battery consumption which is based on microscopic driving characteristics (such as acceleration, deceleration, stops, etc.) along the traveled route for each BEV. A solution procedure is proposed to solve the DUE model, in which the battery consumption is computed using a vehicle simulator ADVISOR based on the microscopic driving characteristics of each BEV generated using the microscopic traffic simulator AIMSUN.

This study concludes that BEV drivers may select congested routes with longer travel time but lesser battery consumption. This route selection feature of BEV drivers may lead to the improved overall network performance in terms of travel time when the traffic mix contains both BEVs and ICEVs, compared to the case with only ICEVs. This has key implications for traffic system operators in terms of developing operational management strategies to improve the network performance when BEVs are present in the traffic stream.

Ongoing research efforts include the calibration of the generalized cost function using real data for BEVs, and analyzing the effect of the market penetration of BEVs on network performance by considering multiple market penetration levels beyond the two used in the numerical experiments in this study.
REFERENCES


