EFFECT OF ROUTE CHOICE ON BATTERY ELECTRIC VEHICLE ENERGY CONSUMPTION

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ABSTRACT

This study investigates the impact of route selection on battery electric vehicles’ (BEVs’) energy consumption. Drivers typically choose routes that reduce travel time and therefore travel cost. However, BEVs’ limited driving range makes energy efficient route selection of particular concern to BEV drivers. In addition, BEVs’ regenerative braking systems allow for the recovery of energy while braking, which is affected by route choices. State-of-the-art BEV energy consumption models consider simplified; average constant regenerative braking energy efficiency or regenerative braking factors are mainly dependent on vehicle average speed. To overcome these limitations, this study adopted a microscopic BEV energy consumption model, which can identify the effect of transient behaviors on BEV consumption and energy recovery while braking in a congested network. Simulation results indicate that User-Equilibrium (UE) and System Optimum (SO) traffic assignments do not necessarily minimize BEVs’ energy consumption. Furthermore, the study found that faster routes could actually increase BEVs’ energy consumption, and that significant energy savings (48% consumption reduction) were observed when BEVs utilized a longer travel time arterial route. The study also found that BEVs and conventional internal combustion engine vehicles (ICEVs) had different fuel/energy-optimized traffic assignment conditions, suggesting that different assignments be recommended for these different vehicle types. Finally, the study found that regenerated energy was greatly affected by facility types and congestion levels and also BEVs’ energy efficiency could be significantly influenced by regenerated energy.

Keywords: Electric Vehicles, Regenerative Braking Energy Efficiency, Energy Consumption, Eco-Routing.
INTRODUCTION

This study quantifies the impact of route selection on battery electric vehicles’ (BEVs’) energy consumption. A BEV (also referred to as a battery-only electric vehicle or an all-electric vehicle) is a type of electric vehicle (EV) that uses electric power from battery packs and is capable of being charged from an external source without internal combustion engines (ICEs) and/or fuel cells for propulsion. Due to BEV’s limited driving range, eco-routing and energy efficient route selection are of major concern to BEV drivers. A recent study found that BEVs’ energy efficiency is significantly affected by the driving cycle (1). Further, in urban driving conditions, increased braking allows BEVs to recover more energy due to the presence of regenerative braking systems. Specifically, the electric motor works as a generator by sending energy from the vehicle’s wheels to the electric motor, where it is then stored in the battery system. A previous study found that BEVs were much more efficient when driving “intermittent” urban routes when compared to uninterrupted freeways because of this regenerative braking system (2).

Route selection, for most motorists, usually involves finding the fastest, easiest way to get to destinations so travel time, and therefore travel cost, is minimized. However, the trip-planning process can also be complicated by attempts to reduce travel delays and improve travel time reliability by avoiding traffic congestion. The route selection process is generally based on drivers’ experience and current information on travel time, trip distance, and other trip-related factors. Thus, drivers sometimes select longer routes if they produce travel cost savings. However, energy/fuel consumption impacts are not typically factored into the decision-making process.

One of the main advantages of EVs is their use of a regenerative braking system to recover energy while braking. State-of-the-art vehicle energy consumption models utilize either an average constant regenerative braking energy efficiency or regenerative braking factors that are mainly dependent on vehicle speed. These simple models cannot assess an energy efficiency relationship relating the regenerative braking efficiency to the vehicle deceleration level.

The commonly used User-Equilibrium (UE) and System Optimum (SO) traffic assignments models typically utilize minimum travel time as a generalized cost to assign traffic flows over a network. However, given that UE and SO assignments are estimated based on travel time, conditions in these assignments may not produce optimum energy efficiency route conditions, which, for BEVs, is critical due to battery capacity and limited driving range.

This study investigates the impacts of route choice decisions on BEVs’ energy consumption using GPS data gathered during the morning commute near a suburb in the Washington, DC metropolitan area. Fuel consumption impacts of route selection on internal combustion engine vehicles (ICEVs) and BEVs are also compared. The study analysis is further expanded by conducting a sensitivity analysis using microscopic traffic simulation to analyze scenarios not observed in the field. Finally, the study quantifies the impacts of regenerated power during various traffic assignment scenarios.

LITERATURE REVIEW

A number of studies have been conducted to develop and evaluate eco-routing strategies for EVs and AFVs. Richter et al. (2012) presented a study to show the energy saving potentials and differences between routes for an ICEV, BEV and plug-in hybrid electric vehicle (PHEV). The analysis was performed using the ULTraSim traffic simulator, which incorporated submicroscopic vehicle models of BEVs, PHEVs and ICEVs. The study examined the fuel savings of the eco-route for each type of vehicle in comparison to the shortest route, finding that the saving potential was dependent on route planning. The study recommends considering the different drive trains in eco-route calculation (3).

Liu et al. (2014) presented a minimum-cost path optimization scenario for real-time pricing (RTP) with multiple charging stops in long distance origin/destination (OD) trips for BEVs. The study utilized dynamic programming to solve the optimum cost problem with a travel time limitation that considered charging control. The authors designed Improved Chrono-SPT (ICS) and simplify-charge-control (SCC) algorithms to reduce the computational complexity and the simulation results proved the effectiveness of the proposed approach (4).
Artmeier et al. (2010) investigated an energy-efficient path for BEVs with recuperation in a graph-theoretical context, which extended a general shortest path problem (SP). The study modeled energy-optimal routing as a shortest path problem with various constraints. The study also considered energy costs or gains that might result from speed variability cost with different cruise speeds. The developed model was implemented into an energy-efficient prototypic navigation system (5).

Energy-optimal routing for BEVs was also investigated by Sachenbacher et al. (2011). Their study claims that standard routing does not work for EVs due to their use of regenerative braking, along with the complexity of a number of parameters, such as vehicle load and auxiliary usages, and battery capacity limitations. The study proposes an Energy A* search algorithm to overcome the challenges and shows how battery constraints can be dynamically incorporated into the algorithm. Experimental test results with real road networks found that the proposed method was effective and faster compared to the generic framework using the Dijkstra or Pallottino strategy (6).

Bhavsar et al. (2014) performed a study in which they developed an integration simulation tool, CUIntegration, to evaluate vehicle routing strategies’ effects on energy consumption and other traffic related measures for ICEVs and AFVs, including PHEVs and BEVs. CUIntegration incorporates a routing strategy developed using MATLAB with the VISSIM microscopic traffic simulation software. The simulation study found that energy optimization resulted in about 30% savings in the EV’s energy consumption, and travel time optimization resulted in about 65% savings in travel time with increased overall energy consumption (7).

The impact of driver behavior on BEVs’ energy consumption was investigated by Bingham et al. (2011). The study found that energy consumption could be significantly reduced by eliminating acceleration and deceleration behavior throughout the tested driving cycle. The study reports that good driving can reduce total energy consumption by 30% compared to more aggressive driving based on the specific cases analyzed. The study also recommended considering ‘hotel loads’ (i.e. air-conditioning and heating) for energy efficiency evaluation. Further, the study suggests using appropriate traffic management techniques by reducing periods of transient acceleration/deceleration and promoting consistent speed levels to improve fuel economy (8).

A number of other researchers have focused on the effects of routing on EVs’ energy consumption. However, these efforts have typically utilized aggregate energy models and simplified mathematical expressions to compute EV’s energy consumption rates without considering instantaneous energy consumption. Further, most studies didn’t take into account the energy that BEVs regenerate—a critical element in identifying the impacts of route selections. These simple approaches can be accepted for general energy estimation, but are not adequate to quantify the energy consumption impact of route choice, particularly on congested networks, due to significant transient behaviors typical of such networks.

To overcome these limitations, this study adopted a microscopic EV energy consumption model, VT-CPEM, which models the effect of transient behaviors in congestion networks on EV energy consumption and energy recovered during braking. Furthermore, the study analyzed GPS data collected under current traffic signal operations on a section of road in an urban area during the morning commute period and various traffic assignment scenarios, which were generated from a microscopic traffic simulation to represent real-world traffic conditions.

FIELD DATA COLLECTION

To identify the energy consumption impacts of route choice behavior, morning commute GPS data were collected in the Northern Virginia area. As shown in Figure 1, the arterial route, VA Route 7, extends over 22.6 km (17.25 mi) and covers 32 signalized intersections. The study section started at the intersection of VA 28 (Sully Road) to the west and extended to the intersection of I-66 to the east. The corridor’s entire length is divided, with a four-lane cross-section on the eastern side and a six-lane cross-section on the western side. The posted speed limits range from 56 km/h (35 mi/h) on the congested east side to 88 km/h (55 mi/h) on the west side. The highway route connects two highway sections and two arterial sections as shown in Figure 1.
The highway section extends from the intersection of VA 28 (Sully Road) and Route 7 to the south and connects to a section of VA 267 (Dulles Toll Road) and a section of I-495 and finally connects to Route 7. The distance of the highway route is 35.85 km, of which 22.56 km traverses highways (VA 267 and I-495). The arterial section of this route consists of a section of VA 28 that extends over 9.94 km and covers four signalized intersections and a section of Route 7, which is 3.35 km long and has six signalized intersections.

Traffic flows along the corridors are typically directional. During the morning peak, traffic generally moves eastbound, toward downtown Washington, DC and Fairfax, Virginia. The eastern portion of the study section, which has closely-spaced signalized intersections on VA 7, is typically more congested than other portions of the study section. The study corridors are controlled by a centralized, computerized signal system with an optimized cycle length of 180 s or 210 s depending on the time of day. Most of the signal cycle time is assigned to the main routes: VA 7 and VA 28.

FIGURE 1 Highway and arterial study corridors.

The directional distribution of signal timing varies according to the time of day and, during the morning peak, more signal timing is assigned to the eastbound direction. These signal timings are continuously optimized by Virginia Department of Transportation (VDOT) staff and thus represent the state-of-practice in optimal signal control. Since this study only investigates the impact of different route choices on vehicle fuel consumption and emission rates, a detailed description of the traffic signal operations on the study corridor is beyond this paper’s scope.

The study utilized a portable Wide Area Augmentation System (WAAS)-enabled GPS receiver, which provides longitude and latitude data to an accuracy of 2 m, altitude data to an accuracy of 3 m, and speed measurements to an accuracy of 0.1 m/s. The GPS unit recorded date, time, vehicle longitude, vehicle latitude, vehicle speed, vehicle heading, and the number of tracking satellites.

The GPS floating-car travel data were collected using a test vehicle on weekdays. The trip route (highway or arterial) was randomly selected on the day of data collection. To record the aggregate characteristics of traffic flow, the probe vehicle maintained the average speed of the traffic stream. The travel data were recorded at a 1-s resolution and downloaded to a personal computer. The minimum sample size \( N \) was calculated to satisfy the 95% confidence limits (Z value 1.96) using the standard deviation \( \sigma \) value and travel time error \( d \) (see Equation (1)). The GPS data that were gathered exceeded the required minimum sample size. In total, 39 valid trips were recorded, of which 21 were traveled on...
the highway route and 18 were traveled on the arterial route. Ten trips on the highway route and 11 trips on the arterial route were required to satisfy the minimum sample size considering a 95% confidence limit. 

\[ N = \left( \frac{1.96}{\delta} \right)^2 \sigma^2 \]  

(1)  

While both morning and evening commute data were gathered, only morning commute data were used for the analysis. A MATLAB code was developed to extract the study section data from the entire morning commute travel data. The software automatically identified the first and last GPS points within the study corridor using the coordinates of the boundary study sections. Following the data reduction, a unique trip number was assigned to each trip.  

ENERGY CONSUMPTION MODEL  

The study utilized microscopic energy/fuel consumption models to identify the impact of routing options on BEVs and ICEVs. The following sections briefly describe each model and how the models were utilized in this study.  

BEV Energy Model  

The Virginia Tech Comprehensive Power-based EV Energy consumption Model (VT-CPEM) is a quasi-steady backward highly-resolved power-based model. The model uses instantaneous speed, acceleration, and grade information as input variables. The outputs of the model are the energy consumption (EC) (kWh/km), the instantaneous power consumed (kW), and the final level of the state of charge (SOC) of the electric battery (%). A Nissan Leaf was utilized for the study. 

The power at the electric motor \( P_{Electric\ motor} (t) \) is computed, given the power at the wheels, considering the driveline efficiency \( \eta_{Driveline} = 92\% \) (13) and assuming that the efficiency of the electric motor is \( \eta_{Electric\ Motor} = 91\% \). This is a reasonable assumption according to SAE standards (14), and, in fact, the efficiency of the electric motor of the Nissan Leaf is between 85% and 95%. Also, in this range, 91% is the value that minimizes the average error between the real and the estimated consumption values. 

While the vehicle is in traction mode, energy flows from the motor to the wheels. In this case the power at the electric motor is higher than the power at the wheels and the power at the wheels is assumed to be positive. Alternatively, in the regenerative braking mode, energy flows from the wheels to the motor. The power at the electric motor is lower than the power at the wheels and the power is assumed to be negative. 

While decelerating, the electric power is negative and the regenerative braking energy efficiency \( \eta_{RB} \) is computed when \( P_{Electric\ motor} (t) < 0 \) using Equation (2). 

\[ P_{Electric\ motor} (t) < 0 \rightarrow P_{Electric\ motor} (t) = P_{Electric\ motor} (t) \cdot \eta_{RB} (t) \]  

(2)  

The final SOC (%) is computed using Equation (3). 

\[ SOC_{Final} (t) = SOC_0 - \sum_{i=1}^{N} \Delta SOC_{(i)} (t) \]  

(3)  

\[ \Delta SOC_{(i)} (t) = \frac{P_{Electric\ motor\ _net\ (i)} (t)}{3600 \cdot \text{Capacity}_{Battery}} \]  

(4)  

Here \( P_{Electric\ motor\ _net\ (i)} (t) \) is the electric power consumed considering a battery value of \( \eta_{Battery} = 90\% \) (15). In addition, the power consumed by the auxiliary systems (\( P_{Auxiliary} = 700 \text{ [W]} \)) (16) is considered. Capacity_{Battery} is the capacity of the battery in (Wh). The operation range of SOC is
between 20% and 95% to guarantee the safety of the battery system (17); the initial SOC is assumed to be
$SOC_0 = 95\%$.

Given the SOC, it is possible to compute the energy consumption (EC) in (kWh/km) using Equation (5).

$$EC \left[ \frac{kWh}{km} \right] = \frac{1}{3600000} \int_0^t P_{Electric \, motor_{net}}(t) \, dt \cdot \frac{1}{d}$$  \hspace{1cm} (5)

Here $d$ is the distance in (km). The parameters related to the specific electric vehicle used are reported in (12) where all the characteristics of the electric vehicle used are shown.

The VT-CPEM model was validated against experimental data collected by the Joint Research Centre (JRC) (10) of the European Commission and by the Idaho National Laboratory (INL) (11) of the United States Department of Energy (U.S. DOE), and accurately estimates the energy consumption, producing an average error of 5.9% relative to empirical data. More details about the VT-CPEM model are reported in (1).

**ICEV Fuel Consumption Model**

The VT-Micro model was utilized to estimate the vehicle fuel consumption level for ICEVs using the second-by-second speed profiles derived from field collected GPS data and simulation runs. The VT-Micro model is a mathematical model that estimates vehicle fuel consumption and emission levels for individual and/or composite vehicles using instantaneous speed and acceleration as explanatory variables. The VT-Micro model was developed as a regression model from experimentation with numerous polynomial combinations of speed and acceleration levels to construct a dual-regime model of the form.

The model utilizes a number of data sources, including data collected at the Oak Ridge National Laboratory (ORNL) (nine vehicles) and the Environmental Protection Agency (EPA) (101 vehicles). In this study, ORNL vehicles and EPA light duty vehicles type 2 (LDV2) were utilized for the analysis. The VT-Micro model fuel consumption and emission rates were found to be highly accurate compared to the original data with coefficients of determination ($R^2$) ranging from 0.92 to 0.99. The model is easy to use for the evaluation of the environmental impacts of operational-level projects, including ITS. A more detailed description of the model derivation is provided in the literature (20-22).

**RESULTS**

This section reports impacts of route selection on the energy/fuel consumption of BEVs and ICEVs. The study evaluated the route choice impact using individual vehicle trips and vehicle trajectory data from a microscopic traffic simulation model.

**Field Data Analysis**

In total, 39 valid trips were analyzed—21 were highway route trips and 18 were arterial route trips. The collected GPS data demonstrates that the highway trips reduced travel time by 4.27 minutes compared to the arterial trips, even though the highway trips were 30% longer (35.9 km versus 27.6 km). Table 1 also demonstrates that the highway trips had a significantly higher average speed (85.42 km/h) than the arterial trips (56.62 km/h). Since drivers typically use routes that minimize their travel time, it is logical that drivers selected the highway route in this case.

<table>
<thead>
<tr>
<th>TABLE 1 Field Trip Data Characteristics</th>
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<tr>
<td>Average travel time (min)</td>
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<td>95 percentile of travel time</td>
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This study investigated the impact on energy consumption for BEVs and ICEVs for two routes. Figure 2 shows the energy consumption results of the highway and arterial trips for both the BEV and ICEVs. The figure includes the energy recovered by the BEV during the trips. Results show that the BEV’s energy consumption results were not correlated to the ICEVs’ fuel consumption for either highway or arterial trips. In particular, the BEV’s most energy efficient trips were not the most fuel-efficient trips for the ICEVs. For instance, while highway route trip 11 and arterial trip 10 required the most energy use for the BEV, those trips were relatively fuel-efficient for ICEVs. Further, results show that the most fuel-efficient trips for ICEVs were not necessarily the most energy-efficient for the BEV.

The energy regenerated (recovered) from the BEV during the trips is illustrated in Figure 2. The results demonstrate that the arterial trips produced more regenerated energy than the highway trips, even though the highway trips consumed more energy than the arterial trips. Also, note that the regenerated energy rates are significantly different among trips. In particular, highway route trip 9 (1,807 Wh) generated 214% extra energy compared to highway route trip 21 (576 Wh), even though the two trips showed similar total energy consumptions (6,176 Wh vs. 5,904 Wh).
Figure 3 compares the average energy/fuel consumption for the highway and arterial trips. For this specific case study, Figure 3 demonstrates that the BEV’s energy consumption can be reduced by 48% if motorists use the arterial instead of the highway route. Further, the results show that regenerated energy, which is typically generated during stop and go traffic conditions, was increased by 20% when using the arterial route. Results also indicate that the BEV regenerated 14.8% and 26.2% of the total energy consumption for the highway and arterial trips, respectively. For this specific case study, an average lower speed and more regenerated energy, caused by more frequent braking actions, reduced the energy consumption for the arterial trips.
Figure 3 also shows an ICEV driver can save 21.6\% in fuel costs on average by using the arterial route. The results demonstrate that when motorists sacrifice 4.3 minutes (17\%) of travel time, energy/fuel efficiency is significantly improved for both BEVs and ICEVs.

![Energy consumption on highway and arterial routes.](image)

**FIGURE 3 Energy consumption on highway and arterial routes.**

### Simulation Results

This section investigates the network-wide impacts of routing choices on BEVs’ energy consumption. A microscopic traffic simulation model, INTEGRATION, was utilized for the analysis. A simple network was constructed to identify the energy consumption impacts of BEVs. The OD (origin-destination) demand is 2,000 vehicles per hour (veh/h), and there are two routes available. The network, as illustrated in Figure 4, consists of a highway route and an arterial route between an origin and a destination. A total of 2,000 trips were simulated for one hour and the simulation was continued for two hours to complete all 2,000 trips.

The highway route is 5 km long with two lanes for the first 3 km section, one lane for the next 1 km section, and two lanes for the last 1 km section. It has a capacity of 1,800 veh/h/lane and the jam density is set to 100 veh/km. The first 3 km and the last 1 km sections have a free-flow speed of 88 km/h (55 mph) and the middle 1 km section has a 72 km/h free-flow speed. The arterial route is a 4 km long section that has three signalized intersections located every 1 km and has an identical jam density and lane capacity as the highway route. The three signals on the arterial route have a 60-second cycle length with a 0.5 g/C ratio (effective green time to cycle length ratio), and are partially coordinated.
Six traffic assignment scenarios were utilized in this case study. Figure 5 shows the traffic assignment scenarios simulated using the INTEGRATION software. The vehicles assigned to the arterial route were increased from 250 vehicles (scenario 1) to 1,500 vehicles (scenario 6) in increments of 250 vehicles; for example, scenario 3 shows that 750 vehicles were assigned to the arterial route and 1,250 vehicles were assigned to the highway route. In total, 2,000 vehicles were utilized in each scenario.

The results show that the SO condition is achieved in scenario 2, which has the smallest total travel time of the entire network. In this case study, the UE condition is also attained in scenario 2, which has a similar average travel time for the two routes. The travel times of the average highway and arterial routes are 299 s and 285 s, respectively. The study demonstrates that total delays are significantly increased as 1,000 veh/h or more are assigned to the arterial route due to the over-saturated delay at signalized intersections.
Figure 6 shows the ICEVs’ fuel consumption and the BEVs’ energy consumption in the sample network. The fuel/energy consumption rates were estimated using the VT-Micro and the VT-CPEM models, respectively. The figure illustrates that Scenario 3 is the fuel consumption-optimized traffic assignment for ICEVs, while Scenario 6 is the energy consumption-optimized traffic assignment for BEVs. The simulation results show that Scenario 2, which are the UE and SO conditions, isn’t the assignment that minimize the fuel/energy consumption for both ICEVs and BEVs.

The average fuel consumption during ICEV trips in Scenario 3 is 0.314 liters, which is a 15.4% reduction in fuel consumption compared to Scenario 6. Figure 7 (a) also illustrates that the fuel consumption rates on the arterial route increase during highly congested conditions, as represented in Scenarios 4, 5, and 6. The stop and go behavior under the oversaturated conditions at the signalized intersections contributed to this increased fuel consumption.
The energy efficient traffic assignment results for BEVs are illustrated in Figure 7(b), and are different than the most fuel efficient ICEV assignments. The simulation results demonstrate that total energy consumption can be reduced by as much as 11.6% if Scenario 6 (0.566 kW) is selected as compared to Scenario 1 (0.632 kW). These results indicate that BEVs should use a different traffic assignment method to attain the energy efficient SO condition. Figure 7(b) also illustrates that BEVs can significantly reduce energy consumption by using the case study’s arterial, rather than highway, route. For example, in Scenario 6, the travel times of arterial and highway trips are 23.0 minutes and 4.1 minutes, respectively, but the BEVs’ energy consumption is reduced by around 37.0% when the arterial route is selected. Note that ICEVs show a 14.3% increase in fuel consumption when selecting the arterial route in Scenario 6. The different scenario results indicate that BEVs’ energy consumption can be significantly increased when the fuel-optimized assignments are utilized.

(a) ICEV fuel consumption

(b) EV energy consumption
Figure 8 highlights the BEVs’ average regenerated energy during the arterial and highway trips. The results show that each scenario produces different regenerated energy rates, as the regenerated energy is greatly affected by facility types and congestion levels in the case study. In general, the regenerated energy is increased with the increased level of traffic delay. The maximum regenerated energy is observed in Scenario 6 when the congestion level is the highest. Also, the arterial trips of Scenario 6 produce an extra 106% of regenerated energy compared to Scenario 1. This indicates that the regenerated energy is maximized in highly congested traffic conditions and that BEVs’ energy efficient route assignment can be influenced by the amount of potential regenerated energy.

CONCLUSIONS

This study investigated the impacts of route choice on energy consumption in BEVs using second-by-second GPS commute data and a micro-simulation study. VT-CPEM and VT-Micro models were utilized to estimate the energy/fuel consumption rates of BEVs and ICEVs, respectively. The results of the case studies indicate that a UE and SO traffic assignment does not necessarily minimize BEVs’ energy consumption. Furthermore, the study found that the use of a faster route could actually increase BEVs’ energy consumption. In addition, significant energy consumption savings (48% reduction) were observed when BEV motorists utilized the arterial route, sacrificing 4.3 minutes (17%) of travel time. Results of case studies lead to the conclusion that BEVs and ICEVs have different fuel/energy-optimized assignment conditions, and that different energy-optimized assignments should therefore be recommended for different vehicle types. Results of this traffic assignment simulation study also show that minimum BEV energy consumption is achieved when most of the vehicles are assigned to the congested and low-speed arterial route. Furthermore, BEVs’ energy consumption can be significantly increased when the fuel optimized assignment methods are utilized and, as such, new traffic assignment methods should be proposed to attain the most energy efficient BEV SO condition.

Finally, this study identified the impacts of regenerated power during various traffic assignment scenarios. One of the main advantages of EVs is the possibility of recovering energy while braking using a regenerative braking system. Study results showed that regenerated energy was greatly affected by facility types and congestion levels and the most energy efficient route assignment for BEVs could be significantly affected by the regenerated energy.
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