A COMPARATIVE ASSESSMENT OF CO_2 EMISSION BETWEEN GASOLINE, ELECTRIC, AND HYBRID VEHICLES: A WELL-TO-WHEEL PERSPECTIVE USING AGENT-BASED MODELING

by

MD MAMUNUR RAHMAN

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To my loving daughter, Moontaha Mariya

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Abstract

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Md Mamunur Rahman, PhD

The University of Texas at Arlington, 2020

Supervising Professors: Yuan Zhou and Jamie Rogers

Road transports in the U.S. are almost entirely dependent on the consumption of fossil fuel. This high dependency on fossil fuel is significantly contributing to carbon dioxide (CO_2) emission, one of the leading Green House Gases (GHGs) responsible for global warming. Electrification of passenger vehicles could be an effective strategy to curb GHG emissions. Though Electric Vehicles (EVs) have zero tailpipe emissions, the power required to charge EV batteries may not necessarily come from carbon-free power plants. In this study, for a comprehensive comparison between EV and Gasoline Vehicle (GV), we developed an agent-based simulation model for the entire energy pathway (Well-To-Wheel) and estimated the associated CO_2 emissions. Taking into consideration the electricity production mix of the 50 U.S. states, our simulation results revealed that the benefits of EVs are not the same across all states. Unfortunately, in some states where the major portion of electricity comes from dirty energy sources, e.g., coal, oil, or gas fired power plants, EV might emit double the amount of CO_2 to the environment as GV. We also studied the performance of Plug-in Hybrid Electric Vehicle (PHEV), and on average, in most states, PHEV performs environmentally better than EV according to the year 2018 energy mix data. We conducted a detailed sensitivity analysis of these vehicles under the

city and highway driving cycles. These research findings will help decision-makers design effective policies for EV and PHEV adoption to achieve maximum environmental benefits.

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Abbreviations

CI	Confidence Interval
CO_2	Carbon Dioxide
ER	Emission Ratio
EV	Electric Vehicle
fps	Feet per second
FTR	Fail To Reject
GHG	Green House Gas
GV	Gasoline Vehicle
GWh	Gigawatt Hour
HWFET	Highway Fuel Economy Test cycle
INL	Idaho National Laboratory
kmph	Kilometers per hour
kWh	Kilowatt Hour
LCA	Life Cycle Analysis
mph	Miles Per Hour
NCTCOG	North Central Texas Council of Governments
NEDC	New European Driving Cycle
PHEV	Plug-in Hybrid Electric Vehicle
PTW	Pump-To-Wheel
rpm	Revolutions Per Minute
SFTP-US06	US06 Supplemental Federal Test Procedure
TCO	Total Cost of Ownership
UDDS	Urban Dynamometer Driving Schedule
VELA	Vehicle Emission Laboratories
VSP	Vehicle Specific Power
WLTC	Worldwide harmonized Light-duty Test Cycle
WMTC	Worldwide Motorcycle emission Test Cycle
WTP	Well-To-Pump
WTW	Well-To-Wheel

Mathematical Symbols

F_{tract}	Tractive force
F_{acl}	Acceleration force
F_{hl}	Hill climbing force
F_{rr}	Rolling resistance force
F_{in}	Inertia force
F_{ad}	Aerodynamic force
m	Mass
a	Acceleration
g	Gravitational acceleration
θ	Road grade or slope
μ_{rr}	Rolling resistance coefficient
C_f	Mass correction factor
ρ_a	Ambient air density
C_d	Aerodynamic drag coefficient
A_f	Vehicle frontal area
v	Velocity
P_{tract}	Tractive power
t	Time
P_{engine}	Engine output power
η_{dt}	Drivetrain efficiency
P_{acc}	Vehicle accessories power demand
ϕ	Fuel-to-air mass ratio
k	Engine friction factor
N	Engine speed
V	Engine displacement
η_{engine}	Engine efficiency
ψ	Fuel calorific value

N_{idle}	Idle engine speed
α_{axle}	Axle gear ratio
α_{tr}	Transmission gear ratio
d_{tire}	Tire diameter
V_{fuel}	Fuel volume
T	Driving cycle duration
f_1	Fuel energy density
f_2	WTP CO_2 emission factor
η_{bat}	Battery efficiency
η_{inv}	Inverter efficiency
η_{mot}	Motor efficiency
η_{pt}	Power train efficiency
η_{dist}	Distribution efficiency
η_{g2bar}	Grid to battery efficiency
P_{bat_input}	Battery power input
P_{brk}	Braking power
P_{reg}	Regenerative braking power
η_{rb}	Available braking power percentage
$E_{net\_bat\_input}$	Net battery energy input
E_{power_plant}	Power plant energy output
c	Grid carbon intensity
r	Power plant CO_2 emission factor
S	Set of power plants
$d_{electric}$	Electric mile percentage

Chapter 1

INTRODUCTION

1.1 Research Context and Motivation

Road transports in the U.S. are almost entirely dependent on the consumption of fossil fuel. This high dependency on fossil fuel is significantly contributing to CO_2 emission, one of the leading Green House Gases (GHGs) responsible for global warming. According to the data reported in 2019, on average, petroleum consumption by the U.S. transportation sector is 14.15 million barrels per day which accounts for 69% of total domestic petroleum consumption (Davis & Boundy, 2020). Since light duty vehicles (LDVs) account for 65% of the total U.S. transportation petroleum use (Davis & Boundy, 2020), electrification of passenger vehicles is one of the alternatives to curb GHG emission. To increase the number of Electric Vehicles (EVs) in the current passenger vehicle fleet, the U.S. government is offering up to $7,500 federal tax credit per EV (U.S. EPA, 2020). Although in 2018 EV sales were below 2% of the total sales of LDVs, it is expected that EV sales will reach around 21% and 65% by 2025 and 2050, respectively (EVAdoption, 2019; Rissman, 2017). Although an EV has zero tailpipe emission, the power required to charge EV batteries may not necessarily come from carbon-free power plants. In reality, if the electricity required for charging EV batteries comes from coal-fired power plants, EVs might be responsible for releasing significantly higher level environmental emission compared to conventional Gasoline Vehicles (GVs). It is, therefore, necessary to quantify GHG emissions cautiously from EV, Plug-in Hybrid Electric Vehicle (PHEV), and GV for the evaluation of the true impact on the environment.

1.2 Research Questions

This study has focused on the following research questions:

1. Are EV and PHEV environmentally cleaner compared to GV?
2. Is there any difference of CO_2 emission between city and highway driving cycles?
3. What is the impact of congestion on CO_2 emission from EV, PHEV, and GV?
4. Is there any spatial difference of the EVs and PHEVs environmental performance? Do EV and PHEV perform equally in reducing CO_2 emission across the 50 U.S. states?

1.3 Research Objectives

The objectives of this study are listed below:

1. To compare CO_2 emissions from GV, EV, and PHEV for different traffic conditions, including high, moderate, and light traffic volumes.
2. To compare emissions between city and highway driving cycles.
3. To evaluate the performance of EV and PHEV across all the 50 states of the U.S. considering the states' electricity generation mix.
4. To perform a detailed sensitivity analysis by alternating the vehicle, road, and state related parameters.

1.4 Scope of the Study

EVs have zero tailpipe emission but the power required for driving the vehicle must come from somewhere. For a comprehensive comparison between EV and GV, it is necessary to consider the emitted CO_2 associated with the entire energy pathway. As illustrated in Figure 1.1, the entire Well-To-Wheel (WTW) CO_2 emission pathway can be divided into two segments: (a) Well-To-Pump (WTP) emission which includes the emissions due to fuel/energy source exploration, production, refining, and distribution activities; (b) Pump-To-Wheel (PTW) emission which includes mainly vehicle tailpipe emissions.

It should be noted that that the WTW assessment considered in this study is only for the energy pathway of fuel (energy production and use); materials required for manufacturing the vehicles are not considered.

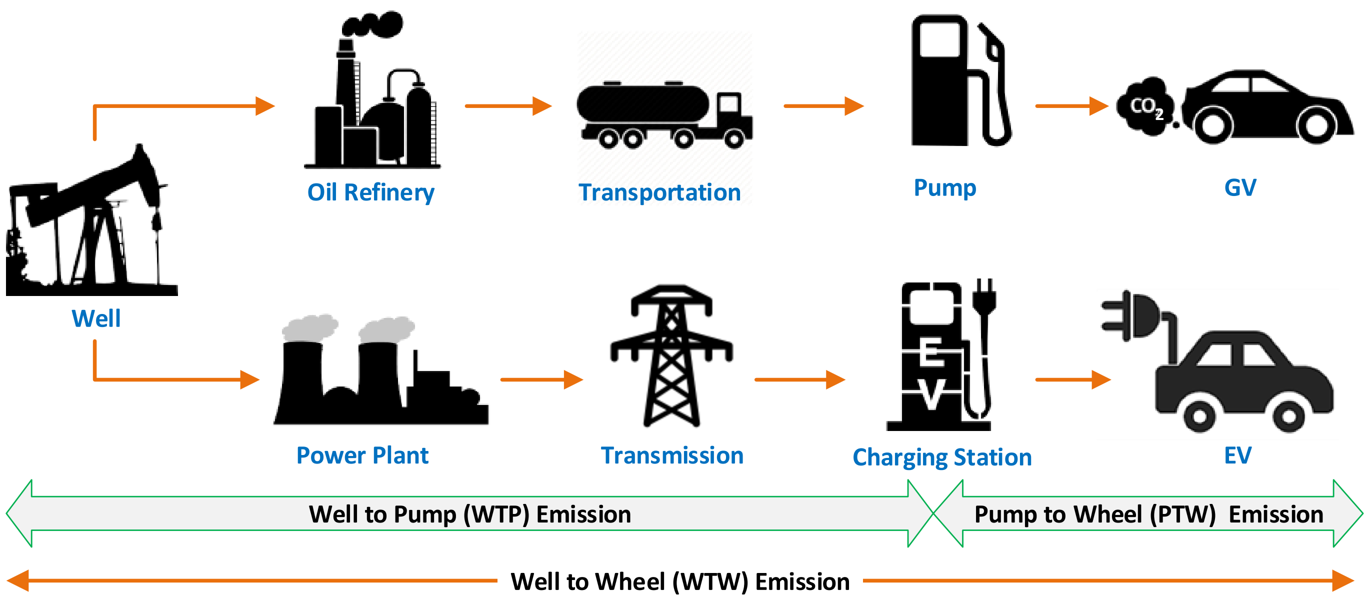


Figure 1.1 Well to Wheel CO_2 emission of GV and EV

Chapter 2

LITERATURE REVIEW

2.1 Summary of the Studies on EV and PHEV emissions

The methods used to calculate vehicular emissions can be categorized into two groups: average speed model and instantaneous emission model (Achour, Carton, & Olabi, 2011).

Average speed model, a macro scale calculation method, is the most common technique found in the literature to determine vehicular emission (M. J. Barth & Tadi, 1996; Burón, López, Aparicio, Martín, & García, 2004; Ekström, Sjödin, & Andreasson, 2004; Fujita et al., 2012; Nesamani, Chu, McNally, & Jayakrishnan, 2007; Tang, Roberts, & Ho, 2003; Yerramalla, 2007). In this technique, the vehicular emission is a function of average speed, vehicle type, and fuel type only. Some examples of emission calculation software that use average speed model are COPERT (Computer Programme to estimate Emissions from Road Transport) (Ntziachristos et al., 2000), MOBILE (U S Environmental Protection Agency, 2003), and EMFAC (Emission Factors) (California Air Resources Board, 2017) developed by the European Environment Agency, U.S. Environmental Protection Agency, and California Air Resources Board, respectively. Average speed model does not address the fact where similar average speed can be found for different driving cycles with different driving behavior, road geometry, and vehicle dynamics which can cause significantly different amount of emissions for the same average speed. However, the main advantage of this model is the minimum amount of data (traffic volume, average speed, and length of the road) required for the calculation of vehicular emissions but it is limited in terms of applicability and accuracy. Studies show that in most of the cases the actual quantities of different emissions are underestimated by applying this model (Negrenti, 1999; Ryu, Jung, & Bae, 2015).

On the other hand, instantaneous emission model is a microscopic approach to estimate vehicular emissions at any point of time. Several researchers have worked to develop the Vehicle Specific Power (VSP) based instantaneous emission model for GVs (Jimenez-Palacios, 1998). Later the model was further developed and validated as part of MOVES project, the latest emission modelling software by the U.S. Environmental Protection Agency (EPA) (Frey, Unal, Chen, Li, & Xuan, 2002; US Environmental Protection Agency, 2014; Younglove, Scora, & Barth, 2005), and the modelling technique has been used successfully in different emission studies (Li, Wu, & Zou, 2011; Liu, Chen, Wang, & Han, 2013; Papson, Hartley, & Kuo, 2012; Song, Yu, & Tu, 2011; Song, Zhou, & Yu, 2015; Yao, Wei, Perugu, Liu, & Li, 2014).

In literature, many studies are found to compare the emissions among GV, EV, and PHEV. Table 2.1 presents a summary of these studies related.

Table 2.1 Overview of the studies on GV, EV, and PHEV emissions found in literature

Study	Objective	Studied region and year	Energy and emission calculation	Emissions	Vehicle class	Powertrains compared	Scope
(Tseng, Wu, & Liu, 2013)	Study the economic and environmental benefits	USA; 2012	GREET model and car manufacturers' data	CO, PM, VOC, SOx, GHG	Passenger car	GV, HEV, PHEV15, PHEV35, EV	WTW
(Michalek et al., 2011)	Evaluate air emission and oil consumption benefits	USA; 2010	GREET model	NOx, SO2, PM, CO, GHGs	Passenger car	GV, HEV, PHEV20, PHEV60, EV	CTG
(Thomas, 2012)	Estimate GHGs and oil consumption reduction potential	USA; 2015	GREET model	GHGs	Passenger car, LD truck, small van	EV, FCEV	WTW
(McLaren, Miller, O'Shaughnessy, Wood, & Shapiro, 2016)	Compare emission impacts due to different charging scenarios and electricity generation mix	USA; 2015	Published data from various sources	CO2	Passenger car	GV, PHEV10, PHEV20, PHEV30, PHEV40, EV	n/a

Study	Objective	Studied region and year	Energy and emission calculation	Emissions	Vehicle class	Powertrains compared	Scope
(Manjunath & Gross, 2017)	Develop a comprehensive metric to quantify the emission of CO2	USA; 2010	Model based	CO2	Passenger car	GV, EV	WTW
(Palencia, Furubayashi, & Nakata, 2012)	Study the energy and CO2 reduction potential	Colombia; 2010, 2050	Simulation (PAMVEC)	CO2	Passenger car	GV, EV, FCHEV	WTW
(Jochem, Babrowski, & Fichtner, 2015)	Estimate CO2 emission	Germany; 2030	Model based	CO2	Passenger car	EV	n/a
(Donateo, Ingrosso, Licci, & Laforgia, 2014)	Estimate environmental impact	Lecce, Italy; 2013	On-board measurement	CO2, CO, PM, NOx, VOC, CH4, SOx, Metals	Passenger car	EV	WTW
(Nanaki & Koroneos, 2013)	Perform economic and environmental comparison	Greece; 2012, 2025	published data from various sources	GHGs, CO, NOx, SOx, VOC	Passenger car	GV, HEV, EV	WTW

Study	Objective	Studied region and year	Energy and emission calculation	Emissions	Vehicle class	Powertrains compared	Scope
(Doucette & McCulloch, 2011)	Estimate CO2 emission	USA, France, China, India; 2010	Simulation (OVEM)	CO2	Passenger car	GV, EV	PTW
(Offer, Howey, Contestabile, Clague, & Brandon, 2010)	Compare lifecycle cost	UK; 2010, 2030	Published data from various sources	n/a	Passenger car	GV, EV, FCEV, FCHEV	Ownership cost
(Onat, Kucukvar, & Tatari, 2015)	Investigate the temporal and spatial variation on emission and energy consumption	USA; 2014	Published data from various sources	GHGs	Passenger car	GV, HEV, PHEV18, PHEV62, EV	WTW
(Qiao, Zhao, Liu, Jiang, & Hao, 2017)	Compare energy consumption and GHG emissions	China; n/a	Published data from various sources	GHGs	Passenger car	GV, EV	CTG
(Bubeck, Tomaschek, & Fahl, 2016)	Compare total ownership cost among	Germany; 2015, 2030, 2050	Published data from various sources	CO2	Passenger car, minivan	GV, HEV, EV, FCHEV	Ownership cost

Study	Objective	Studied region and year	Energy and emission calculation	Emissions	Vehicle class	Powertrains compared	Scope
(Zhao, Doering, & Tyner, 2015)	Evaluate life cycle private cost and social cost of emission	China; 2014, 2031	Published data from various sources	CO2	Passenger car	GV, EV	Ownership cost
(Doucette & Mcculloch, 2011)	Estimate the potential reduction of CO2 emission	France, USA, China; 2010	Simulation (OVEM)	CO2	Passenger car	GV, PHEV20, PHEV40, PHEV80, EV	WTW
(Abdul-Manan, 2015)	Determine the uncertainty of GHG emission	Not country specific; n/a	Simulation (@Risk)	Equivalent CO2	Passenger car	GV, HEV, EV	Cradle to Grave
(Vliet, Sjoerd, Kuramochi, Broek, & Faaij, 2011)	Study energy consumption, emission, and cost of ownership	Netherlands; 2015	Published data from various sources	Equivalent CO2	Passenger car	GV, HEV, PHEV, EV	WTW
(Elgowainy et al., 2013)	Estimate ownership cost, emission, and fuel consumption	USA; 2012, 2035	Simulation (Autonomie)	Equivalent CO2	Passenger car	GV, HEV, EV, FCEV	WTW

Study	Objective	Studied region and year	Energy and emission calculation	Emissions	Vehicle class	Powertrains compared	Scope
(Granovskii, Dincer, & Rosen, 2006)	Perform environmental and economic comparisons	n/a	Published data from various sources	Equivalent CO_2 and NO_x	Passenger car	GV, HEV, EV, FCEV	WTW

Abbreviations: GV- Gasoline Vehicle, HEV- Hybrid Electric Vehicle, EV- Electric Vehicle, FCEV- Fuel Cell Electric Vehicle, PHEV- Plug-in Hybrid Electric Vehicle, LCA- Life Cycle Analysis, WTW- Well to Wheel, TTW- Tank to Wheel, CTG- Cradle to Gate, TCO- Total Cost of Ownership, CO_2- Carbon Dioxide, CO-Carbon Monoxide, CH_4- Methane, GHG- Greenhouse Gas, NO_x- Nitrogen Oxides, SO_2- Sulfur Dioxide, VOC- Volatile Organic Compound, PM- Particulate Matter, LD- Light Duty.

Note: The numbers after PHEV denote the average electric range in miles.

The studies found in literature on EV emissions can be divided into three groups based on research methodology:

a. Life cycle analysis (LCA)
b. On-board measurement
c. Simulation-based

LCA

This is the most common type of study discussed in the existing literature. The emissions of EVs are compared assuming a constant emission factor (e.g., 123 g/mile) based on average speed and a lifetime driving distance (e.g., 120,000 miles) (Granovskii et al., 2006; Michalek et al., 2011; Nanaki & Koroneos, 2013; Onat et al., 2015; Qiao et al., 2017; Thomas, 2012; Tseng et al., 2013; Vliet et al., 2011). Though, this approach for estimation of EV emission offer the ease of simplicity, the possible uncertainty and variability are completely ignored. Furthermore, in this approach, it is very difficult to address the impact of traffic dynamics, e.g., city driving, freeway driving, and traffic congestions, on EV emissions.

On-board measurement

The number of studies on EV emissions utilizing on-board measurement is very few (Donateo et al., 2014). In this method, first, the real time power consumption for a test vehicle driving on a road is measured using an installed on-board apparatus and later the corresponding environmental emissions are calculated based on grid electricity generation mix. The main disadvantage of this type study is the lack of experimental control. For example, it is very difficult to assess the impact of control variable on emissions, such as the impact of speed limit and level of traffic congestions.

Simulation

Recently, some studies have been conducted to estimate the EV emissions based on simulation (Abdul-Manan, 2015; Doucette & Mcculloch, 2011; Doucette & McCulloch, 2011; Elgowainy et al., 2013; Palencia et al., 2012). However, these simulation studies did not include the real-world driving environment, e.g., presence of other vehicles on the road, traffic congestion, traffic signals, and interaction among the vehicles. Hofer et al. simulated tailpipe CO_2 emissions from passenger cars for a European city using agent-based modeling (Hofer, Jäger, & Füllsack, 2018). However, the authors used constant emission factors (e.g., 132 g/km for compact cars, 245 g/km for mid-size cars, and 204 g/km for large cars) in their simulation model which completely disregarded the variations of emissions due to driving dynamics, traffic congestions, and speed variations.

Overall, the studies found in literature did not consider the potential difference of CO_2 emission between the city and highway driving, impact of congestion, and the possible spatial differences of the environmental performances of EV and PHEV across the breadth of the 50 U.S. states.

2.2 Research Contributions

In this research, a Well-To-Wheel (WTW) emission modeling framework has been developed for GV, EV, and PHEV using Agent-based Modeling (ABM) approach. To best of our knowledge, there are no existing studies in the literature that compared WTW emissions from GV, EV, and PHEV using ABM. ABM allows modeling a complex traffic system by simulating local interactions among the low-level system components like vehicle agents utilizing the bottom-up approach. This modeling technique is a more natural way to address our research questions and allows us to estimate vehicular emissions based on explicitly represented vehicle agents' behavior in a traffic environment.

For the estimation of vehicular emissions, MOVES software (US EPA, 2014a) is very popular among air pollution modelers. However, the software can only be used to estimate Pump-To-Wheel (PTW) vehicular emissions; not capable of estimating Well-To-Pump (WTP) emissions (US EPA, 2014b). Therefore, vehicular emissions for an entire WTW fuel energy path cannot be estimated using MOVES. Since the software has no provision to model the WTP emissions, it cannot estimate the indirect emissions by EV and PHEV. These limitations have been addressed in this research work. Moreover, a Python library has been developed for WTW vehicular emission estimation as part of this research work.

Chapter 3

METHODOLOGY

3.1 Emission Modeling

3.1.1 Well-To-Wheel (WTW) Emission of GV Powertrain

For GVs, WTW emissions can be divided into two parts: (a) Pump-To-Wheel (PTW) emission due to vehicular activity; (b) Well-To-Pump (WTP) emission due to the burnt fuel exploration, production, refining, and distribution activities.

3.1.1.1 Pump-To-Wheel (PTW) Emission

Tractive force required at wheels to propel a vehicle forward by overcoming different resistance forces can be calculated using standard kinematic equations. According to the force balance principle, this tractive force (F_{tract}) equals the summation of acceleration force (F_{acl}), hill climbing force (F_{hl}), rolling resistance force (F_{rr}), inertia force (F_{in}), and aerodynamic drag force (F_{ad}), as shown in equation (1).

$$F_{tract} = F_{acl} + F_{hc} + F_{rr} + F_{in} + F_{ad} \tag{1}$$

Force due to acceleration F_{acl} (in N) can be calculated according to the Newton's second law of motion as shown in equation (2), where m (in kg) is the total mass of the vehicle, and a (in m/s^2) is the value of linear acceleration of the vehicle.

$$F_{acl} = ma \tag{2}$$

Hill climbing force F_{hc} (in N) is the component of gravity force along the road slope as shown in equation (3), where g (in m/s^2) is the gravitational acceleration, and θ (in $radian$) is the road grade or slope.

$$F_{hc} = mg\ sin\theta \tag{3}$$

Rolling resistance force F_{rr} (in N) arises due to the rolling of tire on the road surface which can be expressed as equation (4), where μ_{rr} is the rolling resistance coefficient.

$$F_{rr} = \mu_{rr} mg\ cos\theta \tag{4}$$

Inertia force F_{in} (in N) is created due to the rotating parts of the engine or motor and can be calculated according to equation (5), where C_f is the mass correction factor.

$$F_{in} = C_f ma \tag{5}$$

Aerodynamic drag force is the opposing force created due to the motion of the vehicle into the air and can be calculated using equation (6), where ρ_a (in kg/m^3) is the ambient air density, C_d is the aerodynamic drag coefficient, A_f (in m^2) is the vehicle frontal area, and v (in m/s) is the velocity of the vehicle.

$$F_{ad} = \frac{1}{2}\rho_a C_d A_f v^2 \tag{6}$$

Finally, tractive power P_{tract} (in W) required at wheels to move the vehicle at speed v (in m/s) can be calculated using equation (7).

$$P_{tract} = vF_{tract} \tag{7}$$

$$\Rightarrow P_{tract} = v(F_{acl} + F_{hc} + F_{rr} + F_{in} + F_{ad})$$

$$\Rightarrow P_{tract} = v\left(ma +\ mg\ sin\theta + \mu_{rr} mg\ cos\theta + C_f ma + \frac{1}{2}\rho_a C_d A_f v^2\right)$$

$$\Rightarrow P_{tract} = vm\big(a +\ g\ sin\theta + \mu_{rr} g\ cos\theta + C_f a\big) + \frac{1}{2}\rho_a C_d A_f v^3 \tag{8}$$

Vehicle specific power (VSP) (in KW/ton) is a convenient single measure of vehicle activity to model the relationship between the power demand per unit vehicle mass and environmental emission. VSP at any time t can be calculated using equation (9).

$$VSP(t) = \frac{P_{tract}(t)}{m}$$

$$\Rightarrow VSP(t) = v(t)\big(a(t) +\ g\ sin\theta(t) + \mu_{rr} g\ cos\theta(t) + C_f a(t)\big) + \frac{1}{2m}\rho_a C_d A_f v^3(t) \tag{9}$$

A previous study has shown that the calculated VSP values can be categorized into 14 bins and the corresponding CO_2 emission rates (g/s) can be found from Table 3.1.

Table 3.1 VSP bin and corresponding CO_2 emission rate for vehicles with odometer reading less than 50,000 miles and engine displacement less than 3.5 liters. Source: (Frey et al., 2002).

VSP	Bin	CO_2 (g/s)
vsp < -2	1	1.6711
-2 ≤ vsp < 0	2	1.4579
0 ≤ vsp < 1	3	1.1354
1 ≤ vsp < 4	4	2.2332
4 ≤ vsp < 7	5	2.9199
7 ≤ vsp < 10	6	3.5253
10 ≤ vsp < 13	7	4.1075
13 ≤ vsp < 16	8	4.6350
16 ≤ vsp < 19	9	5.1607
19 ≤ vsp < 23	10	5.6325
23 ≤ vsp < 28	11	6.5348
28 ≤ vsp < 33	12	7.5852
33 ≤ vsp < 39	13	9.0242
vsp ≥ 39	14	10.0884

The PTW CO_2 (in g) for a driving cycle of duration T (in s) can be estimated using equation (10), where the emission rate ER (in g/s) can be obtained from Table 3.1. In this study, the time step Δt is one second and it is assumed that ER remains constant over this small time step.

$$PTW_{CO2} = \sum_{t=1}^{T} ER(t)\,\Delta t \tag{10}$$

3.1.1.2 Well-To-Pump (WTP) Emission

To translate tractive power P_{tract} (in W) at wheel into engine output power P_{engine} (in W) at any time instant t, equation (11) can be utilized, where η_{dt} is the vehicle drive train efficiency, and P_{acc} (in W) is the power demand for running the vehicle accessories such as air conditioning, sound system, and other electrical equipment.

$$P_{engine}(t) = P_{tract}(t)/\eta_{dt} + P_{acc}(t) \tag{11}$$

To compute the fuel rate FR (in ml/s) at a given time instant t for an GV, equation (12) can be utilized, where $\phi, k, N, V, \eta_{engine}, \psi$, and ρ are the fuel-to-air mass ratio, engine friction factor, engine speed (in rev/min), engine displacement (in L), engine efficiency, fuel calorific value (in KJ/g), and fuel density (in g/ml), respectively (M. Barth, Younglove, & Scora, 2005; Ross & An, 1993).

$$FR(t) = \frac{\phi}{\psi\rho}\left(kN(t)V + \frac{P_{engine}(t)}{1000 * \eta_{engine}}\right) \tag{12}$$

The engine speed N (in rev/min) at time instant t can be calculated using equation (13), where N_{idle} is the idle engine speed, α_{axle} is the axle gear ratio, α_{tr} is the transmission gear ratio, v_{mph} is the vehicle speed (in $mile/hr$), and d_{tire} is the tire diameter (in $inch$).

$$N(t) = Max\left(N_{idle}, \frac{336.13 \times \alpha_{axle}\alpha_{tr}v_{mph}(t)}{d_{tire}}\right) \tag{13}$$

The amount of fuel V_{fuel} (in ml) required by the GV for a driving cycle of duration T (in s) can be calculated using equation (14).

$$V_{fuel} = \sum_{t=1}^{T} FR(t)\,\Delta t \tag{14}$$

Once we have the required amount of fuel V_{fuel} for a driving cycle, the corresponding WTP CO_2 emission (in g) can be estimated using equation (15), where f_1, f_2 are the fuel energy density (in MJ/L) and WTP CO_2 emission factor (in g/MJ), respectively. The value of f_1 is 34.2 MJ/L for gasoline (petrol) and the value of f_2 (in gm/MJ) can be obtained from GREET® model (Argonne National Laboratory, 2019).

$$WTP_{CO2} = f_1 f_2 \left(\frac{V_{fuel}}{1000}\right) \tag{15}$$

3.1.2 Well-To-Wheel (WTW) Emission of EV Powertrain

As we mentioned earlier, there is no tailpipe emission for EV ($PTW_{CO2} = 0$), but the energy required to drive the vehicle comes from an electric power plant ($WTP_{CO2} \neq 0$). The amount of CO_2 emission, therefore, depends on the electricity generation mix. To estimate the associated EV emission, first it is required to calculate the tractive power necessary to drive the vehicle and translate it into the required battery energy. During braking, the motor of an EV acts as a generator and is capable of converting a portion of the braking energy into usable electric energy which can be stored in the EV battery. This recovered energy is known as regenerative brake energy. Figure 3.1 presents the flow of grid and regenerative brake energy with possible losses between different stages.

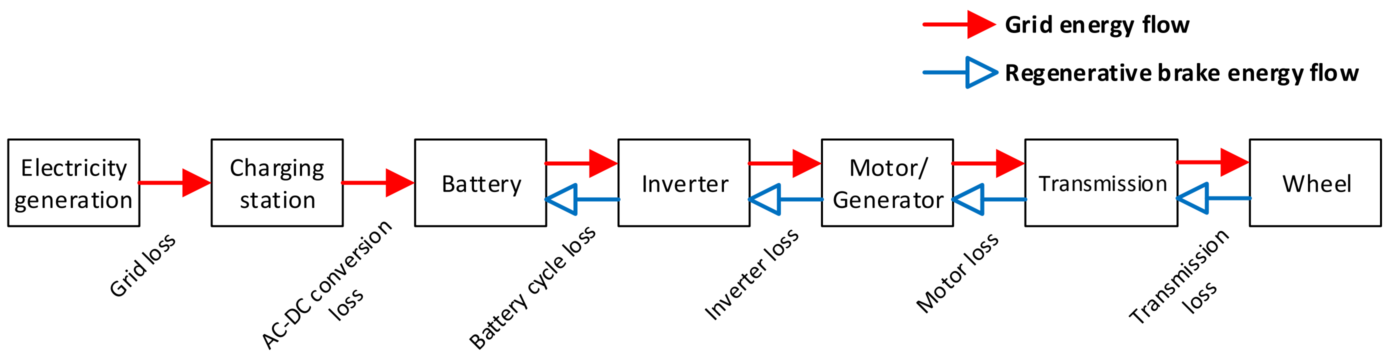


Figure 3.1 Energy flow and losses between different stages of a typical EV

The tractive power required at wheels P_{tract} (in W) to drive an EV at speed v (in m/s) can be calculated using equation (8) in the similar way discussed in previous section. To translate this tractive power into required battery power input P_{bat_input} (in W), equation (16) can be utilized; where, η_{bat}, η_{inv}, η_{mot}, and η_{tran} are efficiency of battery, inverter, motor, and transmission, respectively.

$$P_{bat\_input} = P_{tract}/(\eta_{bat}\eta_{inv}\eta_{mot}\eta_{tran}) \tag{16}$$

If power train efficiency η_{pt} of an EV can be defined by equation (17), equation (16) can be re-written as equation (18).

$$\eta_{pt} = \eta_{bat}\eta_{inv}\eta_{mot}\eta_{tran} \tag{17}$$

$$P_{bat\_input} = P_{tract}/\eta_{pt} \tag{18}$$

As we mentioned earlier, during braking an EV, unlike a GV where the total braking power is wasted, part of the braking power can be recovered. The recovered braking power P_{reg} (in W) to be stored in battery can be estimated using equation (19).

$$P_{reg} = \eta_{rb}P_{brk} \tag{19}$$

where η_{rb} is the percentage of available braking power (P_{brk}), that can be recovered and known as the regenerative braking factor. According to the study by Fiori et al. (Fiori, Ahn, & Rakha, 2016), the value of P_{brk} and η_{rb} can be estimated utilizing equation (20) and (21), respectively.

$$P_{brk} = \left|P_{tract}^{(-)}\right| \tag{20}$$

$$\eta_{rb} = \begin{cases} \left[e^{\frac{0.0411}{|a|}}\right]^{-1}, & a < 0 \\ 0, & a \geq 0 \end{cases} \tag{21}$$

Where, $\left|P_{tract}^{(-)}\right|$ is the absolute value of the negative portion of tractive power P_{tract} at wheel.

The recovered regenerative energy will be sent back to battery where it will be stored for future use. Therefore, the net energy input in EV battery $E_{net\_bat\_input}$ (in J) for a driving cycle of duration T (in s) can be calculated using equation (22).

$$E_{net\_bat\_input} = \left(\sum_{t=0}^{T} P_{bat\_input}(t)\,\Delta t - \eta_{pt}\sum_{t=0}^{T} P_{reg}(t)\,\Delta t\right) \tag{22}$$

Finally, the electric energy required to produce by the power plants E_{power_plant} (in J) can be enumerated using equation (23), where η_{dist} and η_{g2bar} are the grid electricity distribution efficiency and grid to battery efficiency (AC-DC converter), respectively.

$$E_{power\_plant} = E_{net\_bat\_input}/(\eta_{dist}\eta_{g2bat}) \tag{23}$$

If the electricity generation mix is known, we can translate it into grid carbon intensity c (in g/MJ) using equation (24), where p_i is the percentage of generated electricity from power plant i, r is the CO_2 emission factor (in g/MJ) of power plant i, and S is the set of power plants. Finally, the associated CO_2 emission (in g) due to EV driving can be estimated using equation (25).

$$c = \sum_{i \in S} p_i r_i \tag{24}$$

$$WTP_{CO_2} = WTW_{CO_2} = cE_{power\_plant} \times 10^{-6} \tag{25}$$

3.2 Development of the Simulation Model

In this research, we followed the Agent-Based Modeling (ABM) methodology to build a high-resolution microscopic traffic simulation model. ABM is a bottom-up approach where a complex system is modeled by simulating local interactions among the low-level system components known as agents (Bonabeau, 2002). The interactions of the agents can be nonlinear, complicated, and discrete (Castle & Crooks, 2006). In many cases, the ABM approach is more natural to model a system like traffic flow where it is more logical to describe how agents or vehicles move on the roads and the high-level emergent properties of the system like traffic density or congestion arise from these local interactions of the agents.

We have used AnyLogic (University Researcher version 8.5.1) (AnyLogic, 2020), a popular Java-based multimethod simulation software, to develop our microscopic simulation model. The software is gaining increasing popularity among researchers to model complex transportation problems (Karaaslan et al., 2018; Rahman, Jahan, & Zhou, 2020; Rahman, Zhou, & Rogers, 2019).

Figure 3.2 portrays the overall traffic simulation framework followed in this study. Three test vehicles (GV, EV, and PHEV) are considered as three agent classes in the model. In addition, a fourth agent class, General Vehicle (GenV), is considered which includes regular vehicles in the road network. These GenVs are an important part of the traffic dynamics but their statistics are not collected as the focus is primarily on the test vehicles. There is also a Main class containing a list of global parameters that can be accessed by the agent classes. The agents are placed in a traffic environment that includes roads, intersections, traffic signs, and traffic signals. The parameters and variables defined under each agent class are presented in Figure 3.2. The simulation model runs until all test vehicles complete their travel route. Second by second statistics are collected by the model after the initial warm-up time which is set as 15 minutes.

Figure 3.3 illustrates the methodology followed to process the collected statistics for the estimation of corresponding WTW CO_2 emissions from the three test vehicles. GV emits CO_2 directly to the environment while indirect emissions are involved in the case of an EV. Depending upon charge sustaining or depleting mode, a PHEV emits CO_2 directly or indirectly to the environment. All the necessary steps with corresponding equations are shown in the figure to estimate second by second vehicular emissions. At the end of a simulation run, the estimated second by second vehicular emission and distance values are summed up to calculate per kilometer CO_2 emission by the test vehicles.

We considered Toyota Camry 2016, Tesla Model S 2019, and Honda Clarity 2019 as test vehicles for GV, EV, and PHEV, respectively, and the associated vehicle attribute data are collected from the manufacturers' websites and vehicle manuals.

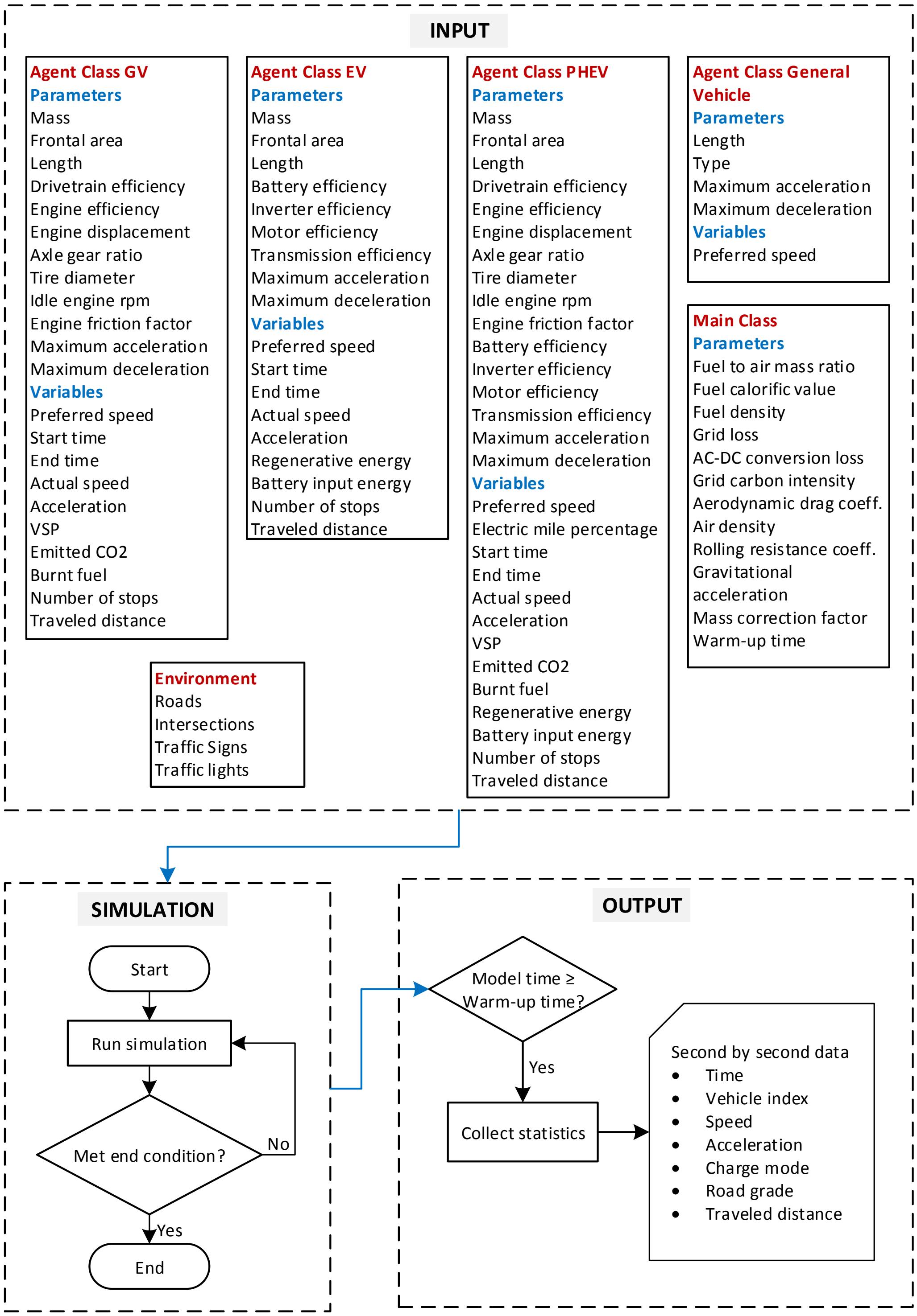


Figure 3.2 Traffic simulation framework

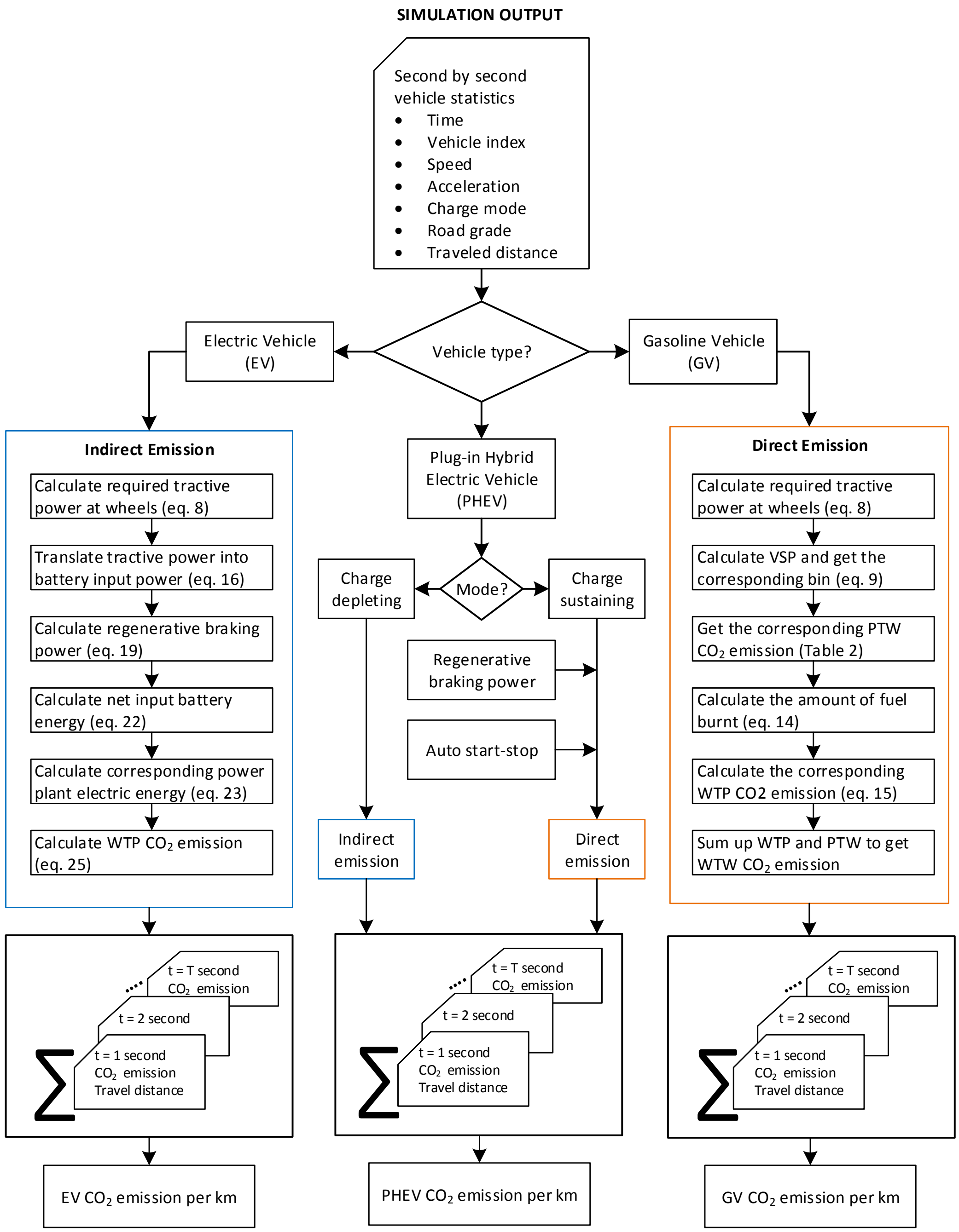


Figure 3.3 Methodology followed for the estimation of CO_2 emission from GV, EV, and PHEV

The following assumptions are made during our analyses.

a. Drivers maintain lane disciplines under all traffic circumstances.

b. Drivers follow the posted road speed limit.

c. Road grades are not considered ($\theta = 0$).

d. The impacts of environmental variables (like temperature, humidity) on engine efficiency are not considered.

e. Power consumptions by vehicle accessories like sound system, headlight, and air conditioning are not considered ($P_{acc} = 0$).

f. EV battery performance due to the temperature variation, and humidity are not considered.

g. Temporal variations (e.g., day versus night) of electricity grid carbon intensity are not considered.

3.3 Data Collection and Travel Route

For the city driving cycle, a closed loop route inside Arlington, Texas has been selected. This is one of the fastest-growing communities located in Texas and the 48^{th} most populous city in the United States (US Census Bureau, 2018). For the highway driving cycle, a portion of I-30 interstate highway between Fort Worth and Dallas has been selected. The length of the city and highway driving cycles are approximately 10.2 and 18.2 miles, respectively, and Figure 3.4 shows the actual maps of the selected routes. The necessary traffic data (e.g., peak hour traffic counts, signal timing, turn movements at intersections, road speed limits) are collected from the office of Public Works and Transportation, City of Arlington and the North Central Texas Council of Governments

(NCTCOG) (City of Arlington, 2019; NCTCOG, 2019). Road geometry data are collected from field survey and Google map (Google LLC, 2019).

Figure 3.5 (a) displays the road speed limits and traffic light positions of the Arlington city driving route and Figure 3.5 (b) shows the location of entry and exit points through ramps along with speed limits of the I-30 interstate highway route. The city driving route has 2.06 traffic signals per mile and the highway driving route has 0.71 and 0.66 entry and exit points per mile, respectively.

Table 3.2 presents the values of different parameters used in our simulation model for GV, EV, and PHEV. Table 3.3 displays the electricity generation mix categorized by energy sources, distribution and transmission losses of produced electricity, and the corresponding CO_2 emission factors of the 50 states of U.S. during the year 2018 (U.S. EIA, 2020).

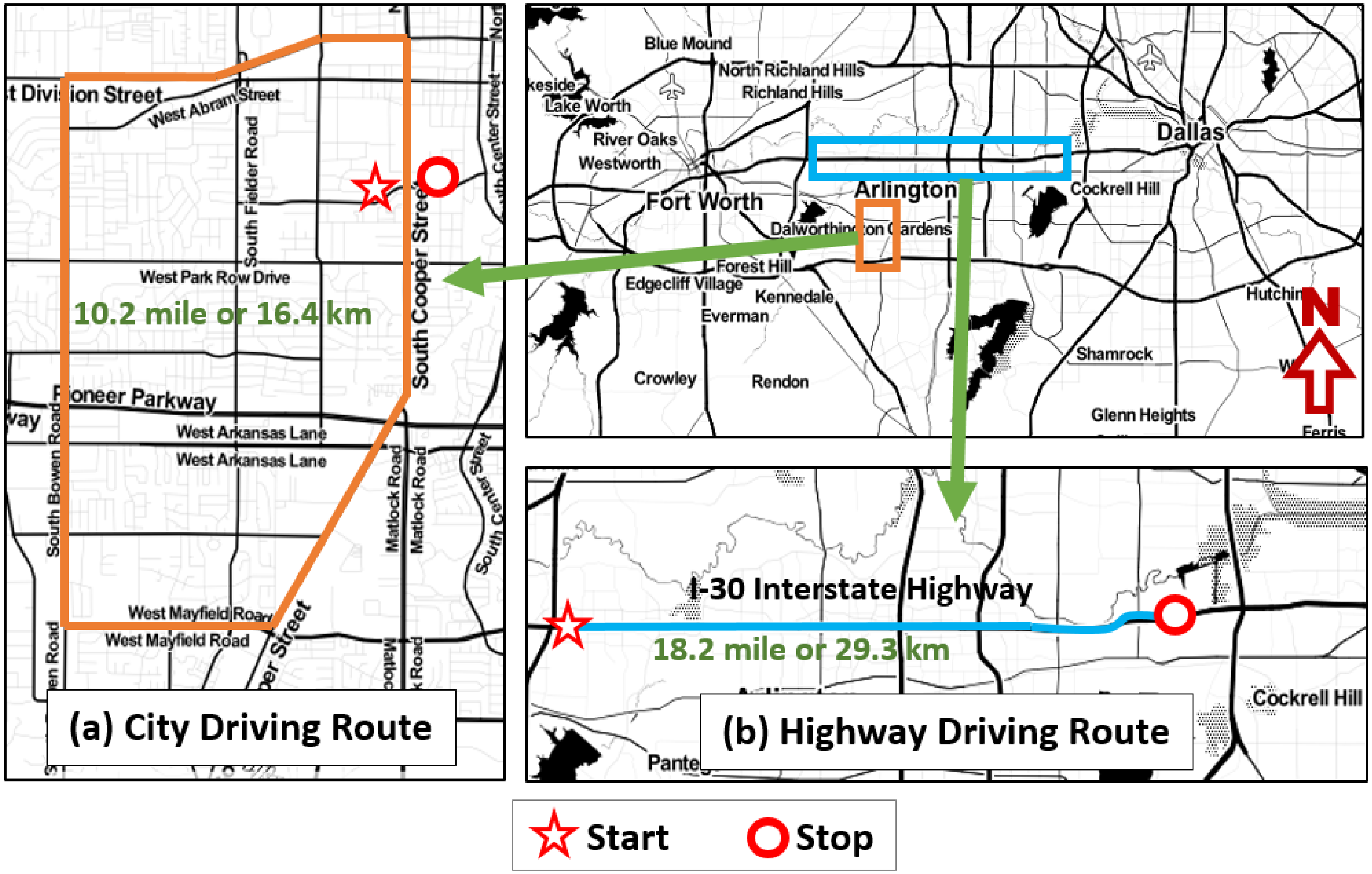


Figure 3.4 Selected routes for city and highway driving, base map source: (Story, 2020)

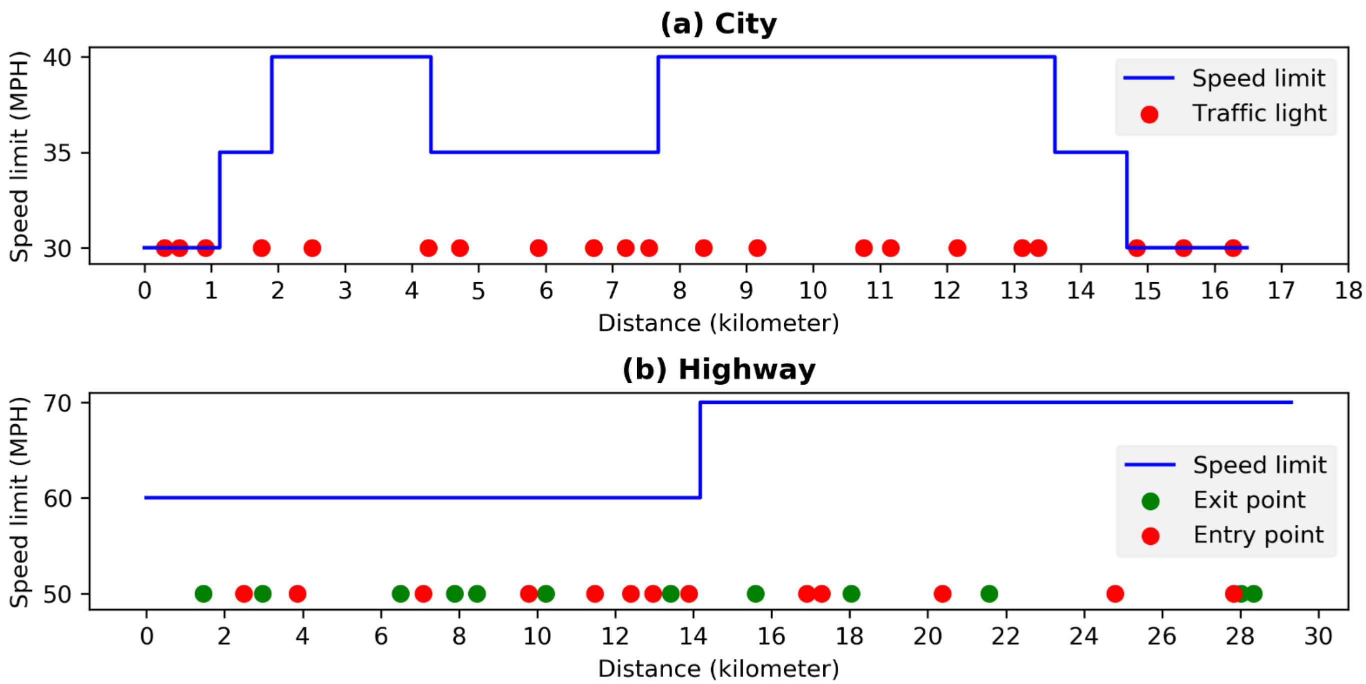


Figure 3.5 Road speed limits of different sections of the routes: (a) Arlington city driving cycle with traffic light locations; (b) I-30 interstate highway driving cycle with exit and entry points through ramps.

Table 3.2 Model parameters used in the simulation for GV, EV, and PHEV

Parameter name	Notation	Powertrain	Value	Unit	Source
Vehicle mass	$m_{vehicle}$	GV	1470	kg	Manufacturer’s website
		PHEV	1838	kg	Manufacturer’s website
		EV	2241	kg	Manufacturer’s website
Driver mass with cargo	m_{driver}	All	130	kg	Reasonable value
Frontal area	A_f	All	2.5	m^2	(Simpson, 2005)
Aerodynamic drag coefficient	C_d	All	0.32	-	Reasonable value
Ambient air density	ρ	All	1.225	kg/m^3	Reasonable value
Rolling resistance coefficient	C_{rr}	All	0.01	-	(Abdul-Manan, 2015)
Mass correction factor	C_f	All	0.05	-	(Genikomsakis & Mitrentsis., 2017)
Tire diameter	d_{tire}	GV, PHEV	26.5	in	Manufacturer’s website
Axle gear ratio	α_{axle}	GV, PHEV	3.63	-	Manufacturer’s website
Engine friction factor	k	GV, PHEV	0.2	-	Reasonable value
Engine idling speed	N_{idle}	GV	600	rpm	Manufacturer’s website
Engine displacement	V	GV	2.5	L	Manufacturer’s website
		PHEV	1.5	L	Manufacturer’s website
Fuel to air mass ratio	ϕ	GV, PHEV	1 : 14.7	-	Reasonable value
Fuel calorific value	ψ	-	45.8	KJ/g	Reasonable value
Fuel density	ρ	-	0.7489	g/ml	Reasonable value
Gravitational acceleration	g	-	9.81	m/s^2	Reasonable value

Parameter name	Notation	Powertrain	Value	Unit	Source
Engine drive train efficiency	η_{dt}	GV, PHEV	0.85	%	Reasonable value
Engine efficiency	η_{engine}	All	30	%	Reasonable value
Electric mile percentage	$d_{electric}$	PHEV	60	%	Reasonable value
Grid to battery efficiency	η_{g2bat}	EV	89-96	%	(Vliet et al., 2011)
Battery efficiency	η_{bat}	EV	95	%	(Genikomsakis & Mitrentsis., 2017)
Inverter efficiency	η_{inv}	EV	95-98	%	(Burke, Jungers, Yang, & Ogden, 2007)
Motor/generator efficiency	η_{mot}	EV	92	%	(Campanari, 2009)
Transmission efficiency	η_{tran}	EV, PHEV	92	%	(Rakha, Ahn, Moran, Saerens, & Bulck, 2011)

Table 3.3 Electricity generation and distribution profile of the 50 states of U.S. during the year 2018

States	Electricity production mix (GWh)					Total Electricity (GWh)	CO_2 (g/KWh)	Distribution efficiency (%)
	Coal	Natural gas	Petroleum	Nuclear	Renewable			
Alabama	31778	58800	66	39463	11500	145058	386	96.674
Alaska	629	2948	809	0	1819	6247	542	94.875
Arizona	30745	37168	50	31097	12653	111925	417	96.385
Arkansas	29996	20624	36	12721	3212	67999	563	96.158
California	281	89604	69	18214	79017	195265	223	95.220
Colorado	26382	16398	12	0	12633	55386	626	95.121
Connecticut	330	20006	339	16881	673	39454	243	96.184
Delaware	273	5400	201	0	55	6241	511	95.121
Florida	30272	171872	2077	29312	2645	244252	440	95.121
Georgia	32181	51972	436	34363	5693	129239	423	95.121
Hawaii	1311	0	6749	0	993	9797	733	94.858
Idaho	20	3279	0	0	14318	18172	97	95.123
Illinois	59642	17241	53	98102	12112	188003	384	95.999
Indiana	77455	26817	131	0	5951	113460	805	95.121
Iowa	28553	7340	111	4895	22270	63381	539	95.671
Kansas	20474	3006	52	9168	18942	51710	458	95.799
Kentucky	59168	14615	70	0	4457	78804	839	95.121
Louisiana	11787	61782	4378	17153	1181	102128	496	95.121
Maine	71	2331	189	0	5657	11281	195	95.313
Maryland	10067	13850	260	14988	3798	43810	406	95.121
Massachusetts	0	18386	461	4442	2333	27173	367	95.121
Michigan	42331	30987	1214	30479	7145	115837	529	95.487
Minnesota	23455	8555	47	14601	12809	61517	484	95.144
Mississippi	5280	49482	27	6919	326	63474	411	95.783
Missouri	63355	7050	100	10655	3754	85095	770	95.121
Montana	13360	476	446	0	13592	28213	552	97.283
Nebraska	23305	965	12	5632	6958	36966	689	95.626

States	Electricity production mix (GWh)					Total Electricity (GWh)	CO_2 (g/KWh)	Distribution efficiency (%)
	Coal	Natural gas	Petroleum	Nuclear	Renewable			
Nevada	2485	26689	10	0	10374	39640	352	95.122
New Hampshire	660	2992	178	10062	1762	17087	128	96.683
New Jersey	1193	38863	362	31982	1049	75034	251	95.121
New Mexico	13402	11628	21	0	7603	32674	563	96.183
New York	690	50810	1591	42919	33926	132521	210	95.125
North Carolina	31690	43446	633	42077	13259	134249	369	95.121
North Dakota	27541	1019	38	0	13913	42615	733	97.555
Ohio	58727	44215	1316	18315	2113	126185	617	95.121
Oklahoma	14907	41613	18	0	29435	86224	399	96.079
Oregon	1476	17923	5	0	43638	64114	137	96.034
Pennsylvania	44086	76391	626	83477	7891	215386	357	96.342
Rhode Island	0	7897	76	0	192	8375	399	95.288
South Carolina	19497	21654	344	52716	3524	99364	290	95.663
South Dakota	2339	1168	6	0	9103	12616	231	95.121
Tennessee	20967	13399	130	36176	10501	81555	358	95.121
Texas	111723	239713	129	41186	80032	477352	481	95.133
Utah	25912	8724	37	0	4391	39375	723	95.832
Vermont	0	2	3	0	1748	2179	5	97.602
Virginia	9266	50160	950	29252	2528	95509	350	95.121
Washington	5383	10535	24	9708	88785	116757	91	96.039
West Virginia	62039	1420	159	0	3618	67249	894	97.401
Wisconsin	33322	16799	138	10129	4069	65937	632	95.121
Wyoming	39679	896	40	0	5034	46112	953	98.046

3.4 Performance Metrics

The performance metrics considered in this study are defined as below.

- Average speed: It can be calculated as the total traveled distance of a driving cycle divided by the total travel time.
- Number of stops per mile: If we divide the total number of stops by the total traveled distance, we will get the number of stops per mile. A stop is counted if the speed of a vehicle drops below 10 feet per second (fps) or 6.8 miles per hour (mph). To avoid multiple stop counts for a vehicle moving in a queue with a very low speed, it must have to reach at least 15 fps or 10.2 mph before counting additional stops (Trafficware, 2013).
- CO_2 emission per kilometer: It can be measured as the amount of total CO_2 emission divided by the traveled distance measured in kilometer.
- CO_2 emission ratio: It can be defined as the ratio of the WTW CO_2 emission from an EV to the WTW CO_2 emission from a GV under exactly similar driving conditions and driving distance.

For each simulation run, three test vehicles - one GV, one EV, and one PHEV, completed the travel routes shown in Figure 3.4 with other regular vehicles (GenV) on the roads. We have considered 15 minutes as warm-up time which means that the test vehicles enter the roads after running the simulation for 15 minutes.

3.5 Simulation Replications

For a stochastic simulation model, a variability of the performance metrics can be observed depending on the random number seed value. The number of replications required to keep the performance metrics within an acceptable tolerance limit can be evaluated using equation (26) (Toledo & Koutsopoulos, 2004).

$$d_n = \frac{t_{n-1,\alpha/2}\left(\frac{S_n}{\sqrt{n}}\right)}{\bar{X}_n} \tag{26}$$

Where,

n : number of replications

d_n : desired tolerance as a fraction of the sample mean

$t_{n-1,\alpha/2}$: critical value of the student's t-distribution

α : level of significance

S_n : sample standard deviation

$\bar{X}_n$: sample mean

We ran our simulation model for 50 replications and found that the tolerance values of the performance metrics are always within our acceptable limit, 5%.

3.6 Simulation Experiments

Table 3.4 presents the three scenarios and their corresponding traffic volumes investigated in this study. Under the baseline scenario, the average hourly traffic volume during morning peak hours (7:00 am – 9:00 am) has been considered. It has been assumed that the moderate and low traffic scenarios correspond to 50% and 25% of the baseline traffic volume, respectively.

Table 3.4 Simulation experiments considered in this study

Scenarios	Traffic volume	
	City driving cycle	Highway driving cycle
Peak hour traffic (baseline)	100%	100%
Moderate traffic	50%	50%
Low traffic	25%	25%

3.7 Validation of the Simulation Model

To validate our simulation model, we collected data (i.e., total travel time, traveled distance, and the number of stops) of the simulated routes by driving a passenger test vehicle. We collected 12 samples for the city driving cycle and 10 samples for the highway driving for the baseline scenario, peak hour traffic. Then we measured several important characteristics of driving cycles (i.e., average speed, and the number of stops per mile) from the field survey and compared with the simulated driving cycles. Table 3.5 summarizes the output of Student's t-test. According to the p-values, for all the cases, we fail to reject the null hypothesis; there is no statistically significant difference between the mean values. Therefore, the means of the average speed and number of stops per mile between simulation and field survey data are not statistically different at 0.05 level of significance. Hence, the developed simulation models fairly represent the actual driving cycle characteristics.

Table 3.5 Student's t-test output for comparison between simulation results and field survey data

t-test output	City Driving Cycle		Highway Driving Cycle	
	Speed (mph)	Speed (mph)	Number of stops/mile	
Sample size (Simulation)	50	50	50	50
Sample size (Survey)	12	12	10	10
Mean (Simulation)	15.854	2.351	37.009	0.036
Mean (Survey)	16.460	2.271	38.241	0.049
Variance (Simulation)	1.284*	0.035**	1.895*	0.003**
Variance (Survey)	3.402*	0.022**	4.586*	0.005**
p-value (two-tail)	0.296	0.176	0.108	0.492
Decision	FTR Ho	FTR Ho	FTR Ho	FTR Ho

Note: *Unequal variance; **Equal variance; mph – Miles per hour; FTR Ho – Fail to reject the null hypothesis.

Table 3.6 compares the EV energy consumption between laboratory test results and our model. Vehicle Emission Laboratories (VELA), Ispra, Italy measured the power consumption of Nissan Leaf EV for three driving cycles - Worldwide harmonized Light-duty Test Cycle (WLTC), Worldwide Motorcycle emission Test Cycle (WMTC), and New European Driving Cycle (NEDC) (De Gennaro et al., 2015). Besides, Idaho National Laboratory (INL), Idaho, USA measured the power consumption of Nissan Leaf EV for three US driving cycles - Highway Fuel Economy Test cycle (HFET), Urban Dynamometer Driving Schedule (UDDS), and US06 Supplemental Federal Test Procedure (SFTP-US06) (Jeremy Diez, 2018). As per the table, the weighted average error compared to the three driving cycles is 5.1% where the route distances of the driving cycles have been considered as the weight values.

Table 3.6 Comparison of EV energy consumption between laboratory test results and our model

Parameters	VELA, Italy			INL, USA		
	WLTC	WMTC	NEDC	HWFET	UDDS	SFTP-US06
Distance (km)	23.19	28.92	10.93	16.52	12.07	12.90
Lab test result (kWh/100 km)	16.98	18.29	15.69	14.30	12.45	20.73
Our model (kWh/100 km)	16.86	19.10	14.74	14.92	14.26	21.91
Error	-0.7%	4.4%	-6.1%	4.3%	14.5%	5.7%

Chapter 4

RESULTS AND DISCUSSIONS

Figure 4.1 (a) and (b) present the driving cycles (speed versus time) of city driving and highway driving, respectively, for different traffic congestion levels, i.e., peak hour, moderate, and low. The city travel route simulation took 2400, 1981, and 1553 seconds for peak, moderate, and low traffic scenarios, respectively. On the other hand, the highway travel route simulation took 1887, 1419, and 1051 seconds for peak, moderate, and log traffic scenarios, respectively. The city driving cycle is comparatively smooth because most of the idling time is caused by the controlled delays by traffic signals. On the contrary, in case of highway driving cycle, the traffic flow is mostly interrupted by the merging vehicles from the access ramps and it caused abrupt frequent changes of driving speed, particularly for peak hour traffic volume.

Table 4.1 summarizes the main characteristics of traffic cycles simulated in this study and six other cycles known as WLTC, WMTC, NEDC, HWFET, UDDS, and SFTP-US06. The parameters considered in this table are traveled distance, average speed, standard deviation of speed, number of stops per mile, average acceleration, average deceleration, acceleration time percentage, deceleration time percentage, and idling time percentage. The parameters of our Arlington city driving cycle and I30 Highway driving cycle during moderate traffic is close to the UDDS, and HWFET driving cycles, respectively.

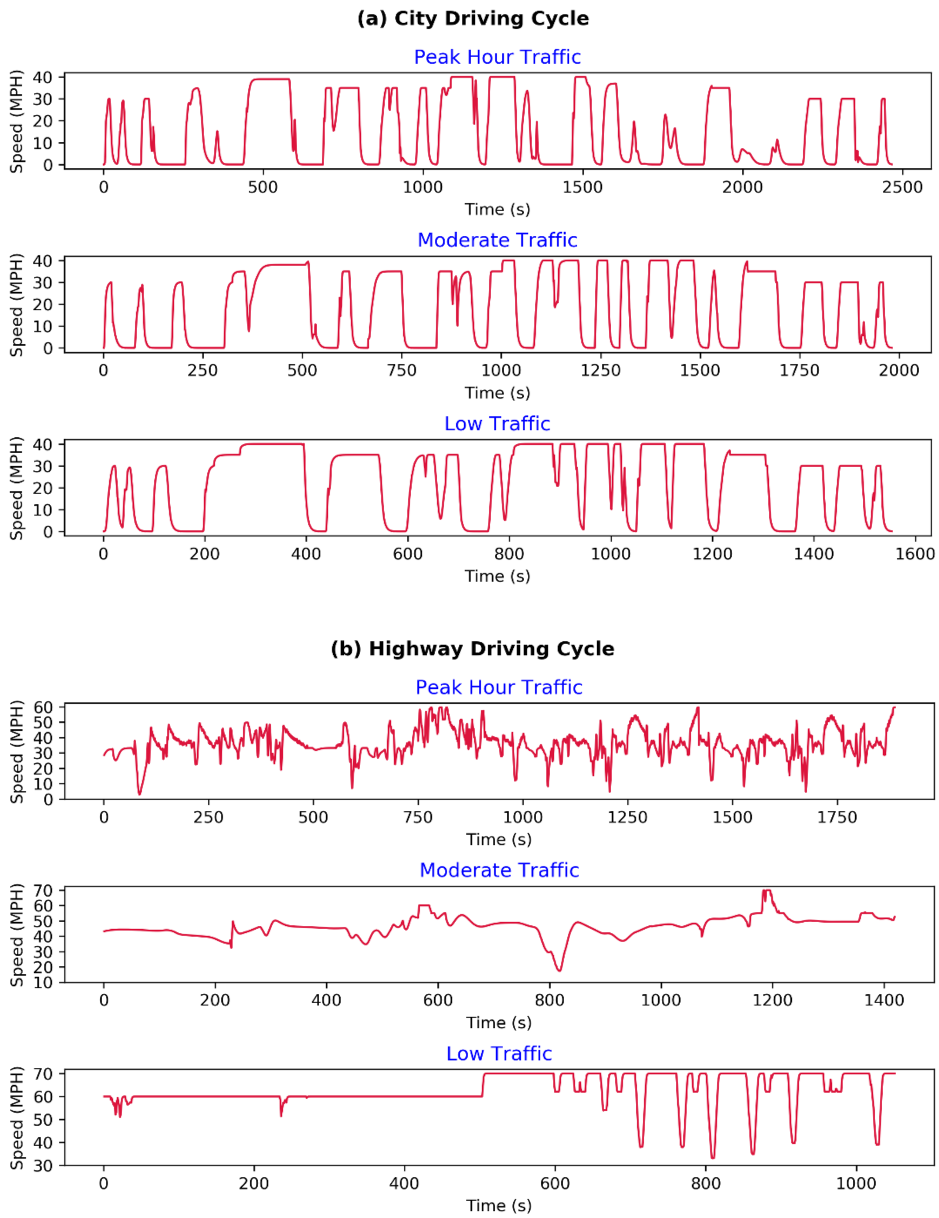


Figure 4.1 City and highway driving cycles

Table 4.1 Main characteristics of the traffic cycles considered in this study and other six cycles

Driving Cycles	d_km	v_kmph	sigma_v_kmph	Stops/km	acc_avg (m/s2)	dec_avg (m/s2)	acc_mod (%)	dec_mod (%)	idl_mod (%)
Arlington City peak	16.4	24.0	25.4	1.46	0.523	-0.370	27.3	38.4	28.3
Arlington City moderate	16.4	29.9	26.5	1.21	0.554	-0.494	30.7	34.5	26.3
Arlington City low	16.4	38.1	25.3	0.97	0.585	-0.642	31.3	28.5	14.0
I30 Highway peak	29.3	58.1	14.5	0.10	0.819	-0.859	50.1	47.0	0.0
I30 Highway moderate	29.3	74.5	10.6	0.00	0.154	-0.114	39.6	50.8	0.0
I30 Highway low	29.3	100.8	11.4	0.00	0.614	-1.469	21.9	8.8	0.0
WLTC	23.2	46.4	36.1	0.35	0.388	-0.446	44.8	38.9	13.3
WMTC	28.9	57.8	37.9	0.38	0.387	-0.491	47.8	37.6	9.6
NEDC	10.9	33.4	31.1	0.82	0.541	-0.789	23.0	15.8	24.8
HWFET	16.5	77.6	16.5	0.06	0.194	-0.221	44.1	38.8	0.8
UDDS	12.0	31.5	23.7	1.50	0.505	-0.578	39.7	34.6	19.2
SFTP-US06	12.9	77.2	39.6	0.54	0.670	-0.728	45.8	42.1	7.8

Note: d_km = total distance of the driving cycle (kilometer); v_kmph = average speed (kmph); sigma_v_kmph = standard deviation of the speeds (kmph); stops/km = number of stops per kilometer; acc_avg = average acceleration; dec_avg = average deceleration; acc_mod (%) = acceleration mode in percentage; dec_mod (%) = deceleration mode in percentage; idl_mod (%) = idling mode in percentage.

Figure 4.2 displays the box plots of WTW CO_2 emissions (g/km) from GV, EV, and PHEV for different traffic congestion levels, i.e., peak hours, moderate and low, for city and highway driving. The plots are created for Texas for 50 replications of the simulation model. In the box plots, the red line inside a box represents the median, the box represents the middle 50% of the data, the left whisker represents the bottom 25% of the data, and the right whisker represents the top 25% of the data, excluding the outliers. The black circles outside the whiskers represent the probable outliers. Figure 4.3 represent the histograms of the data and the red dotted lines represent the probability densities of the corresponding data. For city driving, for all the three traffic congestion levels, CO_2 emission from the GV is the highest, followed by PHEV and EV. However, for the GV, the emitted CO_2 increases sharply with the increase in traffic congestion while the emission from EV changes a little with the change of traffic congestion. The effect of congestion on PHEV is a little higher compared to EV but significantly lower compared to GV. For example, when the traffic congestion increases from low to moderate, CO_2 emission increases by 7.2%, 3.2%, and 1.9% for GV, PHEV, and EV, respectively. Again, when traffic congestion increases from moderate to peak hour, CO_2 emission increases by 16.0%, 7.1%, and 4.5% for GV, PHEV, and EV, respectively. It should be noted that EV and PHEV both have the automatic start-stop feature, a technology that helps to prevent idle power or fuel consumption by shutting the motor or engine off when the vehicle does not move. Therefore, this technology reduces idle power consumption considerably due to frequent stops as a result of high traffic congestions. Moreover, EV and PHEV have regenerative braking power technology which helps to generate electric power from braking energy when the vehicles decelerate. The generated electric power is stored in batteries for future use. Consequently, frequent stops due to traffic congestion have a comparatively low adverse effect on fuel economy and hence on CO_2 emission for EV and PHEV. On contrary, GV does not have any of these features and hence suffers significantly in terms of fuel economy and CO_2 emission due to frequent stops and long idle time at traffic signals due to high traffic congestions.

For highway driving, the CO_2 emission from PHEV is the minimum of all the three traffic congestion levels compared to GV, and EV. When the traffic congestion increases from low to moderate, CO_2 emission decreases by 2.5%, 6.4%, and 12.1% for GV, PHEV, and EV, respectively. Again, when the traffic congestion increases from moderate to peak hour, CO_2 emission decreases by 15.7% and 35.8% for PHEV and EV, respectively, but increase by 13.2% for GV. Therefore, according to the results, it is apparent that the CO_2 emission form EV and PHEV is a monotonic function of traffic congestion for the speed range 36 to 63 mph (58 to 101 kmph) while it is not true for GV. During low traffic volume, vehicles move at high speed and speed variation is low. Consequently, produced electric energy from the regenerative braking feature for EV and PHEV is insignificant. On the other hand, according to equation (6), aerodynamic drag force increases proportionally to the square of vehicular speed which causes a high resistance force at high speed. Consequently, EV and PHEV consume comparatively high energy at high speed and hence emit more CO_2.

A study done by Argonne National Laboratory shows that midsize conventional GV achieves the maximum fuel economy for the speed range of 45 to 55 mph and vehicle fuel efficiency decreases as speed increases or decreases from this optimum speed range (Argonne National Laboratory, 2016). According to our simulation results, the average speed at peak hour, moderate, and low traffic volumes are 37.0, 46.3, and 62.3 mph, respectively. It is apparent that the average speed during moderate traffic volume lies between the maximum fuel economy speed range, 45 to 55 mph. So, the CO2 emission from GV during moderate traffic is the minimum. Therefore, our results agree with the findings of the Argonne National Laboratory study.

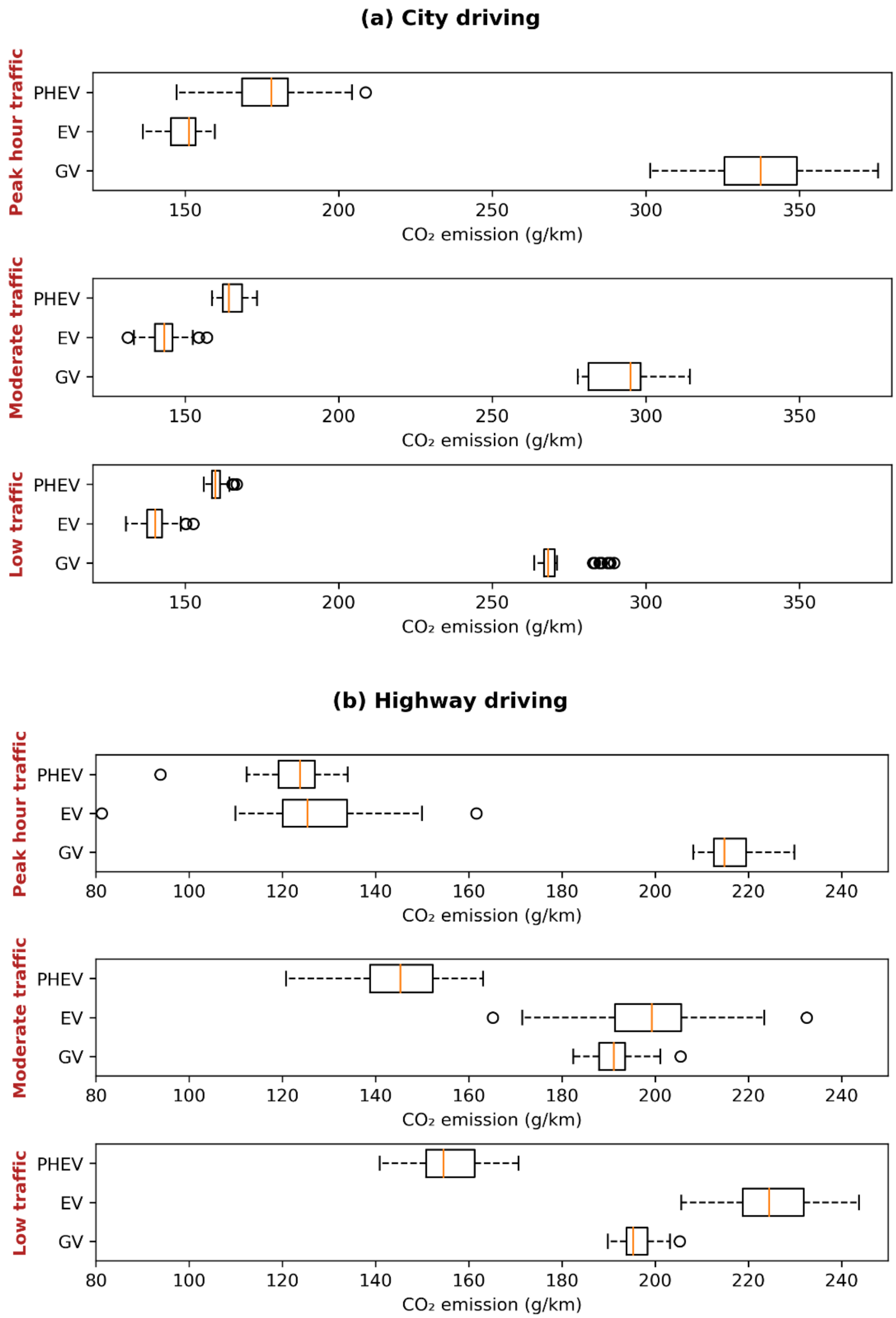


Figure 4.2 Box plots of CO_2 emission by GV, EV, and PHEV in Texas for different traffic scenarios: (a) city driving; (b) highway driving

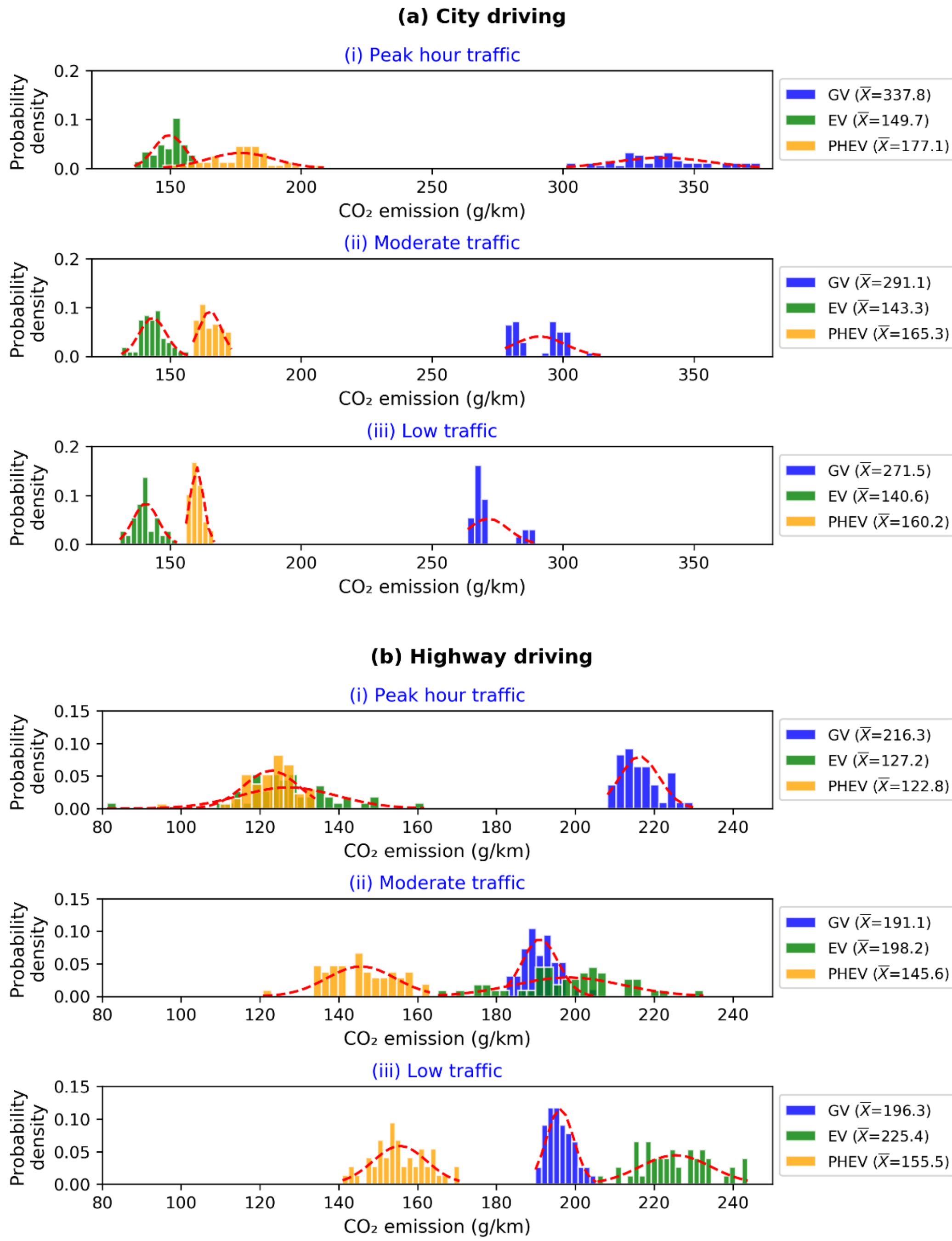


Figure 4.3 Distributions of CO_2 emission by GV, EV, and PHEV in Texas for different traffic scenarios: (a) city driving; (b) highway driving.

Overall, GV and PHEV emit less CO_2 for highway driving than the city for all the three traffic scenarios. On the contrary, EV emits more CO_2 for highway driving than the city for all the scenarios except the peak hour traffic.

Table 4.2 and 4.3 present the summary of the mean CO_2 emission statistics for city and highway driving in Texas, respectively. The tables show the means, standard deviations, and 99% confidence intervals (CI) for GV, EV, and PHEV for different traffic congestion scenarios. Table 4.4 displays the grouping information using Tukey pairwise comparison method at 99% confidence. According to the table output, for city driving, there is no statistical difference between the mean CO_2 emissions for the scenarios – PHEV moderate traffic versus PHEV low traffic, EV peak hour traffic versus EV moderate traffic, and EV moderate traffic versus EV low traffic. The rest of the mean CO_2 emission values are statistically different with 99% confidence for city driving cycle. On the other hand, for highway driving cycle, there is no statistical difference between the mean CO_2 emissions for the scenarios – GV moderate traffic versus GV low traffic, GV low traffic versus PHEV peak hour traffic, and PHEV peak hour traffic versus EV peak hour traffic. The rest of the mean CO_2 emission values are statistically different with 99% confidence for highway driving.

Table 4.2 Summary of mean CO_2 emission statistics for city driving in Texas

Factor	N	Mean	StDev	99% CI
GV peak hour traffic	50	337.78	18.25	(334.43, 341.12)
EV peak hour traffic	50	149.73	5.77	(146.38, 153.07)
PHEV peak hour traffic	50	177.05	12.63	(173.71, 180.40)
GV moderate traffic	50	291.08	9.79	(287.73, 294.42)
EV moderate traffic	50	143.33	5.04	(139.98, 146.67)
PHEV moderate traffic	50	165.25	4.25	(161.91, 168.59)
GV low traffic	50	271.48	7.59	(268.14, 274.83)
EV low traffic	50	140.62	4.77	(137.28, 143.97)
PHEV low traffic	50	160.17	2.53	(156.82, 163.51)

Table 4.3 Summary of mean CO_2 emission statistics for highway driving in Texas

Factor	N	Mean	StDev	99% CI
GV peak hour traffic	50	216.27	4.97	(213.17, 219.38)
EV peak hour traffic	50	127.17	12.35	(124.07, 130.28)
PHEV peak hour traffic	50	122.84	6.81	(119.73, 125.94)
GV moderate traffic	50	191.08	4.51	(187.98, 194.18)
EV moderate traffic	50	198.19	13.77	(195.09, 201.29)
PHEV moderate traffic	50	145.64	8.67	(142.54, 148.75)
GV low traffic	50	196.13	3.44	(193.02, 199.23)
EV low traffic	50	225.41	8.97	(222.31, 228.51)
PHEV low traffic	50	155.53	6.81	(152.42, 158.63)

Table 4.4 Grouping information of CO_2 emission for city and highway driving using the Tukey method and 99% confidence

Factor	Grouping for city driving	Grouping for highway driving
GV peak hour traffic	A	H
GV moderate traffic	B	I
GV low traffic	C	I, J
PHEV peak hour traffic	D	K
PHEV moderate traffic	E	L
PHEV low traffic	E	M
EV peak hour traffic	F	K
EV moderate traffic	F, G	J
EV low traffic	G	N

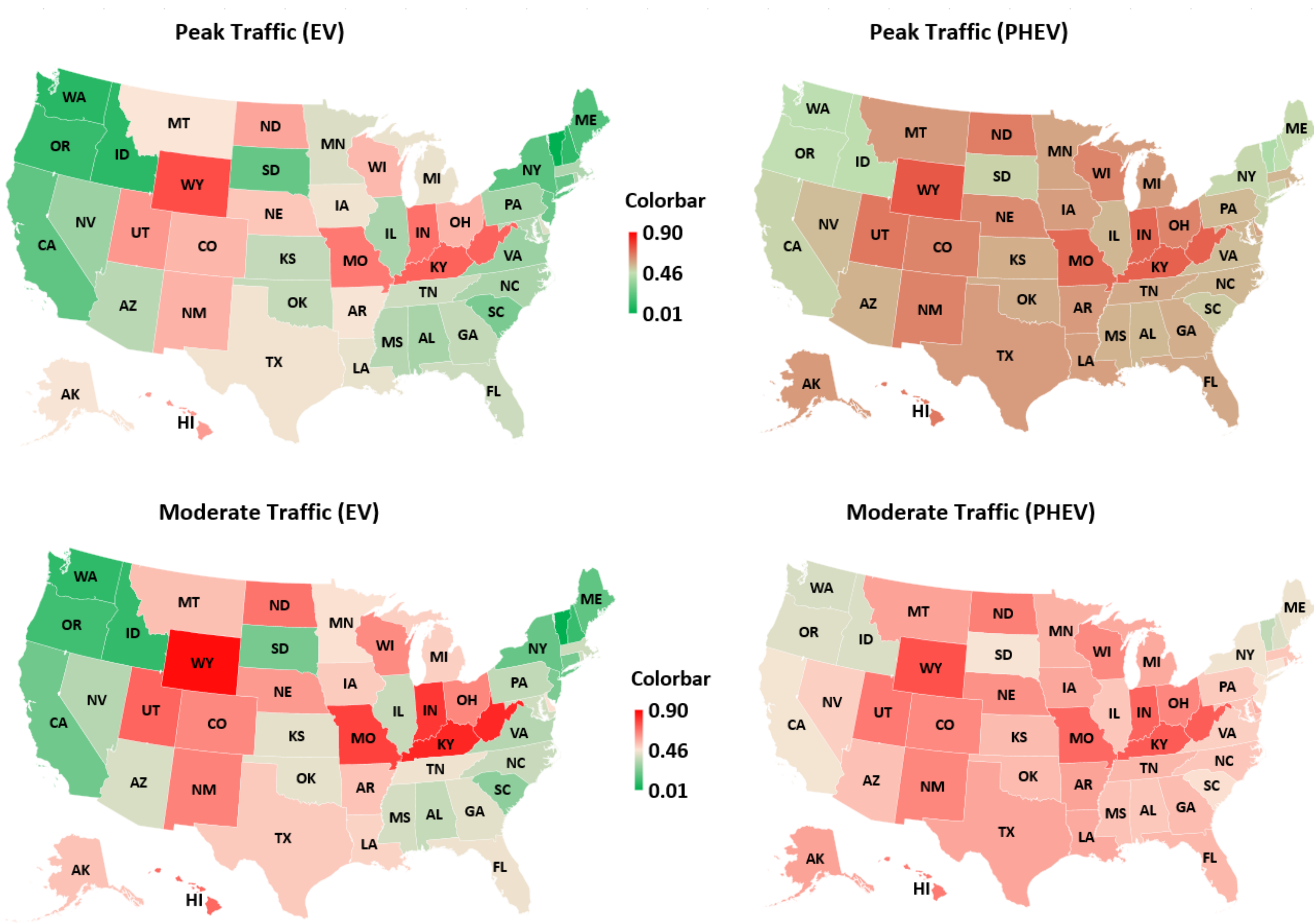
Note: Factors that do not share a letter are significantly different

Figures 4.4 and 4.5 show the CO_2 emission ratios (ER) for EV and PHEV with respect to GV at different traffic congestion scenarios for city and highway driving, respectively. The maps are produced for all the 50 states of U.S. by varying the state level parameters (state electricity production mix and electricity transmission and distribution efficiency) as discussed under the methodology section. For city driving, we used a fixed colorbar scale from 0.01 to 0.90 for all the three traffic scenarios, peak hour, moderate, and low, for making comparisons. Since, the maximum ER value is 0.90, EV and PHEV always emit less CO_2 compared to GV in all the states under all traffic scenarios. Overall, EV performs better than PHEV with respect to CO_2 emission. Besides, for both EV and PHEV, CO_2 emission is inversely proportional to the traffic congestion. This is because, as we discussed earlier, the regenerative braking technology produces electric energy during deceleration which is very frequent at high traffic and the auto start-stop technology shuts the engine/motor off during idling.

On the other hand, in case of highway driving, we used a colorbar scale from 0.01 to 2.0 for all the three traffic scenarios for making comparisons. Since the value of ER is greater than 1.0 for several states, the environmental performances of EV and PHEV are worse compared to GV. Overall, PHEV always performs better compared to EV, and in most of the states performs better than GV, with respect to CO_2 emission. Again, the environmental performance for both EV and PHEV is inversely proportional to the traffic congestion.

According to the Bureau of Transportation Statistics, U.S. Department of Transportation, on average 40% of VMT (vehicle miles travelled) comes from highway driving and rest of the VMT comes from city driving (US DOT, 2019). Figure 4.6 exhibits CO_2 emission ratios of EV and PHEV considering 60% city and 40% highway driving distance. As per the figure, the environmental performance of a PHEV is better than an EV for almost all the states of U.S.

According to ER, top five states where EV and PHEV perform the best are Vermont, Washington, Idaho, New Hampshire, and Oregon. On the contrary, the least performing five states are Wyoming, West Virginia, Kentucky, Indiana, and Missouri.


Peak Traffic (EV)
Peak Traffic (PHEV)
Colorbar
0.90
0.46
0.01
Moderate Traffic (EV)
Moderate Traffic (PHEV)
Colorbar
0.90
0.46
0.01

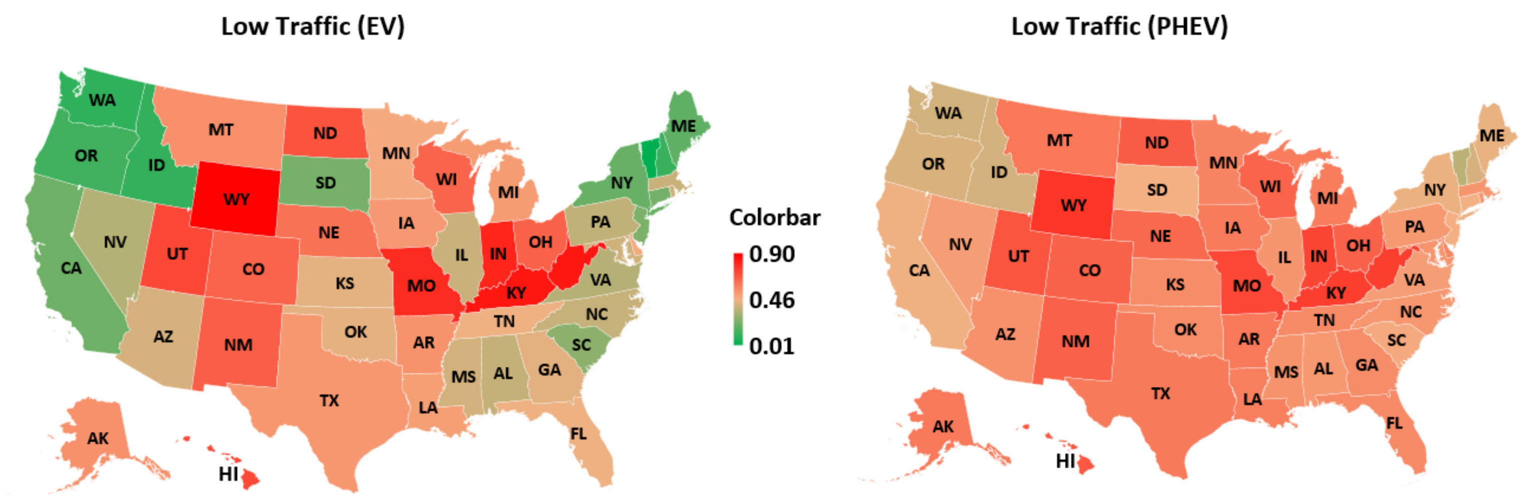
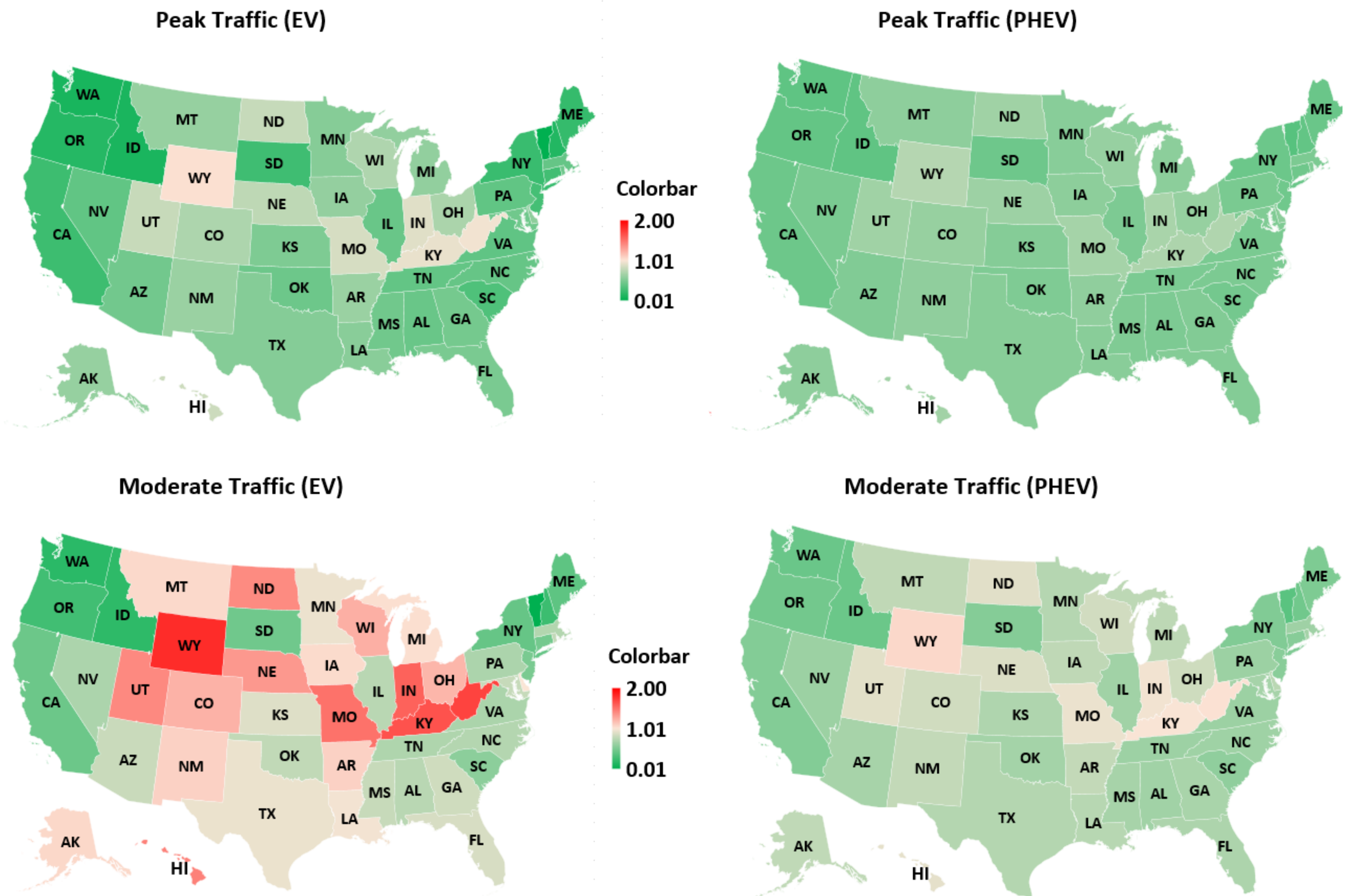


Figure 4.4 CO_2 emission ratios in different states of U.S. for city driving


Peak Traffic (EV)
Peak Traffic (PHEV)
Colorbar
2.00
1.01
0.01
Moderate Traffic (EV)
Moderate Traffic (PHEV)
Colorbar
2.00
1.01
0.01

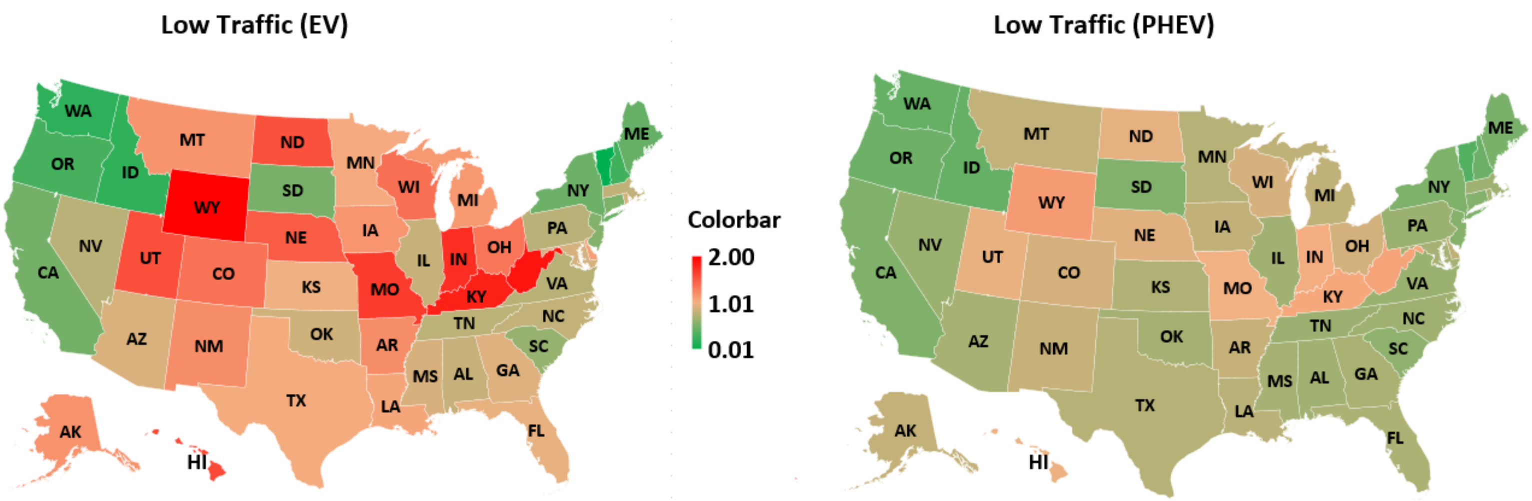
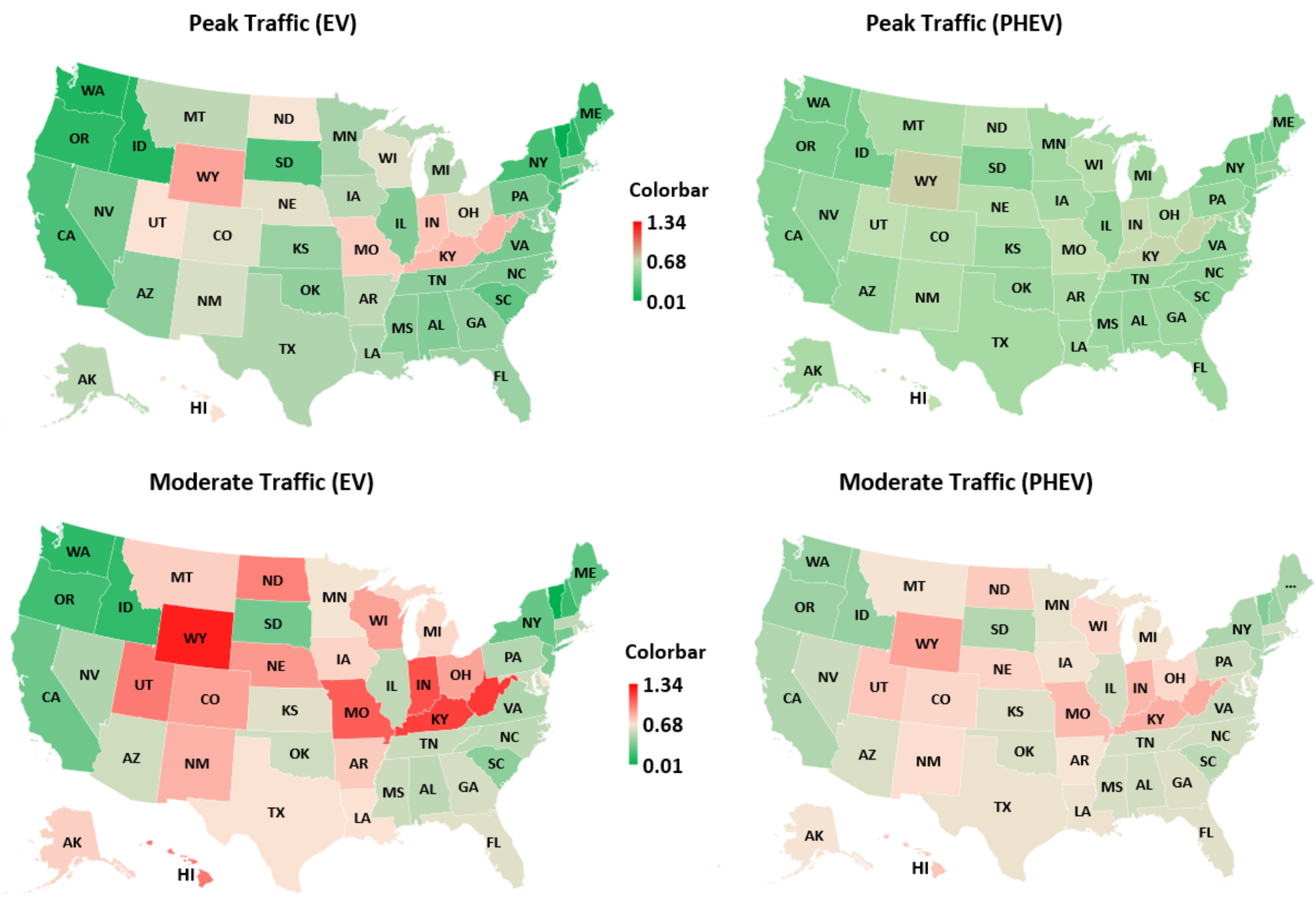


Figure 4.5 CO_2 emission ratios in different states of U.S. for highway driving


Peak Traffic (EV)
WA OR ID MT ND MN SD WY WI MI NY ME NV UT CO NE IA IL IN OH PA CA KS MO KY VA AZ NM OK AR TN NC SC MS AL GA TX LA FL AK HI
Colorbar
1.34
0.68
0.01
Peak Traffic (PHEV)
WA OR ID MT ND MN SD WY WI MI NY ME NV UT CO NE IA IL IN OH PA CA KS MO KY VA AZ NM OK AR TN NC SC MS AL GA TX LA FL AK HI
Moderate Traffic (EV)
WA OR ID MT ND MN SD WY WI MI NY ME NV UT CO NE IA IL IN OH PA CA KS MO KY VA AZ NM OK AR TN NC SC MS AL GA TX LA FL AK HI
Colorbar
1.34
0.68
0.01
Moderate Traffic (PHEV)
WA OR ID MT ND MN SD WY WI MI NY ... NV UT CO NE IA IL IN OH PA CA KS MO KY VA AZ NM OK AR TN NC SC MS AL GA TX LA FL AK HI

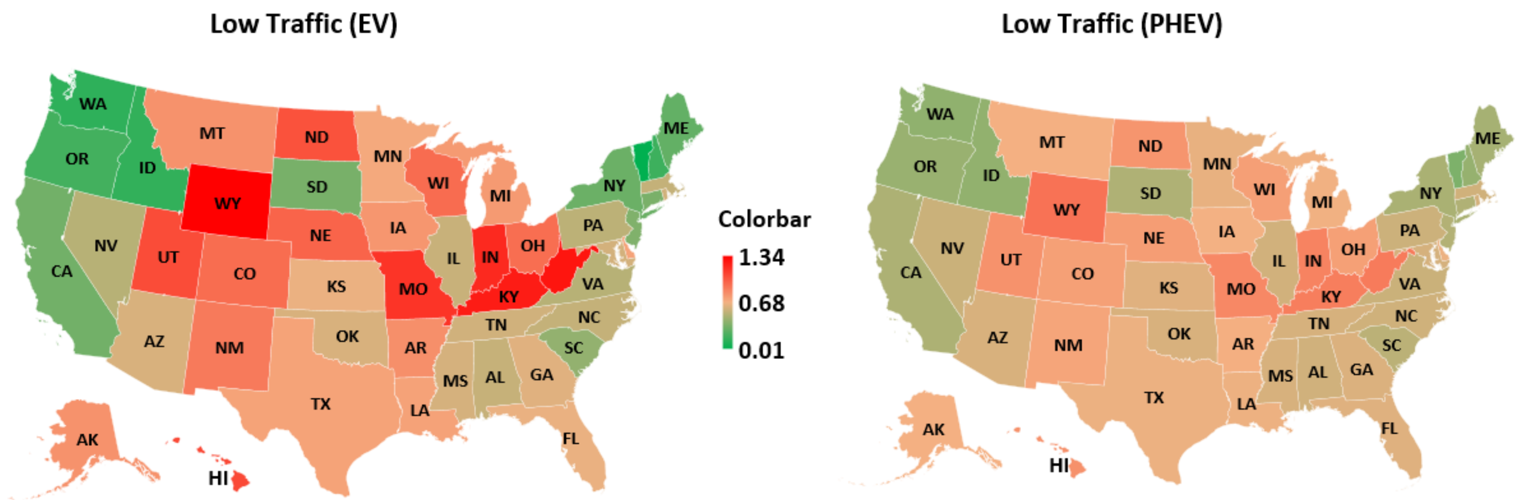


Figure 4.6 CO_2 emission ratios in different states of U.S. for combined cycle (60% city and 40% highway driving distance)

Figure 4.7 exhibits the contribution of clean energy to the total electricity production of the U.S. 50 states as per the energy mix data during the year 2018 (U.S. EIA, 2020). Clean energy sources include solar, wind, hydro, geothermal, and nuclear energy. On the other hand, energy from coal, gas, petroleum, and other fossil fuels are considered as dirty sources. In the U.S., the average CO_2 emission factor from coal, natural gas, and petroleum fired power plants are 974, 449, and 793 g/kWh, respectively (Cai, Wang, Elgowainy, & Han, 2012). According to our simulation results, EV performs very well for the states (e.g., Vermont, Washington, Idaho, and New Hampshire) where a significant percentage of electricity comes from clean energy sources. On the contrary, EV emits more CO_2 in states like Wyoming, West Virginia, and Kentucky, where the lion's share of the electricity comes from coal-fired power plants.

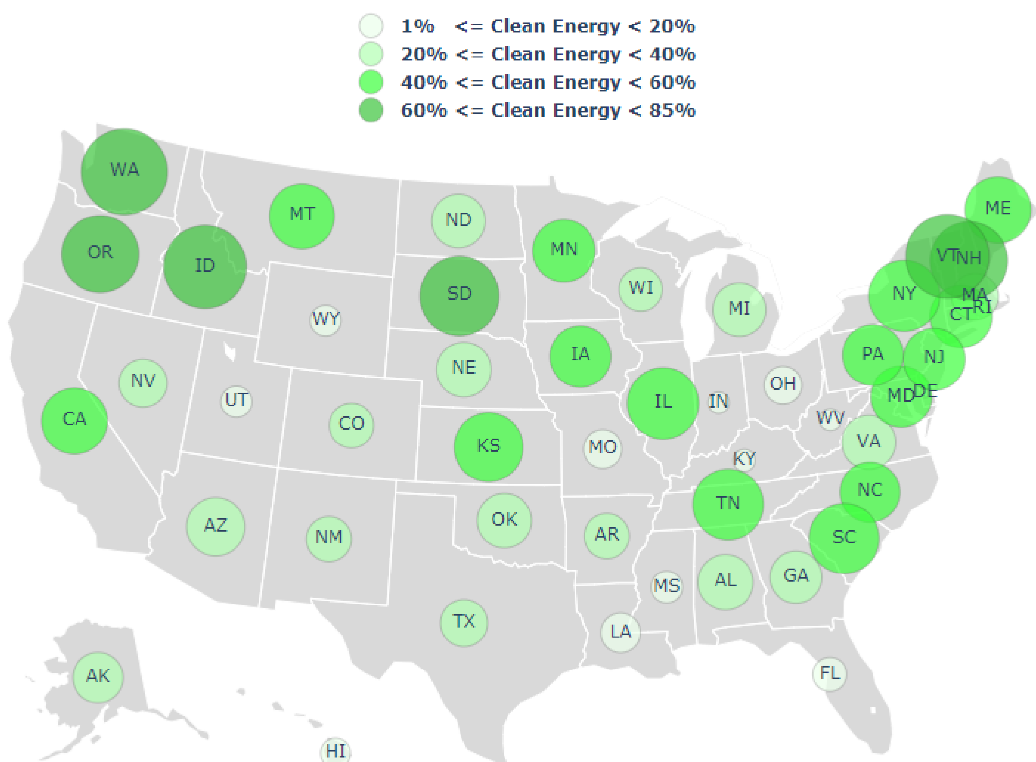


Figure 4.7 Percentage of clean energy of the total electricity for the 50 U.S. states

Figure 4.8 presents the break-even point (BEP) analysis between GV and EV. According to the plots, EV emission linearly increases with the electricity grid carbon intensity (g/kWh). The BEPs for peak hour, moderate, and low traffic volumes are 988.5, 730.7, and 665.1 g/kWh, respectively. Therefore, for the states where the grid carbon intensity is below 665.1 g/kWh, EVs are expected to emit less CO_2 compared to GV under all traffic scenarios.

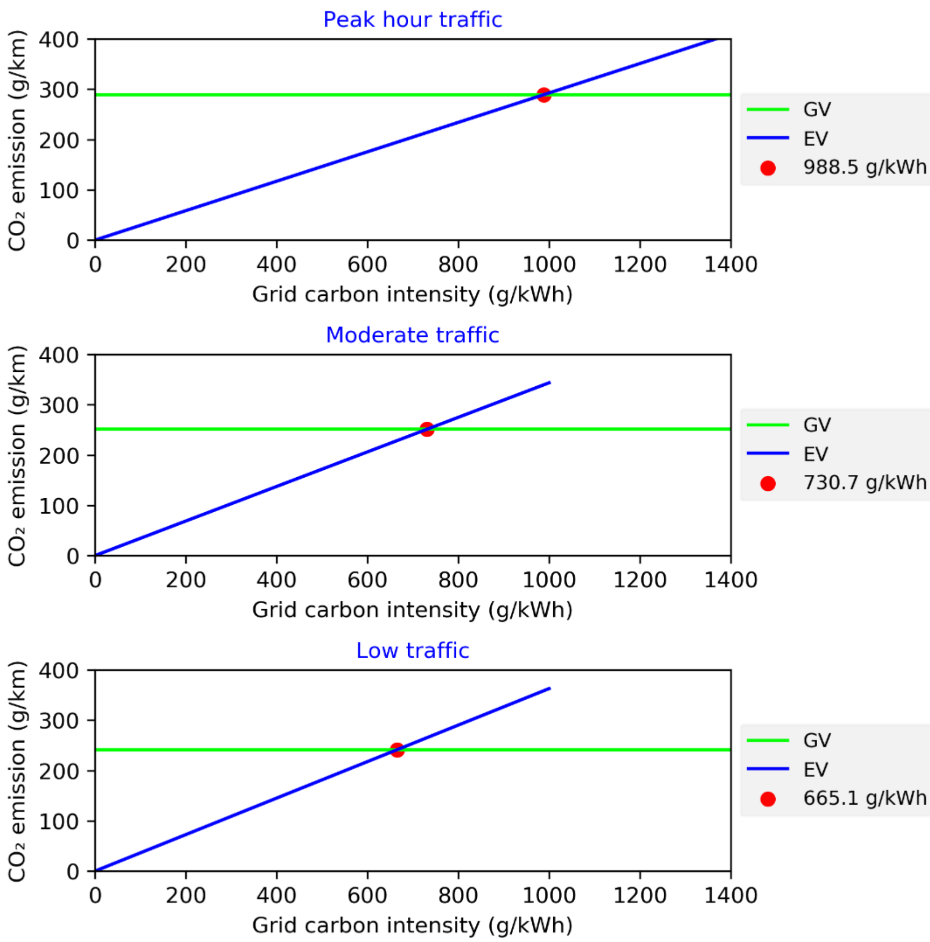


Figure 4.8 Break-even point analyses between GV and EV

Tornedo plots have been utilized in Figure 4.9 to depict the findings of sensitivity analysis of GV, EV, and PHEV where the relevant parameters were increased or decreased by 15% and the corresponding change of CO_2 emissions were measured in percentage with respect to Texas baseline scenario – peak hour traffic. According to the plots, for the GV, engine displacement, vehicle mass, and vehicle frontal area have positive relationships with CO_2 emission while road speed, engine and drivetrain efficiencies have inverse relationships with CO_2 emission. For both driving cycles, city and highway, engine displacement and vehicle frontal area appeared to be the most and least sensitive factor on CO_2 emission, respectively. The sensitivity order of the rest of the factors changes with the city and highway driving cycles. Therefore, there is an impact of vehicle speed on CO_2 emission sensitivity. On the other hand, in case of EV and PHEV, motor power train efficiency and vehicle frontal area appeared to be the most and least impactful factor on CO_2 emission, respectively. Again, the sensitivity order of the rest of the factors changes with the city or highway driving cycles. Overall, irrespective of driving cycles, engine displacement, vehicle mass, grid carbon intensity, and vehicle frontal area have positive relationships with CO_2 emission while motor powertrain efficiency, electric mile percentage, engine efficiency, and drivetrain efficiency have inverse relationships. However, road speed has an inverse and positive relationship with CO_2 emission for city and highway driving cycles, respectively.

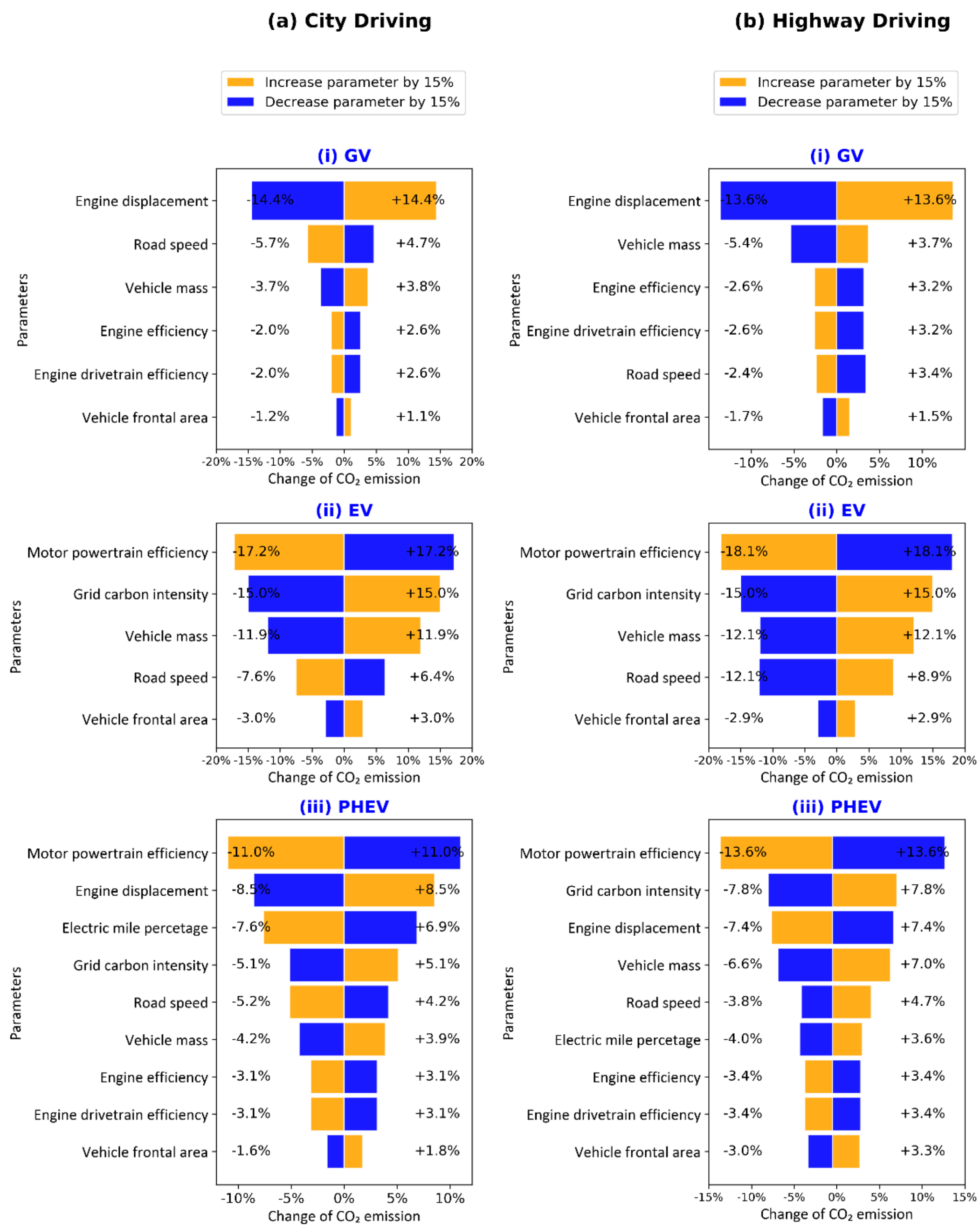


Figure 4.9 Tornedo plots for sensitivity analysis: (a) city driving; (b) highway driving

Chapter 5

CONCLUSIONS

In this study, a WTW simulation model has been developed to compare the environmental performance of GV, EV, and PHEV for city and highway driving cycles using ABM methodology. Three traffic scenarios have been considered – peak hour, moderate, and low. The spatial differences of CO_2 emission from EV and PHEV are studied for all the 50 states of the U.S. utilizing the year 2018 energy mix data. The findings can be summarized as follows –

- For the city driving cycle, CO_2 emission sharply increases with the level of traffic congestion for GV. On the other hand, for EV and PHEV, CO_2 emission also increases with the level of traffic congestion, but the impact is comparatively low.
- For highway driving, the amount of CO_2 emission from GV is a non-monotonic function of traffic congestion where emission is minimum for moderate traffic and maximum for peak hour traffic. On the contrary, the amount of CO_2 emission from EV and PHEV decreases monotonically with the level of traffic congestion for the speed range 36 to 63 mph.
- There is a significant difference in the environmental performance of EV and PHEV across the states of the U.S.
- EV and PHEV emit less CO_2 compared to GV across all the states of the U.S. for the city driving cycle.
- Overall, performance of PHEV is better than EV assuming at least 50% of the driving distance of PHEV comes from electric mode.

According to our findings, as per energy mix data of the year 2018, many states are not ready to adopt EV for achieving the desired environmental benefits. This study will help the decision-makers to better design their policy for EV and PHEV adoption.

Limitations and Future work

There exist temporal variations of grid electricity carbon intensity, e.g., the contribution of renewable energy during night hours reduces since solar energy is not available during night hours. Therefore, the amount of indirect emission from EV and PHEV depends on the time of the day batteries are charged. This temporal variation of grid carbon intensity is not considered in our model. Besides, the performance of the engine and EV battery differs due to the change of weather-related factors like temperature and humidity, which are not considered in this study. It should be also noted that the margin of error of the CO_2 emission ratio would be high if the characteristics of the city and highway driving cycle vary greatly across the states. In addition, the WTW assessment is conducted only for the energy pathway of fuel; emissions from materials required for manufacturing the vehicles and after use disposal are not considered.

Future work scopes are summarized as below:

- Perform a comprehensive Cradle-To-Grave analysis upon the availability of reliable data.
- Develop an optimal charging policy of EV batteries considering the temporal variation of grid carbon intensity.
- Incorporate weather-related variables in the model.
- Extend the work for other countries using the developed research framework.

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Appendix A

Additional Simulation Outputs

Table A.1 Emission ratios of the U.S. 50 states for city driving

State	EV_peak	PHEV_peak	EV_moderate	PHEV_moderate	EV_low	PHEV_low
AL	0.31	0.53	0.36	0.51	0.37	0.52
AK	0.45	0.59	0.52	0.58	0.53	0.60
AZ	0.33	0.55	0.39	0.53	0.40	0.53
AR	0.45	0.59	0.52	0.58	0.53	0.60
CA	0.18	0.48	0.21	0.44	0.21	0.45
CO	0.54	0.64	0.63	0.63	0.65	0.65
CT	0.19	0.48	0.22	0.45	0.22	0.45
DE	0.40	0.57	0.46	0.56	0.47	0.57
FL	0.37	0.56	0.43	0.54	0.44	0.55
GA	0.35	0.55	0.41	0.53	0.42	0.54
HI	0.60	0.66	0.70	0.66	0.71	0.68
ID	0.08	0.44	0.10	0.39	0.10	0.39
IL	0.31	0.54	0.36	0.51	0.37	0.52
IN	0.68	0.69	0.79	0.70	0.81	0.73
IA	0.43	0.59	0.50	0.58	0.52	0.59
KS	0.36	0.56	0.41	0.54	0.42	0.55
KY	0.71	0.71	0.83	0.72	0.85	0.74
LA	0.42	0.58	0.49	0.57	0.50	0.58
ME	0.15	0.47	0.18	0.43	0.18	0.43
MD	0.32	0.54	0.38	0.52	0.38	0.53
MA	0.32	0.54	0.37	0.52	0.38	0.52
MI	0.42	0.59	0.50	0.57	0.51	0.58
MN	0.40	0.57	0.46	0.56	0.47	0.57
MS	0.33	0.54	0.38	0.52	0.39	0.53
MO	0.66	0.69	0.77	0.70	0.79	0.72
MT	0.45	0.60	0.53	0.59	0.54	0.60
NE	0.51	0.62	0.60	0.62	0.61	0.63
NV	0.28	0.52	0.33	0.50	0.34	0.51
NH	0.09	0.44	0.11	0.40	0.11	0.40
NJ	0.20	0.49	0.23	0.45	0.23	0.46
NM	0.55	0.64	0.65	0.64	0.66	0.66
NY	0.16	0.47	0.19	0.44	0.20	0.44
NC	0.31	0.54	0.36	0.51	0.37	0.52

ND	0.58	0.65	0.67	0.65	0.69	0.67
OH	0.55	0.64	0.64	0.64	0.65	0.65
OK	0.36	0.56	0.42	0.54	0.43	0.55
OR	0.10	0.45	0.12	0.40	0.12	0.41
PA	0.30	0.53	0.35	0.51	0.36	0.51
RI	0.32	0.54	0.37	0.52	0.38	0.53
SC	0.22	0.50	0.26	0.47	0.27	0.47
SD	0.19	0.48	0.22	0.45	0.22	0.45
TN	0.37	0.56	0.43	0.54	0.44	0.55
TX	0.43	0.59	0.51	0.58	0.52	0.59
UT	0.60	0.66	0.70	0.67	0.72	0.68
VT	0.01	0.40	0.01	0.35	0.01	0.35
VA	0.28	0.52	0.33	0.50	0.34	0.51
WA	0.08	0.44	0.09	0.39	0.09	0.39
WV	0.71	0.71	0.82	0.72	0.84	0.74
WI	0.54	0.63	0.63	0.63	0.64	0.65
WY	0.75	0.73	0.88	0.74	0.90	0.77

Table A.2 Emission ratios of the U.S. 50 states for highway driving

State	EV_peak	PHEV_peak	EV_moderate	PHEV_moderate	EV_low	PHEV_low
AL	0.42	0.51	0.74	0.65	0.82	0.67
AK	0.60	0.57	1.06	0.77	1.18	0.80
AZ	0.46	0.52	0.81	0.67	0.89	0.69
AR	0.62	0.58	1.09	0.78	1.21	0.82
CA	0.25	0.44	0.44	0.53	0.48	0.53
CO	0.69	0.61	1.22	0.83	1.36	0.87
CT	0.27	0.45	0.47	0.54	0.52	0.55
DE	0.57	0.56	1.00	0.75	1.11	0.78
FL	0.49	0.53	0.86	0.69	0.96	0.72
GA	0.47	0.52	0.83	0.68	0.92	0.70
HI	0.82	0.65	1.44	0.92	1.59	0.97
ID	0.11	0.39	0.19	0.44	0.21	0.43
IL	0.42	0.51	0.74	0.65	0.82	0.67
IN	0.89	0.68	1.58	0.97	1.75	1.03
IA	0.59	0.57	1.05	0.77	1.16	0.80
KS	0.50	0.54	0.89	0.71	0.99	0.73
KY	0.93	0.69	1.64	1.00	1.82	1.05
LA	0.55	0.55	0.97	0.74	1.08	0.76
ME	0.22	0.43	0.38	0.51	0.42	0.51
MD	0.45	0.52	0.80	0.67	0.88	0.69
MA	0.41	0.50	0.72	0.64	0.79	0.65
MI	0.59	0.57	1.03	0.76	1.14	0.79
MN	0.54	0.55	0.95	0.73	1.05	0.75
MS	0.45	0.52	0.80	0.67	0.89	0.69
MO	0.85	0.67	1.51	0.94	1.67	1.00
MT	0.60	0.57	1.06	0.77	1.17	0.80
NE	0.76	0.63	1.34	0.88	1.49	0.92
NV	0.39	0.50	0.69	0.63	0.76	0.64
NH	0.14	0.40	0.25	0.46	0.27	0.45
NJ	0.28	0.45	0.49	0.55	0.54	0.56
NM	0.62	0.58	1.09	0.78	1.21	0.82
NY	0.23	0.44	0.41	0.52	0.46	0.52
NC	0.41	0.50	0.72	0.64	0.80	0.66
ND	0.79	0.64	1.40	0.90	1.55	0.95

OH	0.68	0.60	1.21	0.83	1.34	0.87
OK	0.44	0.51	0.77	0.66	0.86	0.68
OR	0.15	0.41	0.27	0.46	0.29	0.46
PA	0.39	0.50	0.69	0.63	0.76	0.64
RI	0.44	0.51	0.78	0.66	0.86	0.68
SC	0.32	0.47	0.56	0.58	0.62	0.59
SD	0.26	0.45	0.45	0.54	0.50	0.54
TN	0.40	0.50	0.70	0.63	0.78	0.65
TX	0.53	0.55	0.94	0.73	1.04	0.75
UT	0.80	0.64	1.41	0.90	1.56	0.95
VT	0.01	0.35	0.01	0.37	0.01	0.35
VA	0.39	0.49	0.69	0.63	0.76	0.64
WA	0.10	0.39	0.18	0.43	0.20	0.42
WV	0.97	0.71	1.71	1.02	1.89	1.08
WI	0.70	0.61	1.24	0.84	1.37	0.88
WY	1.03	0.73	1.81	1.06	2.00	1.13

Table A.3 Emission ratios of the U.S. 50 states for combined cycle (60% city and 40% highway driving distance)

State	EV_peak	PHEV_peak	EV_moderate	PHEV_moderate	EV_low	PHEV_low
AL	0.35	0.52	0.51	0.57	0.55	0.58
AK	0.51	0.59	0.74	0.66	0.79	0.68
AZ	0.38	0.54	0.56	0.58	0.60	0.60
AR	0.51	0.59	0.75	0.66	0.80	0.68
CA	0.20	0.46	0.30	0.48	0.32	0.48
CO	0.60	0.62	0.87	0.71	0.93	0.74
CT	0.22	0.47	0.32	0.49	0.34	0.49
DE	0.46	0.57	0.68	0.63	0.73	0.65
FL	0.42	0.55	0.60	0.60	0.65	0.62
GA	0.40	0.54	0.58	0.59	0.62	0.61
HI	0.69	0.66	0.99	0.76	1.07	0.80
ID	0.09	0.42	0.13	0.41	0.14	0.41
IL	0.36	0.52	0.52	0.57	0.55	0.58
IN	0.76	0.69	1.11	0.81	1.18	0.85
IA	0.50	0.58	0.72	0.65	0.77	0.67
KS	0.41	0.55	0.60	0.60	0.65	0.62
KY	0.80	0.70	1.15	0.83	1.24	0.87
LA	0.47	0.57	0.68	0.64	0.73	0.65
ME	0.18	0.45	0.26	0.46	0.28	0.46
MD	0.37	0.53	0.54	0.58	0.58	0.59
MA	0.35	0.52	0.51	0.56	0.54	0.58
MI	0.49	0.58	0.71	0.65	0.76	0.67
MN	0.45	0.56	0.66	0.63	0.70	0.64
MS	0.38	0.53	0.55	0.58	0.59	0.59
MO	0.74	0.68	1.07	0.80	1.14	0.83
MT	0.51	0.59	0.74	0.66	0.79	0.68
NE	0.61	0.63	0.90	0.72	0.96	0.75
NV	0.33	0.51	0.47	0.55	0.51	0.56
NH	0.11	0.43	0.16	0.42	0.17	0.42
NJ	0.23	0.47	0.33	0.49	0.36	0.50
NM	0.58	0.62	0.82	0.70	0.88	0.72
NY	0.19	0.46	0.28	0.47	0.30	0.47
NC	0.35	0.52	0.51	0.56	0.54	0.58

ND	0.66	0.65	0.96	0.75	1.03	0.78
OH	0.60	0.62	0.87	0.71	0.93	0.74
OK	0.39	0.54	0.56	0.59	0.60	0.60
OR	0.12	0.43	0.18	0.43	0.19	0.43
PA	0.34	0.52	0.49	0.56	0.52	0.57
RI	0.37	0.53	0.54	0.58	0.57	0.59
SC	0.26	0.49	0.38	0.51	0.41	0.52
SD	0.21	0.47	0.31	0.48	0.33	0.49
TN	0.38	0.54	0.54	0.58	0.58	0.59
TX	0.47	0.57	0.68	0.64	0.73	0.65
UT	0.68	0.66	0.98	0.76	1.05	0.79
VT	0.01	0.38	0.01	0.36	0.01	0.35
VA	0.33	0.51	0.47	0.55	0.51	0.56
WA	0.09	0.42	0.12	0.41	0.13	0.40
WV	0.81	0.71	1.18	0.84	1.26	0.88
WI	0.60	0.62	0.87	0.72	0.93	0.74
WY	0.86	0.73	1.25	0.87	1.34	0.91

Biographical Information

Md Mamunur Rahman was born and raised in Bangladesh. He received his B.S. and M.S. degrees in Industrial Engineering from Bangladesh University of Engineering and Technology (BUET), Dhaka, Bangladesh in 2011 and 2015, respectively. He earned his Ph.D. in Industrial Engineering in 2020 from The University of Texas at Arlington, TX, USA. His research articles have been published in different Journals and International Conferences. One of his conference articles won the best paper award in the IISE 2019 conference, Orlando, FL, USA. His other article won the best paper finalist award in the CSS 2018 conference, Santa Fe, NM, USA. His research interests include agent-based and discrete event simulation, data science, machine learning, and predictive modeling of real-world problems.