Socio-economic Implications of Large-scale Electric Vehicle Systems

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The objective of the Socio-economic Implications of Large-scale Electric Vehicle Systems project was to develop models to evaluate the socio-economic implications of a large-scale electrified transportation sector. The developed model included effects of vehicle and infrastructure safety requirements, standardization of vehicle components for safety and charging, electric vehicle supply and after-market economies, displacement of petroleum fuels and impacts of sustainable development (social, environmental and economic). The work was conducted by Dr. Omer Tatari, Principal Investigator and his research team of the College of Engineering and Computer Science at the University of Central Florida.

Note is made that the results of the research from this project has been used in the following five PhD dissertations:

1. Onat, Nuri (2015). “Integrated Sustainability Assessment Framework for the U.S. Transportation,” Ph.D. Dissertation, Department of Civil, Environmental, and Construction Engineering, University of Central Florida.
2. Noori, Mehdi (2015) “Development of Regional Optimization and Market Penetration Models for the Electric Vehicles in the United States,” Ph.D. Dissertation, Department of Civil, Environmental, and Construction Engineering, University of Central Florida.
3. Alirezaei, Mehdi (2016). “Getting to Net Zero Energy Building: A Holistic Techno-Ecological Modeling Approach,” Ph.D. Dissertation, Department of Civil, Environmental, and Construction Engineering, University of Central Florida.
4. Ercan, Tolga (2017). “Sustainability Assessment Models for Electric Buses and Fleets,” Ph.D. Dissertation, Department of Civil, Environmental, and Construction Engineering, University of Central Florida.
5. Zhao, Yang (2017) “A Comprehensive Assessment of Vehicle-to-Grid Systems and Their Impact to the Sustainability of Current Energy and Water Nexus,” Dissertation, Department of Civil, Environmental, and Construction Engineering, University of Central Florida.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ABM	Agent Based Model
AER	All-electric range
AFLEET	Alternative Fuel Life-Cycle Environmental and Economic Transportation
ANL	Argonne National Laboratory
APE	Air pollution externalities
APEEP	Air pollution emission experiments and policy analysis
ATRI	American Transportation Research Institute
BAU	Business as Usual
BEV	Battery Electric Vehicle
BE	Battery electric
CAFE	Corporate Average Fuel Economy
CAISO	California independent system operators
CNG	Compressed natural gas
CDF	Cumulative Distribution Function
CO	Carbon monoxide
CO_2	Carbon Dioxide
CPI	Consumer Price Index
DOE	Department of Energy
EDC	Environmental Damage Cost
EIA	Energy Information Agency
EIO-LCA	Economic Input-Output Life Cycle Assessment
EMA	Exploratory Modeling and Analysis
EPA	United States Environmental Protection Agency
ERCOT	Electric Reliability Council of Texas
EREV	Gasoline Extended Range Electric Vehicle
EV	Electric Vehicle
EVTC	Electric Vehicle Transportation Center
EVRO	Electric Vehicles Regional Optimizer
EVReMP	Electric Vehicle Regional Market Penetration
FHWA	Federal Highway Administration
gCO2-eqv	Carbon dioxide equivalent
GDP	Gross domestic product
gha	Global hectare area
GHG	Greenhouse gas
GREET	The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation
GWP	Global warming potential
HDT	Heavy-duty Truck
HEV	Hybrid electric vehicle
ICV	Internal combustion vehicle
IEA	International Energy Agency's
IPCC	Intergovernmental Panel on Climate Change
ISO-NE	Independent system operators of new England region
ISO	International standards organization

ISO/RTO	Independent system operators/regional transmission organizations
kWh	Kilowatt hour
LAVE-Trans	Light-duty Alternative Vehicle Energy Transitions
LCA	Life Cycle Analysis
LCC	Life Cycle Cost
LCEE	Life Cycle Environmental Emissions
LCI	Life Cycle Inventory
LCSA	Life cycle Sustainability Assessment
LDV	Light-duty Vehicle
Li-ion	Lithium-ion
LNG	Liquefied natural gas
LSFE	Load specific fuel economy
lt	Liter
M&R	Maintenance and Repair
MDV	Medium-duty Vehicles
MJ	Mega joule
MOVES	Motor vehicle emission simulation
MPDGE	Miles per diesel gallon equivalent
MRIO	Multi-regional Input-Iutput
NAICS	North American Industry Classification System
NEMS	National Energy Modeling System
NERC	North American electricity reliability corporation
NGRS	Natural Gas Refueling Station
NHTS	National Household Travel Survey
NIST	National Institute of Standards and Technology
NO	Nitrogen oxide
NPCC	Northeast Power Coordinating Council
NREL	National renewable energy laboratory
NYISO	New York independent system operators
P-LCA	Process-based Life Cycle Assessment
PHEV	Plug-in Hybrid Electric Vehicle
PJM	Pennsylvania-New Jersey-Maryland interconnection RTO
$PM_{2.5}$	Particulate matter 2.5 microns
PM_{10}	Particulate matter 10 microns
PV	Photovoltaic
S-LCA	Social Life Cycle assessment
SETAC	Society of Environmental Toxicology and Chemistry
SO_2	Sulphur dioxide
SOC	State-of-charge
st	Standard ton
TBL	Triple Bottom Line
TBW	Tire & brake wear
UF	Utility Factor
UNEP	The United Nations Environment Programme
V2G	Vehicle-to-grid
VBA	Visual Basic for Application

VMT	Vehicle Miles Traveled
VOC	Volatile organic compound
WBCSD	World Business Council for Sustainable Development
WFP	Water Footprint
WTP	Well-to-pump
WTW	Well-to-wheel
ZEV	Zero Emission Vehicle

Final Research Project Report

Socio-economic Implications of Large-scale Electric Vehicle Systems

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July 2017

1.0 Abstract

Transportation is a complex, technology-intensive socio-technical system, which needs to be tackled in an integrated manner. Also, transportation as a sector is a significant component of any national economy, and has far-reaching implications both with regard to socio-economic and environmental well-being of the society and within the context of sustainability science. For this reason, sustainable transportation is not only an important field of research within the academia but also an indispensable constituent of a sustainable economy. Therefore, investigating the path to sustainable transportation requires a holistic approach, encompassing the three dimensions of sustainability, i.e. environment, society, and economy. There are several proposals as to how to transition to a more sustainable transportation sector globally, and one of the most promising options is the electrification of vehicles. Hence, it is crucial to look at the electrification of transportation from different angles, and scrutinize different aspects to this matter.

This project developed several integrated sustainability assessment models that include the socio-economic as well as the environmental implications of an electrified transportation sector. These developed models covered a wide variety of means and aspects of an electrified transportation such as passenger vehicles, electric vehicle (EVs) market penetration, electric buses and long-haul trucks, vehicle to grid (V2G) technology that included delivery trucks, and the potential use of electric vehicles as a source of energy both for the grid and homes, i.e. vehicle to home technology (V2H). In the modeling, consideration was applied to stochastic costs, electricity mix sustainability, and life cycle impacts such as environmental, e.g. life cycle greenhouse gas emissions, social, e.g. life cycle health costs, and economic, e.g. life cycle costs. In-depth comparison between electric vehicles and other alternative fuel vehicles (AFVs) (incl. hybrid-electric, plug-in hybrid-electric, liquefied-natural gas, compressed-natural gas, biodiesel-powered vehicles) was carried out to investigate the major advantages and/or disadvantages of electrifying different means and types of transportation, e.g. passenger vehicles, transit buses, and long-haul trucks.

The final output was a dynamic simulation models of EV adoption that included a comprehensive cradle-to-grave life cycle assessment including uncertainties that capture the social, economic, and environmental impacts of EVs. Some of the critical findings of this project are as follows: Environmental benefits of EVs highly depend on

the electricity generation mix; battery-electric transit and school buses have larger battery capacity than passenger vehicles, making them more feasible candidates for V2G service; there is an enormous potential to neutralize operation related emissions by the use of V2G service for school buses and delivery trucks; battery-electric Class 8 trucks yield important improvements in terms of life-cycle costs, life-cycle emissions, and life-cycle air pollution externalities; buildings and EVs can be considered together in term of energy supply and consumption; and V2H technology can drastically reduce the cost of electricity through storing electricity in the battery during off-peak hours and deplete it during on-peak hours.

2.0 Introduction

Transportation sector is an ever-growing, sophisticated socio-economic terrain that comprises of complex and dynamic interactions between several stakeholders, e.g. consumers, technology providers, and energy/fuel providers, as well as different components such as mobility, e.g. passenger and sport-utility vehicles and public transportation, and logistics, e.g. delivery and long-haul trucks. Hence, the state of transportation sector requires a holistic approach that will enable the relevant stakeholders to tackle with sustainability-related problems emerging from the (mal)functioning of transportation sector in an integrated fashion. This is particularly important when considering the implications of transportation sector with regard to environmental quality and socio-economic well-being of the society. For example, transportation sector consumes 67% of the U.S. total petroleum production, and accounts for 28% of the U.S. total energy consumption and greenhouse gas (GHG) emissions [1]. Additionally, with their relatively lower fuel economy medium-duty vehicles, i.e. delivery trucks (pickup trucks or step vans), contribute considerably to the energy consumption by the transportation sector [2]. Similarly, Class 8 heavy-duty vehicles were responsible for the consumption of 29 billion gallons of fuel (over 15% of the total fuel consumption by highway vehicles) in 2013 despite being only approximately 1% of U.S. on-road vehicles [3]. On the other hand, transit buses helped save 4 billion gallons of gasoline-equivalents of fuel reducing the vehicle-miles travelled by private vehicles despite, of course, also contributing to fuel consumption and GHG and other air pollutant emissions [4]. Doubtlessly, any improvements made in the transportation sector leads to important increase in environmental and socio-economic standards experienced by the society. There are several proposals as to how to bring about such improvements so as to be able to transition to a more sustainable transportation sector globally, and one of the most promising options is the electrification of vehicles.

Not only does electrifying the transportation sector have a potential to pave the way for energy independence, ensure energy security, and substantially improve socio-ecological quality through lesser externality costs to both the environment and the society but also it can provide a source of energy both for the main grid, i.e. Vehicle to Grid (V2G) technology, and residences, i.e. Vehicle to Home (V2H) technology, [5,6]. It is estimated that the total power capacity of U.S. light-duty vehicles is significantly greater (about 24 times) than the whole utility system [7]. Hence, understanding the implications of electrifying the transportation sector requires a holistic view on and an integrated approach to various components pertaining to the overall system. To be able to grasp a bigger picture, several questions asked include, but not limited to, the followings:

- What are the life cycle impacts of EVs under techno-economic uncertainties? And how do EVs perform compared against each other (e.g. passenger EVs, heavy-duty EVs etc.) as well as conventional (internal combustion engine) vehicles (ICVs)?

- What is the advantages and/or disadvantage of EVs compared to ICVs, taking into account the dynamism of the U.S. transportation system arising from the complex interactions among the system variables?
- How do differences in regional driving patterns and electricity grid mixes, and uncertainties inherent to the overall system affect the sustainability performance of vehicle technologies?
- Which states are better-off with the implementation of the EV technologies?
- How likely is the market penetration of EVs going to look like under the circumstances where different states have different power mixes and there are significant uncertainties regarding the techno-economic state of EVs prevail?

For that purpose, this project examines and develops integrated sustainability assessment models that include the socio-economic as well as the environmental implications of an electrified transportation sector. In the initial years, four modeling efforts were developed. These models are an integrated sustainability assessment model of electric vehicles, a stochastic cost simulation model for electric vehicles, an electricity mix sustainability model for EVs and a life cycle impact model of alternative fuel options. In the later project time frame, the four modeling efforts were combined into a dynamic simulation model of EV adoption that include a comprehensive cradle-to-grave life cycle assessment including uncertainties that will capture the social, economic, and environmental impacts of EVs. The models were applied to passenger vehicles, buses, delivery trucks, Class 8 trucks, and the integration of V2H technology.

The project resulted in 19 journal publications that are posted on the EVTC website and respective journals and presentations to 14 technical conferences. The citations for these journal papers are as follows:

Passenger Vehicles

1. Onat, N., Kucukvar, M., and Tatari, O. (2015). “Electric conventional, hybrid, plug-in hybrid or electric vehicles? State-based comparative carbon and energy footprint analysis in the United States.” *Applied Energy, Elsevier,* 150(2015), 36-49, *IF: 5.261*. DOI: 10.1016/j.apenergy.2015.04.001
2. Onat, N., Kucukvar, M., and Tatari, O. (2014). “Towards life cycle sustainability assessment of alternative passenger vehicles.” *Sustainability*, *6*(12), 9305-9342, 2015 IF: 1.343. DOI:10.3390/su6129305
3. Onat, N., Kucukvar, M., Tatari, O., and Zheng, Q. D. (2016). “Combined application of multi-criteria optimization and life-cycle sustainability assessment for optimal allocation of alternative passenger vehicles in the United States.” *Journal of Cleaner Production, Elsevier*, 291-307, *2014 IF: 3.844*. DOI: 10.1016/j.jclepro.2015.09.021
4. Onat, N. C., Gumus, S., Kucukvar, M., and Tatari, O. (2016). “Application of the TOPSIS and intuitionistic fuzzy set approaches for ranking the life cycle

sustainability performance of alternative vehicle technologies." *Sustainable Production and Consumption, Elsevier*, 6(2016), 12-25. DOI: 10.1016/j.spc.2015.12.003

5. Onat, N., Kucukvar, M., Tatari, O., and Egilmez, G. (2016). "Integration of System Dynamics Approach towards Deepening and Broadening the Life Cycle Sustainability Assessment Framework: A Case for Electric Vehicles." *International Journal of Life Cycle Assessment, Springer,* 21(7), 1009-1034. *2014 IF: 4.844*, DOI: 10.1007/s11367-016-1070-4

6. Onat, N.C., Kucukvar, M., and Tatari, O. (2016). "Uncertainty-embedded dynamic life cycle sustainability assessment framework: An ex-ante perspective on the impacts of alternative vehicle options." *Energy, Elsevier,* 715-728, DOI: 10.1016/j.energy.2016.06.129

Market Penetration Models for Electric Vehicles

7. Noori, M., Gardner, S., and Tatari, O. (2015). "Electric vehicle cost, emissions, and water footprint in the United States: Development of a regional optimization model." *Energy, Elsevier*, 89(2015), 610-625, *2014 IF: 4.844*, DOI: 10.1016/j.energy.2015.05.152

8. Noori, M., and Tatari, O. (2016). "Development of an agent-based model for regional market penetration projections of electric vehicles in the United States." *Energy, Elsevier*, 96(2016), 215-230, *2014 IF: 4.844*. DOI: 10.1016/j.energy.2015.12.018

9. Noori, M., Zhao, Y., Onat, N., Gardner, S., and Tatari, O. (2016). "Light-duty electric vehicles to improve the integrity of the electricity grid through vehicle-to-grid technology: Analysis of regional net revenue and emissions savings." *Applied Energy, Elsevier*, 168(2016), 146-158, *2014 IF: 5.261*. DOI: 10.1016/j.apenergy.2016.01.030

Buses

10. Ercan, T., and Tatari, O. (2015). "A hybrid life cycle assessment of public transportation buses with alternative fuel options." *International Journal of Life Cycle Assessment, Springer*, 20(9), 1213-1231, *2014 IF: 3.988*. DOI: 10.1007/s11367-015-0927-2

11. Ercan T., Onat N.C., and Tatari O. (2016). "Investigating Carbon Footprint Reduction Potential of Public Transportation in U.S.: A system Dynamic Approach." *Journal of Cleaner Production, Elsevier,* 133(2016), 1260-1276, *2014 IF: 3.844.* DOI: 10.1016/j.jclepro.2016.06.051

12. Ercan, T., Yang, Z., Tatari, O., and Pazour, J. (2015). "Optimization of transit bus fleet's life cycle assessment impacts with alternative fuel options." *Energy, Elsevier*, 2015, 323-334, *2014 IF: 4.844*. DOI: 10.1016/j.energy.2015.09.018

13. Ercan, T., Noori, M., Zhao, Y., and Tatari, O. (2016). "On the front lines of a sustainable transportation fleet: Applications of vehicle-to-grid technology for transit and school buses." *Energies,* 9(4), 230, 1-22, 2014 IF: 2.077. DOI: 10.3390/en9040230

Vehicle to Grid Technology and Trucks

14. Zhao, Y., Onat, N., and Tatari, O. (2016). "Comprehensive Life Cycle Assessment of Electric Delivery Truck." *Transportation Research Part D: Transport and Environment, Elsevier*, 47(2016), 195-207, *2014 IF: 1.937*. DOI: 10.1016/j.trd.2016.05.014
15. Zhao, Y., Ercan, T., and Tatari, O. (2016). "Life Cycle Based Multi-Criteria Optimization for Optimal Allocation of Commercial Delivery Truck Fleet in the United States." *Sustainable Production and Consumption, Elsevier*. DOI: 10.1016/j.spc.2016.04.003
16. Zhao, Y., and Tatari, O. (2015). "A hybrid life cycle assessment of the vehicle-to-grid application in light duty commercial fleet." *Energy, Elsevier,* 1277-1286, *2014 IF: 4.844*. DOI: 10.1016/j.energy.2015.10.019
17. Zhao, Y., Noori, M., and Tatari, O. (2016). "Vehicle to Grid regulation services of electric delivery trucks: Economic and environmental benefit analysis." *Applied Energy, Elsevier,* 170(2016), 161-175, *2014 IF: 5.261*. DOI: 10.1016/j.apenergy.2016.02.097
18. Sen, B., Ercan, T., and Tatari, O. (2017). "Does a battery-electric truck make a difference? – Life cycle emissions, costs, and externality analysis of alternative fuel-powered Class 8 heavy-duty trucks in the United States." *Journal of Cleaner Production, Elsevier,* 141, 110-121, 2015 IF: 4.959. DOI: 10.1016/j.jclepro.2016.09.046

Vehicle to Home Technology

19. Alirezaei, M., Noori, M., and Tatari, O. (2016). "Getting to net zero energy building: investigating the role of vehicle to home technology." *Energy and Buildings, Elsevier.* 2014 IF: 2.884. DOI: 10.1016/j.enbuild.2016.08.044

The list of conference presentations are as follows:

1. Ercan, T., Onat, N., and Tatari, O. (2016). "Sustainable Transportation Assessment for Mode Shift of Commuters: An Integration of System Dynamics and Discrete Event Choice Modeling Approaches" The International Symposium on Sustainable Systems and Technology (ISSST), Phoenix, Arizona, USA.
2. Onat, N., Kucukvar, M., Tatari, O., and Egilmez G. (2016). "Dynamic Sustainability Assessment of Electric Vehicles: A System Dynamics Approach" The Institute for Operations Research and the Management Sciences (INFORMS) International Conference, June 12-15, 2016, Waikoloa Village, Hawaii, USA.
3. Onat, N., Kucukvar, M., and Tatari, O., and Egilmez G. (2016). "Systems Thinking in Life Cycle Sustainability Assessment: The Case for Alternative Vehicle Options" 5th International Social LCA Conference Harvard, June 13-15, 2016, Cambridge, USA.
4. Onat, N., Kucukvar M., and Tatari, O., and Egilmez, G. (2016). "From Conceptual to Operational Life Cycle Sustainability Assessment Framework: A Case for U.S.

Transportation" The International Symposium on Sustainable Systems and Technology (ISSST), Phoenix, Arizona, USA.

5. Noori, M., and Tatari, O. (2016). "Future Market Share of Electric Vehicles in United States", International Conference on Sustainable Design, Engineering and Construction, Tempe, AZ.
6. Alirezaei, M., Noori, M., and Tatari, O. (2016). "Towards Zero Net Energy Buildings: A Techno- Ecological Modeling Approach to Vehicle to Home Technology" International Conference on Sustainable Design, Engineering and Construction, Tempe, AZ.
7. Noori, M., Sen, B., and Tatari, O. (2016) "The Impact of United States Corporate Average Fuel Economy (CAFE) Standard and Vehicle to Grid (V2G) Service on Market Share of Electric Vehicles:Â An Agent-Based Modeling Approach." International Symposium for Sustainable Systems and Technology Phoenix, AZ.
8. Ercan, T., Noori, M., Zhao, Y., and Tatari, O. (2016). "Understanding the Future of Electricity Grid Integrity: Applications of Vehicle-To-Grid Technology in Transit and School Buses". International Symposium for Sustainable Systems and Technology, Phoenix, AZ.
9. Alirezaei, M., Noori, M., and Tatari, O. (2016) "Investigation of Alternative Fuel Vehicle's Role in Achieving a Net Zero Energy Building." International Symposium for Sustainable Systems and Technology, Phoenix, AZ.
10. Zhao, Y., Noori, M., and Tatari, O. (2016). "Vehicle to Grid Regulation Services of Electric Delivery Trucks: Economic and Environmental Benefit Analysis." International Symposium for Sustainable Systems and Technology, Phoenix, AZ.
11. Onat, N.C., Kucukvar, M., Tatari, O., and Egilmez, G. (2016). "Dynamic Life Cycle Sustainability Assessment Framework for Electric Vehicles in the U.S." Transportation Research Board (TRB), 95th Annual Meeting, January 10-14, 2016, Washington, D.C, USA.
12. Onat N.C., Kucukvar, M., and Tatari, O. (2015). "System Dynamics Approach to Analyze the Environmental, Social, and Economic Sustainability of Transportation Systems." Big Data Analytic and Education Conference, Europe, July 30-31, Istanbul, Turkey.
13. Onat, N.C., Kucukvar, M., Tatari, O. (2014). "Energy and Carbon Footprints of Alternative Vehicle Options: Inclusion of State-specific Variations." INFORMS Annual Meeting, November 9-12, 2014, San Francisco, USA.
14. Kucukvar, M., Onat, N.C., and Tatari O. (2014). "Water footprint of alternative vehicle technologies in the United States." INFORMS Annual Meeting, November 9-12, 2014, San Francisco, USA.

In this final report, we include the summary of the critical assessment models that are developed as well as the results of the studies undertaken throughout the project.

3.0 State-based Comparative Carbon and Energy Footprint Analysis of Electric Vehicles

3.1 Introduction

Analyses of alternative vehicle technologies, energy sources, transportation fuels, and more efficient ways to use resources have become increasingly popular topics in the literature and industry.[1] Among the various vehicle alternatives, electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) are often considered as better options than internal combustion vehicles (ICVs) in terms of GHG emissions and energy consumption. In reality, however, making such a decision among these vehicle options is not so straightforward due to temporal and spatial variations, such as regional driving profiles and the sources of the electricity used. For example, the electricity used to power EVs or PHEVs might come from an energy source that is more energy and carbon intensive than petroleum. PHEVs use an on-board battery to travel in electric mode and consume gasoline when the battery charge is depleted. Therefore, the all-electric range (AER), or the range for which a PHEV can operate in electric mode, is one of the most important parameters to determine its energy use and GHG emission rate. In addition to the effects of the AER, the length of vehicle trips determines the fraction of total vehicle travel that is powered by either gasoline or electricity. According to the National Household Travel Survey (NHTS) in 2009, vehicles that traveled less than 48 kilometers comprised 63% of the daily passenger vehicle miles travelled (VMT) in the U.S [8]. Therefore, a significant amount of daily travel can be powered by electricity, and using PHEVs can reduce the impacts of gasoline use. On the other hand, this percentage might be different depending on the driving characteristics of a specific region. Hence, the inclusion of these spatial variations is crucial when deciding which vehicle technology is the most suitable for the associated region in terms of GHG emissions and energy use.

This model differs from previous LCA studies by making comparisons across 50 states, including their representative average and marginal electricity generation mixes and regional driving patterns. Additionally, GHG emissions and energy consumption during vehicle and battery manufacturing and vehicle maintenance are also included in the scope of this study. The objectives of this model development are as follows:

1. to investigate the impacts of regional driving patterns and electricity generation mix scenarios (marginal and average) on the energy use and GHG emissions of alternative passenger vehicle technologies currently available in the market,
2. to highlight how these spatial and temporal variations affect the carbon footprint and energy consumption performances of these vehicles,
3. to demonstrate the relative impacts of battery and vehicle manufacturing on GHG emissions and energy consumption within the total life cycle of vehicles,

[1] The contents of this section were partly published in Onat, N., Kucukvar, M., and Tatari, O. (2015). "Electric conventional, hybrid, plug-in hybrid or electric vehicles? State-based comparative carbon and energy footprint analysis in the United States." *Applied Energy, Elsevier,* 150(2015), 36-49, *IF: 5.261*. DOI: 10.1016/j.apenergy.2015.04.001

4. to investigate potential GHG emission reductions and energy savings considering the potential market size and market penetration scenarios.

3.2 Methodology

LCA is a widely accepted method to quantify the environmental impacts of products or processes throughout the production, use, and end-of-life phases [9]. Traditionally, there are two main LCA methodologies in the literature: process based LCA (P-LCA) and input-output based LCA (IO-LCA). On the other hand, sometimes a combination of these two is found as more powerful way of conducting a LCA; in the literature, this is known as hybrid LCA [10–14]. In this work, P-LCA, hybrid LCA, and IO-LCA were utilized depending on the associated content. The production and maintenance of each of these vehicles, as well as the upstream emissions from the gasoline supply chain, were analyzed with Economic Input-Output Life Cycle Assessment model (EIO-LCA) [15], while the electric power supply and battery manufacturing phase were analyzed with P-LCA. Data used is collected from publicly available sources such as the U.S. Life Cycle Inventory (LCI) database [16], the GREET vehicle cycle model [17], the eGRID database [18], and the National Household Travel Survey (NHTS) [8]. Figure 3.1 shows the system boundary of the analysis.

Five passenger vehicle types representing different vehicle technologies have been comparatively evaluated based on their energy consumption and GHG emissions for 50 states in the U.S. All vehicles are ranked based on their GHG emissions and energy consumption for each state. To account for variability in the electricity generation profiles across the 50 states, three different electricity generation scenarios are considered:

1) State-based average electricity generation mix: This scenario is based on average state-level electricity power generation profiles in 2009, with derived data from the most recent eGRID database [18].

2) State-based marginal electricity generation mix: This scenario uses estimated state-based marginal electricity mix profiles in 2020, with derived data from the National Oak Ridge Laboratory's estimations [19] and from the literature [20].

3) 100% solar powered charging stations: This is a futuristic scenario where there are solar charging stations and rooftop solar panels to charge electric vehicles; currently these technologies are more commonly used in residential and commercial buildings.

The vehicle technologies considered are ICVs, HEVs, PHEVs, and EVs. The Toyota Corolla (ICV), Toyota Prius (HEV), plug-in Toyota Prius (PHEV-AER18), Chevrolet Volt (PHEV-AER62), and Nissan Leaf (EV) have been selected to represent each vehicle technology. The useful lifetime for all vehicles is assumed to be 240,000 kilometers (150,000 miles) of vehicle travel; the functional unit is 1 kilometer (km) of vehicle travel. GHG emissions are reported in grams CO_2 equivalents (g CO2-eq.) based on 100 years of time horizon Global Warming Potential values recommended by the Intergovernmental Panel on Climate Change [21].

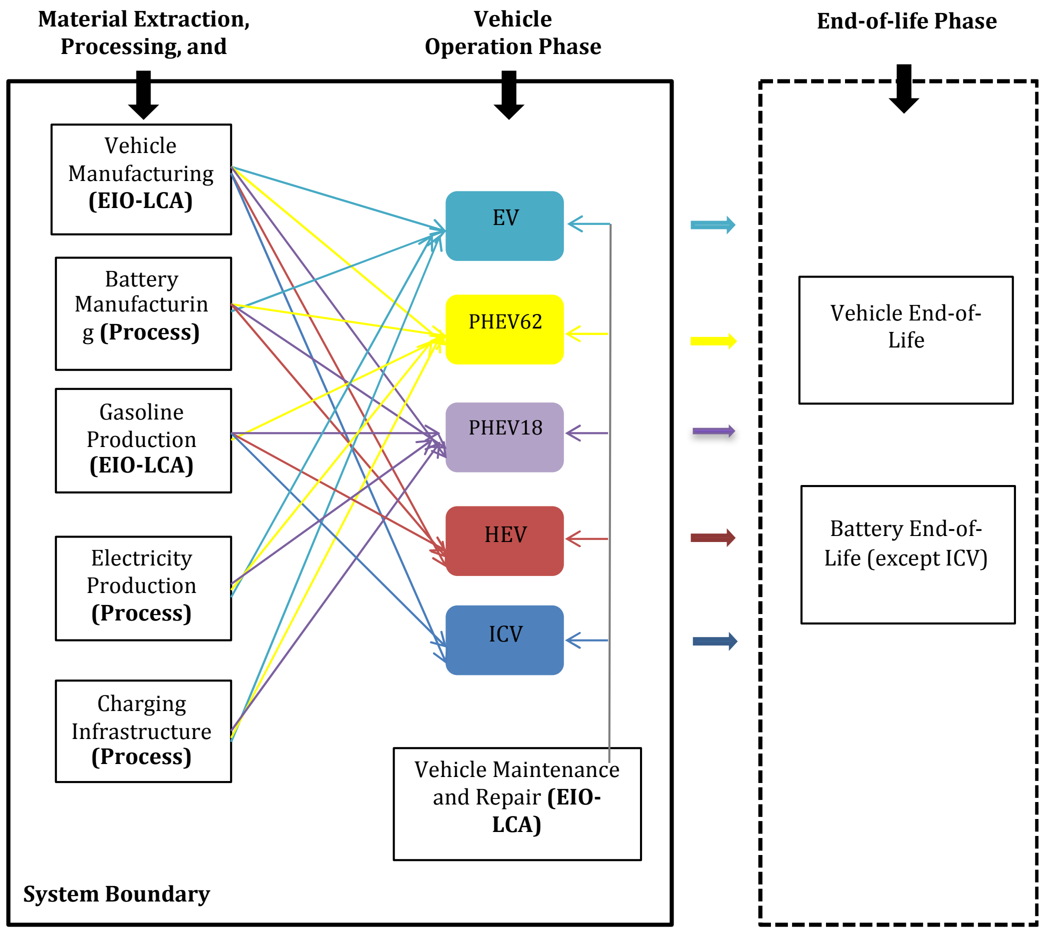


Figure 3.1 System Boundary of the Analysis

3.2.1 Vehicle Production

Energy consumption and GHG emissions from automobile manufacturing are calculated for each vehicle type via the EIO-LCA model [15], which consists of identical sectors and their interactions, thereby forming the entire U.S. economy. In the EIO-LCA model, there is a sector named Automobile Manufacturing (NAICS 336111) where the producer price of the vehicle is an input to calculate a set of environmental impacts, including GHG emissions and energy consumption. Additionally, the impacts from material production are separately calculated with the EIO-LCA model after determining the material composition of each vehicle. The material composition of each vehicle type is estimated with the GREET 2.7 vehicle cycle model by using their real weights. In the GREET model, the material composition of each vehicle part is calculated using the total weight of each of the vehicles. After calculating the weight of each material, their respective costs are determined and entered as an input for the relevant sector(s) in the EIO-LCA model in order to calculate impacts from vehicle material production separately. When calculating vehicle manufacturing impacts, battery manufacturing impacts are excluded because the price premiums for HEVs, PHEVs, and EVs over conventional vehicles mainly stem from the additional battery and electronics [22]. Battery production impacts are calculated with the P-LCA model. Impacts from vehicle and battery production are assumed to be independent of regional variations since a majority of the vehicles are manufactured in specific places and driven throughout the entire country. End-of-life GHG emissions and energy consumption have been found to be quite small compared to other life cycle phases and are therefore neglected in this analysis [23]. However, as fuel efficiency standards increase, the relative contribution of manufacturing-related impacts can increase. It is expected that automobile manufacturers will probably use more energy intensive materials such as aluminum, which can increase the GHG emissions and energy consumption associated with the vehicle production phase, and the recycling of these materials may be more important [24–26].

3.2.2 Battery Production

The choice of battery for the vehicle technologies depends on cost, lifetime, performance characteristics (such as depth of discharge), and behavior under high and low temperature, energy density, and environmental impacts. EVs and PHEVs typically use lithium ion (Li-ion) batteries, while nickel–metal hydride batteries (Ni-MH) are generally preferred to power HEVs due to their relatively lower costs [27]. Major advantages of Li-ion batteries is that they provide a high power and energy density, and that they require little maintenance and there is no scheduled cycling to prolong the battery's life, in addition to small self-discharge and no memory effects [28]. Because Ni-MH batteries have lower energy densities (Wh/kg), they can increase the weight of the vehicle considerably, which is not desirable since increased weight generally results in loss of fuel efficiency. Li-ion batteries are expected to be the most common battery technology in EVs in the near future due to their higher energy density and decreasing cost [29].

The HEV in our analysis uses a Ni-MH battery, while others (PHEVs and EVs) have Li-ion batteries. The GREET 2.7 vehicle cycle model was used to calculate GHG emissions and energy use from battery production. The weights of the batteries are determined from equations in the GREET 2.7 model using peak battery power and battery energy values, which were obtained from each manufacturer's website. The weights of the batteries calculated from the GREET model were also compared with those published by vehicle manufacturers, and the results were quite similar. According to the analysis results, GHG emissions from li-ion batteries were 5.68, 5.59, and 1.98 gCO_2-eq./km for the PHEV-AER62, the EV, and the PHEV-AER18, respectively. In the literature, the GHG impacts from li-ion battery production range between 1 to 12 gCO_2-eq./km. One of the key sources of variability in the results relates to battery lifetime assumptions. The lifetime is generally defined as a certain amount of charge-discharge cycles, but there is no certain agreement regarding the unit of lifetime of batteries because of the uncertainties in use patterns and consumer behavior, which can directly affect the charge-discharge cycles [29]. Another important source of variability is that the studies compared are within the last 15 years, whereas battery technology has significantly improved in recent years. Therefore, we selected more recent studies to make better comparisons between the results. In this analysis, the battery lifetimes are assumed to be same as the vehicle lifetimes, meaning that it is assumed that the batteries are never replaced during the vehicles' operation phase. If the battery is replaced in the future, the impacts from battery production may not necessarily be doubled because the battery industry is improving rapidly, and so it is possible the intensities of the energy requirements and GHG emissions of battery production may be lower than they are today. Impacts from battery production are assumed to be independent of regional variations so as to maintain consistency with the same assumptions made for the vehicle production phase.

3.2.3 Vehicle operation phase

The use phase is the most carbon and energy intensive phase in the life cycles of all of the analyzed vehicles [22,30,31]. The vehicles compared in this analysis are either powered with gasoline or electricity. Hence, analyzing the impacts of electricity generation, gasoline combustion, and the upstream impacts of each energy source are critical. Additionally, the GHG emissions and energy consumption rates associated with vehicle maintenance and repair (M&R) are also quantified; these impacts are generally smaller than those of the fuel supply and vehicle operation. Impacts stemming from M&R of vehicles are calculated with the EIO-LCA tool with purchases from NAICS sector 81111 (Automotive Repair and Maintenance). The costs associated with M&R are obtained from the U.S. Transportation Energy Data book [32]. The M&R cost for an ICV was approximately 5 U.S. cents per km in 2012; this cost is converted into 2002 dollars using consumer price indexes. The total lifetime M&R cost for an ICV is calculated as $8,970. The M&R cost for an EV is approximately 65-80% of that of an ICV due to fewer components and moving parts, as well as lower maintenance requirements for electric motors in EVs [33,34]. In this analysis, the M&R costs of the EV are assumed to be 70% of those of the ICV, while M&R costs of the PHEVs are assumed to be 80% of the ICV, and the M&R costs for the HEV are assumed to be same as those of the ICV.

The upstream emissions and energy use associated with the gasoline supply chain are also calculated with the EIO-LCA tool using NAICS sector 324110 (Petroleum Refineries). The producer price for a liter (L) of gasoline was $0.76 in 2002, after deducting taxes and profits [35]. Upstream GHG emissions to produce 1 L of gasoline are found to be 0.56 kgCO_2-eq., whereas the upstream energy consumption is calculated as 6.37 MJ per L of gasoline. Direct tailpipe emissions resulting from burning 1 L of gasoline are found to be 2.26 kg kgCO_2-eq. [36]. The GHG emissions and energy consumption for the ICV, the HEV, and the gasoline operation mode of the PHEV are calculated by determining the energy requirements of each vehicle per km of vehicle travel, while the energy delivered to the wheels per L of gasoline is 8.9 kWh [37]. Fuel economy labels reported by the EPA are used to calculate energy consumption and GHG emissions from the vehicle operation phase in gasoline mode. The major sources of variability in GHG emissions and energy consumption in the operation phase of vehicles are electricity generation mixes and regional driving patterns.

Although electricity use in EVs and PHEVs does not cause tailpipe emissions, the electricity generation source(s) used will play a crucial role in determining the resulting GHG emissions and energy consumption from operating vehicles in electric mode. The GHG emissions and energy consumption from the electricity generation sector are calculated for each state using the electricity generation mix profiles in 2009 published by the eGRID database [18], which also provides the GHG emissions for each state. However, upstream emissions (such as those resulting from extraction of raw materials, processing, and transportation of fuels for power generation) were not included in the eGRID database. Therefore, both upstream and onsite emissions associated with each power generation method based on different resources (such as coal, natural gas, solar, hydropower, etc.) are calculated using data from the U.S. LCI database [16]. The U.S. average GHG emission factor is calculated as 663.4 gCO_2-eq/kWh using the 2009 U.S. average power generation mix as provided by the eGRID database, as well as the emission factors data from the U.S LCI database. State-based emissions are calculated with the same methodology and data sources. On the other hand, it was assumed that the existing electricity generation capacity in the U.S. could support additional energy demand from the use of PHEVs and EVs for up to 50% of conversion of the U.S. light duty automobile fleet to these vehicle types [26,38,39]. For the third scenario, which proposes widespread use of solar charging stations, upstream emissions and energy consumption to construct the required infrastructure for solar charging stations are also included [40]. The LCA inventory and power generation capacity of the solar charging station is obtained from literature [40,41]. This solar charging station was in Uppsala, Sweden, where average annual sun-hours are approximately 2.5 hours a day. The total lifetime electric power generation capacity of this particular charging station is 76 MWh. To estimate its potential life time electric power generation capacity in each state, state-specific sun-hour data from the U.S. National Renewable Energy Laboratory (NREL) is used [42]. The total lifetime GHG emissions and energy consumption of the solar charging station is divided by state-specific potential electric power generation capacity for each state to obtain state-specific GHG emissions and energy consumption per kWh of solar electric power generation.

Since the GHG intensity of electricity generation is highly dependent on the energy source, the generation mix of the incremental electricity demand (the marginal electricity) from EVs and PHEVs should be also taken into account. The inclusion of marginal electricity to calculate associated GHG emission intensity has already been suggested by many researchers [43–47]. Marginal electricity demand is usually provided through fossil fuels, which have significantly high GHG intensities and therefore cause higher operation phase emissions for EVs and PHEVs. This is because the low-GHG-intensity power generation sources (nuclear, solar, wind, etc.) are generally 100% in use, and so any remaining fluctuating electricity demand must be met using nonrenewable energy generation sources (such as natural gas, coal, and petroleum) due to their relatively lower short-run marginal costs [30]. The utilized production capacity of renewable energy sources are generally not restricted or driven by the change in electricity demand, but rather they are influenced by the availability of sunlight for solar panels, wind for wind turbines, weather conditions for hydropower, security reasons for nuclear power plants, etc. [45]. The marginal electricity mix profiles are obtained from a study conducted by Hadley and Tsvetkova at the Oak Ridge National Laboratory (ORNL) [19], in which they calculated marginal electricity mix profiles for 13 different regions as defined by the North American Electricity Reliability Corporation (NERC) and then estimated marginal electricity mix profiles for 2020 and 2030. Their estimation is based on 6 different charging scenarios; the base case (no additional load on grid), and different combinations of two charging times and three charging rate scenarios. They assumed that 25% of the existing fleet is replaced by PHEVs between 2020 and 2030. Sandy [20] simplified the analysis conducted by Oak Ridge Laboratory and averaged the marginal grid results of the 6 scenarios. Additionally, Sandy calculated marginal electricity mix profiles for Alaska and Hawaii, which were not included in the ORNL's study. Marginal electricity profiles for each region are derived from Sandy's study. Considering that these regions are not bound by state borders, a state can be within multiple regions. In these cases, the state-based marginal emissions are calculated for each region associated with these states, and multiple results are provided. In addition to the inclusion of marginal electricity mix profiles, electricity transmission loss factors for each region are also taken into consideration for both scenarios.

Another important source of variability among the states' data is driving patterns. This refers to actual daily vehicle km travel patterns. Since PHEVs use both gasoline and electricity, determining the portions of total km of vehicle travel in each mode is crucial for calculating their impacts. The percentage of the distance traveled in electric mode is represented as the utility factor (UF), which depends on the AERs of the PHEVs in that a longer AER will provide a greater share of kilometers traveled in electric mode and thus leads to a higher UF. A cumulative distribution of actual daily vehicle km travelled was constructed to calculate state-based UFs. This distribution indicates the percentage of cumulative daily vehicle kilometers travelled that is less than a given distance per day. For instance, 35% of the vehicle kilometers traveled are less than 18 km in the state of Florida, which means the utility factor of the PHEV-AER18 (Prius) is 0.35. It should be noted that the PHEVs are assumed to be fully charged once per day.

3.3 Results and Discussions

The results for the U.S. average case (on a national scale) are given as a base scenario for comparison with Scenarios 1, 2, and 3. Also, the contribution of each life cycle phase is calculated. According to the national-scale results, the PHEV18 reduces the GHG emissions by 29% compared to the ICV, while the GHG emissions for the EV, the HEV, and the PHEV18 are relatively similar. Emissions from vehicle and material manufacturing range from 11% to 23% of total life cycle emissions, and these emissions are highest for the EV. GHG emissions from battery manufacturing are found to be insignificant compared to total life cycle emissions, although these emissions were highest for production of li-ion batteries for the EV and the PHEV62. The operation phase is the most dominant phase for both GHG emissions and energy consumption. Figure 3.2 shows the total life cycle impacts and contribution of each phase per vehicle kilometer traveled. Comparing the results found for the LCA's of alternative vehicles is not an easy task, due to variations in the assumptions made for critical parameters such as electricity generation mix, driving patterns, vehicle specifications, and useful lifetime.

In the literature, e GHG emissions of the operation phase of EVs range from 0.9 gCO_2-eqv/km (hydroelectricity) to 231 gCO_2-eqv/km (coal electricity). For more information about the comparison of the results with the literature, please see the following review studies [29,48].

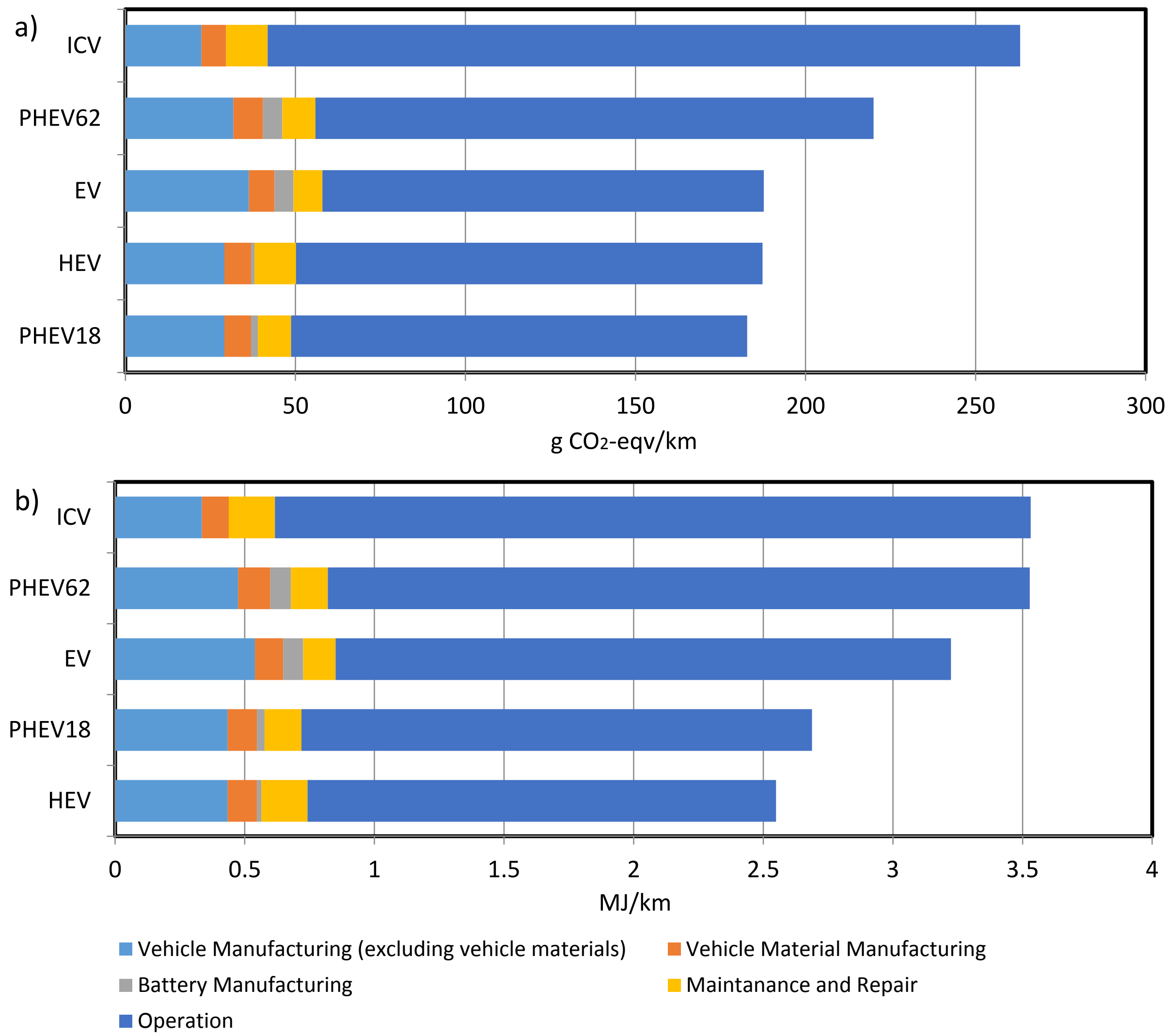
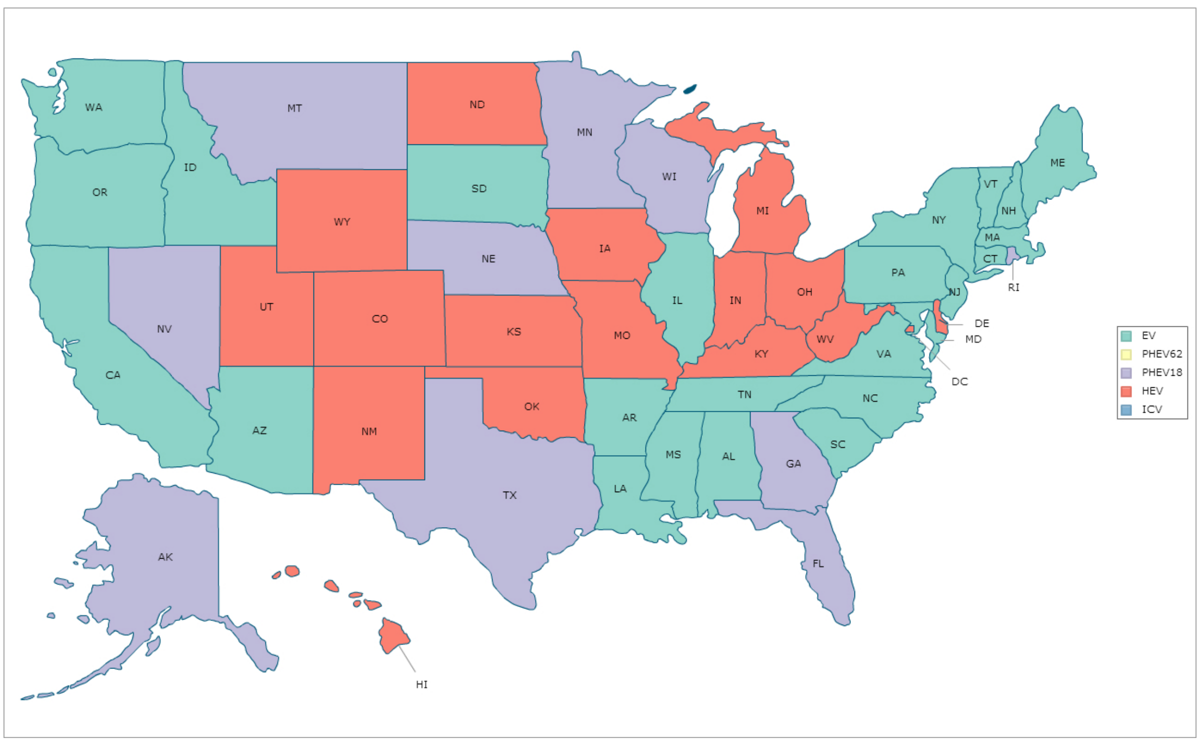


Figure 3.2 Life cycle impacts of each vehicle type; a) GHG emissions, b) Energy consumption

From an energy-consumption perspective, the HEV is found to be the best option, as the EV and the longer-range PHEVs were all found to be less energy efficient. This might be due to energy efficiency losses during the transmission, distribution, and generation of electric power. Based on 2009 electricity generation mix in the U.S., 2.37 kWh (Feedstock+fuel) of energy is required per kWh of electricity generation [17,18]. The contributions of each phase to total life cycle impacts are similar for GHG emissions as well. Since the energy consumption and GHG emission impacts are both highly dependent on the electricity generation mix used, the results for each state will vary significantly.

3.3.1 State-based Average Electricity Generation Mix Scenario

When state-specific average electricity generation mixes and driving patterns are taken into account, the results for each state are quite different compared to the national-scale U.S. average results. Figure 3.3 shows the best vehicle option for each state in terms of GHG emission and energy consumption. According to the results of Scenario 1, EVs are the least carbon-intensive vehicle option in 24 states, which accounts for a market size of 38% of the number of registered LDVs in the U.S. In other words, the total number of vehicles can be replaced by EV accounts of 38% of the LDVs in the U.S. Considering that the range of the EV analyzed in this work is 135 km, drivers who must drive longer distances are not within the targeted market by the EV. On the other hand, 10 states (with 16% of the total number of LDVs) favor the PHEV18 based on spatial characteristics from a GHG emissions perspective. HEVs are better options for 17 states (with 21% of the total number of automobiles). The PHEV62 and the ICV were not ranked as a best option in any state.



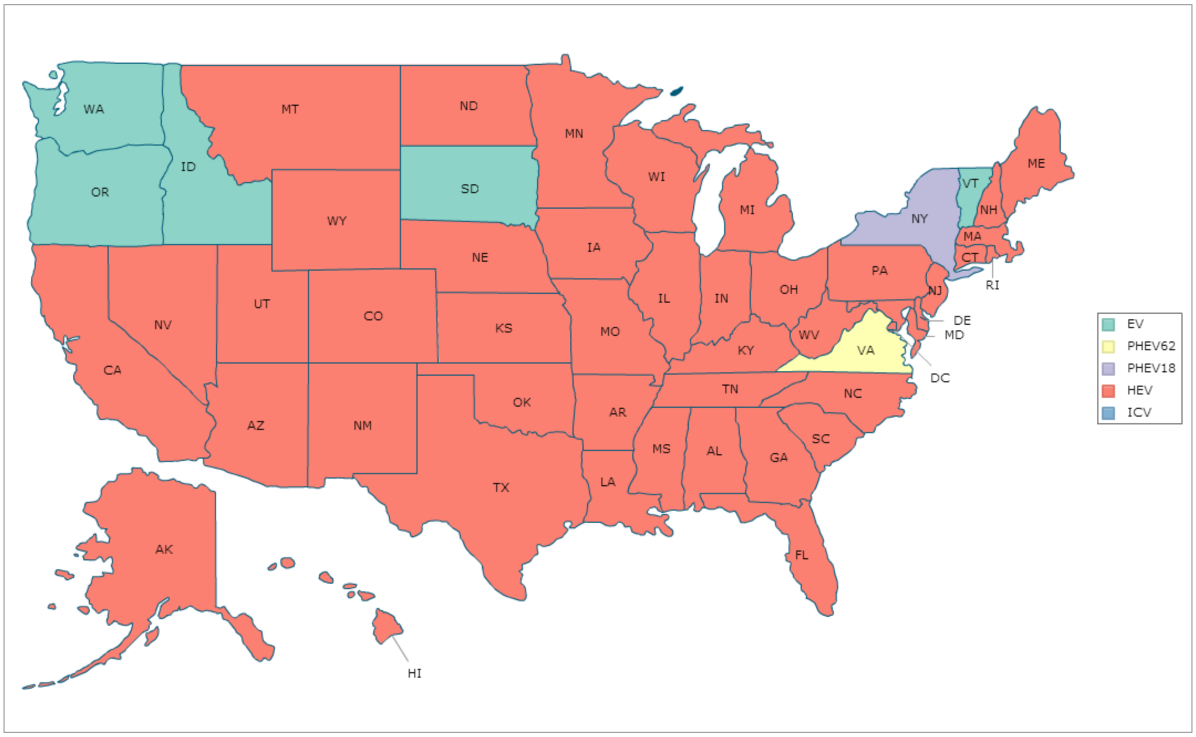


Figure 3.3 State level vehicle preference according to scenario 1; a) GHG emissions, b) Energy consumption.

Energy consumption results are relatively homogeneous compared to GHG emission results. HEVs are ranked as the best option in 45 states (61% of the total number of LDVs), while EVs were found to be the better option in only 5 states. All other states found PHEV18s to be the best option in terms of energy consumption.

3.3.2 State-based Marginal Electricity Generation Mix Scenario

According to the marginal electricity generation mix scenario, the HEV is the least GHG intensive option in most of the states. The state-level preference results based on GHG emissions for Scenario 2 are presented in Figure 3.4. Although Scenario 2 is calculated based on NERC regions that are not bounded by state borders, those states that lie within multiple regions indicate the same result. The results for the states that fall into more than one regions are given for each region.

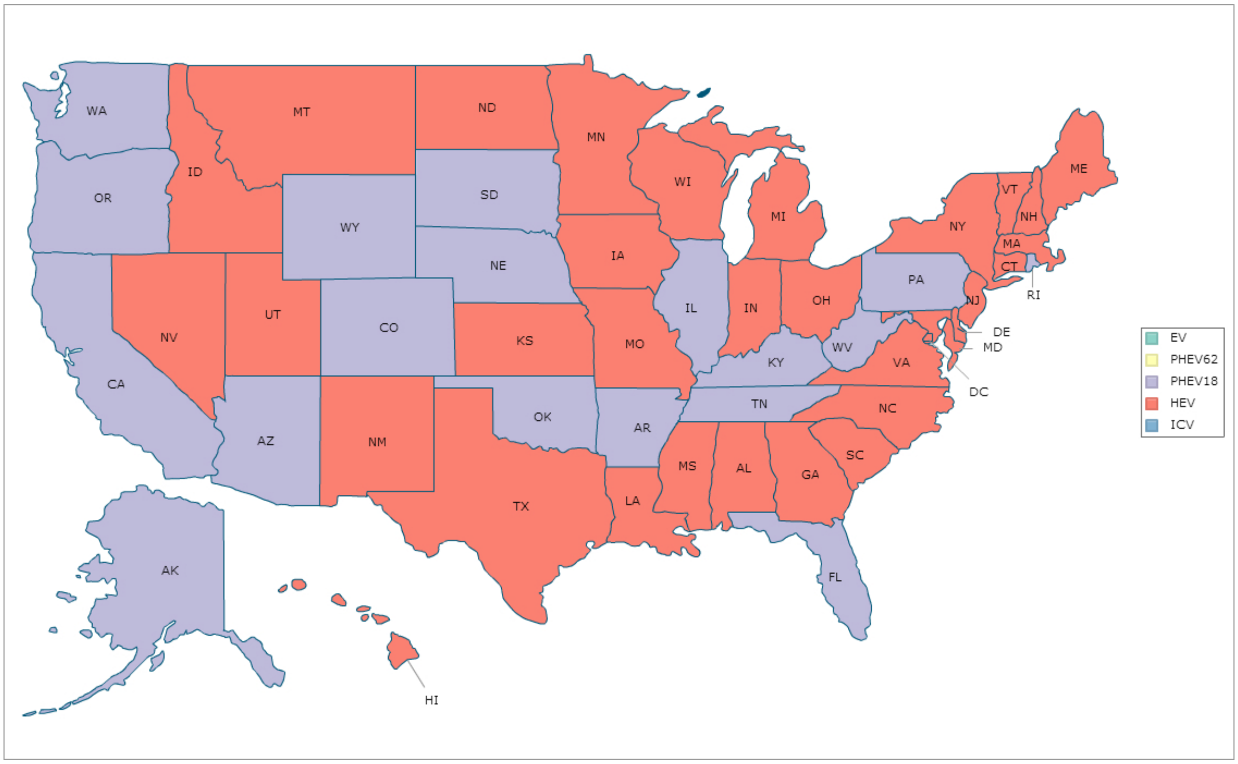


Figure 3.4 State level vehicle preference in the terms of GHG emissions for scenario 2.

According to Scenario 2, only two vehicle types are selected based on state-specific GHG emissions. There is a significant change in the GHG emission results of EVs compared to the previous scenario. EVs are not ranked as the best vehicle option in any state. HEVs are ranked as the best option in 33 states (39% of the total number of LDVs), while PHEV18s are selected as the best option for 18 states (28% of the total number of LDVs). Like with EVs, PHEV62s and ICVs are not favored by any of the states.

HEVs are found to be the best option based on the energy consumption performance of each vehicle type in every state. Therefore, the state-specific results were not shown in a separate map. The second best option is PHEV18s for all of the states as well. The rest of the ranking order (3rd, 4th, and 5th) may differ based on state-specific marginal electricity mixes and driving pattern characteristics.

3.3.3 Solar Energy Scenario

As scenario 3 proposes the widespread use of solar power to charge EVs, the GHG intensity and energy requirements to produce electricity are both significantly reduced. According to scenario 3, EVs are ranked as the best vehicle technology option in every state for both GHG emissions and energy consumption impacts. Therefore, state-specific results are not presented in separate maps. Utilization of solar power provided an electricity source with very low carbon intensity (26-58 gCO2-eq / kWh) and quite low energy requirements (0.04-0.09 kWh/kWh) to generate electricity. Additionally, the transmission and distribution losses are also saved compared to previous scenarios. The total life cycle GHG emissions and energy consumption per kilometer traveled are calculated for EVs ranges between 101-110 gCO2-eq. and 2-3 MJ, respectively. According to scenario 3, the GHG emission reductions that can be achieved with EVs range between 73%-75%, while the energy consumption reduction is calculated as 54 to 57% compared to ICVs. These are the highest reduction rates compared to other scenarios.

3.3.4 Sensitivity of Key Parameters

Sensitivity analysis is conducted to account for variability in GHG energy emission factors, energy consumption rates, and UFs. Sensitivity analysis is conducted by varying one input variable while keeping other values at their baseline. In Figures 3.5 and 3.6, the U.S. national average values are used as a baseline, which are based on average electricity generation mix scenario. LCA impacts of vehicle options are presented as a function of GHG and energy intensity in Figure 3.5. For the purpose of the sensitivity analysis, the UF values for the PHEV18 and the PHEV62 are assumed to be constant and equivalent to U.S. average values. As can be seen from the figure, the PHEV62 has a higher GHG emission rate than the ICV when the GHG intensity of the electricity supply is above 950 gCO2-eqv/kWh. Any GHG emission factor below 600 gCO2-eqv/kWh makes EVs the least carbon intensive option. From an energy consumption perspective, per km energy consumption of EVs are the least when the energy required to generate 1 kWh of electricity is less than 1.25 kWh. Any power generation scenario above 1.75 kWh/kWh of energy consumption makes the HEV the most energy efficient option, while the PHEV18 is the least energy intensive option in the range between 1.25 and 175 kWh/kWh.

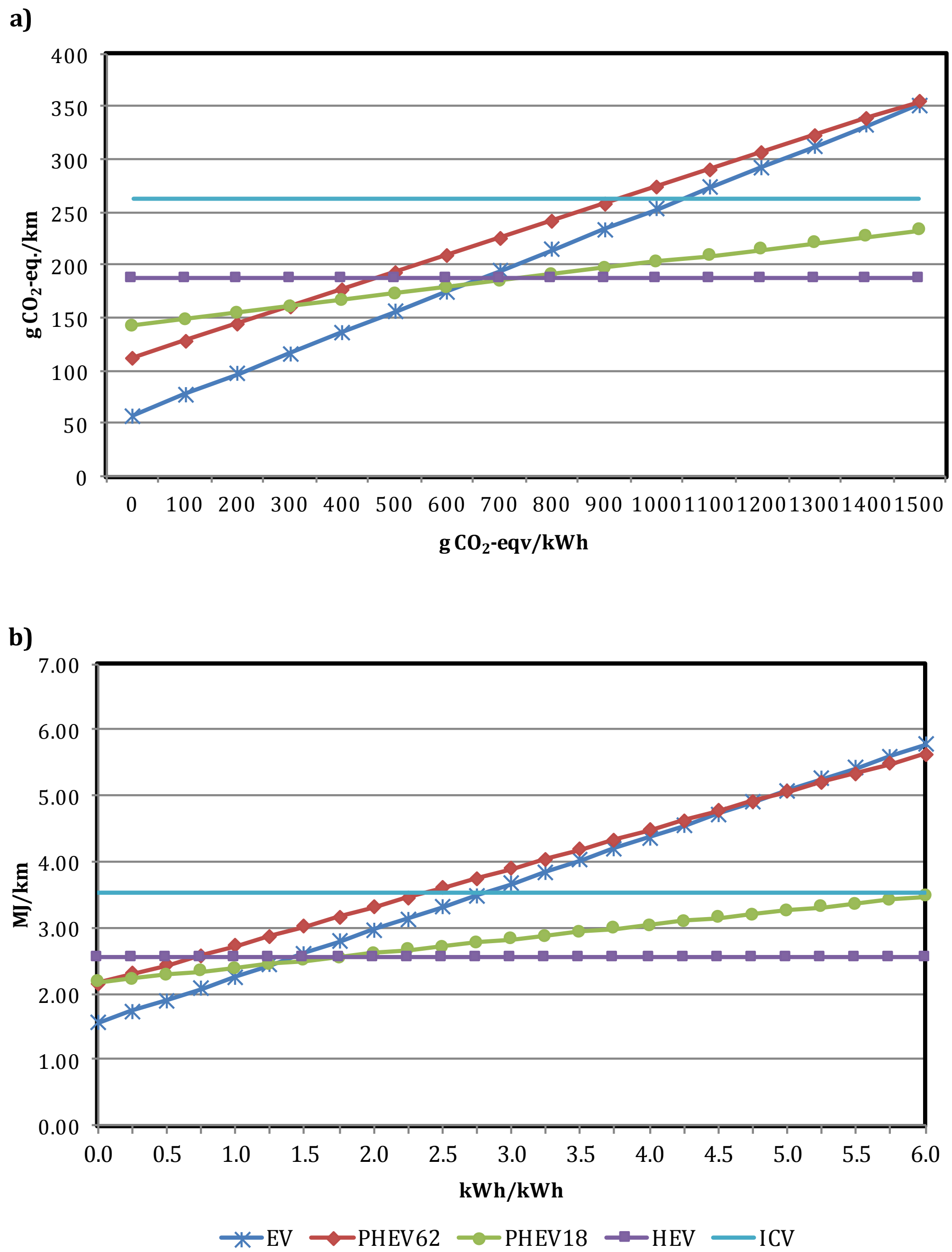


Figure 3.5 LCA impacts as a function of GHG and energy intensity, a) GHG emissions, b) Energy consumption per kilometer vehicle traveled.

The sensitivity of UFs are also important when considering the performance of PHEVs under different charging and driving scenarios. In this regard, GHG emissions and energy consumption of the vehicle options are also analyzed as a function of various UFs ranging from 0 to 1, and the results are presented in Figure 3.6. The GHG emission intensity and energy consumption factors are the U.S. average values and kept constant for the purpose of the sensitivity analysis. The variation starts from UF=0, meaning that PHEVs are in full gasoline mode, to UF=1.00, meaning that PHEVs are operating in full electric mode. If a PHEV charged twice a day, its utility factor would be doubled, assuming that it is fully charged each time. Although the applied methodology to estimate UFs are very common in literature [22,46,49–53] and used by EPA fuel economy labeling, it has some uncertainties related to driver characteristics and mixed adoption. This is, of course, a fleet-wide estimate. The caution from EPA that “your mileage may vary” should be highlighted here, if your driving style and especially your daily driving distances can change the fuel economy significantly. To account this variability, these sensitivity figures can be helpful to assess performance of PHEVs under different circumstances. As can be seen from Figure 3.6, life cycle GHG emissions of the PHEV62 is more sensitive under varying UFs due to its less efficient gasoline mode then the PHEV18’s. The LCA carbon footprint of the EV and HEV are almost the same and follow a constant trend. The UFs affect only LCA impacts of PHEVs. Energy consumption per vehicle kilometer travel for PHEVs has a different trend and PHEV62 consumes more energy than PHEV18 in all of the cases. It can be also concluded that the shift from gasoline consumption to electricity consumption increases the energy intensity of the vehicle operation. In other words, the efficiency of gasoline utilization is more efficient than the utilization and generation of the electric power. This might be because of the significant losses in the power generation through non-renewable energy sources and transmission & distribution losses in the power generation sector. In addition to those energy losses, the electric motor will have additional energy losses depending on its efficiency.

In addition to sensitivity analysis of national level parameter, a state-specific sensitivity analysis for UFs is conducted. Due to high number of states, certain states, which represent the highest, medium, and lowest carbon and energy intensities, are selected and presented in Figure 3.7. These figures are based on the average electric power generation mix scenario. Figure 3.7(a) shows the sensitivity of UFs on the total LCA GHG emissions of WV, which has the highest GHG emission rate per kWh of electric power generation. Therefore, as the UF increases per km GHG emissions of PHEVS steeply increases. In Figure 3.7(b), When the GHG emission rate per kWh of electric power generation reduces, the impact trends of PHEVs are reversed, which means the GHG emission rate of electricity becomes less than that of gasoline combustion. In Figure 3.7(c), the sensitivity of UFs increased due to greater gap between GHG emission rates of gasoline combustion and electricity production. The GHG emission trends in the rest of the states are in between the lines shown in Figure 3.7 (a) and (c), which have the highest and lowest GHG emission rates, respectively. The sensitivity of UFs is higher for energy consumption, shown in Figure 3.7 (d) through (f). Similarly, states having highest, medium, and lowest, energy consumption rates per kWh of electric power generation. If the energy efficiency of power generation is worse than that of using gasoline, the utilization of electric power increases the overall energy consumption of PHEVs.

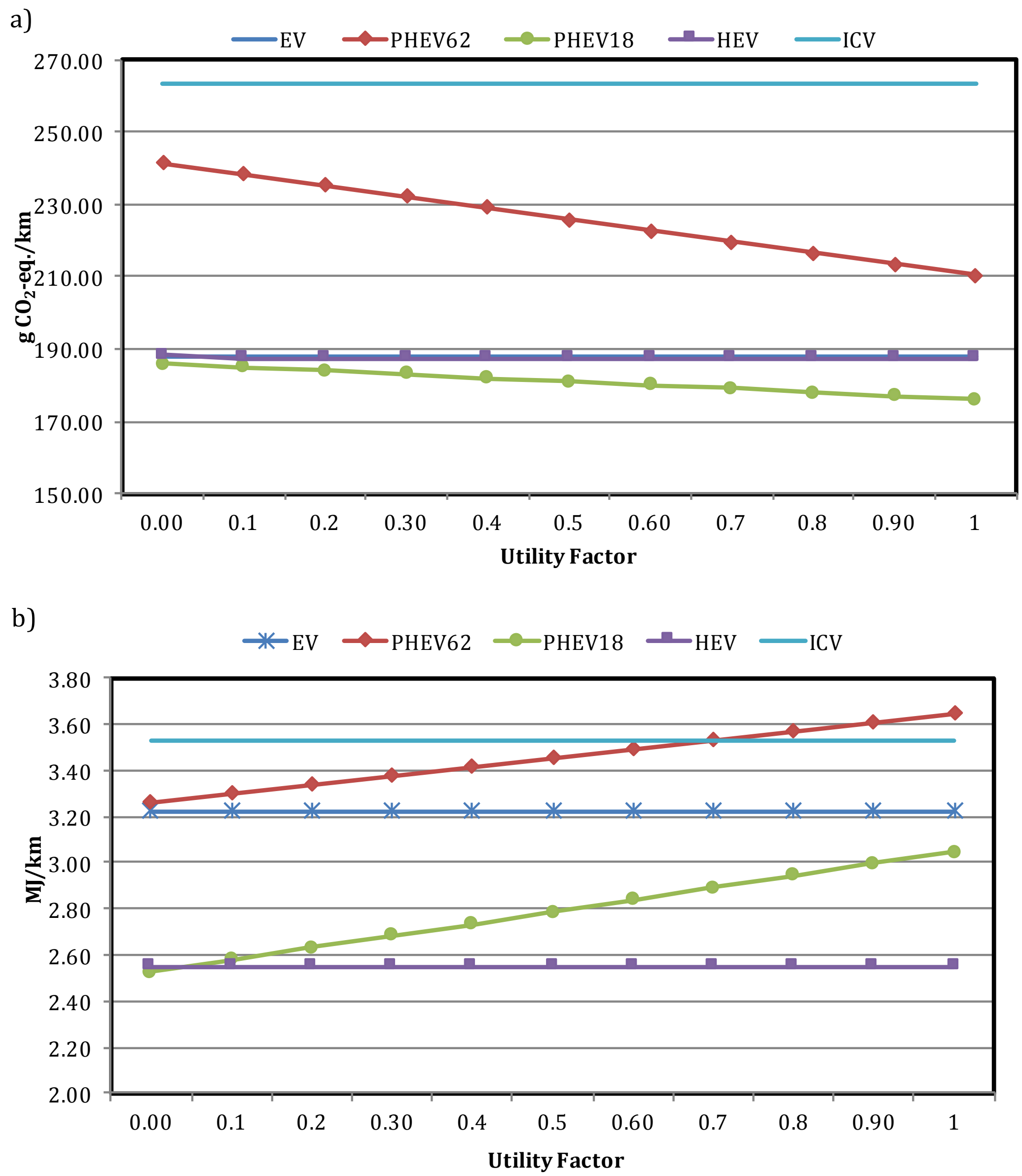


Figure 3.6 LCA impacts as a function of UF varying from 0 to 1, a) GHG emissions, b) Energy consumption per kilometer vehicle travels.

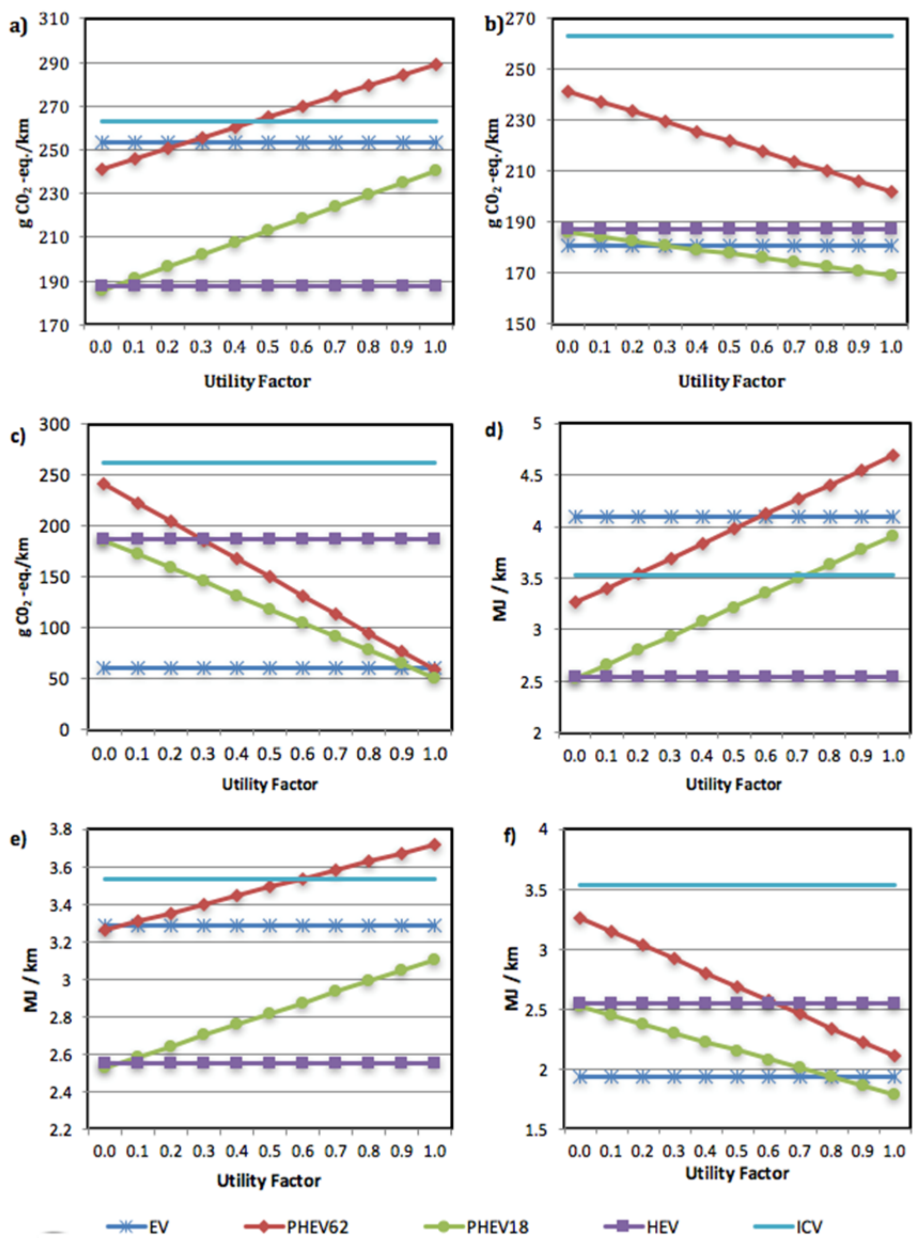


Figure 3.7 State-specific sensitivity results based on average electric power generation mixes a) WV, b) MN, c) VT, d) DC, e) NE, f) ID

3.3.5 GHG Emission Reduction and Energy Saving Potentials

Several market penetration scenarios are considered to show the relative GHG emission reduction and energy saving potential of replacing the current passenger vehicles (excluding SUVs, minivans, pickup trucks). To assess the potential market share for EVs, PHEVs, and HEVs, the data for the proportions of the different class sizes is required. However, such data was not available in the publicly accessible sources. Therefore, we estimated the number of LDVs in the different EPA size classes on road by analyzing the number of LDVs since 1975 [54]. Then the annual sale numbers were multiplied by the survival rates, which are functions of model year, which was obtained from a technical report by the National Center for Statistics and Analysis [55]. After the current LDV composition by EPA size class is estimated, the targeted market for the analyzed vehicle composition is estimated. According to this estimation, 67% of LDVs are composed of passenger cars, which corresponds to around 95 million vehicles in the U.S. However, the percentage share might be different for each state. However, we were not able to find state-specific data for the LDV composition. Therefore, the estimated national LDV composition is assumed to be identical for all states. Since the number of automobiles (including both passenger vehicles and SUVs) are available for each state, the number of passenger vehicles in each state can be derived from the estimated LDV composition [56]. Furthermore, the existing market share and percentage of annual sales of HEVs, PHEVs, and EVs are also estimated by using the estimated market size and annual sales of each alternative passenger vehicle type (excluding SUVs and pickups) [57]. The current market share of HEVs, PHEVs, and EVs are 0.00269%, 0.000113%, 0.000095%, respectively. Although current market shares are quite low, the numbers of annual sales are increasing exponentially. The potential GHG reductions and energy savings are considered for three different market penetration scenarios. In the first scenario (MP-S1), we estimated the 2020 market shares of each vehicle type for each state via regression analysis using the sale trend of each vehicle type. Moreover, optimistic scenarios such as %5 (MP-S2) and %20 (MP-S3) market penetrations are also investigated for the 2020 marginal state-specific electricity generation mix. In all of the states, the energy savings potentials are 0.0007%, 0.88%, and 3.5% of the total energy consumption for the market penetration scenarios of 0.004% (estimated with regression), 5%, and 20%, respectively. Likewise, the impacts of various penetration rates on emission reduction and energy saving potentials are also investigated. It should be noted that EVs are not a favorable candidate for drivers who must drive longer distances than the EV's AER (135 km). Therefore, this vehicle cannot penetrate the segment of a market composed of people driving more than 135 km. The market size of EV is calculated by subtracting this segment using cumulative daily travel distance data obtained from NTHS [8]. Figure 3.8 shows the sensitivity of percentage savings of each vehicle type under different market penetration rates ranging from 0% to 100%. This sensitivity analysis was conducted based on national average energy consumption and carbon footprint results.

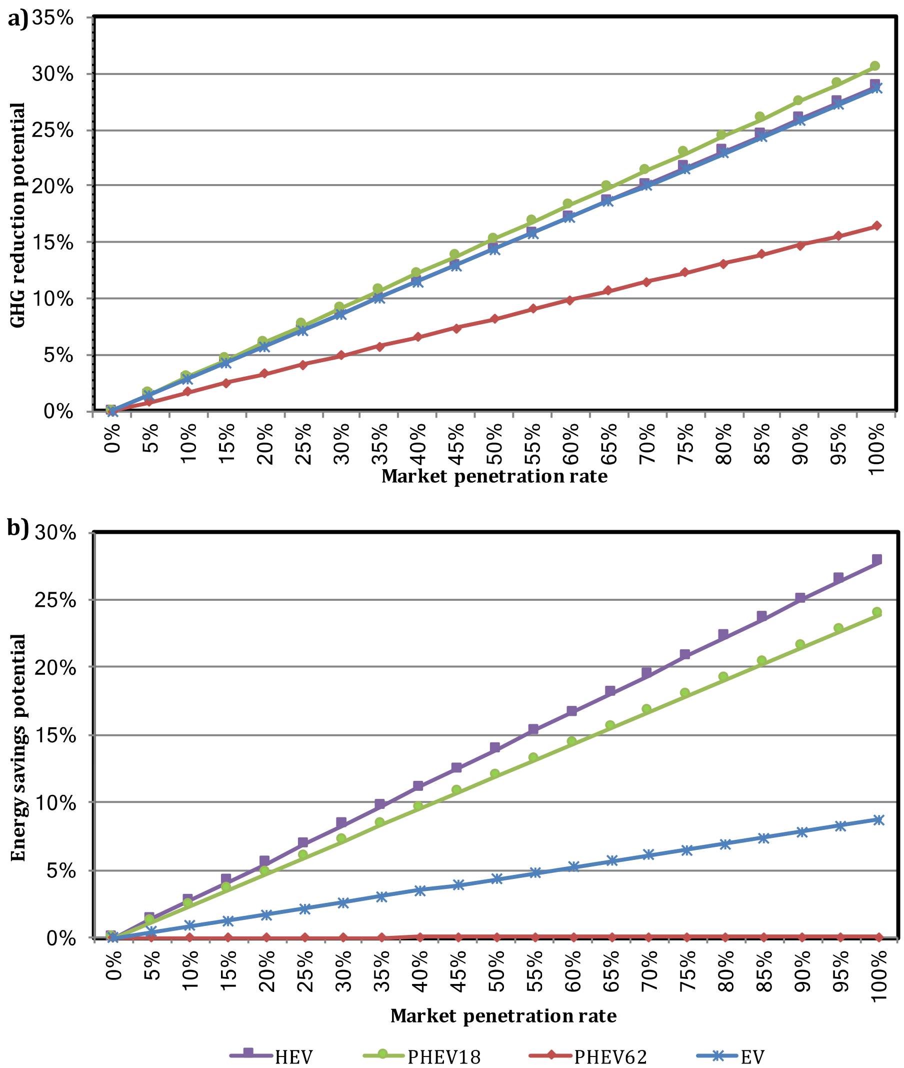


Figure 3.8 Reduction potentials as a function of market penetration rates, a) percentage reduction of GHG emissions, b) Percentage reduction of energy consumption

The GHG emission reduction potentials of PHEV18s, EVs, and HEVs are relatively higher than those of PHEV62s. As their market penetration increases, this emission reduction can be achieved by increasing adoption of PHEV18s, which have a higher slope than any other option. On the other hand, HEVs and PHEV18s are superior to EVs and PHEV62s in terms of energy savings. The life cycle energy consumption values for PHEV62s and ICVs are very similar, and therefore, the PHEV62 does not achieve significant energy savings.

3.4 Conclusions and Recommendations

This model demonstrates the effects of spatial and partially temporal variations (scenario 2) on the GHG emissions and energy consumption rates of alternative vehicle passenger technologies (HEVs, PHEVs, and EVs) and highlights how these factors can influence the vehicle technology preference of any given state. Summary of the results are as follows:

- ❖ The impacts of battery and vehicle manufacturing were found to be much smaller than those of the operation phase of the vehicles in all of the proposed scenarios.
- ❖ The inclusion of spatial and temporal variations changed the LCA energy consumption and GHG emissions results significantly.
- ❖ U.S. average results indicated that PHEV18s and HEVs have the lowest GHG emissions and energy consumption rates, respectively.
- ❖ According to Scenario 1, EVs are the least carbon-intensive vehicle option in 24 states, corresponding the 38% of the number of registered LDVs in the U.S. On the other hand, HEVs are found to be the most energy-efficient option in 45 states.
- ❖ The results of Scenario 2 demonstrate that widespread adoption of EVs is not a favorable strategy given the existing and near-future marginal electricity generation mix, as EVs are not ranked as the best vehicle option in any state. Instead, HEVs are found to be most energy-efficient option in all of the states in this scenario.
- ❖ The widespread use of solar power improved the performance of PHEVs and EVs significantly. According to Scenario 3, the adoption of EVs can result in reductions of up to 73% and 55% in GHG emissions and energy consumption, respectively. These are the highest reduction rates that can be achieved compared to other scenarios.
- ❖ Variations of GHG emission factors of electric power generation showed that any GHG emission factor below 600 gCO2-eqv/kWh would make EVs the least carbon intensive option. On the other hand, EVs can be superior to other alternatives in terms of energy-consumption, if the required energy to generate 1kWh of electricity is less than 1.25 kWh. Life cycle GHG emissions of PHEV62s are more sensitive under varying UFs due to their less efficient gasoline mode compared to PHEV18s.
- ❖ The results of the market penetration analysis showed that the GHG emission reduction potentials of PHEV18s, EVs, and HEVs are relatively higher than those of PHEV62s. In terms of energy savings, HEVs and PHEV18s are relatively better options as opposed to EVs or PHEV62s. On the other hand, estimated state-specific market penetration rates for alternative vehicle options showed that these savings are quite limited due to low market penetration rates in the near future.
- ❖ Based on a comparative evaluation of three different scenarios, it can be concluded that the use of renewable energy sources to power EVs and PHEVs should be encouraged to achieve reductions in GHG emissions and energy consumption.

Although solar energy has become increasingly popular as a renewable energy source, the number of solar charging stations is still very limited. Increased concerns regarding the highly carbon intensive structure of the current U.S. electricity grid have stimulated the development of more effective electricity generation methods for EVs and PHEVs. Considering that there are significant energy losses during electricity generation, distribution, and transmission, the use of on-site solar energy can reduce these losses and thus provide a more efficient means of powering EVs and PHEVs. Additionally, the market share of PHEVs is expected to increase [58], which might require additional upgrades in the transmission and distribution systems and the construction of new power plants in the future. The increased electricity demand is usually met either with conventional means, with large power plants located far from the demand center, or with smaller power generation options utilizing renewable energy sources. The latter is known as distributed generation, which can be provided through utilization of Photovoltaic (PV) systems [59]. As the power generation unit cost has been declining for solar technologies, the use of PVs is expected to be greater [60]. PVs can serve as charging stations for EVs and PHEVs, and may also serve as a power generation source to the grid. Similarly, rooftop PV panels in residential and commercial buildings can serve as a distributed power generation source and as an environmental friendly recharging option for EVs and PHEVs.

While results of this work highlight issues related to spatial and temporal variations, there are other sources of variations such as driving behavior and conditions, weather conditions, and uncertainties related to charging behavior, utility factors, and market [61,62]. It should be noted that these factors can change the fuel economy and associated impacts significantly. Therefore, state-wide decisions should be studied in further detail to account for all possible outcomes and develop more effective local and national policies.

This work addressed spatial and temporal aspects of GHG emissions and energy reduction. However, criteria pollutants in EV life cycle may constitute a larger portion of social costs than GHG emissions [63]. There are certain counties which do not meet the national primary or secondary ambient air quality standards. Additionally, many policies to promote EVs do not primarily aim to reduce GHGs only but rather to reduce oil consumption. Hence, any regional policy prescription should not be based on GHG or energy consumption estimates alone. Although this work does not investigate the economic feasibility of each of these scenarios, the use of renewable energy to power electric vehicles is inevitably required to achieve a carbon-free transportation system in the U.S. It should also be noted that the marginal electricity scenario is the most realistic scenario among the proposed policies, and its inclusion is therefore suggested by various researchers [20,43–47]. Hence, the implementation of renewable-energy-based charging options for EVs and PHEVs is highly recommended.

Moreover, the reduction potentials of the evaluated alternative passenger vehicle options in Scenarios 1 and 2 are marginal reductions, which may not be enough to reduce or even stabilize the GHG's stored in the atmosphere. Estimating these impacts from such a dynamic system requires a holistic dynamic system approach in which all of the variables of the system and the interactions among them are captured [50]. On the other hand, because the sustainability concept is an optimization process among three pillars encompassing environmental, economic, and social dimensions [64–67], impacts from the adoption of alternative vehicle technologies should be analyzed with inclusion of these three types of dimensions. Therefore, the next step to analyze the impacts of alternative vehicle technologies should be an integration of all sustainability dimensions with a dynamic modeling approach.

4.0 Socio-Economic Life Cycle Sustainability Assessment Framework for Electric Vehicles

4.1 Introduction

The U.S. transportation sector's environmental impacts are growing steadily, and transportation-related environmental pressures such as energy requirements and climate change are increasingly scrutinized because of concerns related to sustainability.[2] In this regard, alternative vehicle technologies, as an option to reduce negative environmental impacts of transportation, have gained a tremendous interest in literature as well as in industry. Even though there are numerous efforts presenting life-cycle based methodologies to investigate the environmental viability of alternative transportation options, the socio-economic aspects of transportation sustainability are not addressed sufficiently [68]. The environmental dimension of sustainability is an important pillar of sustainable development; however social and economic dimensions have to be integrated into a holistic quantitative sustainability assessment framework to propose economically viable, socially acceptable, and environmentally benign policies [66,69,70].

The efforts aiming to estimate the sustainability impacts of the alternative vehicle options are often limited by narrowly defined system boundary and lacks of a system perspective. Although product level assessment methods are useful, they are not capable of answering macro-level questions and providing a more comprehensive framework [70–72]. Analysis of alternative vehicle systems needs a holistic sustainability accounting which requires a set of environmental, economic and social indicators [73]. The difficulties related to analyzing the social and economic impacts of transportation stem from lack of appropriate methods, tools and availability of data. The majority of the studies which have conducted an environmental life-cycle assessment of alternative vehicles mainly focused on the limited environmental impact categories including greenhouse gas emissions, energy consumption, and some atmospheric pollutants [29]. However, the socio-economic effects of transportation should be considered since the society and economy are among the three main pillars of sustainability which are critical for the quality of life [74]. In this regard, life cycle sustainability assessment models can be critical for assessing the long-term sustainability of alternative vehicle technologies not only from environmental perspective but also from social and economic standpoints. While there are several approaches analyzing the environmental, economic, and social impacts of alternative vehicle technologies, these approaches only provide a snapshot analysis with an isolated view of all pillars of sustainability and neglecting the bigger picture as a system.

[2] The contents of this section were partly published in Onat, N., Kucukvar, M., Tatari, O., and Egilmez, G. (2016). "Integration of System Dynamics Approach towards Deepening and Broadening the Life Cycle Sustainability Assessment Framework: A Case for Electric Vehicles." *International Journal of Life Cycle Assessment, Springer,* 21(7), 1009-1034. *2014 IF: 4.844*, DOI: 10.1007/s11367-016-1070-4

This model develops a more deepened and broadened approach from a system perspective in order to provide an in-depth sustainability impact assessment of alternative vehicle technologies. The proposed model is capable of capturing social, economic, and environmental impacts considering the dynamic interdependencies and causal relationships among these impacts of the transportation system, and its components.

4.1.1 Life cycle sustainability assessment

Almost 12 years have passed since Walter Klöpffer and his colleagues introduced the life-cycle sustainability assessment (LCSA) framework where three individual life cycle assessment methodologies are combined: Environmental Life Cycle Assessment (LCA), Social Life Cycle Assessment (SLCA), and LCA-type Life Cycle Costing (LCC) [75,76]. This framework was then put into the conceptual formula (LCSA = LCA + LCC + SLCA) by Klöpffer (2007). Heijungs et al. (2012) provided a computational structure for LCSA and developed a transparent description of how to calculate the LCC and the value added across the life cycle. In the literature, the applications of LCSA for large systems are still rare. Guinée et al. (2011), Guinée (2016) and Zamagni et al. (2013) emphasized the importance of the LCSA framework and discussed the necessity of system-based sustainability accounting methods for future LCSA models.

In this regard, some studies used input-output based LCA and hybrid LCA for a system-based LCSA analysis. For instance, Wood and Hertwich (2012) discussed the comprehensiveness of input-output analysis in LCSA, particularly for socio-economic analysis. In response to the current research needs for system-based LCSA methods, Kucukvar et al. (2014b) developed an optimization model in which a hybrid LCSA and compromise programming methods are conjunctively used to carry out a multi-criteria decision analysis of hot-mix and warm-mix asphalt mixtures. In other work, Kucukvar et al. (2014c) presented a fuzzy multi-criteria decision making method applied to ranking problem based on the life cycle sustainability performance of different pavement alternatives constructed with hot-mix and warm-mix asphalt mixtures. Onat et al. (2014c) also used the LCSA framework for a (Triple-bottom-line, TBL) sustainability analysis of U.S residential and commercial buildings and demonstrated the usefulness of input–output modeling to quantify sustainability impacts as integration into the LCSA framework. Onat et al. (2014a) built a hybrid LCSA model by using 19 macro level sustainability indicators for comparative life cycle sustainability performance of conventional gasoline, hybrid, plug-in hybrid with four different all-electric ranges, and full battery electric vehicles in the United States. In recent works, Onat et al. (2015a) presented an application of TOPSIS and intuitionistic fuzzy set approach for ranking the life cycle sustainability performance of alternative vehicle technologies. Additionally, Onat et al. (2016) presented an integrated novel approach by combining multi-criteria optimization with LCSA framework for the optimal distribution of alternative passenger cars in the United States. However, only a handful of studies addressed this issue and expand the system boundary of LCSA to economy-wide analysis.

4.1.2 Broadening and deepening the LCSA framework

LCSA framework is still under development and there is an ongoing research to eliminate the current shortcomings of the proposed LCSA framework and advance it for future applications [85,86]. The Coordination Action for innovation in Life Cycle Analysis for Sustainability (CALCAS) is a partnership-based project, funded by the European Commission under 6th Framework Programme [87,88]. In general, the CALCAS project has the following two objectives to further improve the life-cycle modeling for sustainability assessment [89,90]:

1. **Deepening LCA** by considering the dynamic relationships among the LCA parameters and analyzing the complex causality mechanism between the system parameters, and
2. **Broadening LCA** by including environmental, social and economic aspects and broaden the system boundary from micro-level analysis to macro-level.

In a Deliverable 17 Final Report of CALCAS project, several models are suggested to broaden and deepen the existing LCA framework (CALCAS, 2009). For instance, material flow analysis, substance flow analysis, environmentally-extended input-output analysis, hybrid life cycle models and general equilibrium models are listed among the most useful analytical models for deepened and broadened LCA [92]. However, most of these methods provide a snapshot analysis without considering the dynamics of life cycle sustainability impacts over a period of time. Also, using these analytical approaches, mostly life cycle inventory of products of systems analyzed in isolation and causalities between the environmental, social and economic indicators and complex interactions among the three pillars of sustainability are not fully investigated. In a recent paper on Concept, Practice and Future Directions for the LCSA, the following weaknesses are highlighted for the current LCSA framework [80]:

- Social aspects of LCSA framework is less developed and there is a further research needs on developing SLCA,
- Mechanistic understanding by looking at the environmental LCA, social LCA and life cycle cost assessment results individually,
- Lack of understanding the mutual dependencies and complex interactions among the three pillars of the sustainability.

According to the aforementioned comments that address critical points for future LCSA, broadened and deepened LCSA should go beyond the identifying the snapshot of sustainability hotspots [80]. Hence, LCSA requires the consideration of dynamic relationship between LCSA indicators and provide additional insights regarding the dynamic effects of products or systems' sustainability implications. At this point, system dynamics can be a superior modeling approach to address the future research needs of advanced LCSA. The importance of dynamic modeling approach in LCSA is also highlighted in the literature addressing the issue of developing integrative approach for LCSA which attempts to develop more holistic sustainability assessment framework and link dynamic interrelations between LCSA indicators over a period of time (Cucurachi and Suh, 2015; Halog and Manik 2011; Marvuglia et al. 2015).

4.1.3 Motivation and research objectives

As a response to knowledge gaps found in the literature, this research aims to advance the state-of-the art in LCSA literature and broaden and deepen the current understanding of LCA. To alleviate this goal, the proposed research will explore the dynamic interrelationships between the environmental, social, and economic aspects of

U.S. passenger cars' sustainability impacts from life cycle sustainability perspective and study the scenario-based projections for the long-term policy making. With the overall goal of advancing the state-of-the-art in LCSA framework and state-of-practice of transportation sustainability, the main objectives of this study are presented as follows:

1) Broaden the existing LCA framework by considering macro-level environmental, economic and social impacts in an integrated way,
2) Deepen the existing LCA framework by capturing the complex dynamic relationships between social, environmental, and economic indicators through causal loop modeling,
3) As an effective approach towards understanding the dynamic complexity of transportation sustainability, develop a SD simulation model that can be utilized to understand the triple bottom line impacts of alternative vehicles, and finally
4) Investigate the impacts of extreme customer choice scenarios as a novel approach for selection of a macro-level functional unit considering all of their inherent mutual relationships in the environmental, social, and economic aspects.

Overall, this research is a first and an important step towards developing integrated and dynamic LCSA framework for sustainability assessment of new generation transportation systems.

4.2 Methodology

System dynamics modeling is utilized to model the U.S. passenger transportation system and its interactions with economy, the environment, and society. The proposed model aims to quantify the macro-level social, economic, and environmental, TBL, impacts of passenger vehicles from an integrated system analysis perspective. Analysis covers the TBL impacts related to manufacturing and operation phases of internal combustion vehicles (ICVs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs). The Electric Vehicles (EV) is a typical type of battery electric vehicles (BEV), has an electric motor powered by a battery. The hybrid electric vehicle (HEV) is a vehicle utilizing both an electric motor and an internal combustion engine. The Plug-in Hybrid Electric Vehicle (PHEV) can be charged either from the electricity grid or using the internal combustion engine [94]. The useful lifetime is assumed to be 150,000 miles per vehicle. The comparison is made based on extreme scenarios for each vehicle such as market share for BEVs is to be 100% by 2050.

A total of seven macro level impact categories are selected and the impacts are quantified from 1980 to 2050. The proposed SD model is composed of four comprehensive sub-models: environmental, economic, social, and transportation, which contains smaller modules such as population, travel need and on-road fuel efficiency, CO_2 emissions and climate change, particulate matter formation (PMF), photochemical oxidant formation (POF), vehicle ownership cost, human health, public welfare, employment, etc.

4.2.1 Problem statement

Problem definition is a formal step of SD modeling. The reference mode is selected as the change in temperature (°C) of the atmosphere and upper ocean compared to preindustrial levels due to greenhouse gas emissions [95]. Figure 4.1 shows the annual mean surface air temperature change between 1980 and 2015.

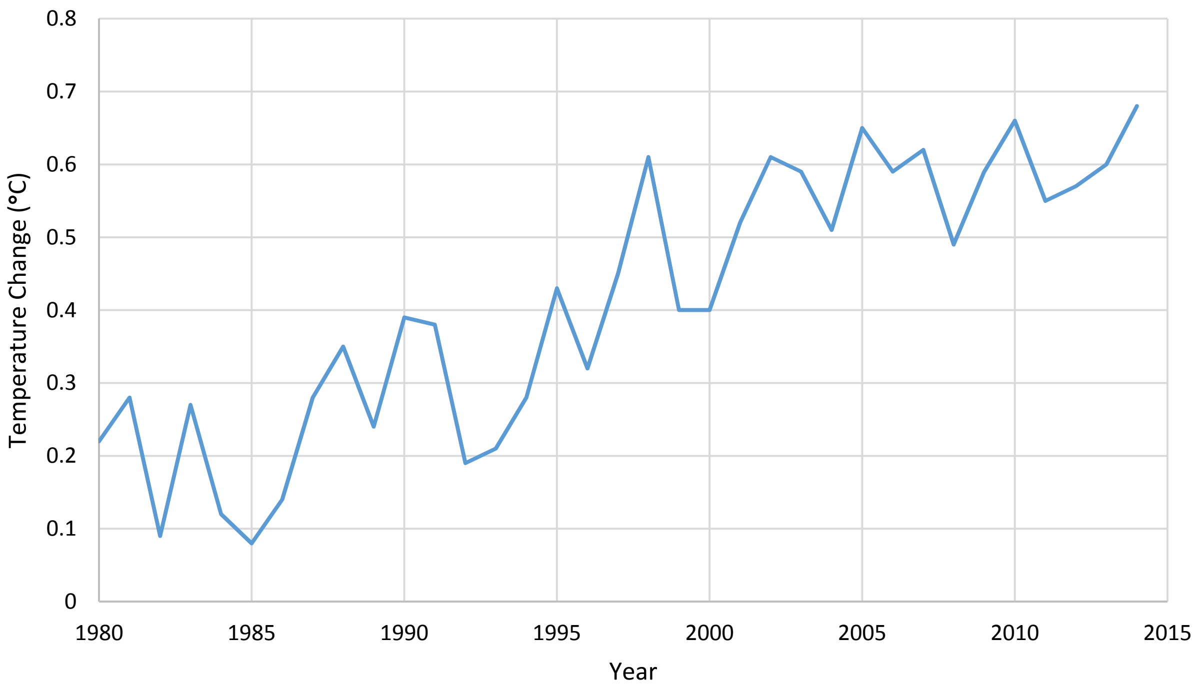


Figure 4.1 Atmospheric temperature change between 1980 and 2014

4.2.2 Indicator selection and identification of parameters

Parameters for environmental impact categories, contribution to climate change and atmospheric emissions are selected. The majority of the past studies conducted an environmental LCA of conventional and electric vehicles mainly focused on these impact categories due to dominant impacts of transportation activities on the atmospheric pollution [29,96]. Furthermore, the socio-economic effects of transportation should be considered since they are highly critical for the quality of people's lives [74].

In this research, contribution to GDP, cost, employment public welfare and human health are considered among the most critical socio-economic indicators of sustainable transportation. The importance of these socio-economic indicators have already been discussed in previous studies. For instance, Offer et al. (2010) focused on the economic impacts of electric vehicles using a life-cycle cost analysis based on capital cost, running cost, and end-of-life cost. Stone et al. (2012) used the Global Trade Analysis Project (GTAP) database in order to analyze the socio-economic impacts of transportation projects considering a wide range of socio-economic indicators such as contribution to gross domestic product (GDP), income, public welfare, and import.

The World Bank's report on social analysis of transportation projects also revealed important insights regarding the significance of socio-economic aspects of transportation in terms of employment, road safety, health impacts, and accessibility. The World Bank (2006), in a report published by the European Commission, listed contribution to GDP, employment, external cost of transportation activities such as congestion, emission and safety, taxation, average passenger travel time, and affordability as key indicators to assess the socio-economic sustainability aspects of transportation activities in the EU member states [100]. As can be seen from the reviewed works, the selection of socio-economic indicators shows differences between the studies; however, life cycle cost, employment, human health impacts, contribution to GDP and public welfare can be seen as commonly used quantitative indicators that are addressed. Several other socio-economic indicators including accessibility, affordability, equity, travel time, congestion, accident and noise are excluded from the scope of this research due to lack of appropriate data for new electric vehicle technologies and difficulties in integration with a proposed dynamic life cycle assessment approach. The model boundary is presented in Table 4-1 by identifying the most important exogenous, endogenous, and excluded variables in the model. Exogenous variables are externally defined variables representing behaviors or values that are not within the boundary of the model, whereas endogenous variables are calculated based on the interactions and mathematical relationships among the variables.

Table 4-1 Model boundary

	Endogenous variables	Exogenous variables	Excluded variables
Transportation Sub-model	New passenger vehicle sales Travel need index Average annual VMT On-road fuel efficiency* Population Fertility rate Number of potential drivers Total number of vehicles on-road	Vehicle disposal* Market share of vehicles* Fuel efficiency of vehicles*	End-of-life impacts Recycling and reuse Insurance cost Other environmental impact categories
Environmental Sub-model	Emissions from vehicle man.* Emissions from vehicle op.* PMF from vehicle man.* PMF from vehicle op.* POF from vehicle man.* POF from vehicle operation* Deep Ocean Temp Atmos. U. Ocean Temp Economic climate damage fraction	Vehicle man. emission rate Petroleum supply emission Electricity supply emissions Tail pipe emissions CO_2 emissions from rest of US CO_2 emissions from rest of US	
Economic Sub-model	Annual vehicle operation cost* Annual vehicle ownership cost* Gross Domestic Product (GDP) contribution of manufacturing phase GDP contribution of operation phase GDP increase rate	Battery cost M&R cost Useful life time Electricity cost Gasoline cost GDP from rest of the U.S. Economy	
Social sub-model	Human health impacts from transportation Adjusted life expectancy Employment from vehicle op. Employment from vehicle man. Employment from rest of the U.S. Public welfare Education index Income index Life expectancy index	Life expectancy HH characterization factors Max life expectancy Life expectancy norm	

* These variables are used for each vehicle type separately and are represented by single name in this table.

4.2.3 System conceptualization

System conceptualization is explained with the causal loop diagram (CLD) and a brief description of each loop. The CLD is presented in Figure 4.2 which includes major sub-models and the causal relationships among each variable or sub-model. It should be noted that the CLD is an overview of the system observed where the complex relationships are explained in a simplified form.

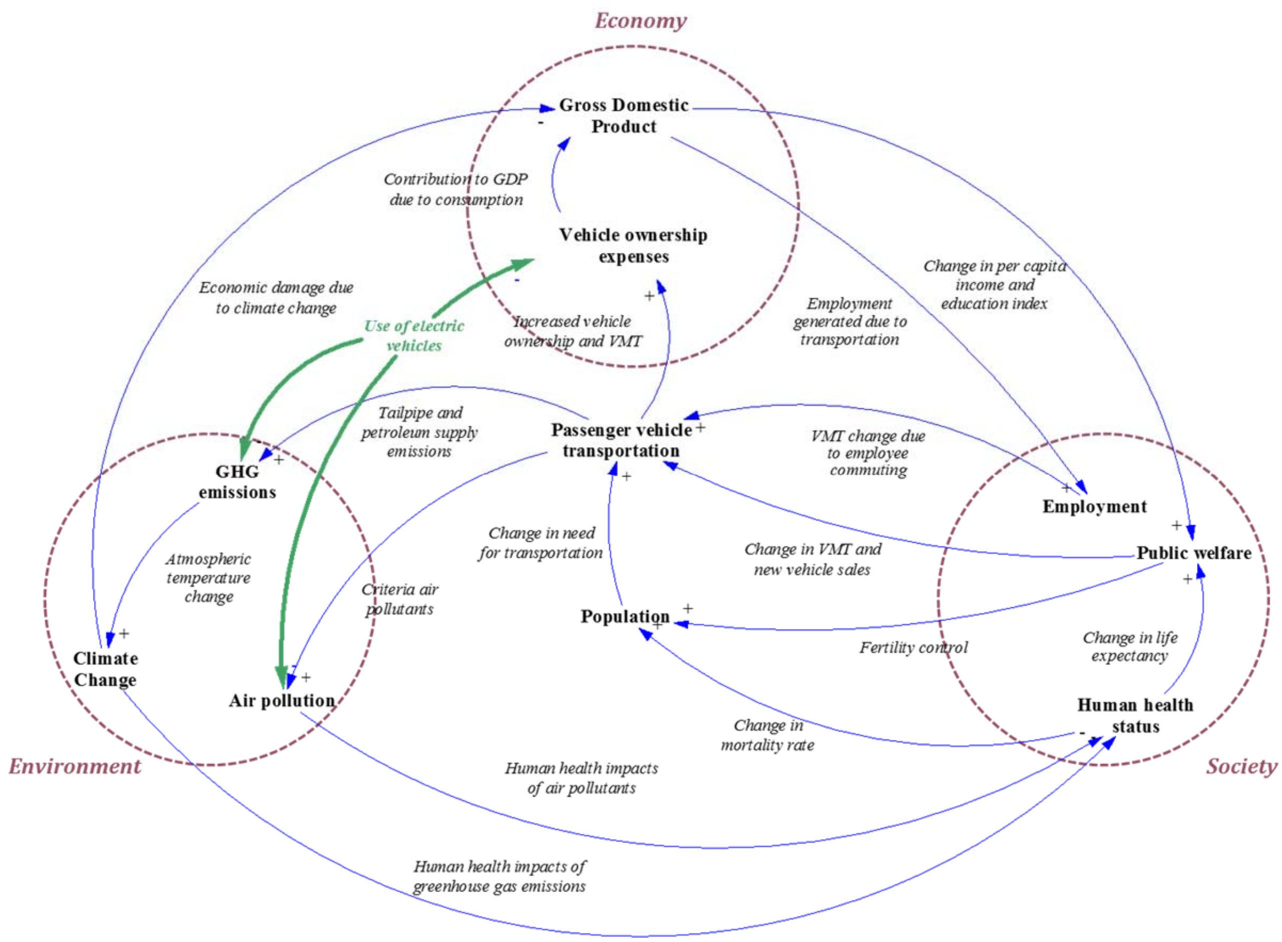


Figure 4.2 Causal loop diagram of the model

A typical CLD consists of loops which can be reinforcing (an increasing impact of a cause on an effect is an increase) or balancing (an increasing impact of a cause on an effect is a decrease). In the proposed SD model, nine balancing and three reinforcing loops are considered (See Figure 4.2). In Figure 4.2, positive signs indicate a reinforcing effect, whereas the negative signs indicate a balancing relationship. The reinforcing and balancing loops are briefly explained as follows:

Balancing Loops 1, 2, and 3

1) Passenger vehicle transportation →(+) GHG emissions →(+) Climate Change→(-) GDP→(+) Public welfare →(+) Passenger vehicle transportation
2) Passenger vehicle transportation →(+) GHG emissions →(+) Climate Change→(-) GDP →(+) Employment →(+) Passenger vehicle transportation

3) Passenger vehicle transportation →(+) GHG emissions →(+) Climate Change→(-) GDP →(+) Public welfare →(+) Population→(+) Passenger vehicle transportation

As transport and mobility activities increase, the related GHG emissions increase and accelerate climate change. Steeply increasing atmospheric temperature damages economy by reducing the growth rate of GDP, which reduces the public welfare through change in income status, loss of jobs. In balancing loop 3, any change in public welfare influence the population through fertility rates. This impact can be both reinforcing and balancing depending on the income level. However, the threshold value for the income level for the U.S. is not expected to serve as a balancing effect due to expected income level trends in the U.S. Passenger vehicle transportation includes the modules of travel need index and number of new vehicle sales, which are functions of employment, population, and public welfare. The feedback impacts to the passenger vehicle transportation module occur via changes in employment, population, and public welfare.

Balancing Loops 4, 5 and 6

4) Passenger vehicle transportation →(+) GHG emissions →(+) Climate Change→(-) Human health status→(+)Population→(+) Passenger vehicle transportation
5) Passenger vehicle transportation →(+) GHG emissions →(+) Climate Change→(-) Human health status→ (+) Public welfare →(+) Passenger vehicle transportation
6) Passenger vehicle transportation →(+) GHG emissions →(+) Climate Change→(-) Human health status→(+) Public welfare →(+) Population→(+) Passenger vehicle transportation

Climate change has also impact on human health, which effects the population through life expectancy. Population increases the travel demand and new vehicle sales, which increases the impacts of passenger vehicle transportation in the loop 6. As the human health status changes due to GHG emissions resulting from passenger vehicle transportation, public welfare status changes accordingly. Public welfare affects the new vehicle sales through income level and on population through fertility rates. The loops are completed by the impacts of population and public welfare on the passenger public transportation.

Balancing Loops 7, 8 and 9

7) Passenger vehicle transportation →(+) Air pollution→(-) Human health status→(+)Population→(+) Passenger vehicle transportation
8) Passenger vehicle transportation →(+) Air pollution→(-) Human health status→(+) Public welfare →(+) Passenger vehicle transportation
9) Passenger vehicle transportation →(+) Air pollution→(-) Human health status→(+) Public welfare →(+) Population→(+) Passenger vehicle transportation

The second environmental impact resulting from passenger vehicle transportation is the air pollution, which influences the human health status through life expectancy. Same as in the balancing loops 4, 5, and 6; human health status affects public welfare and population, which are connected to passenger vehicle transportation via their effect on travel demand and new vehicle sales.

Reinforcing loops 1, 2, and 3

1) Passenger vehicle transportation →(+) Vehicle ownership expenses →(+) GDP→(+) Public welfare →(+) Passenger vehicle transportation
2) Passenger vehicle transportation→(+) Vehicle ownership expenses →(+) GDP →(+) Public welfare →(+) Population→(+) Passenger vehicle transportation
3) Passenger vehicle transportation→(+) Vehicle ownership expenses →(+) GDP →(+) Employment →(+) Passenger vehicle transportation

As the travel demand and the new vehicle sales increases, the overall expenses related to transportation, particularly vehicle ownership costs increase. Increased consumption fastens the economic growth through contribution of industrial sectors associated with vehicle manufacturing and operation such as petroleum production and supply and electric power generation for electric vehicles. On the other hand, the demand shift among the sectors would cause a balancing effect as well. However, current trends in the transportation sector indicate that this relationship has a reinforcing effect. These sectorial outputs change the status of public welfare through income per capita and employment. Both public welfare and employment changes the travel demand of people and population structure, which change the impacts of the passenger vehicle transportation in return. For details of model formulation, refer to the journal paper mentioned in the introduction of this section.

4.2.4 Model validation

Model validation where the accuracy of the model behavior's is compared to the existing system behavior, is a critical phase in SD modeling. There are two types of modeling techniques from model validation perspective, namely: causal descriptive and black-box [101]. Causal descriptive models consider the feedback loops in model structure and question "how real systems operate in some aspects". On the other hand, only the aggregate input-output relationship matters in black-box models, which makes them "purely-data driven". In both type of modeling approaches, statistical techniques are typically used for validity tests [102].

The objective of employing a statistical comparison between SD output and the actual data was to validate that there is no statistically significant difference between the output of SD model and real data. Therefore, either a parametric (ANOVA) test or a non-parametric test (if ANOVA requirements are not met) needed to be used.

Mainly, 9 variable sets are considered to be used in the validation analysis, namely: 1) Atmospheric temperature change, 2) New passenger vehicle sales, 3) VMT, 4) Population, 5) On-road fuel efficiency of ICVs, 6) GDP, 7) Life expectancy, 8) Employment and 9) Public Welfare. The validation step is carried out by looking at the actual data and the SD model's output with two statistical tests: ANOVA and Two

Sample Kolmogorov Smirnov. As long as both of the data (model and real) are holding the assumptions of the One-Way ANOVA test, ANOVA is used. For the nonparametric test, Two Sample Kolmogorov Smirnov, is used for the variables that either of the datasets (model or real) does not hold the assumptions of the ANOVA test. ANOVA test mainly requires the following criteria: The two data (since there is 2 groups of data: SD output and actual data) need to be normal. To understand a data is normal or not, normality test is typically used. Normality test aims to find out whether to reject or fail to reject the null hypothesis that the data come from a normally distributed population. Secondly, there needs to be homogeneity of variance (HOV) on for both of the two datasets. HOV is an assumption of the ANOVA that assumes that all groups have the same or similar variance. If any of the above requirements (or assumptions) is not met, ANOVA cannot be used so that non-parametric tests need to be used.

The statistical analysis is performed using SPSS software. Initially, normality tests are performed. According to the analysis results, 7 out of 9 variables were found to be holding assumptions of ANOVA test, thus ANOVA is used for comparing the real and model's output data. The only datasets that were not normal were found to be associated with 3rd and 5th variables, namely: new passenger vehicle sales and VMT. Results of the ANOVA analysis are shown in Table 4-2. It is evident that there is no significant different between the model's output and actual data since all test statistic values are greater than the threshold, 0.05.

Table 4-2 Results of the ANOVA analysis

Variable number	*Variable name*	*One Way ANOVA*	
		F Value	Test Statistic
1	Atmospheric temperature change	1.794	0.185
3	VMT	0.000	0.986
4	Population	0.528	0.470
6	GDP	0.000	1.000
7	Life expectancy	0.170	0.681
8	Employment	0.000	0.984
9	Public Welfare	1.374	0.245

The two variables that contain non-normal data are analyzed with Two Sample Kolmogorov Smirnov. The results of normality tests (Kolmogorov-Smirnov and Shapiro-Wilk) are provided in Table 4-3, which indicate that at least one test statistic is less than 0.05. In Table 4-3, results of non-parametric two samples Kolmogorov Smirnov test are provided, which indicate that there is no significant difference between the model's output and the actual data (Asymp. Sig. (2-tailed) > 0.05).

Table 4-3 Results of Normality Tests

Tests of Normality: New passenger vehicle sales

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Real Data	0.216	34	0	0.653	34	0
Model Output	0.173	34	0.011	0.711	34	0

a. Lilliefors Significance Correction

Tests of Normality: On-road fuel efficiency of ICVs

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Actual Data	.164	34	.021	.969	34	.436
Model Output	.071	34	.200*	.966	34	.358

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Table 4-4 Results of Two Sample Kolmogorov Smirnov

Test Statistics[a]: New passenger vehicle sales

		VAR00008
Most Extreme Differences	Absolute	.182
	Positive	.091
	Negative	-.182
Kolmogorov-Smirnov Z		.739
Asymp. Sig. (2-tailed)		.646

a. Grouping Variable: New passenger vehicle sales

Test Statistics[a]: On-road fuel efficiency of ICVs

		VAR00014
Most Extreme Differences	Absolute	.324
	Positive	.324
	Negative	-.088
Kolmogorov-Smirnov Z		1.334
Asymp. Sig. (2-tailed)		.057

a. Grouping Variable: On-road fuel efficiency of ICVs

4.2.5 Scenario based comparison of each vehicle type

The comparisons of vehicle types are made according to extreme market share scenarios for each vehicle as 100% market share by 2050. Market share represents an annual percentage of new vehicle sales. These market share scenarios are presented in Table 4-5. These extreme scenarios are compared with the forecasts of the VISION model, developed by the U.S. Department of Energy [103]. The rationale behind the selection of ambitious market share target for each vehicle is to capture the effect of all system and reveal the maximum available sustainability impacts from each vehicle type. For instance, if HEVs are sold with a high rate market share, the number of new vehicle sales, population, economic parameters, etc. will be different in the future years depending on the impact of HEVs. Hence, both the maximum potential in the terms of sustainability impacts and the effects of the system parameters are captured. Therefore, the scenario-based comparison provides a more comprehensive comparison between alternatives by considering the behavior of other sub-systems and parameters depending on the vehicle selection as they have causal relationships. This is a better comparison for such macro-level studies since the impacts of the vehicle types are revealed as much as possible by considering a wider system and a deeper mechanism. The results are presented for each scenario in the following section.

Table 4-5 Summary of the extreme scenarios

Scenario name	Year	Market share of new vehicle sales			
		ICV	HEV	PHEV	EV
BAU	2010	95.8%	4.2%	0.005%	0.001%
	2015	93.7%	5.7%	0.584%	0.001%
	2020	91.6%	7.2%	1.164%	0.001%
	2030	87.6%	9.5%	2.924%	0.001%
	2040	85.7%	10.3%	3.969%	0.001%
	2050	84.0%	10.8%	5.217%	0.001%
S-HEV	2010	95.8%	4.2%	0.005%	0.001%
	2015	93.7%	5.7%	0.584%	0.001%
	2020	80.3%	19.2%	0.501%	0.001%
	2030	53.5%	46.1%	0.334%	0.001%
	2040	26.8%	73.1%	0.167%	0.001%
	2050	0.0%	100.0%	0.000%	0.001%
S-PHEV	2010	95.8%	4.2%	0.005%	0.001%
	2020	93.7%	5.7%	0.584%	0.001%
	2016	80.3%	4.9%	14.786%	0.000%
	2030	53.5%	3.3%	43.191%	0.000%
	2040	26.8%	1.6%	71.595%	0.000%
	2050	0.0%	0.0%	100.0%	0.000%
S-EV	2010	95.8%	4.2%	0.005%	0.001%
	2020	93.7%	5.7%	0.584%	0.001%
	2016	80.3%	4.9%	0.501%	14.287%
	2030	53.5%	3.3%	0.334%	42.858%
	2040	26.8%	1.6%	0.167%	71.429%
	2050	0.0%	0.0%	0.0%	100%

4.3 Results and discussion

Results are presented in three sub-sections: environmental impacts, economic impacts, and social impacts.

4.3.1 Environmental impacts

Figure 4.3 shows the CO_2 emissions impacts for each scenario compared the BAU scenario. Manufacturing impacts of S-EV and S-PHEV are relatively higher compared to other scenarios, which is mainly because of emissions from additional battery manufacturing for EVs and PHEVs. On the other hand, for the CO_2 emissions revealed in the operation phase, the EVs are found to be the best option followed by the PHEVs. When total life cycle impacts are considered, the emission savings overwhelms the impacts of manufacturing phase in the operation phase and favor S-EV and S-PHEV. Considering that the battery improvements and associated impacts are taken into account, the technological advance in battery technology favors EVs and PHEVs, while fuel efficiency improvements favor all of the vehicles at different degrees. BAU scenario, which contains much higher number of ICVs, has a declining trend due to fuel efficiency improvements of ICVs.

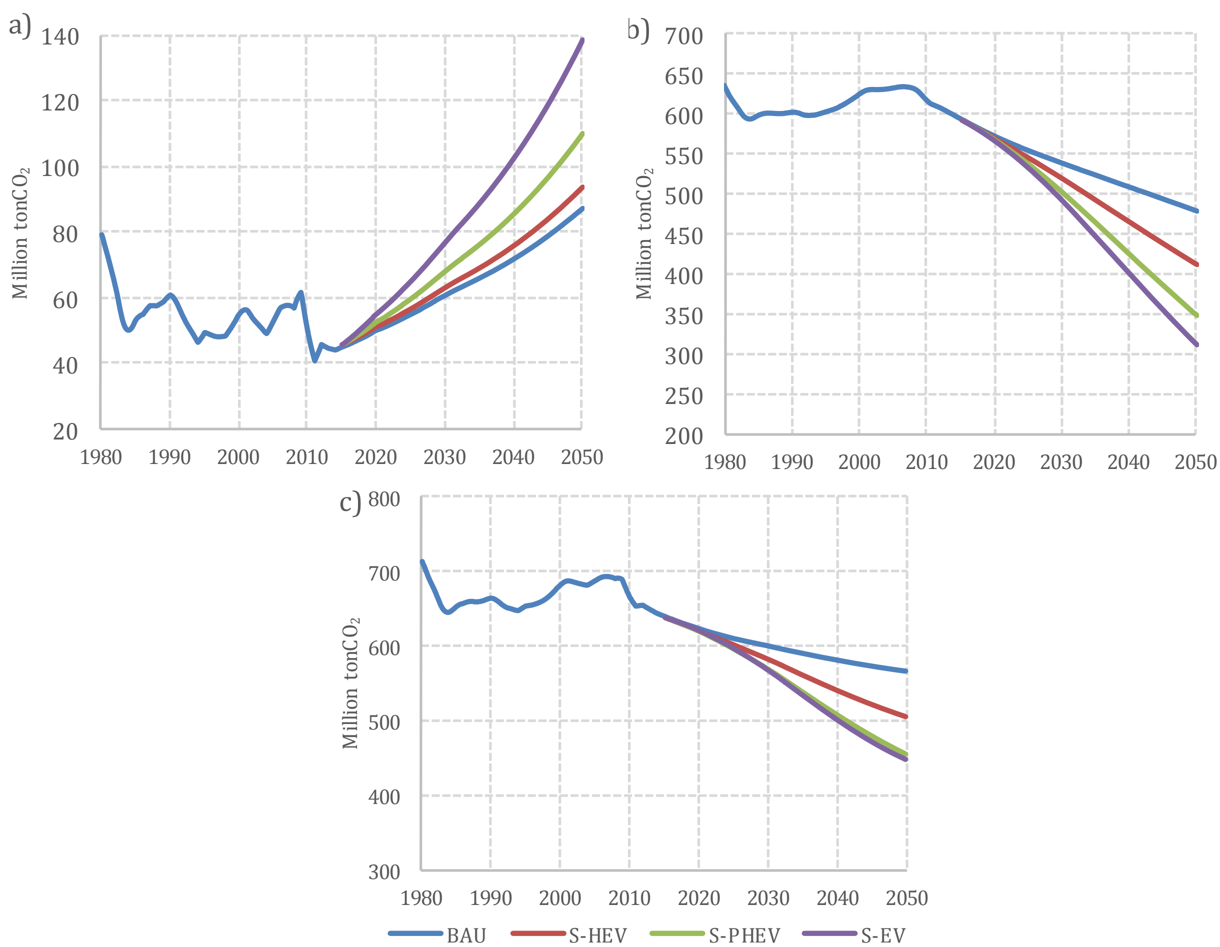


Figure 4.3 CO_2 emissions from vehicle transportation a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle Emissions

PMF impacts of vehicle options are presented in Figure 4.4. PMF impacts have similar trends with those of CO_2 emissions in both of the phases. However, when total life cycle PMF emissions are revealed, the trend is different due to differences in scale between manufacturing and operation phase. PMF of S-EV is highest in the manufacturing phase, whereas it is lowest during the operation phase. PMF of S-PHEV is very close to that of S-EV in the operation phase. The effect of manufacturing phase is quite influential as it changes the total life cycle PMF trend significantly. The increasing trend of manufacturing phase PMF overwhelm the reduced PMF of operation phase for a period of time at the beginning of 2016. There is a decreasing trend between 2017 and 2035 and later this trend is reversed due to relatively less reduction in operation phase compared to sharp increase in manufacturing phase.

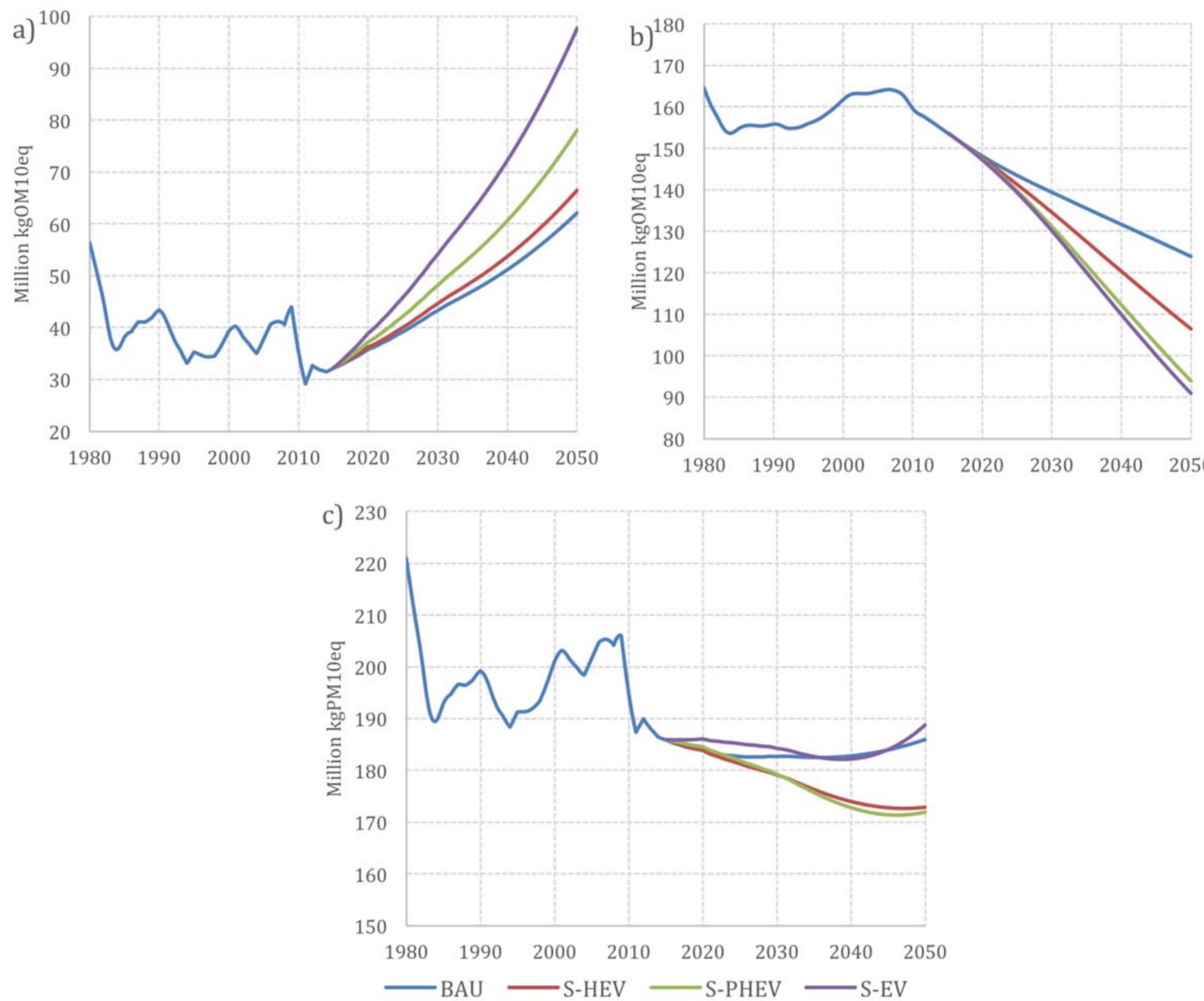


Figure 4.4 PMF from vehicle transportation a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle

Figure 4.5 shows the POF impacts of vehicle options. The trend of manufacturing phase is similar to that of PMF and CO_2 emissions. S-EV performs the worst in manufacturing phase, while it has the second least POF emissions in operation phase. POF impacts of PHEVs are least in the operation phase competed to other vehicles. When these two phases are combined the HEVs are found to be best alternative due to overwhelming manufacturing impacts of PHEVs. EVs can be considered as the worst option for POF impacts since their manufacturing impacts are much more than their saving potential in operation phase. Hence, their total life cycle impacts are worse than the BAU case.

Overall, HEVs and PHEVs are found to be better options to reduce POF impacts from transportation.

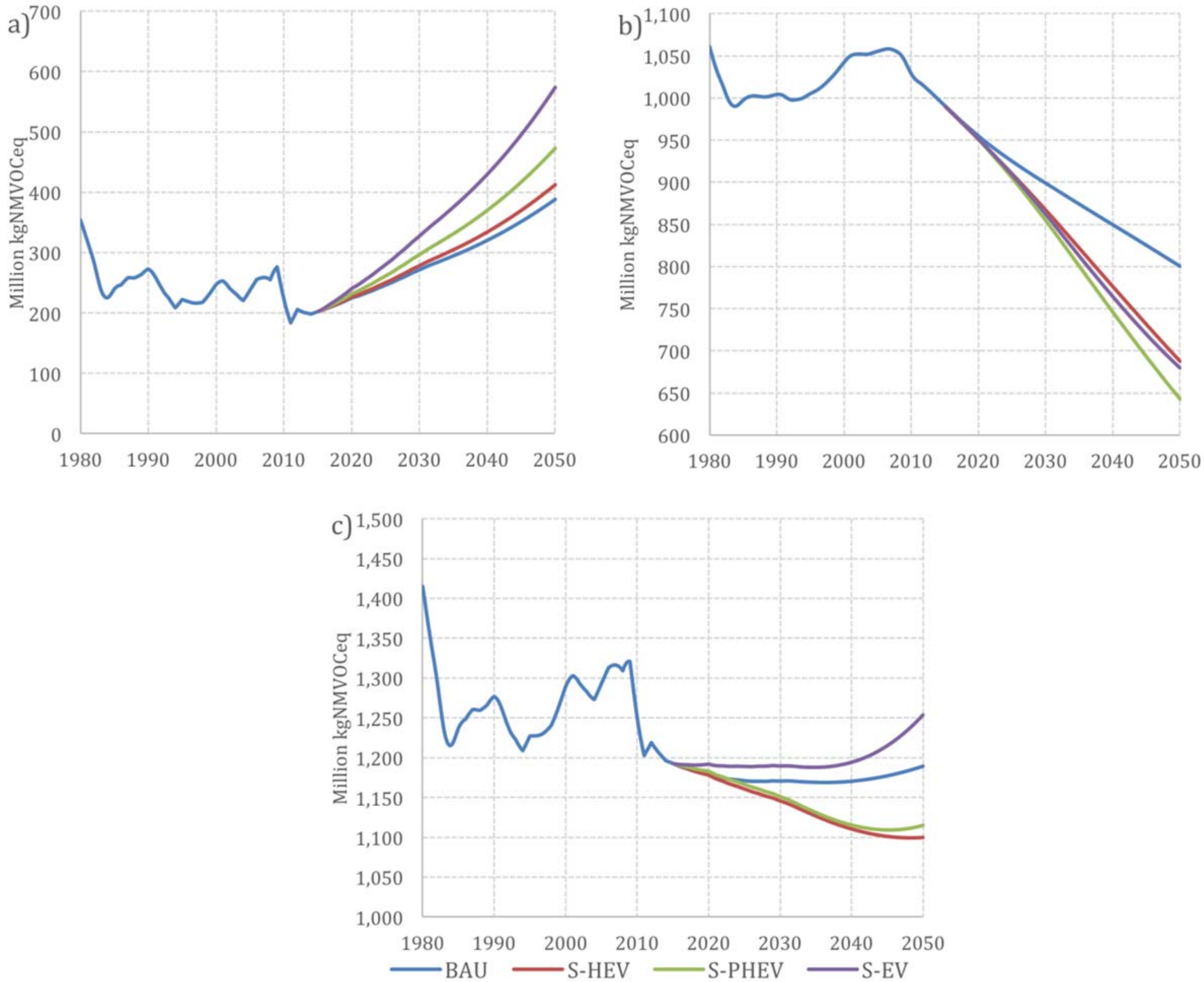


Figure 4.5 POF from vehicle transportation a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle

The rest of the environmental indicators such as atmospheric temperature change and the total CO_2 emissions are not shown in figures due to negligible changes resulted from each scenario. Basically, the overall climate system is much larger than the U.S. transportation sector's size in the terms of emission contributions. Therefore, changes in transportation sector by using different type of vehicles do not affect the atmospheric temperature significantly. Reducing the atmospheric climate change requires much more ambitious targets and international collaborative efforts. The U.S. transportation sector, alone, cannot reduce the rapidly increasing atmospheric temperature and the negative impacts of the global climate change.

4.3.2 Economic Impacts

Economic impacts are evaluated according to vehicle ownership costs to drivers and overall contribution to U.S. GDP. Figure 4.6 shows the vehicle ownership costs during the operation phase and the total life cycle ownership costs. As shown in Figure 4.6, both operation and total life cycle ownership costs have a decreasing trend, which are sharper for the EVs owing to improvement in battery technologies and lower initial costs. Currently, the total life cycle ownership cost of HEVs is slightly lower than the ICVs. Operation phase costs are lowers for PHEVs until 2028 where EVs became the most favorable option afterwards. Another interesting result is that the total life cycle cost of ICVs became as low as PHEVs and slightly lowers than HEVs in 2050 thanks to fuel efficiency improvements. While the cost difference is much larger in early years when the EVs are introduced to the market, the cost difference becomes smaller after 2030.

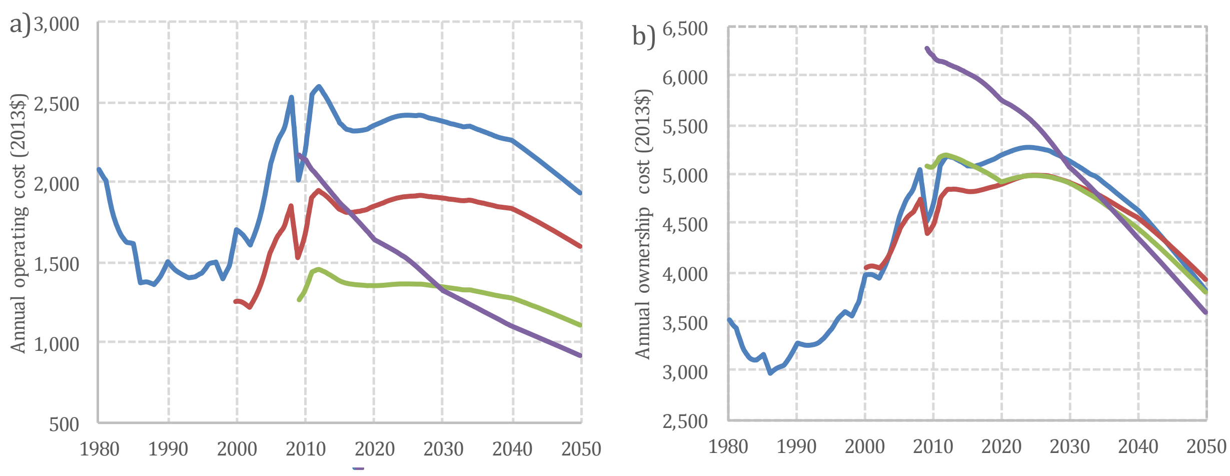


Figure 4.6 Annual vehicle ownership costs a) Operation Phase, b) Total Life Cycle

Figure 4.7 shows the contribution of each life cycle phase to the U.S. GDP for each scenario. GDP contribution in manufacturing phase is dominated by S-EV and S-PHEV. All of the vehicle scenarios have an increasing trend due to increased consumption. While economic sizes of manufacturing and operation phases are similar in the early years, the contribution of manufacturing phase becomes higher as the vehicle performances increase towards 2050. Operation phase contribution have increasing and stable trend for BAU case and S-HEV, whereas the contributions S-PHEV and S-EV decrease. Because, increasing VMT trend stimulated the contribution of HEVs and ICVs, while it could not overwhelm the effect of improved fuel efficiency and batteries for PHEVs and EVs. These improvements pave the way for reduced consumption and less contribution to GDP within the transportation sector for PHEVs and BEVs. The total life cycle contribution of PHEVs and EVs are larger than those of ICVs and HEVs until 2025 and 2030, respectively. The contribution of HEVs became the slightly greater in 2050 with an increasing trend since they are introduced to the market. Overall, all of the scenarios indicated similar trend for total life cycle.

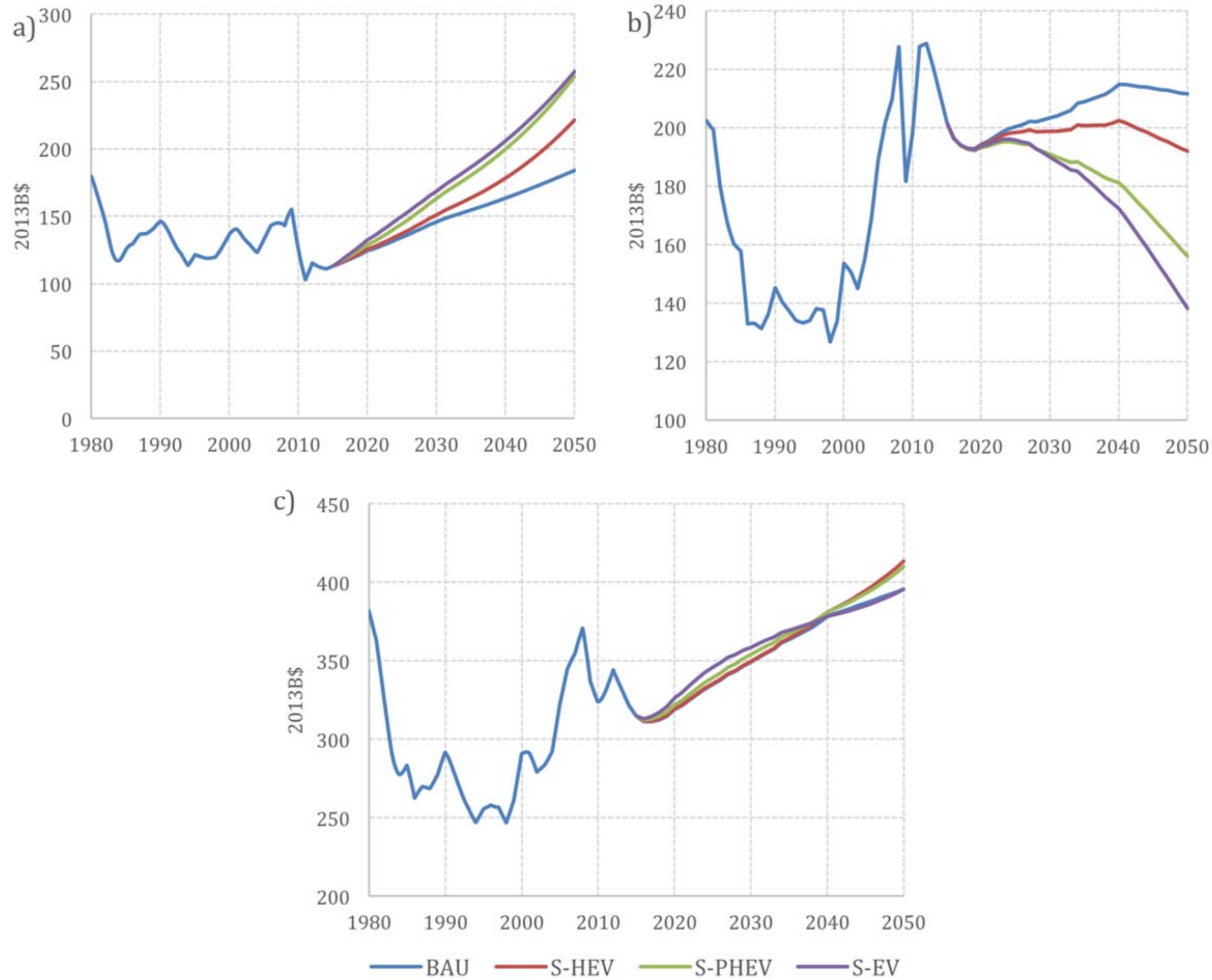


Figure 4.7 Contribution to GDP a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle

4.3.3 Social Impacts

The indicators of employment and human health represent social impacts. Employment contribution of each life cycle phase and vehicles are presented in Figure 4.8. Employment is very similar to contribution to GDP as they have historically strong correlation. Manufacturing phases of PHEVs and EVs have the greatest contribution to employment. Manufacturing phases of all of the vehicle types have increasing trends as the size of the transportation sector grows with the increasing vehicle demand. On the other hand, only employment contribution of ICVs, defined under BAU scenario, has an increasing trend in operation phase, whereas rest of the vehicle types are either stable or decreasing due to transformation by the more technology oriented sectors (increased productivity) and reduced consumption. The total life cycle employment trends have slightly fluctuating structure where newly introduced technologies create more employment at the beginning and reach a stable increase rate afterwards. Overall, the total life cycle employment contribution of S-HEVs and S-ICV are more stable and increases with almost a constant slope mainly due to increased travel demand and developments in the associated sectors. The total life cycle contributions indicated that all of the scenarios have similar trend and contribution in long-run.

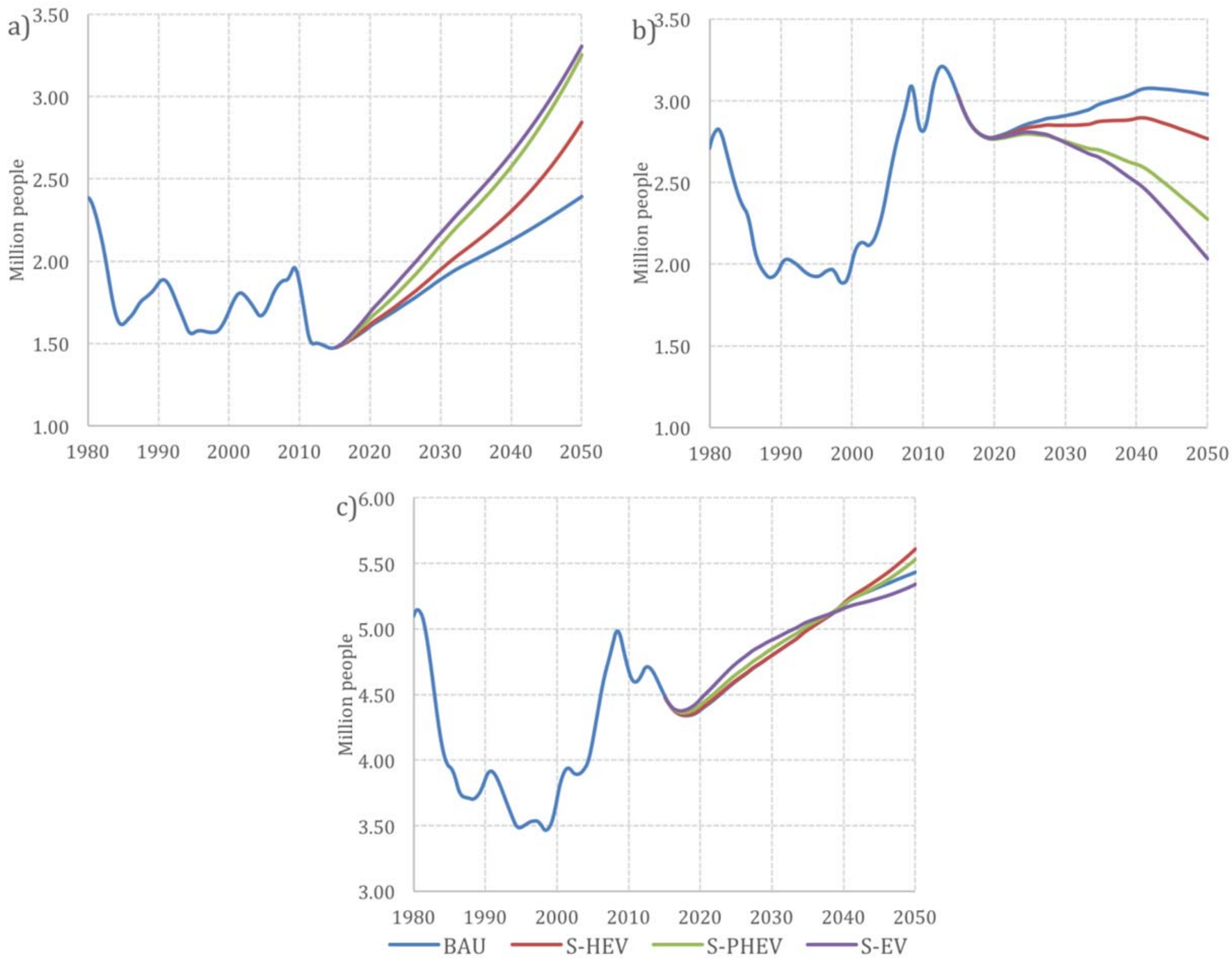


Figure 4.8 Contribution to employment a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle

Human health impacts resulting from PMF, POF, and the global warming are presented in Figure 4.9. The human health impacts in manufacturing phase are much smaller than the operation phase in general. However, as the fuel efficiency and battery technologies improved the relative impacts of operation phase become smaller. Human health impacts in manufacturing phase are dominated by EVs and PHEVs and have an increasing trend over time. In the operation phase, impacts are least for these two vehicle types. Because manufacturing impacts are smaller compared to operation phase impacts, the human health impact potential of EVs, and PHEVs in operation phase dominated the total life cycle impacts and favored these two vehicle types. One of the important effects is that the exposure rate of PM10 is much less in manufacturing facilities compared to PM10 exposure in operation phase of these two vehicles. BAU case indicates that the total life cycle human health impacts have a decreasing trend, which can be fasten with adoption of EVs and PHEVs.

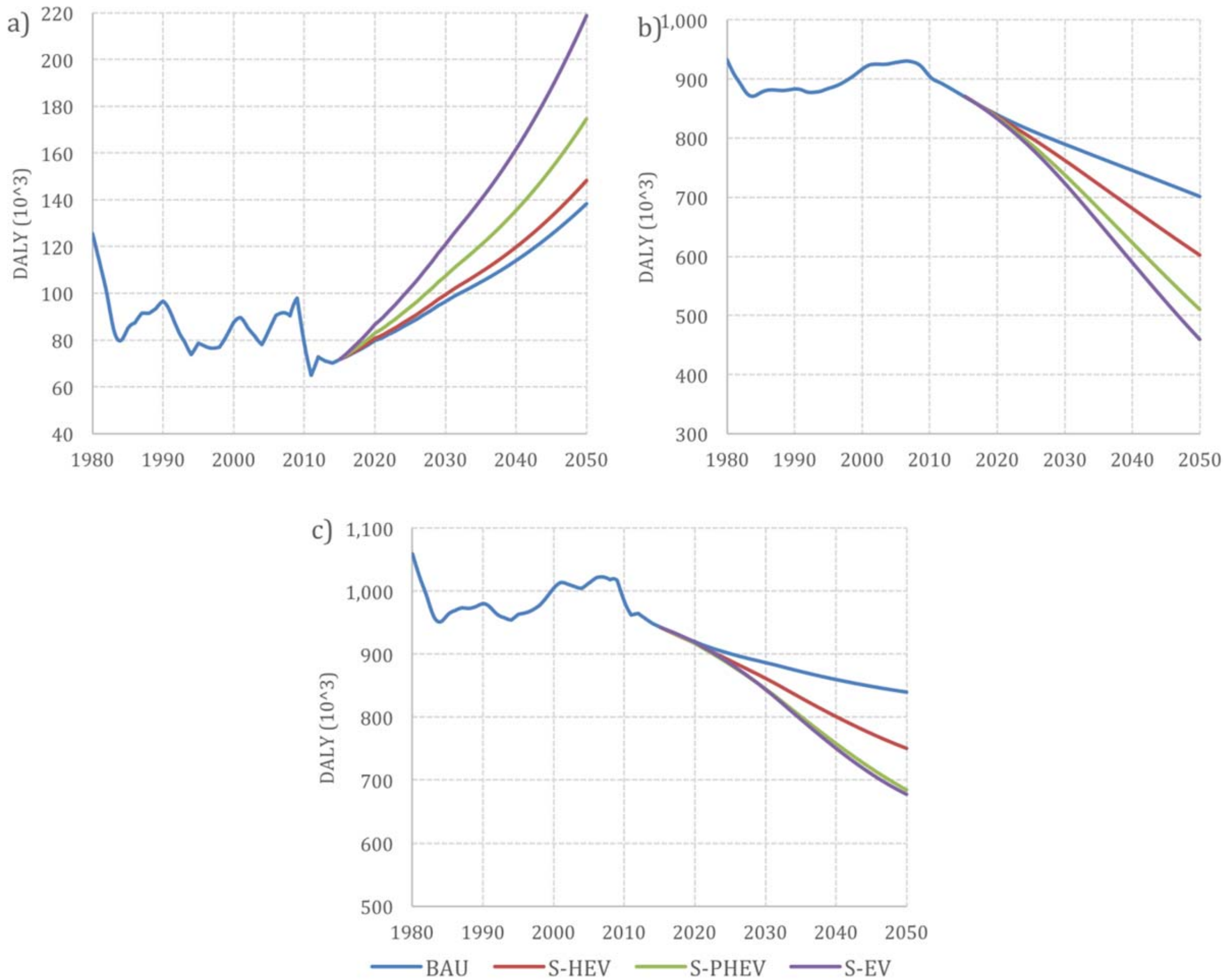


Figure 4.9 Human health impacts a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle

The use of different vehicle types has a small impact on public welfare, which is a function of income, education, and life expectancy indexes. Therefore, the effect of each scenario was not presented in a separated figure. The main reason of this insignificant impact is that the determinants of public welfare do not change significantly as the vehicle preference changes. The effects of vehicle choices on income, education, and life expectancy indexes are very small and geometric average of these indexes are even smaller. However, small changes in public welfare can lead greater changes in society. In fact, there are threshold values for such indices, which can have more impact than expected. For example, while a minor decrease for income index in the span above the threshold value may not disturb the society, same minor decrease may cause much greater disturbance in society when it brings the income index above the threshold value. Therefore, a small measure can be very important in some case. Overall, all of the alternative vehicle scenarios contribute public welfare more than the BAU case. The contribution of S-HEV and S-PHEV is slightly more than that of S-EV. As stated previously, public welfare is a function of life expectancy index, education index, and income index. Over all, S-EV performed best in the life expectancy index, whereas S-HEV and S-PHEV are found to be better for education index and income indexes, with slightly higher rate for S-HEV.

4.3.4 Impact of feedbacks from causal loops

The results for social, environmental, and economic impacts are given in an aggregate form of trends without specifying the impacts of feedbacks and demonstrating the benefits of SD modeling clearly. Although the assumptions associated with battery and fuel efficiency improvements, emission rates at manufacturing facilities, and energy sources play important role in the results, the behavior of the model is also highly influenced by the trend of exogenous variables such as the expected economic growth in the rest of the economy, expected life expectancy for the U.S., etc. In addition to these two major determinants, there are effects resulting from the causal loop relationships at different degrees. The results presented are aggregated impacts stem from accumulation of all of these three major mechanisms (assumptions, exogenous effects, and feedback effects). Affects resulted from the causal loops (feedbacks) are shown explicitly to give a better overview of the benefits of the SD modeling.

Considering that all of the loops (reinforcing and balancing loops) are connected with the transportation sub-model as a central component of the system (please see Figure 4.2 and causal loop identification), it is selected as a major domain to show the differences stemming from the effects of loops. The transportation sub-model is represented by two major parameters: the travelled distance and number of new vehicle sales. These two parameters are functions of population, number of drivers, income index, public welfare, and employment. Hence, changes in these parameters effects the number of new vehicle sales and distance traveled by the on-road vehicles in following years. The differences in travelled distance (in kilometers), and the number of new vehicle sales are revealed for each scenario. These changes in the selected parameters indicate the effects of feedbacks accumulated as a result of 9 balancing and 3 reinforcing loops. For instance, S-EV has a feedback through all of these loops to itself since the VMT and number of new vehicle sales will be different for the future years as a result of its impact in previous years. One of the balancing loops shown below can be a good example of it. Once the market share of HEVs gradually increases, the GHG emissions associated with public transportation will be less than the BAU. So, the climate change impacts will be relatively less on GDP due to lower temperature increase as opposed to BAU case. Hence, less impacted economy will be able to preserve more employment compared to BAU case, which will result in more vehicle travel.

Passenger vehicle transportation →(+) GHG emissions →(+) Climate Change →(-) GDP →(+) Employment →(+) Passenger vehicle transportation

Thus, accumulation of all of these previously defined loops changes vehicle travel and number of new vehicle sales. Table 4-6 shows the accumulated differences between BAU scenario and the other scenarios during the time between 2015 and 2050. For instance, applying S-HEV results in 689,930 more vehicle sales than the estimated vehicle sales in the BAU scenario. Similarly, S-HEV causes 88,240 million kilometers more travel than it is in BAU scenario. These differences stem from the accumulated effects of the causal loops throughout time. The additional vehicle sales and travel will cause more environmental, social, and economic impacts than what can be estimated by traditional modeling approaches.

Table 4-6 The differences in key parameters due to feedback effects between 2015 and 2050.

Parameters	**S-HEV**	**S-PHEV**	**S-EV**
Number of new vehicle sales	689,930	1,330,390	1,732,120
Vehicle travel (million km)	88,240	130,115	156,718

According to these results, S-EV has the highest nominal difference compared to BAU scenario as it causes the highest additional number of new vehicle sales and vehicle travel. As these impacts are the result from the feedbacks of each loop, it is also important to identify the share of each loop in the terms of their degree of impacts compared to one another. Unfortunately, it wasn't possible to track impacts of each loop and distinguish their impacts. Analysis results revealed that the magnitude of these effects is relatively much smaller than the direct impacts such as exogenous trend of economy and population. These feedback impacts did not cause a regime change in the behavior of the indicators. The main reason is that the transportation system is a small component in the terms of indicators quantified in this work. Therefore, the trends of exogenous variables dominate the overall system. On the other hand, this doesn't mean that the feedback impacts should be neglected. Although this work didn't experience such a regime change due to feedback impacts, there might be cases where the behavior changes significantly as a result of feedbacks.

4.4 Conclusion

This research is an important attempt towards advancing the state-of-the-art in LCSA framework and state-of-practice of transportation sustainability. One of the main conclusions is inclusion of dynamic interactions among the sustainability indicators, as wells as the system of interest. This approach can be critical to deepen the existing LCSA framework and go beyond the current LCSA understanding, which provides a snapshot analysis with an isolated view of all pillars of sustainability. One of the main advantages of this approach is its ability to provide a more comprehensive and in-depth analysis as an integrated dynamic LCSA framework, in which the product (alternative vehicles) are assessed considering the environment surrounding it and the interrelations among its sustainability impacts. Some of the important results and general remarks are summarized as follows:

- The impacts from feedbacks are relatively smaller compared to effects of exogenous variables such as GDP growth of the entire economy, population growth, etc. Thus, sustainability impacts of products highly depend on its surrounding environment as it is clearly shown in this study. Therefore, when assessing triple bottom line impacts of any product, the system surrounding it should be taken into consideration.
- Among the tested scenarios, S-EV had the highest effect resulting from the feedback loops. It should be noted that the feedback impacts resulted from 9 reinforcing and 3 balancing loops, indicating a reverse impact and cancel one another depending on their impact scale. This behavior can be different in other systems, which might result in much greater feedback impacts if one of the loops dominates the others (reinforcing or balancing). Hence, when assessing life cycle sustainability impacts of products, these feedback relationships should be taken into consideration.
- Analysis results revealed that vehicle choice affects the public welfare at small scale. Exogenous determinants of public welfare, life expectancy, income, and education overwhelm the effects of vehicle choice. Considering that public welfare is one of the major indicators that society cares about, small variations in that regard may lead to significant changes in society and may greatly affect the overall behavior of the system. Therefore, assessing sustainability impacts of products, systems, or processes should overarch set of social indicators and give insights about possible changes may be resulting from it.
- BEVs are mostly found to be the best option in the CO_2 emissions category. However, they did not perform well in the impact categories of PMF and POF. PMF impacts should be considered along with their health impacts since PMF is more important in the operation phase due to the higher exposure rates. Because BEVs have less tailpipe emissions, the BEVs have the greatest potential on reducing human health impacts due to air pollution.
- While environmental impacts of BEVs are the highest in the manufacturing phase compared to manufacturing phase impacts of other vehicle options, the operation phase CO_2 emissions and PMF and BEVs are found the be the least. It is important to note that these results highly depend on the emission factors at manufacturing facilities. Improvement in emission control systems in vehicle manufacturing facilities can change the amount of emissions significantly. However, the relative performance of BEVs depends on the improvements in battery technology as well as the environmental impacts during battery production since the emission difference between ICVs and BEVs as well as PHEVs stem from the additional battery manufacturing.
- The analysis results revealed that even though the entire U.S. automobile stock was replaced with BEVs, it would have a negligible impact on slowing down to rapidly increasing atmospheric temperature, which would normally take place regardless the substitution of the entire U.S. automobile stock with BEVs. Hence, more ambitious and international efforts are crucial to reverse or slow down the increasing atmospheric temperature. Especially, promoting renewable energy sources and stringent emission control policies are crucially important to slow down rising global temperature.

- GDP and employment contributions of each scenario are more or less similar. Although there are temporal variations throughout time, the overall behavior indicates that GDP and employment contribution of all of the vehicle types are similar. Vehicle ownership costs of BEVs are found to be more until 2030, and become the best option afterwards.

There is a strong need for robust simulation models that would allow us to consider dynamic complexity and deep uncertainty to mainly understand, not just predict, possible future scenarios. Most decisions related to transportation sustainability have to be made in deeply uncertain situations, where the relationships among the main factors of the system, the probability distribution of these varying factors, and the plausible alternative outcomes are inherently complex and uncertain. While the approach presented in this study provides important insights to understand the dynamic complexity and the system as a whole, the model needs certain improvements to account for uncertainties associated with fuel economy, emission rates, driving behavior, spatial variations, etc. In this regard, Exploratory Modeling and Analysis (EMA) should be integrated with the proposed model to account for these uncertainties as well as to explore a range of plausible future scenarios and gain insights regarding the possible outcomes. Hence, the next step will be to integration of EMA approach to strengthen the robustness of the model and to deal with the inherent uncertainty of the transportation system.

5.0 Development of a regional market penetration model for electric vehicles

5.1 Introduction

5.1.1 Introduction and Scope of Work

By diversifying the fuel mix of the U.S. transportation sector, the electric vehicle industry helps to increase energy security and reduce dependence on petroleum.[3] Moreover, the transportation industry has an enormous effect on greenhouse gas (GHG) emissions, and is responsible for 27% of all GHG emissions in the U.S. as of 2013 [104]. Although Internal Combustion Engine Vehicles (ICV) replaced electrified transportation by 1930, Electric Vehicles (EVs) have been around for more than 100 years. The EV market shares have greatly increased in recent years due to energy insecurity concerns, the increasing trends in oil prices, improvements in electrical power storage [105], and electricity's current status as the cheapest and most efficient energy source for the transportation sector in the foreseeable future [106]. Governments are now embracing the development of EVs on the road by setting goals to improve the EV industry. Although the Obama administration has backed off of its goal of one million electric vehicles on the road by 2015 [107], others have set a goal of an EV share of 20% in the U.S. transportation new sales fleet by 2030 [108]. There are also some goals in the state level such as California's Zero Emissions Vehicle (ZEV) mandate [109]. The U.S. Government now offers financial incentives to consumers to lower first-time costs, offering up to $7,500 in tax credits for EVs purchased in or after 2010; this incentive will be phased out after 200,000 vehicles from the qualified manufacturers [110].

Furthermore, the U.S. Government also supports research and development for new technologies to accommodate the movement towards a more electrified vehicle fleet. Additionally, significant cost reductions for EV components such as batteries have further stimulated this market share growth. However, despite all of these efforts and the current collective movement to facilitate the electrification of the U.S. transportation fleet, there are still barriers hindering the widespread adoption of EVs as a viable transportation option, including various technological, financial, market, and policy challenges to the full deployment of EVs. The United States currently has the largest number of electric vehicles on the road, with almost 43 percent of all EVs sold in the U.S. However, EVs only comprised less than 1% of new car sales in the U.S. as of 2014 [111]. Therefore, greater adoption rates must be met in order to achieve the mid-term and long-term market share goals for EVs as described previously [112]. In light of these challenges, it is increasingly necessary to study EV market shares in more detail. Market forecasting is currently a well-developed and well-studied field with implications

[3] The contents of this section were partly published in Noori, M., and Tatari, O. (2016). "Development of an agent-based model for regional market penetration projections of electric vehicles in the United States." *Energy, Elsevier*, 96(2016), 215-230, *2014 IF: 4.844*. DOI: 10.1016/j.energy.2015.12.018

in various other fields (economics, business, finance, systems engineering, etc.), but often fails to consider uncertainties in the different factors affecting market shares. For this reason, market evaluations of new EV technologies is facing increasing degrees of complexity due to difficulty in modeling the relevant system factors [113].

The aim of this work is to study the market penetration of EVs considering the inherent uncertainties involved. To this end, the purchase prices, maintenance and refueling (M&R) costs, environmental damage costs (EDC), and water footprints (WFP) of the studied vehicle types are estimated, considering their respective uncertainty ranges. Next, an agent-based model (ABM) is developed to simulate the market penetration of EVs in the U.S. Finally, different scenarios are applied via the Exploratory Modeling and Analysis (EMA) approach, and the most plausible outcome of this method is analyzed as needed. Five different vehicle types are compared and analyzed: Internal Combustion Engine Vehicles (ICVs), Gasoline Hybrid Electric Vehicles (HEVs), Gasoline Plug-in Hybrid Electric Vehicles (PHEVs), Gasoline Extended-Range Electric Vehicles (EREVs), and All-Electric Vehicles a.k.a. Battery Electric Vehicles (BEVs). For the purposes of this study, it is assumed that PHEVs and EREVs have all-electric range of 10 miles and 40 miles, respectively.

This work distinguishes itself from previous efforts in several ways. First, the previously developed Electric Vehicle Regional Optimizer (EVRO) is used to estimate the M&R cost, the EDC, and the WFP of the studied drive-train. The analysis also considers all of the possible uncertainties of the life cycle cost (LCC), EDC, and WFP analyses to account for all applicable EV characteristics. Second, although some efforts have been made to develop a market share model to simulate the market penetration of EVs in the U.S., most of these efforts have considered an average U.S. electricity grid mix in their respective analyses, while this study considers 22 different electric grid regions and analyses the adoption rate of EVs in each region separately. Finally, an agent-based model (ABM) is developed in conjunction with the Exploratory Modeling and Analysis (EMA) method to integrate the relevant uncertainties into the market share of EVs in the year 2030.

5.1.2 Life Cycle Analysis, Agent Based Modeling, and Market Penetration of Electric Vehicles

Life Cycle Assessments of EVs have been extensively studied in today’s literature. For instance, in one of the most recent publications from the University of Central Florida, a state-based carbon and energy footprint analysis was performed for conventional, hybrid, plug-in hybrid, and electric vehicles [96]. Moreover, The Union of Concerned Scientists published an informative report that investigated emissions from charging electric vehicles on a regional scale, including upstream emissions from building power plants, extracting and transporting fuel, converting fuel into electricity, and delivering electricity to the point of use [114]. In addition, Viñoles-Cebolla et al. developed an integrated model to estimate the life cycle emissions of different vehicles using primary vehicle data such as weight, engine technology, and fuel type [115]. Moreover, Zhang et al. proposed a simulation model to analyze the economic and environmental performance of EVs, testing different conditions such as the electricity generation mix, smart charging control strategies, and real-time pricing mechanisms [116].

Agent-based modeling (ABM) is a simulation method that creates a virtual environment to model the interactions between different agents. ABM is previously used to model vehicle technology adoption, with different agents (consumers, automakers, policy makers, fuel suppliers, etc.) interacting in a virtual environment. For instance, Cui et al. developed a multi agent-based framework for the spatial distribution of PHEV ownerships at local residential household level [117]. In addition, Eppstein et al. developed a spatial explicit ABM to study market penetration of PHEVs and concluded temporary rebates have only short-term impacts on market share and gas prices must rise for a higher penetration rate [118]. Consumers are the primary agents in some aspect of the vehicle technology adoption portrayed with the ABM method, whereas more current models have expanded this environment by considering automakers, policy makers, and fuel suppliers as agents as well. One of the more advanced ABM for evaluating the market share of EVs is the Virtual Automotive Market Place Model (acronym VAMPM) developed by the University of Michigan Transportation Research Institute (UMTRI) [119]. This model characterizes the market share of new technologies in a hypothetical “neighborhood” under different consumer, economic, and policy conditions, and considers four different agent types: consumers, governments, fuel producers, and vehicle producers/dealers. The unit cycle of the analysis is one month, and the agents communicate in each cycle based on their needs and benefits. The results indicate that, by 2015, sales of PHEVs could reach up to 3%. By 2020, sales could potentially reach up to 5 % and up to 20% in 30 years, with a final market penetration of 16% by 2040. One of the advantages of the ABM method is its ability to use both hypothetical and data-driven consumer behavior during the modeling process [113].

Most of the agent-based models in current literature were developed based on utility theory, in which the agent purchases a vehicle that maximizes his/her utility. For instance, Ting Zhang et al. proposed a novel ABM methodology to investigate factors that can facilitate the penetration of the alternative fuel technologies into the market [120], considering four different agents in their analysis: manufacturers, vehicles, consumers, and governments. The mathematical content of abovementioned study is now used as a basis for the formulation of the developed ABM in this research. Moreover, a consumer choice probability model is developed for evaluating the market share of EVs in Iceland by Shafiei et al. [121], with consumers weighing different vehicle attributes based on their own specific preferences. The mathematical content of the consumer choice model is also used to form the developed ABM in this analysis. The mathematical content of the developed Electric Vehicle Regional Market Penetration (EVReMP) Model is described in the next section.

5.2 Methods

First, the developed Electric Vehicle Regional Market Penetration (EVReMP) model and its relationships to other parts of the methodology are illustrated (See Figure 5.1). Second, a summary of the previously developed Electric Vehicle Regional Optimizer

(ERVO) is explained. Third, the concept of Exploratory Modeling and Analysis (EMA) and the mathematical content of the agent-based model (ABM) developed in this study are explained. Fourth, we present the inherent uncertainties in the purchase prices, maintenance and refueling costs, and water footprints of the studied vehicles as applicable. In short, the EVReMP model is a combination of several different methodologies that will enable decision-makers to see what the market penetration of the studied drivetrain would be in the year 2030.

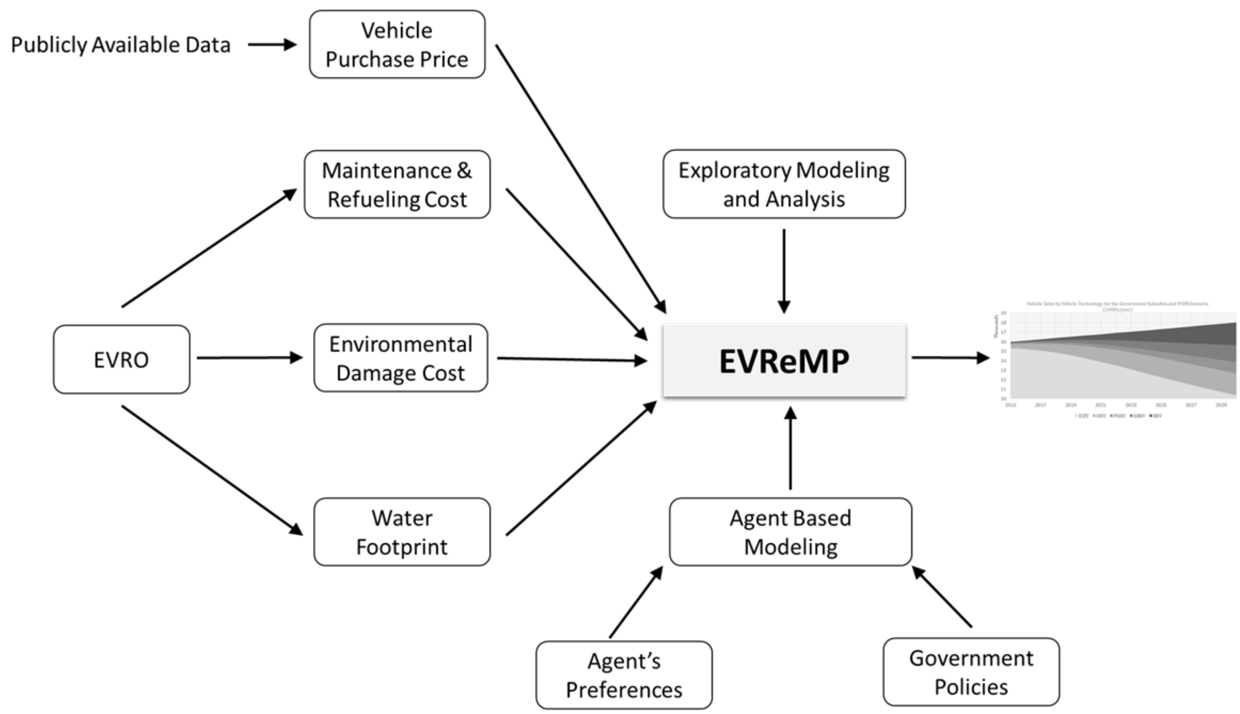


Figure 5.1 Illustration of the EVReMP model

5.2.1 Electric Vehicle Regional Optimizer (EVRO)

EVRO is an optimization model previously developed by the authors [94] that uses several previously established methodologies in Life Cycle Assessment of energy systems [122,123], Multi Criteria Decision Making [13,124], Decision Making Under Uncertainty [125], Intelligence Transpiration Systems [126,127] and Stochastic Optimization [64,128]. It also builds on the Argonne National Lab's Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET) model [129] to estimate the life cycle cost (LCC) and life cycle environmental emissions (LCEE) of the studied vehicle types. The environmental damage cost (EDC) is taken into the account, including the costs associated with the mitigation of GHG and local air pollutant emissions. The water footprint (WFP) of the studied drivetrain is also estimated in the EVRO model, considering the first-tier and higher-tier withdrawals of petroleum extraction and/or electricity generation. Finally, an optimization model is coupled with the concept of Exploratory Modeling and Analysis, and is subsequently applied to the estimated LCCs, EDCs, and WFPs of the studied drivetrain to find the optimal drivetrain combination for the year 2030. Here, the EVReMP model builds on the EVRO model to estimate the maintenance and refueling costs, EDCs, and WFPs of each of the studied vehicles. It is worth noting that the EVRO model considers different uncertainty factors in order to evaluate the attributes of each vehicle type. The overall range of each uncertainty factor in the EVRO model was taken from publicly available data.

5.2.2 Exploratory Modeling and Analysis

Most predictive models are designed so that known facts are consolidated to create a “best estimate” model. Such models are claimed to be an accurate case of that portion of the real world, but in reality they can only be considered valid when there is adequate useful data of sufficient quality so that model designers can use empirical data to validate the model. This validation process is only possible when the situation is observable or measurable, the structure of the problem is constant over time, and sufficient data can be collected [130,131]; for many systems, however, these conditions are not met. Scientists use different terms to express such situations, and subsequent predictions under such conditions are largely rejected as wrong, bad, or useless [130–134]. On the other hand, our actions today affect the future behavior of the system. The degree of uncertainty with respect to the behavior of the system is directly proportional to the level of interaction among economic, social, environmental, and technological factors, and decision making with high levels of interaction involved in the system is said to be under deep (or severe) uncertainty [135–138]. This situation occurs when the overall relationships among the main components are the system cannot be agreed on by decision makers, when the probability distribution of these factors is uncertain, and/or when the most plausible outcome is not precisely predictable [139]. Uncertain aspects of these systems include the initial inputs of the system, the relationships among the parameters in the model, the logic associated with these interactions, the system boundaries, the model structure, and the difference between the real behavior of the system and the estimation presented in the model.

With all of this in mind, The Exploratory Modeling and Analysis (EMA) method is used to model the behavior of the system in this situation, Exploratory Modeling and Analysis is being used. The EMA methodology evaluates the behavior of the system under deep uncertainty, and is based on the prominent work of Bankes [140,141]. More specifically, the EMA method works by forming an ensemble of plausible outcomes using computational experiments based on available knowledge and data, and then using this set of plausible outcomes as a surrogate to predict the behavior of the system. In fact, instead of building one model and verifying it as a representation of the system, the EMA method creates an ensemble of models and explores the implications of these models [130]. By conducting such experiments, one can explore which of the determined plausible outcomes are more likely to occur given the system’s behavior. Although the EMA methodology is relatively new and still under development, it has already been applied to a wide variety of disciplines and research topics, including climate change, production planning, economic analysis, healthcare, sustainable development, and transportation [128,139,141–145].

In this research, the EMA method is used to evaluate all of the plausible outcomes of the developed ABM. This integration of the EMA and ABM methodologies thereby enables decision-makers to generate, explore, and deeply analyze a large number of plausible future outcomes, allowing them to better understand the effect(s) of current uncertainties on the future market shares of electric vehicles. The required steps to apply the concept of EMA to a deeply uncertain problem are as follows [146,147]:

1. Conceptualize the policy problem,
2. Specify the relevant uncertainties,
3. Develop an easily controllable computational model of the system's behavior,
4. Generate numerous plausible future outcomes as needed,
5. Perform a data analysis with respect to the generated outcome(s), and
6. Use the finalized model to define and test different policies as desired.

These steps are taken into account while using EMA in this effort. One of the goals of this study is to apply the concept of Exploratory Modeling and Analysis (EMA) to the developed ABM model to account for the inherent uncertainty levels of the system. In one study by Kwakkel and Yücel, EMA is applied to a developed ABM model in the case of Dutch electricity transition [130], exploring plausible transition trajectories and their conditions for occurring.

5.2.3 Agent-Based Modeling

An Agent-Based Model (ABM) is used to evaluate consumer behavior and to estimate the market penetration of the studied drivetrain. Four different agents (consumers, regions, governments, and vehicles) are considered in this model. Consumers seek to purchase a vehicle, maximizing the utility of the vehicle(s) in question. Governmental policies can affect consumer behavior in various ways, depending on the implications of each specific policy and/or set of policies. Vehicle attributes are derived from the EVRO model, with the EVRO analysis performed for each U.S. electric grid region. Details of the model can be found in the published paper.

5.2.4 Assumptions and Preliminary Data

Table 5-1 summarizes the uncertainty ranges considered in the EVRO model, assuming that all uncertain parameters are uniformly distributed between their respective lower and upper limits. The only exceptions to this assumption are the price(s) of electricity and/or gas, which are selected through a rectangular random function.

How often an agent purchases a vehicle depends on his/her social group. Therefore, different social groups are defined, and each agent is randomly assigned to a social group. The level of income the agent is then randomly selected among the pre-set income levels, and the purchase probability for each social category is estimated as summarized in Table 5-2 for different social and income categories. In 2014, 7.9 million passenger cars were sold in U.S., meaning that approximately 2.5 percent of Americans purchase a passenger car each year [154]. The vehicle purchase probabilities of each social group are taken from [121,155]. Since the data in both of these reports are based on different total populations (Iceland and Denmark, respectively), this study uses a scaled social group probability based on a purchasing rate of 2.5% in the U.S. (Table 5-2).

Table 5-1 Model Parameters in EVRO Model

Parameter	Source	Range
Analysis Period	[148]	2015-2030
Discount Rate	[149]	0.65-1.15
Inflation Rate	[150]	-10% , +10% of CBO's projections
Fuel Economy	[151]	EIA's projected mpg for light duty vehicles & AFLEET
Vehicle Miles Traveled (VMT)	[151]	-10% , +10% of EIA's projections
Electricity Price	[152]	EIA & proposed methodology in EVRO
Gasoline Price	[151,153]	EIA & proposed methodology in EVRO
EDC	Existing literature	Proposed methodology in EVRO
WFP of Fuels	Existing literature	Proposed methodology in EVRO

Table 5-2 Scaled Probability of Purchase

Social groups	Probability of Purchase		
	Low income	Medium income	High income
Single female	0.4%	1.2%	4.8%
Single male	0.6%	1.9%	10.1%
Female living w. parents	0.6%	3.9%	7.8%
Male living with parents	2.1%	3.5%	14.1%
Couple without children (female buyer)	1.1%	2.9%	5.6%
Couple without children (male buyer)	5.6%	8.2%	11.9%
Couple with children (female buyer)	1.3%	2.8%	5.8%
Couple with children (male buyer)	3.5%	7.0%	11.6%

For vehicle purchase prices, AFLEET uses the average purchase price of different vehicle types in each category, but does not consider the regional average costs of vehicles. Instead, truecar.com is used to find the average MSRP of the studied vehicles [156]. The city with the highest population in each region is considered to estimate the purchase price for each region. Table 5-3 shows the minimum and maximum MSRPs of all studied regions for each vehicle type.

Table 5-3 Vehicle Purchase Price (MSRP)

Vehicle Type	Minimum Price ($)	Maximum Price ($)
ICV	18,710	20,245
HEV	22,041	24,349
PHEV	29,810	32,707
EREV	30,510	34,202
BEV	31,812	35,318

Preferences in terms of the purchase price and maintenance and refueling costs are derived from the values found in available literature [121,155]. Since the EDC and the WFP are not amongst the attributes that every single agent cares about, whether the agent cares about these attributes or is indifferent will be randomly determined for each agent. If the agent considers environmental factors when making his/her decision, the associated preference is assumed to follow the values given in Tables 5-4 to 5-6. These preferences are estimated in a way that the overall purchase probability associated with each attribute falls in a same order of magnitude. Tables 5-4 to 5-6 summarize the preferences of agents of different social and income categories with respect to each vehicle attribute.

Table 5-4 Preference Values for Each Cost Attribute (Low Income Category)

Social Category	Purchase Price	Maintenance and Refueling	EDC	WFP
Single female	-3.68	-0.50	-0.03	-0.06
Single male	-3.35	-0.22	-0.01	-0.02
Female living with parents	-3.12	-0.50	-0.03	-0.06
Male living with parents	-2.92	-0.25	-0.01	-0.03
Couple without children (female buyer)	-4.60	-0.31	-0.02	-0.03
Couple without children (male buyer)	-4.31	-0.41	-0.02	-0.05
Couple with children (female buyer)	-4.26	-0.39	-0.02	-0.04
Couple with children (male buyer)	-3.92	-0.35	-0.02	-0.04

Table 5-5 Preference Values for Each Cost Attribute (Medium Income Category)

Social Category	Purchase Price	Maintenance and Refueling	EDC	WFP
Single female	-4.16	-0.40	-0.02	-0.04
Single male	-3.15	-0.29	-0.01	-0.03
Female living with parents	-3.01	-0.38	-0.02	-0.04
Male living with parents	-2.86	-0.33	-0.02	-0.04
Couple without children (female buyer)	-3.20	-0.45	-0.02	-0.05
Couple without children (male buyer)	-3.89	-0.38	-0.02	-0.04
Couple with children (female buyer)	-3.25	-0.44	-0.02	-0.05
Couple with children (male buyer)	-3.64	-0.41	-0.02	-0.05

Table 5-6 Preference Values for Each Cost Attribute (High Income Category)

Social Category	Purchase Price	Maintenance and Refueling	EDC	WFP
Single female	-2.25	0.00	0.00	0.00
Single male	-1.05	-0.29	-0.01	-0.03
Female living with parents	-4.80	-0.23	-0.01	-0.03
Male living with parents	-2.15	-0.28	-0.01	-0.03
Couple without children (female buyer)	-1.01	-0.44	-0.02	-0.05
Couple without children (male buyer)	-1.81	-0.29	-0.01	-0.03
Couple with children (female buyer)	-1.22	-0.33	-0.02	-0.04
Couple with children (male buyer)	-1.36	-0.27	-0.01	-0.03

The government also offers monetary incentives for purchasing EVs, so two types of government incentives (federal and regional) are considered in this analysis; these incentives are summarized in Table 5-7. Federal incentives are applied first, after which any applicable regional incentives are added to the federal incentive amounts to obtain the total incentive amount provided for any given region. The incentive rates listed in Table 5-7 are assumed to be constant for the entire analysis period, but whether or not the government actually offers these incentives is decided by the assumed scenario and also applying a random function to each analysis cycle. For instance, in the first scenario analysis, it is assumed that the government incentives are offered for the first 10 years and then randomly for the rest of analysis period.

Table 5-7 Government Incentives [109,157]

Government Incentives	PHEVs	EREVs	BEVs
Federal	$2,500	$4,000	$7,500
California	$1,500	$1,500	$2,500
Washington	-	-	6.5% of purchase price
Georgia	20% of the cost - Up to $5,000		
Maryland	$550	$1,000	$3,000

To model the willingness of an agent to purchase an EV, this study assumes that said willingness is influenced primarily by the word-of-mouth effect. Likewise, it is assumed that each agent contacts another agent once per month, and that the adoption fraction of the contacted agent is randomly selected as a value of up to 1%. Moreover, since there is no data available to definitively determine whether or not a specific individual within a particular household will decide upon a particular purchase [121], each agent is therefore defined as a household. Furthermore, each agent's tendency to buy a car will differ from one income level to another.

With this in mind, different scenarios can be applied in this analysis. In the developed model, for instance, gasoline and electricity prices are changed regularly using a random distribution given the estimated ranges from the EVRO model, which are based on EIA projections. Moreover, government subsidies can be offered randomly any year. Finally, it is assumed that the economic situation simulated in the model stays the same, with no recessions or major economic improvements occurring during the analysis period. Based on the preliminary data and uncertainty ranges previously described, the ABM model is then run for 10,000 replications to cover most of the possible interactions between the varying factors.

5.2.5 Verification and Validation of ABM

One of the biggest challenges faced during the AB modeling process is the verification and validation of the model and its results. Due to the heterogeneity of the agents in the model, there is a possibility of a new macro-level pattern emerging from the micro-level interactions between agents [158]. Thus, the main challenge in this effort is to determine how to properly validate the model and overcome the methodological obstacles associated with empirical validations. In general, validity for computational models is defined in terms of conceptual, internal, external, cross-model, data-related, and/or security-related validity [159]. Each of these types of validity are compared to an acceptable degree of confidence as defined by the modeler or decision maker. These specific validity types are described in further detail below.

- The model is **conceptually valid** if it represents the conceptual and theoretical characteristics of the real-world problem.
- The model is **internally valid** if its programming code runs without any errors.
- **External validity** means that the model output matches the real-world data.
- **Cross-model validation** compares the developed model with a similar model to check whether or not their respective outcomes match.
- **Data-related validity** means that the data used in the model is adequate and accurate.
- Finally, **security-related validity** means that adequate safeguards have been provided in the model to minimize the impacts of any issues that may adversely affect the model and/or its results.

This study uses the validation/verification process described in [120,160], in which four steps (grounding, calibrating, verifying, and harmonizing) are outlined to validate and verify computational models. After running the model for different numbers of agents, it was found that the number of agents does not significantly affect the market penetration results.

- First, the model is **grounded** based on the research currently being performed by the Electric Vehicle Transportation Center (EVTC) [161]. This project is aimed at preparing transportation systems for the future influx of electric vehicles. The grounding of a model involves discussing why the model is reasonable, what its limitations and scope conditions are, and how it compares with current models. The grounding process can be enhanced by verbally explaining that the model demonstrates the key elements of a specific group and/or social process; in this case, different social and income categories are taken into account, and the model represents the involvement of each of these categories in the purchase of five different types of vehicles.

- **Calibration** is used to tune up the model to fit the real-world data. This is usually an iterative process in which one or more model characteristics are altered as necessary to ensure that the model output come as close to reality as possible. The model is first calibrated using parameters from several studies; parameters related to the purchase probability of a vehicle are derived from [121], while those related to the refueling effect of EVs are derived from [121,162], and all parameters from both of these references have been calibrated for the U.S. by comparing the U.S. population with the respective populations of Iceland and Denmark, for which the parameters had originally been calculated. During the calibration process, it was observed that the model has a consistent tendency to accept HEVs as an appropriate option as well as ICVs, so consumer willingness with respect to HEVs was adjusted accordingly to reflect the real data. The preferences of each agent with respect to the EDC and WFP are likewise calibrated to more accurately reflect customer behavior.
- The **verification** process is performed using a cross-model comparison with output data from the Light-duty Alternative Vehicle Energy Transitions (LAVE-Trans) model and with the Argonne National Lab's VISION model [163,164]. Both models are used to represent a business-as-usual (BAU) case in the National Research Council of the National Academies' (NRCNA) report, "Transition to Alternative Vehicles and Fuels" [165]. Here, first, a base-case model is formed based on average values for the purchase price, M&R cost, EDC, and WFP, while also assuming that no government subsidies are given during the analysis period and that agents do not interact with each other. The comparison reveals that the generated data from the EVReMP's base case model (Figure 5.2) does not differ significantly from the proposed BAU case as presented in [165]. A statistical verification method is used to compare the results of BAU case in NRCNA's report with those from the developed EVReMP base case model. Both One-Way ANOVA and two-tailed small-sampled matched pairs hypothesis tests reveal the significance level of less than 5 %. Statistical approaches are used in numerous studies to validate models and analyze data such as in pavement engineering [166–168], sustainable infrastructure [169–171], and sustainable transportation [126].
- The goal of **harmonization** is to demonstrate that the assumptions made in the model are "in harmony with" (i.e. adequately correspond to) the real world. To this end, the model is first validated by comparing it with the model presented in [165], and is then tested by applying the relevant government subsidies and comparing the resultant model with the model presented in one of the LAVE-Trans' reports [163].

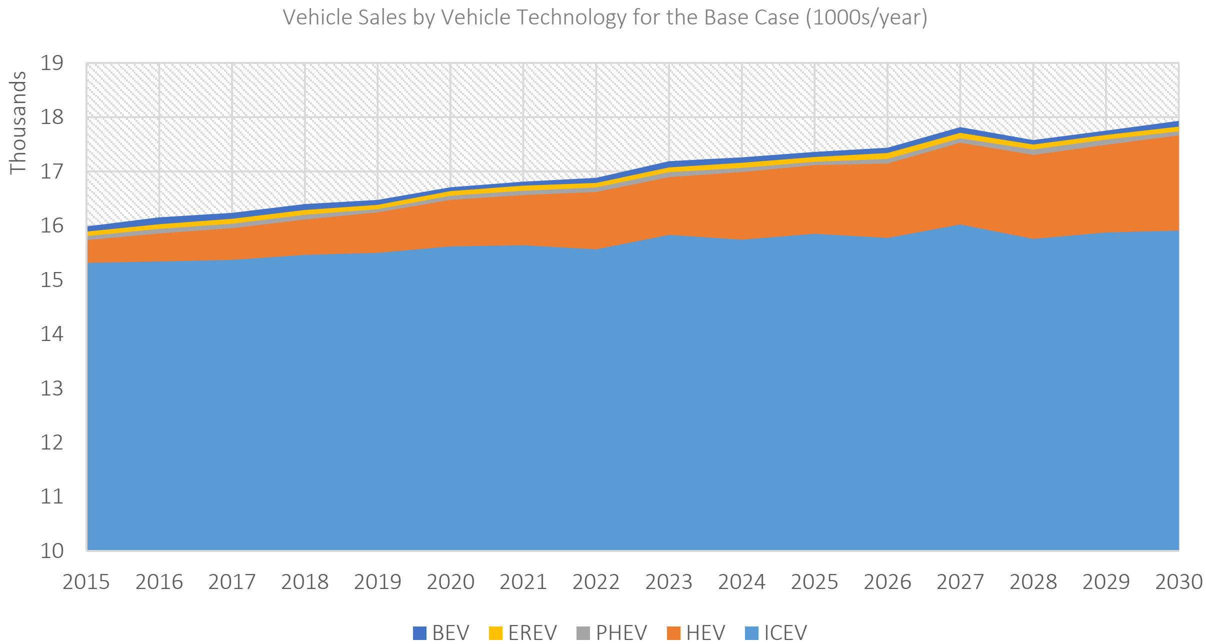


Figure 5.2 Vehicle Sales by Vehicle Technology for the Base Case (1000s/year)

After applying these steps, we are confident that the developed ABM accurately fits the real world and can therefore be used to evaluate the future market share of electric vehicles.

5.3 Analysis Results

The Maintenance and Refueling (M&R) Cost, Environmental Damage Cost (EDC), and Water Footprint (WFP) of the studied drivetrains are presented for each U.S. National Energy Modeling System (NEMS) region in order to illustrate the ranges of uncertainty encountered in the analysis. The NEMS regions and their abbreviations are shown in Figure 5.3.

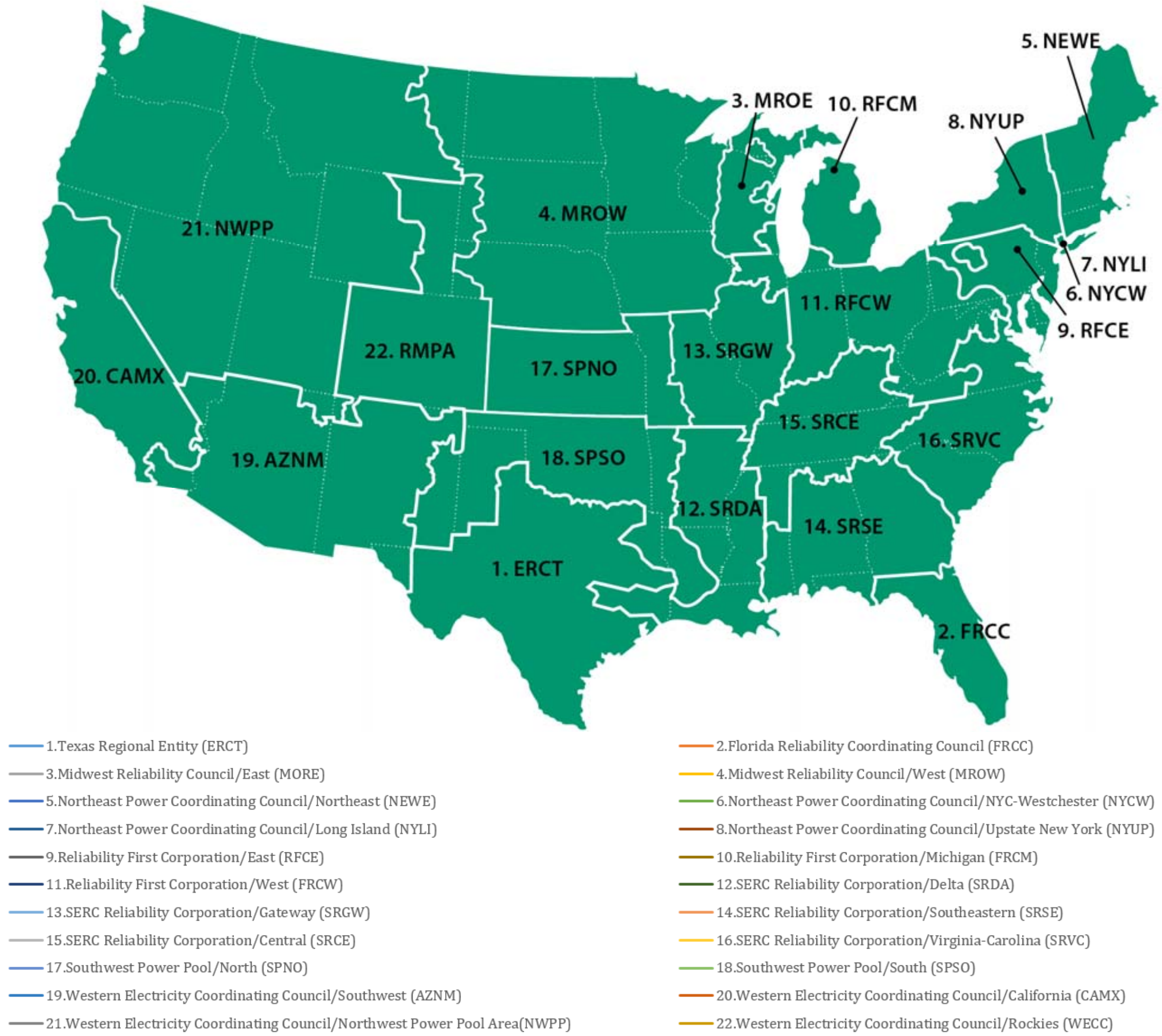


Figure 5.3 NEMS Electricity Market Module Regions [172]

5.3.1 Maintenance and Refueling Cost

The net present value of the Maintenance and Refueling (M&R) costs of the five different vehicle types are presented for a 16-year lifetime. Due to the wide variety of possible results for all 22 regions and for all 5 vehicle types, these M&R costs are shown throughout the U.S. with only the regional variations with respect to ICVs and All-Electric Vehicles (BEVs) shown in this study, since these two vehicle types represent opposite extremes in terms of gasoline versus electricity as fuel options. Figure 5.4 shows the average net present values of the M&R costs for all of the studied regions, calculated in this analysis as the average of all captured M&R costs for all of the replications in all of the considered U.S. regions, with the error bars in the figure representing the M&R cost ranges for each vehicle type.

On average, the ICV has the highest M&R cost with an average of $48,128. The lowest and highest M&R costs for the ICV occur in the New York Up State (NYUP) region at

$44,560 and in the Western Electricity coordination council/Southwest (AZNM) region at $52,329, respectively. Obviously, the M&R cost decreases as the vehicles' fuel economy rates (mpg) increase. The HEV has the second highest average M&R cost at $43,357, followed by the PHEV at $40,192, the EREV at $36,641, and finally the BEV at $33,582. The lowest and highest M&R costs of BEVs are found in the NYC-Westchester (NYCW) region at $31,743 and in the SERC Reliability Corporation/Central (SRCE) region at $35,471, respectively. The data uncertainty ranges decrease when moving from gasoline-powered vehicles to EVs due to better data availability on electricity for the U.S. regions.

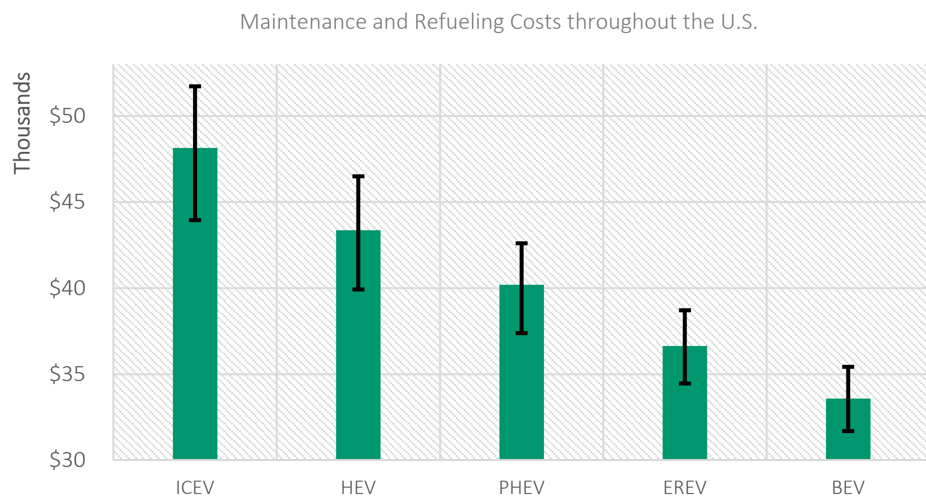


Figure 5.4 Maintenance and Refueling Costs of Studied Vehicles Throughout the U.S. (in Thousands of Dollars)

A regional representation of the data is also possible; here, the regional variations in the M&R costs of ICVs and BEVs are presented in Figures 5.5a and 5.5b, respectively, for a 16-year vehicle lifetime. This comparison is especially useful because ICVs rely completely on gasoline as a fuel source while BEVs likewise rely completely on electricity. On average, driving an ICV in the Texas Reliability Region (ERCT) has the cheapest M&R cost at $47,190, while California is the most expensive region to drive an ICV with an M&R cost of $49,836 (Figure 5.5a).

The M&R costs of BEVs seem to have less variation, with NYWC being the cheapest ($32,862) and SERC Reliability corporation/Gateway the most expensive ($34,195) regions in which to drive a BEV, on average (Figure 5.5b). There are a number of possible reasons for the changes in M&R costs for the studied vehicle types, including future price changes for electricity, future changes in the electricity generation mixes in each region, and/or uncertainties with respect to future gasoline prices in each region.

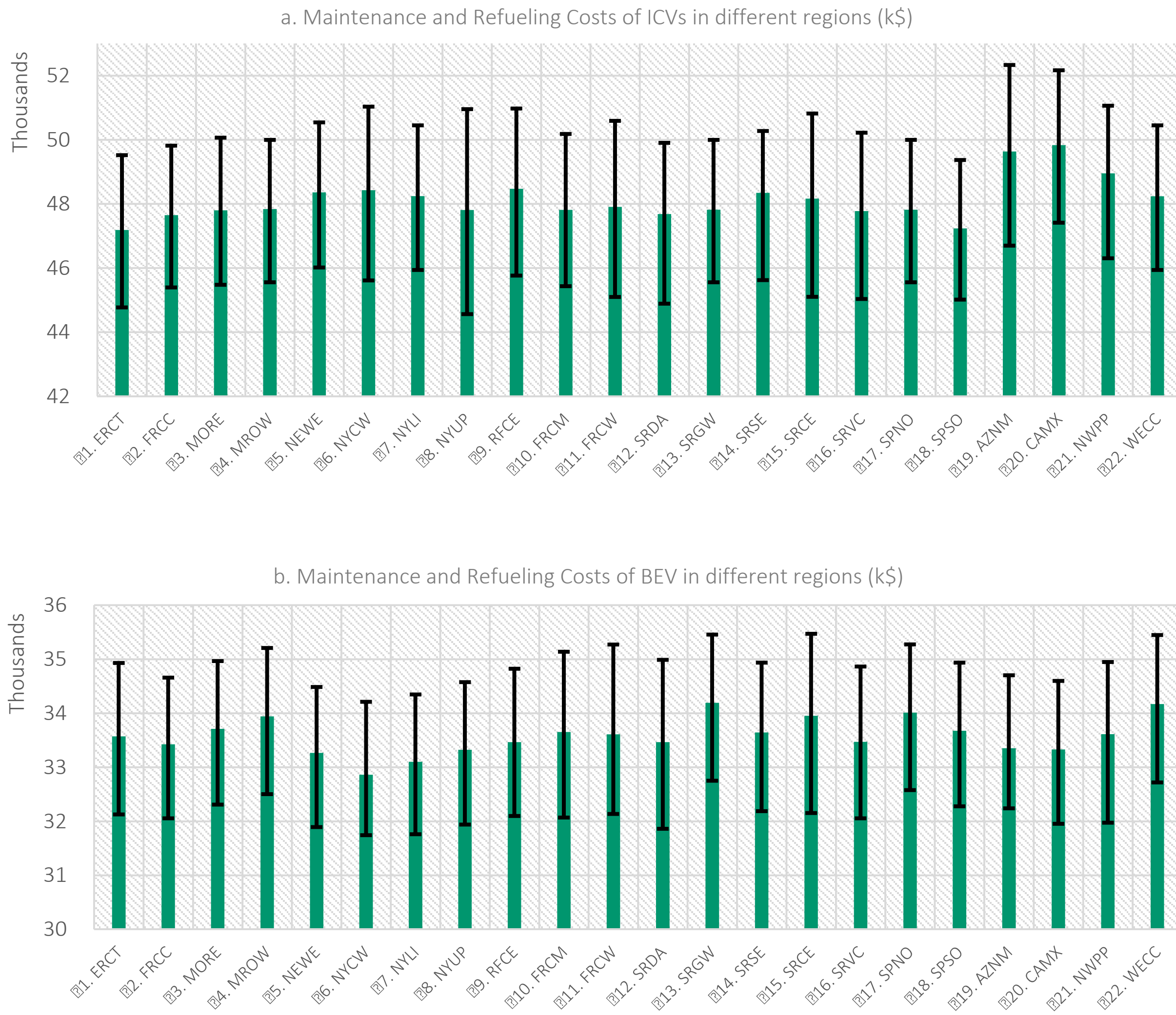


Figure 5.5 a. Maintenance and Refueling Cost of Internal Combustion Engine Vehicle for different regions and b. Maintenance and Refueling Cost of All-Electric Vehicle for different regions, both in Thousand Dollars

5.3.2 Environmental Damage Cost Results

The Environmental Damage Cost (EDC) results for each of the five different vehicle types are presented in Figure 5.6a. Due to wider uncertainty ranges in estimating the EDC, its variation is much higher than that of the M&R cost. The EDC trend is almost the same as that of the M&R cost, with the ICV having the highest EDC out of the five alternatives on average at $5.19 million over the 16-year vehicle lifetime. The lowest and highest EDCs were found in the CAMX and Midwest Reliability Council/East (MORE) with EDCs of $0.74 million and $10.75 million, respectively. The reported pollution emissions for the state of California were found to be the lowest for gasoline, which would explain its lower EDC rate.

Same as M&R cost as shown previously, a transition toward an electrified fleet with higher fuel economy rates dramatically reduce the EDC. The BEV has the lowest average EDC throughout the United States, with an average EDC of approximately $1 million. The Northeast Power Coordinating Council / NYC-Westchester (NYCW) and Western Electricity Coordinating Council/ Northwest Power Pool Area (NWPP) regions have the lowest and highest EDCs for the BEV with EDCs of $0.12 million and $3.27 million, respectively. Moreover, the range of EDCs for the ICV is much higher than those of other vehicle types, owing largely to the higher variability in gasoline-related EDCs and a current lack of data for the unit EDC for gasoline, both of which contribute to greater degrees of uncertainty in the final results. In future studies, more data on EDCs may be available to potentially reduce this level of uncertainty.

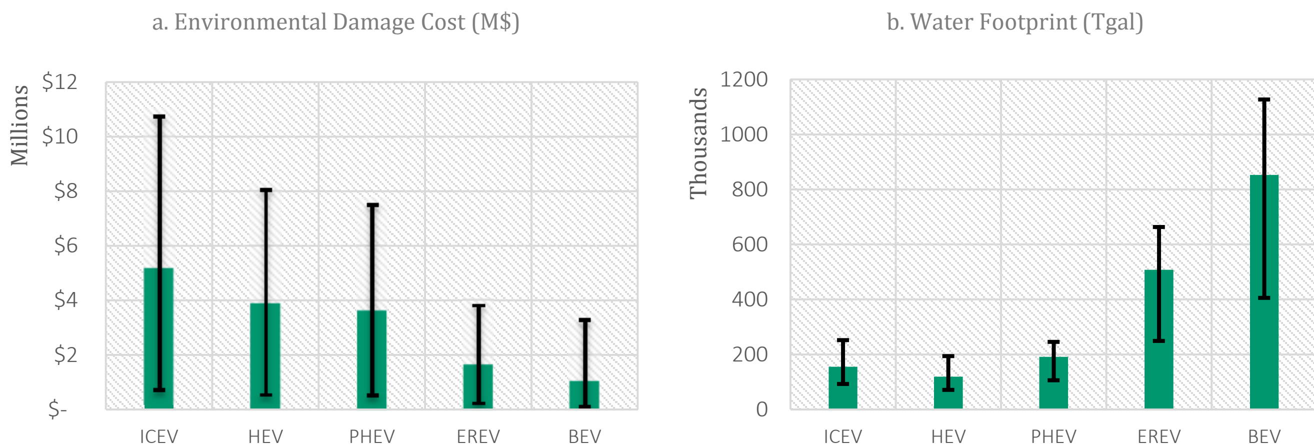


Figure 5.6 Life Cycle Environmental Damage Costs for the studied vehicles in Millions of Dollars (a), and Water Footprints of the studied vehicles in Thousands of Gallons (b)

5.3.3 Water Footprint Results

Figure 5.6b shows the Water Footprints (WFPs) of each of the studied vehicle types. Electric cars are shown to have higher WFPs than gasoline-powered cars, primarily due to the use of water in electricity generation and/or battery production being the main driver for water consumption. Consequently, the BEV has the largest WFP out of all of the considered vehicle alternatives, with a lifetime WFP of approximately 852 thousand gallons (Tgal) of water on average. The SERC Reliability Corporation/ Virginia-Carolina (SRVC) and NYLI regions have the lowest and highest average WFPs for the BEV at 1,127 Tgal and 406 Tgal of water, respectively. On the other hand, HEVs have the lowest average WFP at 119 Tgal of water, owing mainly to the fact that HEVs do not rely on grid-sourced electricity, use less gasoline than ICVs, and have smaller batteries than EVs. The SERC Reliability Corporation/Delta (SRDA) has the lowest WFP for the HEV at 71 Tgal of water consumption, while the CAMX has the highest WFP at 194 Tgal of water.

5.3.4 Agent Based Modeling Results

Figure 5.7 shows how these agents are placed in each of the NEMS regions based on the population and number of registered vehicles in each region. The Reliability First Corporation/West (FRCW) region has the most agents with the California (CAMX) region as a close second, both containing almost 43 percent of the total number of agents in the model. Conversely, the NYC-Westchester (NYCW) has the lowest number of agents, followed by the Southwest Power Pool/North (SPNO) region.

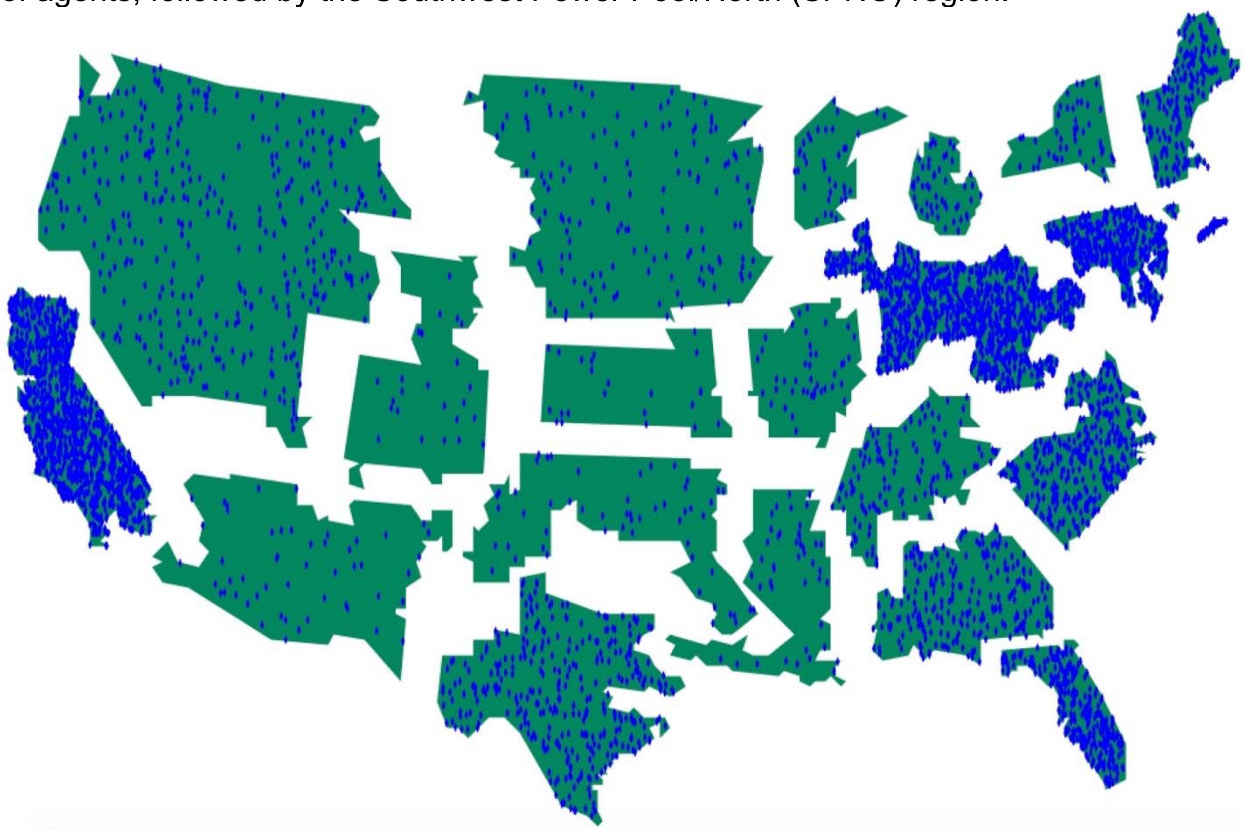


Figure 5.7 Configuration of agents in the ABM model

The effect of different policies can be tested on the market penetration of the EVs; in this study, the effect of government subsidies was tested using the developed EVReMP model. This policy is aligned with one of the LAVE-Trans publications, in which government policies were mandated for the first 10 years [163]. Two types of government subsidies (federal and regional) are considered in this policy, and it is assumed that the government supports EVs penetration for the first 10 years, and a randomly generated factor is used to determine whether the government offers subsidies in each year thereafter. The model is then run for 10,000 replications. The results of this analysis can be shown in any number of forms, including the average market share of all vehicle types for every replication, the changes in the market share of a particular vehicle over time, and the regional variations of the market penetration of EVs. First, the average market penetrations of the studied vehicle types are illustrated in Figure 5.8; compared to the base case model, the market shares of the EVs have increased dramatically, and approximately 26 percent of the fleet will be electrified on average by the year 2030, due to the provided government subsidies.

At the end of analysis period, the BEV dominates the market among the EV technologies, with 11% of the total market share. This is because the M&R costs of the BEV are the lowest among the specific EV types while the offered government subsidies tend to favor all-electric vehicles. The EREV has the second largest market share at 8%, and the PHEV has the lowest market penetration among the electrified drivetrain with a 6% market share. The penetration of the HEV stays almost the same as in the base case, mainly because no incentives are offered to purchase an HEV.

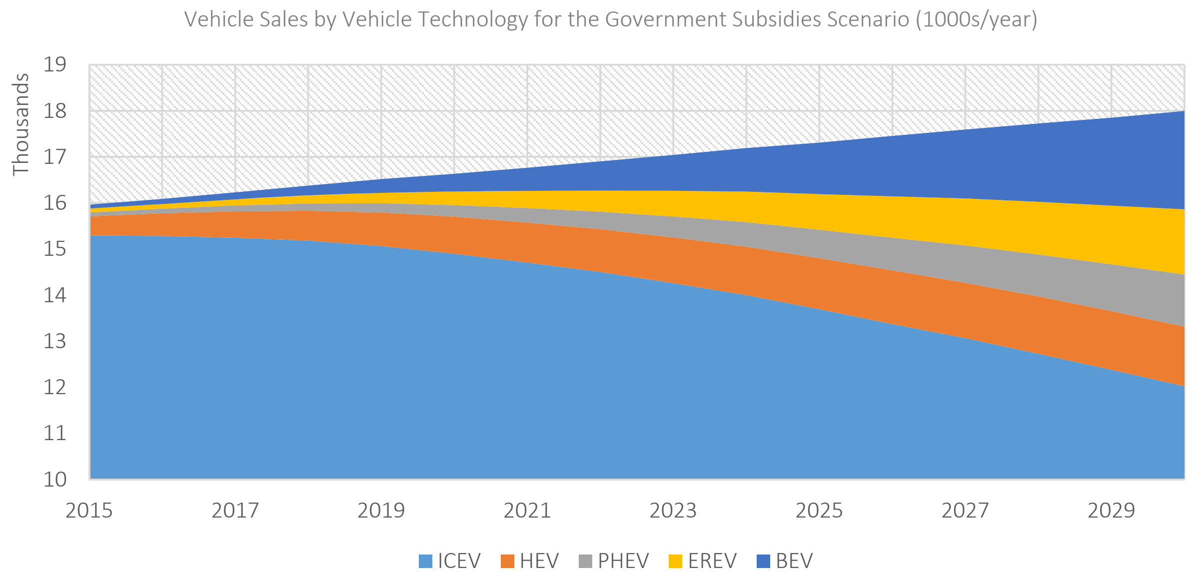


Figure 5.8 Vehicle Sales by Vehicle Technology for the Government Subsidies Scenario (1000s/year)

Another way to look at the results is to illustrate the variations in market penetration for each vehicle type; Figure 5.9 shows the variations in the market penetration of the drivetrain for the first scenario. As this figure shows, the market share of the ICV decreases while the market shares of all other alternatives increase. The variation in the results for the ICV is lower than those for other alternatives, due to less variability in the relevant decision-making factors for purchasing an ICV, while this variation increases over time for all other alternatives.

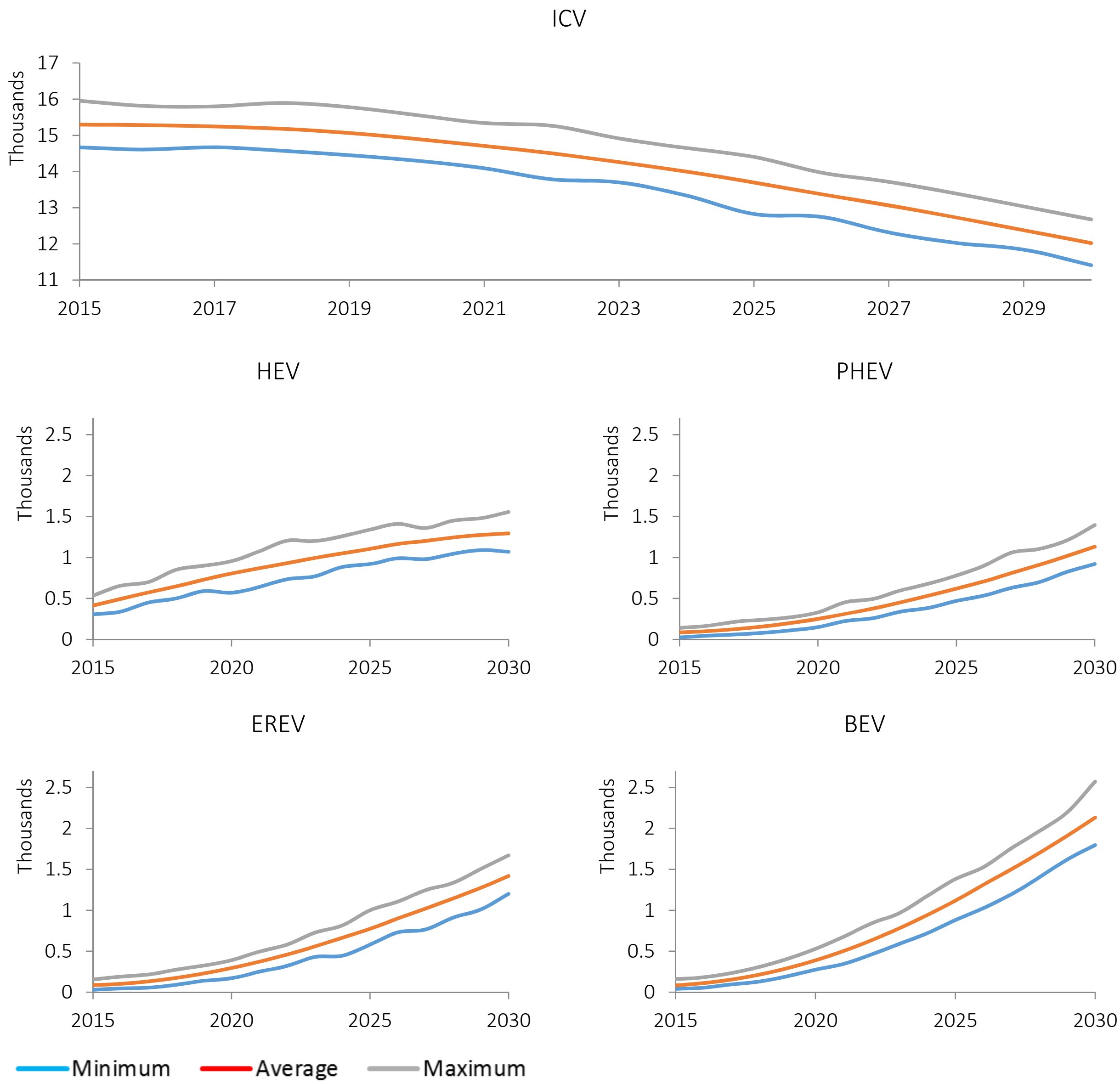


Figure 5.9 Variations in the Market Penetrations of the studied vehicles under the Government Subsidies scenario (1000s/year)

The next policy analysis tests the word-of-mouth effect (or the social acceptability of the EVs) in terms of its effect(s) on EV market penetration. To this end, this policy scenario assumes that all agents are willing to consider purchasing an ICV, meaning that the agents' willingness to purchase an ICV is always 1. However, agents who purchase any other vehicle alternative contact other agents once a month and try to convince these other agents to purchase the non-ICV vehicle type that they own. Whether or not the contacted agent is convinced to consider the non-ICV vehicle type in question is simulated using a randomly generated function in which the probability of the contacted agent being convinced is 10%. Figure 5.10 represents the average market penetration results of the studied drivetrain under these conditions for the entire studied regions in the United States.

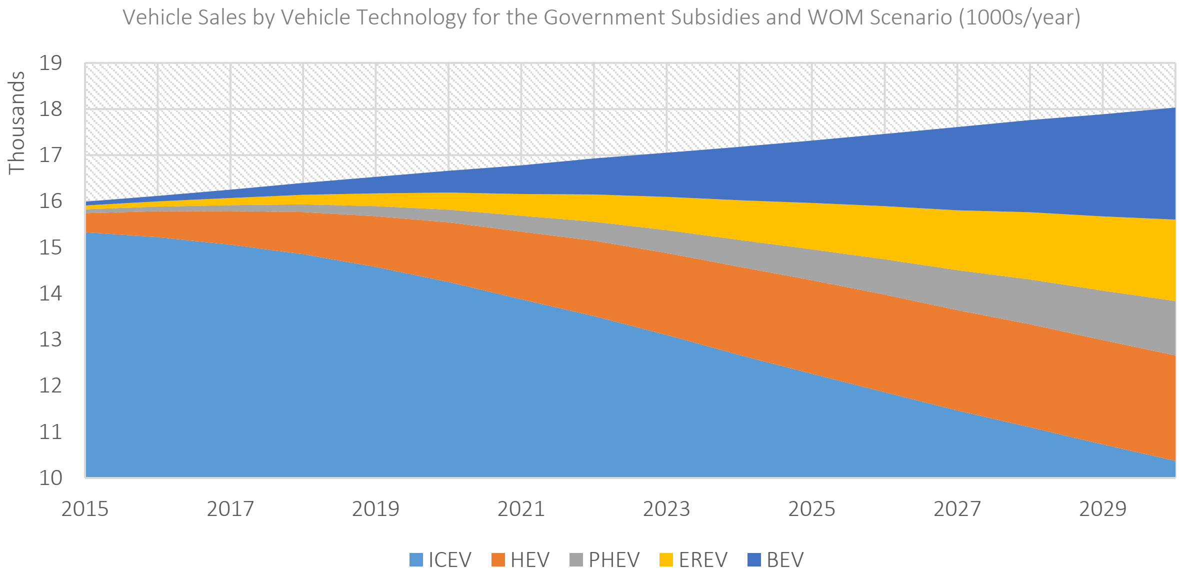


Figure 5.10 Vehicle Sales by Vehicle Technology for the Government Subsidies and WOM Scenario (1000/year)

As shown in the graph above, the overall market penetration of the EVs has significantly increased relative to the previous case, with EVs dominating approximately 30% of the total market share in 2030. The ICV will still have the highest market penetration with a 56% market share on average, but BEVs will have the second largest market share at 14%, followed by HEVs at 13%. Conversely, the PHEV will still have the lowest market share at 6% on average.

5.4 Discussion and Limitations

The objective of this study was to develop the Electric Vehicle Regional Market Penetration (EVReMP) tool to help policy makers and transportation planners to identify the future market shares of electric vehicles in the United States. The EVReMP model compares three different EV technologies with hybrid and internal combustion gasoline vehicles using a developed agent-based model, and predicts the market share of the studied vehicles for the year 2030, accounting for agent preferences in terms of the purchase prices, maintenance and refueling costs, environmental damage costs, and water footprints of all vehicle types in the drivetrain. The purchase price is estimated using current market data, while all other vehicle attributes are estimated using data from the Electric Vehicle Regional Optimizer (EVRO) model, which estimates the variability ranges with respect to the future maintenance and refueling costs, environmental damage costs, and water footprints of the electric vehicle types. An Exploratory Modeling and Analysis (EMA) approach was then applied to the data to properly account for the inherently deep uncertainty associated with market penetration. The EMA approach was also used in tandem with the developed ABM to investigate the future market shares of the considered vehicle types in twenty-two separate electricity grid mix regions in the U.S., after which the EVReMP tool was able to generate a variety of results. In summary, the following conclusions are highlighted:

- All-Electric Battery Vehicles (BEVs) are the most cost-effective vehicle type in terms of M&R costs, with an average M&R cost of $31,743 over vehicle lifetime. The lowest and highest M&R cost for the BEVs occur in the NYC-Westchester (NYCW) and SERC Reliability Corporation/Central (SRCE) regions, respectively.

- The Internal Combustion Engine Vehicle (ICV) has the highest M&R cost among the studied vehicle types, with an average M&R cost of $48,128. The lowest LCC of ICVs was found in the New York UpState (NYUP) region, while the highest M&R cost was found in the Western Electricity coordination council/Southwest (AZNM) region.

- BEVs have the lowest lifetime EDC at approximately $1 million on average, and transitioning to a more electrified fleet reduced the EDC dramatically.

- On the other hand, BEVs consume/withdraw the largest amount of water on average over their lifetimes, owing mainly to the upstream electricity generation and water consumption during battery production. Conversely, HEVs have the smallest WFP on average, since they do not rely on the power grid for electricity, consume less gasoline than ICVs, and have smaller batteries than BEVs. The WFP dramatically increased during transition toward an electrified fleet.

- The EVReMP model reveals that the government subsidies will play a vital role in the market adoption of EVs; compared to the business-as-usual scenario, when government subsidies were mandated for the first 10 years and then randomly granted or denied in subsequent years, the collective market share of the EVs increased from 1.5% to as high as 26% by the year 2030.

- Social acceptability and the word-of-mouth effect will also have a significant effect on EV market shares; when with government subsidies, the combined effects of both policies can increase the market penetration of the EVs to as high as 30% on average case by the year 2030.

- The main lesson learned from this analysis is that the United States can feasibly meet the established goal of a 20% EV market share of new sales by 2030, but such a goal would require mandating government subsidies for at least the first 10 years and encouraging the social acceptability of the EVs via advertisement and other such means. In addition, establishing a regional subsidy policy for regions with more agents (such as the Reliability First Corporation/West (FRCW) region) could potentially increase the social acceptability of EV and thereby improve the market penetration of EVs.

- Ultimately, the results of this analysis reveal that the U.S. vehicle fleet will eventually move away from the ICVs, and that this movement is likely to proceed faster with a small increase in oil prices.

Limitations to the work presented here include the absence of the influence of manufacturers on EV market penetration; in addition to the policy initiatives previously discussed, EV manufacturers can also compete with each other in each analysis year and ultimately yield accelerated improvement in EV technology, resulting in an overall positive impact on EV market penetration. Governments can also enforce the Corporate Average Fuel Economy (CAFE) regulations and thereby influence the manufacturers' benefits in terms of EV market shares; since manufacturers were not considered as an agent in this study, these potential benefits were not taken into account. In addition to the incentives previously discussed, some utility companies offer special discounts for EV consumers to charge their vehicles during off-peak hours and/or during the evening, so the effect of lower electricity rates for the owners of EVs could be considered as a scenario in the analysis. Moreover, the time of day when an EV is charged has a considerable effect on the marginal load that is placed on the power grid; consequently, as more EVs are introduced to the market, the electricity market will most likely face a change in demand levels during on-peak and off-peak hours, which is likely to effect the rate structure of electricity, in turn eventually impacting the refueling costs of EVs. Thus, for a more thorough analysis, the times of day when EVs are charged should be also taken into account.

Moreover, manufacturers and consumers are supporting this technological shift by designing EVs that are more reliable and by helping to mitigate GHG emissions.
The VAAMP model considers a hypothetical "neighborhood" in which some assumptions are still made, such as the assumptions that and wage levels stay the same, that the effect of foreign currency changes on the price of exported vehicles does not affect the market, and there are no distinctions between cars and trucks.

6.0 Applications of Vehicle-to-Grid Technology for Transit and School Buses

6.1 Introduction

Altogether, the power generation and transportation sectors were responsible for 58% of the total greenhouse gas (GHG) emissions in the U.S. in 2013 [173][4]. Therefore, these two main contributors to GHG emissions attract significant amounts of attention from various industries, research institutes, and government organizations as key areas in which to reduce climate change impacts. For this purpose, electric vehicle technologies are a promising alternative fuel initiative for vehicles, and have been supported through a variety of research studies and government incentives [83,84]. Moreover, although energy source of electricity generation is also depended on fossil fuels, electric vehicles are a promising solution for today's high fossil fuel dependency and the environmental emissions of the transportation sector with the increasing availability of renewable energy sources for electricity generation [174]. Since the clean air act cites diesel as one of the most harmful fuel types [175], the adoption of alternative fuel options such as electric vehicles is especially crucial for heavy-duty vehicles, most of which still currently use diesel as their primary fuel source. Fortunately, recent battery and electric motor powertrain developments have removed the main barriers for using electricity as a fuel source for heavy-duty vehicles [176]. Battery electric buses are the most common battery electric heavy-duty vehicle in today's market, and hundreds of transit and school bus examples can be found in the U.S. However, other heavy-duty vehicle deployment is only limited to refuse trucks, which is still under development stage and only two in-use and 13 planned orders can be found in the U.S. [176].

Early stages in the development of battery electric (BE) buses were not feasible for market adoption due to their low ranges, high initial costs, and other factors. Conversely, today's BE transit buses are a competitive alternative to internal combustion engine buses as well as other types of alternative fuel buses, such as natural gas and biodiesel buses. Transit bus fleet statistics indicate that the market shares of diesel, natural gas, and electric/hybrid buses in the total U.S. fleet were (respectively) 86.8%, 12.4%, and 0.3% in 2004 whereas the corresponding 2014 market shares for these same fuel types were 56.3%, 16.8%, and 17.9%, respectively [177]. Although the overall market penetration of electric/hybrid vehicles mostly consists of hybrid (electric-diesel) buses (*i.e.*, battery electric transit bus deployment is lower than 0.04% in electric/hybrid bus fleet [176]), this change in market shares clearly depicts the significant deployment of electric powertrain technologies for transit buses in only ten years. In addition, there are almost 500,000 school buses in today's U.S. fleet, where transit bus fleet only consists of 66,218 buses including bus rapid transit but excluding commuter bus systems [178]. Although reports promoting the greater adoption of

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[4] The contents of this section were partly published in Ercan, T., Noori, M., Zhao, Y., and Tatari, O. (2016). "On the front lines of a sustainable transportation fleet: Applications of vehicle-to-grid technology for transit and school buses." *Energies,* 9(4), 230, 1-22, 2014 IF: 2.077. DOI: 10.3390/en9040230

alternative fuels for school buses date as far back as the early 2000s, alternative fuel school buses have not yet been as widely adopted as alternative fuel transit buses [179].

Transit buses should be in operation most of the time, as they are purchased to serve and earn revenue for transit authorities. Transit bus operation cycles could require heavy payloads, frequently stop-and-go operational patterns, longer route requirements, and operation schedules of typically seven days a week with revenue hours ranging from 8 h to 12 h compared to the operation schedules of school buses [180]. Chandler *et al.*'s report states that revenue hours for transit buses could even reach as many as 24 h per day [181]. On the other hand, school bus operation schedules are more feasible for electric buses, because they travel an average of 50 miles per day within a certain route and are in use for 4 to 5 hours per day on average [182]. Moreover, school buses are in use mostly for school days, which in the U.S. amounts to a total of only 180 days per year [183]. Therefore, school buses could be a promising and convenient candidate for electrification, but the deployment and application of BE school buses is limited to few experiments in the U.S. which is due to safety certification of battery electric school buses are still in the progress of approval in many states and well-known school bus manufacturers have not been involved in developing such school buses [176].

In addition to sustainable transportation ideas using alternative energy sources, another sector's harmful emissions from inefficient power plants could be eliminated using a novel technology called the vehicle-to-grid (V2G) system. The main goal of the V2G technology is to support grid operators for their mission to supply grid by reliable electricity service. Thus, V2G technology uses the stored energy from an electric vehicle's battery during idle times to supply electricity to the local power grid for reliable and sustainable service. The average electricity grid system has several demand fluctuations throughout any given time period, and today's utility service providers use combustion power generation systems to supply these demand changes for continuous service, although these conventional systems have significant environmental emission impacts. Alternately, instead of using combustion power generators, utility service providers may be required to buy electricity from other nearby available providers to supply high demand, but doing so is often inefficient in terms of cost or environmental concerns. On the other hand, grid providers have contracts with V2G service providers (often electric vehicle or fleet owner) for fixed rates of per unit power dispatched. Therefore, grid providers can choose to supply its demand from feasible energy sources which could be V2G system or any other available ancillary service [184].

One of the measures of V2G system capacity is battery storage capacity. BE buses have larger battery sizes compared to electric passenger vehicles, so this study will investigate the potential of V2G service availability from BE transit and school buses in the U.S. in terms of economic and environmental benefits. In addition, these bus types are compared with internal combustion engine diesel buses in terms of cumulative cash flow and air emission externality results for the operation-related downstream (on-site) and upstream (off-site) emission impacts. Since transit and school bus operations generally occur in or near highly populated areas, it is crucial to present air emission externalities as an environmental impact category.

Kempton and Tomic and Kempton *et al.*'s studies [184,7,185] are cited in this research extensively for some of the materials and method that is used for V2G related impact analysis. Furthermore, their studies provide key elements that lead the research of V2G technology and their research is advanced by adding cash flow and environmental impact analyses. As opposed to the most of V2G related studies with passenger vehicle examples, this research used transit and school buses for its analysis. Noel and McCormack [182] presented comparison analysis of diesel and BE school bus using V2G, however it did not consider lifetime cash flow analysis of both buses, V2G related emission savings, and diesel production related (upstream) emission externalities in five ISO regions. Therefore, this study distinguishes itself from previous efforts in the research community by considering both transit and school buses for V2G applications, including regional electricity generation mixes, and completing this analysis with the comparison of diesel buses and air pollution externalities for public health.

6.2 Materials and Methods

6.2.1 Environmental Emission Calculation Methods

LCA method is utilized in this research and it only considers the use phase of transit and school buses, and a well-to-wheel (WTW) approach is used to assess the relevant downstream and upstream emissions. In addition to the use phase of buses, some of other LCA phases are excluded from this study such as manufacturing and end-of-life. Since two different fuel options are considered for two different types of buses, use phase impacts are distinct for the comparison of these bus type combinations and even though the fuel types are different, manufacturing impacts can be assumed similar due to identical body (shell) types for buses [38,4]. Moreover, this research emphasizes on V2G application for transit and school buses, which is affecting the use phase related impacts.

Each fuel type and vehicle type has different emission characteristics. After identifying the bus and fuel types, the analysis could be separated in terms of downstream-phase and upstream-phase impacts. As per the LCA methodology, downstream impacts can be considered to be on-site activity related impacts, which in this case these are quantified as tailpipe and tire & brake wear (TBW) related emissions. Downstream impacts are gathered from the emission data for diesel transit and school buses from environmental protection agency's (EPA) widely utilized MOVES tool with the consideration of yearly emission changes [186].

Diesel production and electricity generation activities are also responsible for upstream impacts, corresponding to emissions from petroleum refineries and the applicable power generation and supply sectors, respectively. Therefore, as a part of overall WTW analysis, upstream impacts (well-to-pump WTP) analysis results are gathered from the tool GREET 2015 [187]. The WTW analysis can then be concluded with the summation of downstream and WTP emissions for each bus and fuel type. In Figure 6.1, the pathway of emissions from diesel bus is graphical illustrated on the upper part where BE bus is shown on lower part of the graph. The only difference that can be captured in this figure relative to regular operation is V2G service availability, which provides support back to the grid as needed.

Figure 6.1 Transit and school buses' environmental emissions data collection and analysis path.

Different independent system operators (ISOs) or regional transmission organizations (RTOs) regulate electricity prices, and each region's power plant types determine the environmental emission rates for that region. Therefore, four ISO regions and one RTO region are utilized in this analysis due to lack of corresponding data from other regions. The regions included in this study are: The *Pennsylvania-New Jersey-Maryland (PJM)* interconnection (RTO region), The *New-York ISO (NYISO)* region, The *ISO-New England (ISO-NE)* region, The *Electric Reliability Council of Texas (ERCOT)* ISO region, and The *California ISO (CAISO)* region.

The downstream electricity generation impacts of these regions are gathered from the GREET model's database [187]. Since the analysis in this study covers the full lifetime of the buses in question, the electricity generation emissions should be adjusted with the energy information administration's (EIA) regional electricity generation mix projection multipliers [174]. Upstream (indirect) impacts related to electricity consumption are calculated with eGRID's gross grid loss factors, allowing the analysis to capture transmission and distribution emissions [188]. Equation (1) calculates the yearly downstream and upstream emissions from electricity generation in each region for each air pollutant type, including a summation of the impacts of each power plant type:

$$\text{Electricity consumption emissions}_{jry} = \left[\frac{(\text{eGRID}_{jry})}{1-\text{GLF}_r}\right] + \left[\sum_{p=1}^{10}(\text{UG}_{jp} * \text{EM}_{pry})\right] \quad (1)$$

The notation expressed in Equation (1) is explained in Table 6-1. It should be also noted that regional electricity generation related emissions are expected to decrease for future years with the promises for renewable energy deployments. Although there are opportunities to power electric vehicle fleets with only renewable energy sources on site, it is out of scope of this analysis and studied in reference [189]. Similarly, V2G-related emissions are calculated using Equation (2) for each region in each analysis year:

$$\begin{aligned}\text{V2G related emission savings}_{ry} \\ &= \left[N_{\text{disp}} * M_{\text{combustion}}\right] \\ &- \left[\left(N_{\text{disp}} * M_{\text{grid}_{ry}}\right) + M_{\text{battery dep}}\right]\end{aligned} \tag{2}$$

where N_{disp} is the dispatched electricity (kWh), $M_{\text{combustion}}$ is the gas combustion turbine emissions rate, M_{grid} is the electricity production emissions rate in *r* region for *y* year, and $M_{\text{battery dep}}$ is the emissions rate corresponding to battery depreciation or wear-out from providing V2G services. It should be noted with respect to Equation (2) that gas combustion turbines have relatively low efficiencies and high environmental emission impacts compared to energy storage methods such as those offered via V2G technology. Moreover, separate studies by Lin *et al.* and by Makarov *et al.* both argued that combustion turbines that are used for regulation services are two to three times less efficient than energy storage systems [190,191]. Based on this assumption, the value of $M_{\text{combustion}}$ in Equation (2) is assumed to be two to three times higher than the theoretical gas combustion turbine emissions. Per unit emission factor projections for each type of power plants are considered as normally distributed with ±10% uncertainty. Battery wear-out emissions are calculated from the Li-Ion battery report of EPA (2012), which considers an environmental-LCA analysis of Li-Ion batteries, including emissions from the raw material extraction phase, manufacturing phase, use phase, and end-of-life phase [192].

Table 6-1 Explanations of notations and indexes.

Notation	Explanation	Type	Index
j	Air pollutant type	GHG CO NO_x PM10 PM2.5 SO_x VOC	$j = 1$ $j = 2$ $j = 3$ $j = 4$ $j = 5$ $j = 6$ $j = 7$
p	Power plant type	Coal Oil Gas Other Fossil Nuclear Hydro Biomass Wind Solar Geo-Thermal	$p = 1$ $p = 2$ $p = 3$ $p = 4$ $p = 5$ $p = 6$ $p = 7$ $p = 8$ $p = 9$ $p = 10$
r	ISO/RTO regions	PJM ISO-NE NYISO ERCOT CAISO	$r = 1$ $r = 2$ $r = 3$ $r = 4$ $r = 5$
y	Analysis period years	-	$y = 2015 - 2027$
i	Bus type	Transit School	$i = 1$ $i = 2$
$eGRID_{jry}$	Yearly (y) emission rate of energy losses in r region for j air pollutant based on eGRID data (lb/kWh)		
GLF_r	Grid loss factor (GLF) for r region based on eGRID data		
UG_{jp}	Well-to-pump (WTP) analysis emissions of energy source for p power plant for j air pollutant (lb/kWh)		
EM_{pry}	Yearly (y) emission rate of electricity production at p power plant in r region (lb/kWh)		
UE_{ij}	Upstream j type of emissions for diesel i type of bus		
UA_{ij}	Upstream j type of air externality cost for diesel i type of bus		
DE_{ij}	Downstream j type of emissions for diesel i type of bus		
DA_{ij}	Downstream j type of air externality cost for diesel i type of bus		
K_i	Lifetime electricity consumption of i type bus		
B_j	Air externality cost of per MWh electricity generation for j type of emission		

6.2.2 Air Pollution Externality Calculation Methods

There is a wide range of applications for reducing air pollutant emissions from the transportation and electricity generation sectors. These air pollutants are not only harmful to the environment, but also to human health and to the economy. The air pollution emission experiments and policy (APEEP) model quantified these harmful impacts by each pollutant type in terms of dollars [193,194]. Furthermore, the APEEP model has been enhanced through Michalek *et al.*'s (2011) research to define air pollutant externalities by their area of impact [63]. Transit and school buses are operated mostly near highly populated areas, so it is crucial to present their air pollutant related damage costs. This is especially crucial for school buses compared to transit buses, as the emissions from school buses mainly affect a non-adult population. On-site emissions are treated differently from upstream emissions in terms of their damage costs, since upstream emissions are more likely to occur in or near rural areas. Total air pollutant externality values for diesel buses and electric buses can in turn be calculated with Equations (3) and (4), respectively:

$$\text{Air Externality}_{\text{Diesel}} = \sum_{j=1}^{7}\left(\text{UE}_{ij} * \text{UA}_{ij}\right) + \sum_{j=1}^{n}\left(\text{DE}_{ij} * \text{DA}_{ij}\right) \text{ (Diesel)} \quad (3)$$

$$\text{Air Externality}_{\text{Electric}} = \sum_{j=1}^{7}\left(K_i * B_j\right) \text{ (Electricity)} \quad (4)$$

where "*i*" represents the bus type (*i* = 1 for transit; *i* = 2 for school). Air pollutant types are indexed using the "*j*" notation, as previously described in Table 6-1 above. It should be noted here that BE bus operation related air pollution externalities are measured based on annual electricity consumption which rely on fuel economy and annual mileage values. Then the V2G related emission savings are quantified due to eliminating use of combustion power plants. The electricity consumption of BE buses is the same with or without V2G system, however combustion power plants' emissions can be extinguished by this system, which also lead to the reduction of air pollution externalities.

6.2.3 Cash Flow and Net Revenue Calculation Methods

Diesel and BE buses for transit and school bus options have different cost parameters due to the specifications required for each bus application. For this reason, the annual cash flow is determined for each bus type, taking into consideration each bus type's initial cost, maintenance cost (excluding battery), fuel cost (diesel or electricity), battery replacement cost, V2G equipment cost for regulation service, charging facility equipment and installation costs, charging facility maintenance cost, and vehicle, V2G equipment, charging station resale value. Costs corresponding to charging facilities are only considered for BE buses, as it is assumed that suitable diesel fueling station infrastructure are already available to fleet operators. Battery replacement cost is also only considered for BE buses due to the larger and more expensive batteries required for BE buses compared to those required for diesel buses. It is also assumed that all vehicles, V2G equipment on the vehicles and charging station equipment are sold at the end of their respective lifetimes, and the resulting profit is considered to be the total resale value. Finally, cash flow indicators include revenue from using the V2G system, which is represented as a negative value for cash flow. Another negative value in cash flow is the tax incentives provided by state governments for purchasing new BE buses.

Table 6-2 Specifications of bus types and V2G system.

Notation	Value		Definition	Unit	Reference
	BE-School Bus	***BE-Transit Bus***			
P_{cap}	80	203	Battery Capacity or max power available from bus	kWh	[182,4,195]
$T_{battery}$	Uniform (2000–6000)		Battery lifetime charging cycles	cycles	[38,184,196,197]
D_{VMT}	50	101	Daily vehicle miles traveled (VMT)	miles	[38]
B_{Range}	0	0	Buffering range to return safely charging facility	miles	-
FE	0.75–2.00 [a]	1.70–2.24 [b]	Fuel economy	kWh/miles	[a] Low range: [182]; High range [198]. [b] Low range: [199]; High range: [38].
$T_{dispatch}$	0.3	0.3	Dispatch time	h	
$X_{convert}$	0.93	0.93	DC to AC conversion factor	-	[200]
$P_{dispatch}$	70–140	70–140	Capacity of charging facility could transfer for revenue	kW	-
T_{plug}	19.5–21	8–12	Number of hours that bus is plugged to the charger	hours	[181,182]
$C_{installation}$	\$5000–\$10,000	\$5000–\$10,000	Charging facility installation cost	\$ (2014)	[201]
$C_{equipment}$	\$12,000–\$20,000	\$12,000–\$20,000	Charging facility equipment cost (Level 3)	\$ (2014)	[201]
$C_{C\text{-}Main}$	\$600–\$1000	\$600–\$1000	Charging facility annual maintenance cost (5% of $C_{equipment}$)	\$ (2014)/year	[201]
$C_{B\text{-}Main}$	\$0.2–\$0.75	\$0.75	Per mile maintenance cost of bus	\$(2014)/mile	[182,202]
C_{bus}	\$230,000	\$800,000	Purchase cost of bus	\$ (2014)	[176,182,203]
$C_{bat\ unit}$	\$600		Battery price per kWh capacity	\$-year/kWh	[204]
C_{V2G}	Uniform (\$1900–\$2100)		Cost of V2G system equipment	\$ (2014)	[184]
D_{rate}	0.65%–1.15%		Annual Discount Rate	percentage	[149]
I_{rate}	±10% of CBO's projections		Annual Inflation Rate	percentage	[205]

Of the regions considered in this study, only New York and California are supplying such incentives for new BE bus purchases [206]. For instance, New York provides support with a tax incentive of up to $60,000 for BE buses [207], whereas California offers up to $117,000 in incentives for BE transit buses. California tax incentives are determined by the battery storage size and purchase cost, so the tax incentives offered for a 40 foot BE-transit bus tax incentive could add up to a total from $95,000 to $117,000, whereas the corresponding available BE-school bus incentives could range from $80,000 to $90,000 [208]. In light of this information on cash flow indicators, annual cash flows can be calculated using Equation (5) (corresponding indexes are presented in Table 6-1 above).

$$\begin{aligned}
&\textbf{Annual cash flow}_{iry} \\
&= \text{Initial Cost}_i + \text{Maintenance Cost}_i + \text{Diesel or Electricity Cost}_{iry} \\
&+ \text{Battery Replacement Cost}_\text{i} \\
&+ \text{Charging facility equipment and installation cost} \\
&+ \text{Charging facility maintenance cost} \\
&+ \text{Cost of V2G Upgrade on Vehicle}_i \\
&- \text{Resale value of vehicle, V2G equipment, charging station} \\
&- \text{Net revenue of V2G service}_{iry} - \text{Tax incentives}_{iry}
\end{aligned} \tag{5}$$

Some of the parameters presented in Equation (5) refer to notations presented in Table 6-1. For instance, the initial cost is C_{bus}, the maintenance cost is $C_{B\text{-}main}$, the battery cost is $C_{battery}$, the charging infrastructure equipment and installation cost is the sum of $C_{equipment}$ and $C_{installation}$ respectively, the charging facility maintenance cost is $C_{C\text{-}main}$, and the cost of V2G upgrades for the vehicle is C_{V2G}.

Annual cash flow could be presented as net present annual cash flow, with the consideration of economic parameters such as discount rates (Equation (6)). Like the above-mentioned cash flow indicators, the considered discount rate (D_{rate}) is also described further.

$$\text{Net present annual cash flow}_{iry} = \frac{\text{Annual cash flow}_{iry}}{(1 + D_{\text{rate}})^y} \tag{6}$$

One of the key parameters for calculating the total annual cash flow is the revenue earned from providing V2G services, which is another value that must be determined using the methodology developed by Kempton and Tomic [184] and improved by Noori *et al.*, Yang and Tatari, and Yang *et al.* by considering the applicable degrees of uncertainty and other relevant parameters [209,210,5], and by following the calculation steps adopted from Noori *et al.*'s EVRO model [94,184]. EVRO is an optimization model previously developed by the authors [94] that uses several previously established methodologies in LCA of energy systems [123,211], Multi Criteria Decision Making [124,212], Decision Making Under Uncertainty [125], Intelligent Transportation Systems [126,213], and Stochastic Optimization [64,128]. The net revenue of using the V2G system can be calculated by simply subtracting the cost of the electricity consumed for charging from the total revenue earned due to providing V2G services. Capacity payments and energy payments are the two main components of total revenue. Capacity payments are measured by the grid operator and rely on the vehicle's available time for providing V2G services (plugged time) as well as available power capacity parameters. Therefore, Equation (7) is used to calculate the total capacity payment revenue:

$$\text{Capacity payment} = C_{\text{cap}} * P_{\text{dispatch}} * T_{\text{plug}} \tag{7}$$

where C_{cap} represents each ISO/RTO region's payment rates for regulation capacity in $/kwh, $P_{dispatch}$ is the available power in kW that could be derived from the vehicle, and

T_{plug} is available time (plugged time) in hours of the vehicle in question for providing V2G services. School buses are parked for 18 h to 24 h. However, this range occurs due to number of school days, where school buses are available for 18 h a day for 180 school days of year and 24 h available for rest of the days of a year. Therefore, T_{plug} value range is calculated with the consideration of number of holidays and school days in a year.

Grid providers also make separate energy payments, the total revenue of which is measured based on the exchanged electricity from regulation signal responses. Equations (8) and (9) (presented below) are used to calculate the total energy payment revenue:

$$\text{Energy payment} = C_{\text{elect}} * E_{\text{dispatch}} \tag{8}$$

$$E_{\text{dispatch}} = \sum_{i=1}^{N_{\text{dispatch}}} P_{\text{dispatch}} * T_{\text{cycle}} \tag{9}$$

where C_{elect} is the retail electricity price in \$/kWh and E_{dispatch} is the total dispatched electricity in kWh. C_{elect} value projections for future study years are derived from the EVRO model [94]. In the formula for E_{dispatch} (Equation (9)), N_{dispatch} represents the number of regulation cycles, P_{dispatch} once again represents the available power in kW, and T_{cycle} is the regulation cycle duration in hours. The value of T_{cycle} is assumed to be a random value between 3.6 and 9 min, due to the random occurrence of regulation cycles [185]. The number of regulation cycles (N_{dispatch}) is a randomly selected value between 30 cycles and 40 cycles, meaning the V2G system responds to regulation request signals 30–40 times [185]. These calculated results are then converted to annual values since the results are to be presented on an annual basis for each projected study year. In order to present results on an annual basis, all of the uncertainties and random selections in the aforementioned calculations are performed for 1000 iterations. Finally, the total revenue is the sum of *Capacity payments* and *Energy payments* as shown in Equation (10):

$$\text{Total Revenue} = \text{Capacity payment} + \text{Energy payment} \tag{10}$$

On the other hand, the cost of providing regulation services is calculated with vehicle's battery degradation taken into account. Equation (11) is used to calculate the cost of providing V2G services for fleet owners:

$$C_{\text{regu}} = \frac{C_{\text{battery}}}{E_{\text{battery}}} * E_{\text{dispatch}} + C_{\text{capital}} \tag{11}$$

where C_{regu} represents the gross cost of providing V2G services (excluding revenue), C_{battery} is the cost of a new battery in \$/kWh, E_{battery} is the total amount of energy dispatched from the battery throughout its lifetime in kWh, E_{dispatch} is the dispatched electricity as previously described in Equations (8) and (9), and C_{capital} is the annualized capital cost of the battery. The components of the value of C_{regu} are calculated using Equations (12) through (14) below:

$$C_{\text{battery}} = P_{\text{cap}} * C_{\text{bat unit}} \tag{12}$$

$$E_{\text{battery}} = T_{\text{battery}} * P_{\text{cap}} * DoD \quad (13)$$

$$C_{\text{capital}} = \frac{C_{\text{battery}}}{E_{\text{battery}}} * E_{\text{dispatch}} * \frac{D_{\text{rate}}}{1-(1+D_{\text{rate}})^{-m}} \quad (14)$$

where P_{cap} represents the battery capacity in kWh, $C_{\text{bat unit}}$ is the unit cost of the battery in \$/kWh, T_{battery} is the total number of charging cycles over the battery's lifetime, P_{cap} is the battery's capacity in kWh, and DoD is the Depth of Discharge of the battery. Moreover, D_{rate} is the discount rate for future years, and m is the lifetime of the battery in years. Finally, the net revenue of V2G service can be calculated using Equation (15):

$$\text{Net Revenue of V2G Service} = \text{Total revenue} - C_{\text{regu}} \quad (15)$$

6.3 Data Collection

6.3.1 Transit and School Bus Specifications

Transit buses and school buses have different operation conditions and requirements and therefore cannot be analyzed as a single bus type, so detailed data is collected on diesel and BE fuel options for transit and school buses. Table 6-2 summarizes the overall inputs utilized in this research. The analysis and data collection steps used in this research are performed for 40' long diesel and BE transit buses and for Type C diesel and BE school buses.

Transit buses and school buses are both assumed to have a lifetime of 12 years. Some studies suggest a lifetime of 16 years, but since the American Public Transportation Association (APTA) and the Federal Transit Administration (FTA) both assume a minimum transit bus lifetime of 12 years, this same assumption is used for purposes of this study [214]. Based on this average assumed lifetime, the study period of this study is also determined from 2015 to 2027. The average annual mileages of the bus types in this study are 37,000 miles for transit buses and 12,000 miles for school buses [182,215]. This is a reasonable difference between these two types because transit buses are expected to operate seven days a week whereas school buses only operate on school days, or 180 days per year on average in the U.S. [183]. Based this annual mileage information, the average daily VMTs (D_{VMT}) are calculated for transit and school buses. It must be noted that, in addition to regular daily school bus activity, school buses can also be deployed for field trip duties, which is not accounted for in the value of D_{VMT} calculated in this study.

The initial costs of BE transit and school buses are presented in Table 6-2. The significant difference between these initial costs for BE buses is also evident for diesel buses. Due to transit buses' cost incentive requirements (low-floor body type, improved powertrain reliability for higher lifetime mileage compared to school buses, *etc.*), transit buses are significantly more expensive than school buses. Compared to BE buses' initial costs, diesel transit buses cost \$340,000 each while diesel school buses cost \$110,000 each [214].

Another key parameter that differs significantly between transit and school buses is battery capacity. Transit buses have longer-range requirements for uninterrupted revenue service compared to the driving cycle ranges school buses. Therefore, the maximum weight limit of 4000 lb (1814 kg) for transit buses is often utilized [38]. Recent Lithium-Ion (Li-Ion) battery developments allow transit buses to reach driving ranges of up to 250 kilometers with a battery capacity of 324 kWh [216]. However, these technologies are still in an experimental phase, so battery capacity (P_{cap}) assumptions are made by using transit buses currently in use for transit agencies in the U.S. [4,195]. It is even more difficult to make an accurate assumption for the battery capacity of BE-school buses, since the current deployment of this type is very small in the U.S. as opposed to BE transit buses. Noel and McCormack's (2014) recent study assumes this battery capacity (P_{cap}) to be 80 kWh [182]. In addition to battery capacity, the replacement time of the battery over the total vehicle lifetime is also crucial for evaluating emission and cost analysis impacts. Moreover, since battery technology is constantly in terms of capacity and lifetime aspects, this parameter also has a degree of uncertainty that must be taken into account. Therefore, the battery lifetime of transit and school buses are included in this study as a range of charging cycles. As shown in Table 6-2, this wide range is applicable for both types of buses, and the corresponding range references include broad discussions about the V2G effects on battery lifetime. The literature is still not clear about the impacts of V2G on battery lifetime, since the extent of the depth-of-discharge impacts has not yet been clearly proven [197,217]. Emissions from battery production are based on those in Noori *et al.*'s study, but one to three times higher than EPA's reports on Li-Ion battery results since it considers upstream emission impacts of battery production [94,218].

Fuel economy is one of the key components of any life cycle analysis. Table 6-2 only presents the fuel economy ranges for BE bus types, but diesel bus types have their own separate fuel economy ranges. BE transit buses have lower fuel economy because the passenger payload, number of stops, traffic congestion, climate effects, and other relevant factors all have a stronger influence on fuel economy than on the driving cycles of school buses. On the other hand, the electricity consumption of BE school bus has been tested and reported in Noel and McCormack's study, where it was found to be as low as 0.75 kWh/mile [182], whereas the California King County School District's BE school bus testing project reported an electricity consumption rate of 2 kWh/mile [198]. The fuel consumption rates of transit and school diesel buses have been tested in many different aspects, and the resulting data is available from multiple sources. Therefore, transit diesel bus fuel economy is assumed to vary between 2.82 and 4.14 MPDGE (miles per diesel gallon equivalent) and 7 MPDGE for diesel school bus [182,4,219].

Charging facility cost is another important requirement for BE vehicle operations, and requires more consideration from fleet owners; in fact, some studies in the available literature aim to optimize the number of charging facilities based on cost limitations [220]. It is assumed that charging facilities should have Level 3 charging for convenient service. Based on these assumptions, the charging facility cost ($C_{equipment}$) is assumed to be same for school and transit BE buses as presented in Table 6-2. In addition, the charging infrastructure's installation ($C_{installation}$) and maintenance ($C_{c\text{-}main}$) costs are gathered separately from Chang *et al.*'s report [201]. It is also assumed that charging infrastructure requires annual maintenance at a cost of 5% of the initial equipment cost. The last cost item considered for cash flow calculations is the cost of the necessary upgrades to the vehicle and to the charging facility for accommodating V2G services. Based on Kempton and Tomic's study, the V2G system equipment cost (C_{V2G}) for buses is expected to be similar to that of other vehicle types from the research, as shown in Table 6-2 [184].

6.3.2 Vehicle-to-Grid System Specifications

The total time in which a vehicle is available to provide V2G services (T_{plug}) is one of the key parameters influencing the total potential revenue that operator could gain from V2G system. From the values of T_{plug} summarized in Table 6-2, it can be assumed that school buses could generate more V2G service revenue, while the charging behavior of transit buses during their normal business hours (opportunity charging, as previously discussed) is not applicable for V2G services, meaning that transit buses can only provide V2G services during overnight charging.

P_{veh} is another key parameter for calculating the overall revenue from BE buses, and is to be determined based on Kempton and Tomic's study [184]. Equation (16) below has been adopted from their study and applied to the variables. For the average fuel economy (FE) values, P_{veh} could be calculated as 132 kW for BE school buses and 9.3 kW for BE transit buses with the consideration of battery to grid conversion efficiency factor (X_{convert}). The significantly low P_{veh} value for transit bus is due to the assumption that transit buses return to their charging facilities with a low remaining battery power percentage. On the other hand, school buses use only a small portion of their battery storage power for two-way trip operations, and therefore return to their charging facilities with more available battery power:

$$P_{\mathrm{veh}} = \frac{\left(P_{\mathrm{cap}} - \frac{(D_{\mathrm{VMT}} - B_{\mathrm{range}})}{FE}\right) * X_{\mathrm{convert}}}{T_{\mathrm{dispatch}}} \tag{16}$$

In addition to P_{veh} values, P_{dispatch} is another factor that determines the allowable power transfer. It is possible for a vehicle's battery to provide 200 kW, but if it is connected to a Level 1 charger, this power transfer will be limited to the charger's maximum electricity transfer capacity. As seen in Table 6-2, P_{dispatch} is assumed to range from 70 kW to 140 kW. Kempton and Tomic's calculation method for V2G service revenue states that the higher value between P_{veh} and P_{dispatch} can be used for later steps [184]. Therefore, P_{veh} can be disregarded in this study, and the aforementioned P_{dispatch} value range is used for calculations.

6.4 Results

6.4.1 Cash Flow Results

The ISO/RTO regions are used as the scope of this study, for which a V2G system application analysis is performed for BE transit and school buses in order to compare them with internal combustion engine diesel transit and school buses. BE bus adoption is still in a relatively early stage for transit and school bus fleet operators due to their high purchase prices compared to diesel and other alternative fuel options. Hence, a cumulative cash flow analysis is performed in this study for different bus types over their full lifetimes.

Figure 6.2 presents the transit bus cash flow results for diesel and BE fuel options. The initial cost of a BE transit bus is almost three times higher than that of a diesel transit bus, and thus diesel transit buses have lower cumulative cash flow results than BE transit buses. Although the results in Figure 6.2 accounted for the V2G system revenues for BE transit buses, and even though diesel transit buses were shown to accumulate significant total lifetime cost, BE transit buses are still not cost feasible. This study assumes that vehicles will be sold at the end of their lifetimes for their resale value, and this negative value on cash flow is shown to be seen significant for BE buses as opposed to diesel buses, again due to the high initial cost requirements of BE buses. Diesel prices are considered with regional projections in the analysis, but since this accounts for the only regional difference in terms of diesel transit bus operation, these regional projections do not yield any significant difference so only average value of cumulative cash flow for diesel transit bus is shown in figure. However, these same regional impacts yielded moderate differences (*i.e.*, the regional difference vary between 7% and14%) in terms of BE bus operation due to regional electricity price variations and its related dependent variables. The New York (NYISO) and California (CAISO) state regions provide relatively close results for BE transit bus operation, both demonstrating lower costs than other regions since they are the only two states that provide tax incentives for BE bus purchases. However, these tax incentives are still far from making BE transit bus competitive with diesel transit bus for overall cash flow analysis.

Same as the transit bus results in Figure 6.2, the school bus cash flow results for the diesel and BE fuel options are compared in Figure 6.3. In contrast to the transit bus results, BE school buses demonstrated lower cost results compared to diesel school buses, at the end of their 12-year lifetime. This is an interesting finding that although diesel school bus has lower initial cost; cumulative cash flow value becomes higher than the value of BE school buses after 4th year in NYISO and CAISO regions where tax incentives are available. Also, like in Figure 6.2, regional variations had no significant effect on the results in Figure 6.3 due to the lower diesel price variability between regions compared to the corresponding electricity price variability so diesel school buses' cumulative cash flow results are presented as average for regions. Moreover, also like Figure 6.2, Figure 6.3 demonstrated lower cash flow results for the NYISO and CAISO regions than those of any other region. Conversely, BE bus operation costs are higher for transit and school bus options in the New England ISO (ISO-NE) region than in any other region.

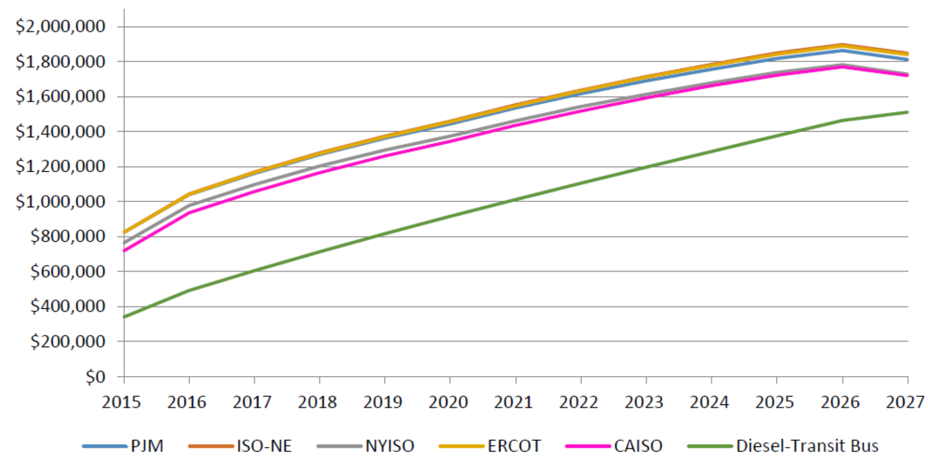

Figure 6.2 Cumulative cash flow of transit diesel (average) and BE (regional) buses.

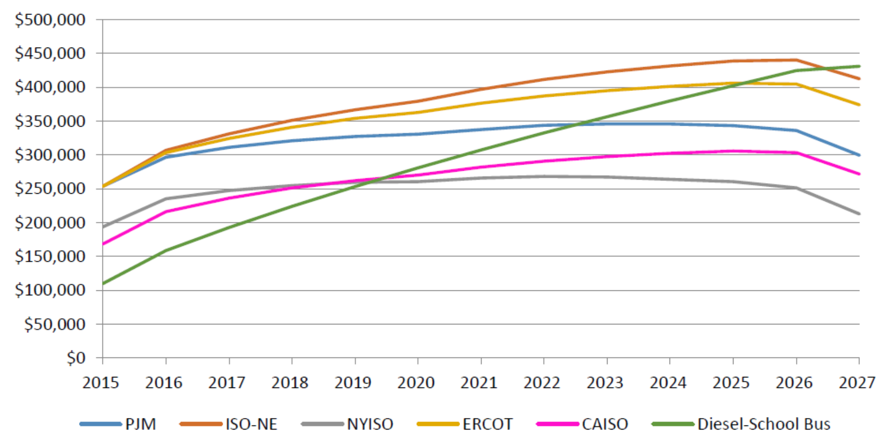

Figure 6.3 Cumulative cash flow of school diesel (average) and BE (regional) buses.

Both figures 6.2 and 6.3 presents the cumulative cash flow analysis for transit and school buses, however it is also crucial to present the components of this cash flow analysis an overall life cycle cost. Table 6-3 depicts the components of costs and revenues that are spent and earned throughout the lifetime of all bus types in CAISO region. Life cycle cost results indicate that although BE buses require two or three times higher initial costs compared to diesel bus types, overall net costs are less than diesel bus ownership for BE buses. Therefore, it can be clearly stated that operating BE buses with V2G technology and allowance of government incentives cost less than traditional diesel buses on top of environmental benefits. In addition to V2G related revenues, this significance difference can be explained with several more aspects such as fuel cost of diesel buses are four to six times higher than BE buses due to low fuel efficiency and higher unit cost of diesel. Maintenance cost is another component that affect life cycle cost of diesel buses compared to BE buses. It should be noted here that battery replacement due to operation and battery degradation costs due to V2G service cause critical increase on results, however, as it stated for initial cost difference, those costs can be eliminated with V2G revenues and government incentives.

Table 6-3 Average lifetime cash flow analysis of transit and school buses in CAISO region.

Value Type	School Bus- BE	School Bus- Diesel	Transit Bus- BE	Transit Bus- Diesel
Purchase price (C_{bus})	\$230,000	\$110,000	\$800,000	\$340,000
Lifetime fuel cost (diesel or electricity)	\$21,915	\$82,494	\$87,181	\$500,113
Maintenance cost ($C_{B\text{-}Main}$)	\$66,814	\$140,461	\$311,892	\$415,856
Charging station purchase cost ($C_{installation}$ + $C_{equipment}$)	\$23,446	\$0	\$23,587	\$0
Charging station maintenance cost ($C_{C\text{-}Main}$)	\$8971	\$0	\$8979	\$0
Battery replacement cost (due to operation) ($C_{battery}$)	\$29,819	\$0	\$76,073	\$0
V2G capacity payment revenue	−\$229,498	\$0	−\$96,261	\$0
V2G energy payment revenue (exchanged electricity)	−\$56,329	\$0	−\$56,469	\$0
V2G cost (V2G equipment + battery degradation) (C_{regu})	\$79,285	\$0	\$79,423	\$0
Resale value	−\$32,658	−\$17,199	−\$106,123	−\$43,810
Government incentives (if applicable)	−\$84,876	\$0	−\$106,146	\$0
Net value	\$**56,888**	\$**315,756**	\$**1,022,135**	\$**1,212,158**

The initial cost difference for BE and diesel school buses is not as significant as that for transit buses, but the cost-effective lifetime performance of BE school buses compared to diesel school buses cannot be explained with only this reason. The primary focus of this study is to demonstrate the potential V2G system benefits, as the resulting revenue for fleet owners will also have an influence on the cash flow of a BE school bus. Therefore, Figure 6.4 depicts the net revenue results for transit and school bus options with V2G service revenues taken into account. Due to the operation specifications of a typical school bus, school buses are highlighted as a better candidate than transit buses for offering V2G services. Figure 6.4 also indicates parallel results to support this theory that school buses provide significantly higher revenues for fleet owner than transit buses. Out of the five regions considered in this study, the New York-ISO region provides the highest rate of revenue on average for both bus types due to its higher capacity price (C_{cap}) ranges compared to other regions. Therefore, it can be concluded that there is a balancing act between school and transit buses in terms of net available revenues from V2G services, since school bus V2G revenues are much higher than those of transit buses whereas the battery capacity of transit buses is much higher than that of school buses. Hence, this balancing act again highlights the importance of the value of T_{plug}, which represents the available V2G service time for BE buses.

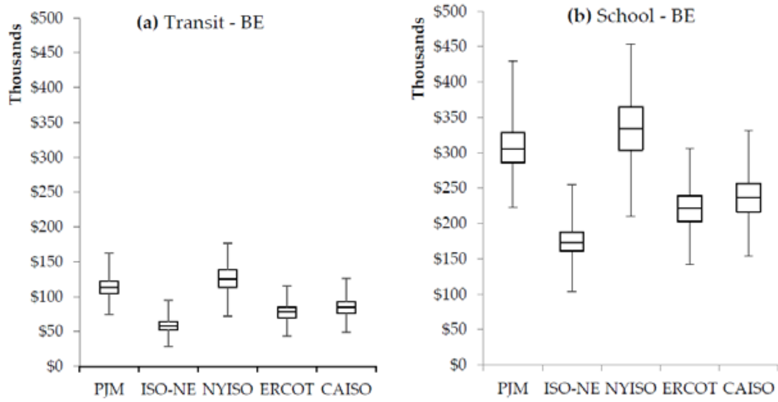

Figure 6.4 Regional net revenue of V2G service for transit (**a**) and school (**b**) bus options.

6.4.2 Environmental Emission Results

There are a significant number of cited studies from available literature that present environmental life cycle assessment analysis results for diesel and BE transit buses and school buses. Furthermore, using V2G technology could eliminate the air emissions caused by combustion power plants (which are not environmentally efficient) when accommodating high electricity demand fluctuations. Hence, per one of the goals of this study, Figure 6.5 presents the potential regional average cumulative environmental emission reductions from the use of V2G services from transit and school buses over their entire lifetimes. It should be noted that Figure 6.5 indicates the cumulative GHG emission benefits in year 2027, which covers the whole lifetimes of BE transit buses and school buses. Figure 6.5 shows that BE transit buses using the V2G system can help to eliminate 1000 metric tons of CO_2-equivalent GHG emissions on average over its lifetime. Similar to the net revenue results in Figure 6.4, the emission benefits are also higher for school buses than for transit buses. However, there is an interesting point that it should be highlighted for Figures 6.4 and 6.5. V2G service related BE school bus net revenues are almost three times higher than BE transit buses and this difference is almost one-and-half times more for emissions savings. The reason behind this difference is basically due to the consideration of battery degradation. Both of these calculations account for battery degradation and related battery replacement cost and emissions are not linearly influencing the net revenue and emission savings for this analysis. Moreover, the impact of battery replacement impacts in terms of emissions and cost are significantly different and it is more sensitive to emission impacts. Therefore, net revenue benefits of BE school buses are much higher than emission saving benefits.

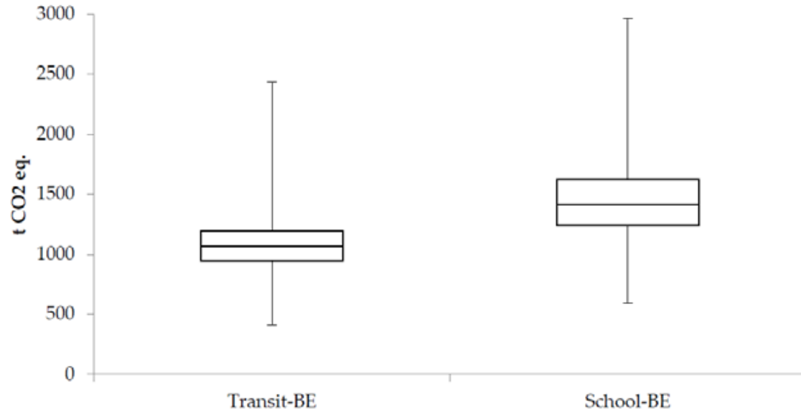

Figure 6.5 Regional average of cumulative GHG emission savings in 2027 for transit and school battery electric (BE) bus due to V2G availability [tons].

6.4.3 Air Pollution Externality Results

Finally, the air emission externalities for BE and diesel transit and school buses are presented in Figure 6.6. In addition to the economic and GHG emission impacts, air emission externalities are another crucial indicator that should be defined for every air emission source, especially when said source operates/emits near highly populated areas. It is important to note that tailpipe emissions contribute the most to these externalities, as the tailpipe emissions for transit and school buses are assumed to occur primarily in and near highly populated areas. Due to high annual mileage values, transit buses cause significantly higher air emission externalities than school buses.

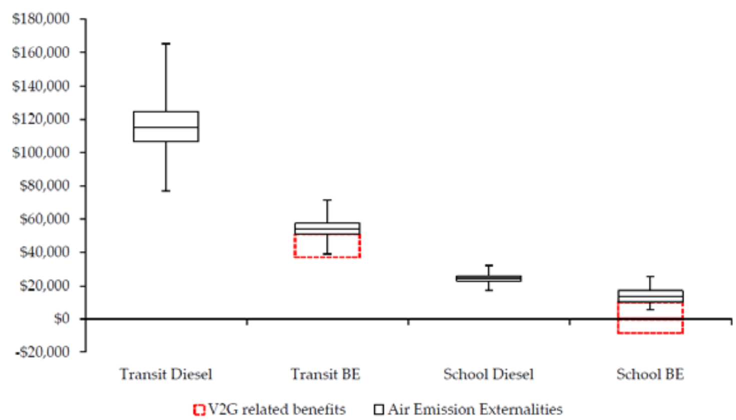

Figure 6.6 Total air pollution externalities of bus and fuel types.

In addition to reducing the public health costs of all of these air emission types, the V2G system could eliminate some of the emissions from combustion power plants, as presented in Figure 6.5. Therefore, the V2G system can provide enough electricity back to the grid to reduce the mean air externality value of transit BE buses by $13,000, which reduce it to almost the maximum air externality rate of diesel school buses (please see red-dotted lines on Figure 6.6 for V2G related reduction). More interestingly, V2G services provided from BE school buses effectively eliminated their mean externality value, and even provided a net benefit due to less electricity generation and emissions from power plants. However, it should be noted that negative externality values do not necessarily mean that BE school bus operations can provide negative emissions, but it does mean that V2G systems can neutralize all of the emission impacts of electricity consumption from BE school bus operations. Hence, Figure 6.6 clearly highlights the potential benefits of V2G technology in terms of public health cost reductions.

6.5 Discussion

V2G technology is a relatively new approach to eliminating some of the barriers hindering the rapid adoption of electric vehicles. Current literature highlights V2G systems as a promising technological application, as they provide a source of revenue for electric vehicle owners as well as an efficient electricity source for utility providers. V2G technology is also emerging as a powerful environmental solution, as it can be used to reduce GHG emissions from the two highest-contributing sectors (transportation and power generation) to such emissions in the U.S.

This study is multi-disciplinary in many ways such as analyzing not only transportation sector related environmental emissions but also investigating the upstream environmental emissions of battery electric buses, economic impacts (*i.e.*, cash flow), and air pollutant externalities for public health with downstream and upstream consideration. Besides, this analysis also integrated the V2G service availability where power generation sector could also eliminate some of the environmental emissions. The multi-disciplinary impacts of the integration of these two sectors is not limited to environmental and economic matters, but also includes integrity and reliability of electricity grid and resiliency of power supply during the extreme events. In other words, this study interacts with the researches where V2G service can increase the reliability of electricity grid and provide energy for vehicle user's home, facility *etc.* during extreme events of long power outages. Furthermore, as the results indicated, heavy-duty vehicles such as buses have potential to provide these benefits more than passenger vehicles that have been studied in current literature broadly for V2G applications.

Therefore, this study investigated possible V2G applications in five different ISO/RTO regions for transit buses and school buses, and performed an additional comparison to internal combustion engine diesel transit and school buses. Based on the methods and data used in this research, the results in this study indicated the following key findings:

1. The cash flow analysis results in this study indicated that BE transit buses are not economically feasible to operate even with V2G net revenues taken into account, and the initial purchase price of a BE transit bus is especially discouraging for fleet owners compared to those of diesel buses and buses with other alternative fuel options. However, this could change in the near future with battery development and market demand trends for alternative fuel transit buses. On the other hand, BE school buses effectively eliminated their high initial cost requirements throughout their lifetimes, whereas diesel school buses did not.
2. Transit buses also yielded less net revenue for fleet owners from V2G service. However, this result does not mean that V2G services are not feasible or applicable for BE transit buses. It should be noted that the primary duty of transit buses is to

serve society for reliable public transportation and to provide a source of revenue for transit agencies. It is therefore still beneficial for transit agencies to collect additional revenue from BE transit buses even while they are not in use. Conversely, with extensive cash flow benefits, BE school buses can easily substitute diesel school buses for the fleet owners' cost perspective.

3. If the total number of transit and school bus fleets in the U.S. is taken into account, the overall potential of V2G system applications and BE bus adoption can be significant. However, it is not clear if the current electricity generation and distribution infrastructure could support such an adoption. Therefore, BE bus deployment levels should be studied further and optimized parallel to current development trends in the utility generation and supply system.
4. In addition to V2G technology, there are other new technologies similar to V2G that provide power as needed from plugged-in electric vehicles back to a home (V2H) or back to a building (V2B). These similar technologies could be an interesting future area of study through which to present the possible benefits of providing electricity from an electric vehicle fleet back to the workplace buildings (administrative, maintenance, *etc.*) of a fleet operator. That said, as highlighted in this research, buses have a significant amount of power available from their batteries compared to any passenger vehicle's capacity. Thus, heavy-duty vehicles are more capable of providing power support to a building than light-duty vehicles are. This concept can also lead to another research area where there is potential of V2G, V2H, or V2B technologies to enhance the resiliency of grid/building during extreme events.
5. The air emission externality results in this study are especially noteworthy because this study focuses on vehicles operating in or near highly populated areas. This is particularly true for school buses, the tailpipe emissions of which are emitted mainly near a non-adult population. Moreover, since air emission externalities are not defined specifically for non-adult populations, the public health damage rates for school bus emissions could be even higher than the average rates used in this study. Also, although electricity generation does not usually occur near populated areas, conventional power generation methods still have high emission rates of hazardous pollutants due to the high fossil fuel dependency of the U.S. power generation sector. These per-kWh emission rates for electricity generation are expected to decrease in future years as the U.S. invests more and more in renewable energy sources and technologies. However, this study shows that V2G technology can already provide significant air emission externality reduction benefits from BE transit buses and school buses.

BE transit and school bus examples are still largely in an experimental phase in the U.S., and so there are still data limitations regarding their operation and especially with respect to V2G application specifications; for this same reason, only five ISO/RTO regions could be considered in this research due to a lack of usable data for other regions. This study could therefore be extended in the future with the inclusion of other U.S. regions as well as additional data on renewable energy deployments.

7.0 Getting to net zero energy building: investigating the role of vehicle to home technology

7.1 Introduction

The world's rapidly growing energy consumption rates, coupled with the associated environmental impacts of such energy consumption, has raised concerns in different communities and among researchers, engineers, and even politicians [221][5]. As buildings are responsible for more than 40% of primary energy usage and 70% of overall electricity usage in the U.S., policy-makers must quickly take action to reduce the energy demand of buildings [222]. The energy consumption of buildings is responsible for 38% of CO_2 emissions to the atmosphere, 52% of SO_2 emissions, and 20% of NO_x emissions [223]. At the same time, the energy usage of buildings faces an increasing trend in the future, considering its existing nexus with population and economic development [221]. Therefore, moving toward sustainability requires minimizing the resource consumption of buildings, meaning that the energy performance of buildings should be maximized without sacrificing their comfort levels [224].

To design energy-efficient buildings, several studies are available that have investigated factors such as thermal insulation and building envelope, age, size, lighting and lighting control systems, outdoor weather conditions, HVAC equipment, building orientation, urban texture, and other applicable factors in an effort to reduce the energy consumption of a particular building [225–228]. Among these is a study by Balaras et al., who investigated the effect of a building's thermal insulation (including floor, window, wall, and roof insulation) on the energy performance of the building [229]. Other studies investigated the potential of smart occupancy sensors to reduce a building's energy consumption [230–232]. In addition, since HVAC system management is another major concern when designing an energy-efficient building, some studies have specifically investigated the influence of HVAC system management on the energy consumption of buildings [233–235].

Most of the above-mentioned studies have focused on specific aspects of a typical building's energy consumption, and have tried to simulate and analyze the effect of those specific components on the energy demand of such a building. However, since one of the goals of this study is to design an energy-efficient building, it is therefore necessary to simultaneously consider all of the most important factors affecting a building's energy consumption in an optimization analysis to select the best design alternatives. In this regard, it is necessary to optimize the parameters that influence the energy and investment costs and the thermal comfort of such a building (envelope, HVAC, etc.) [236]. However, achieving this goal requires a thorough study to find better design alternatives that satisfy a variety of conflicting criteria, such as those pertaining

[5] The contents of this section were partly published in Alirezaei, M., Noori, M., and Tatari, O. (2016). "Getting to net zero energy building: investigating the role of vehicle to home technology." *Energy and Buildings, Elsevier.* 2014 IF: 2.884. DOI: 10.1016/j.enbuild.2016.08.044

to economic and environmental performance [223], so as to help designers overcome the drawbacks of trial-and-error with simulation alone.

There are several studies in available literature on optimization approaches and their suitability for minimizing a building's energy consumption [237]. For instance, Fesanghary et al. investigated the application of a multi-objective optimization model based on a harmony search algorithm to find an optimal building envelope design to minimize life cycle costs and emissions [238]. In addition, Hamdy et al. proposed a modified multi-objective optimization approach based on a Genetic Algorithm to design a low-emission, cost-effective dwelling [239]. It has also been noted that minimizing energy consumption should be taken into consideration along with other constraints such as costs and the comfort levels within buildings [240]. Therefore, this study uses an optimization approach through the use of a built-in optimization tool developed by Designbuilder [241]. With this optimization tool, it is possible to identify different design alternatives with various combinations of costs, energy consumption rates, and comfort levels, using the Genetic Algorithm (GA) method to perform a multi-objective optimization analysis.

Consuming less energy through an optimization process and the selection of the best available design alternatives will be a major step toward a sustainable community. However, in order to fully implement the concept of sustainability, new plans must be devised to integrate renewable energy sources into the energy portfolio of a building. Therefore, developing a new methodology with which to minimize the energy consumption of a building and integrating renewable energy sources with the main electricity source (the power grid) will both contribute greatly to a more sustainable community [242]. In this regard, when moving toward sustainability, not only is it important to reduce the required energy of the building in question but also to find ways to implement new and cleaner energy sources whenever possible. For this reason, shifting the building's energy sources away from the electricity grid (which tends to be the most likely source to emit air pollutants) in favor of onsite renewable energy sources seems to be inevitable. The concept of the net zero energy building (NZEB) has evolved primarily from this idea.

7.1.1 Net Zero Energy Building (NZEB)

The goal of the NZEB concept is to reach a point where a building's onsite electricity production can supply its entire electricity demand [243]. The NZEB concept is no longer perceived as a purely theoretical ideal for future applications, but as a realistic and achievable goal to reduce buildings' energy consumption levels and to subsequently mitigate CO_2 emissions from the building sector [244]. Growing attention to the NZEB concept can be seen in a number of buildings constructed based on this theory as practical examples thereof [245–248]. The Energy Independence and Security Act (EISA) of 2007 authorizes the Net-Zero Energy Commercial Building Initiative to support the goal of net zero energy consumption for all new commercial buildings by 2030, and to extend this goal to reach a net-zero-energy target for 50% of U.S. commercial buildings by 2040 and for all U.S. commercial buildings by 2050 [249]. The Energy Performance of Buildings Directive (EPBD), published in 2002, obliged all EU countries to enhance their buildings' regulations and to introduce energy certification schemes for buildings [250]. To this end, the EPBD Directive of 2010 has set a target of “nearly zero energy buildings” by 2018 for all public buildings and by 2020 for all new buildings [251]. As can be seen from these goals, the international community now regards the NZEB concept as a viable solution to the increasing energy consumption levels and CO_2 emissions of today’s buildings.

Across all definitions and classifications for the NZEB, one basic design rule remains constant; address demand first, and then supply [249]. New types of renewable energy sources should be employed for a NZEB, and in this regard, many studies have investigated the use of various renewable energy sources (solar panels, wind turbines, geothermal heat pumps, etc.) to supply the energy demand of buildings. For example, Charron investigated the use of thermal and solar photovoltaic (PV) technologies to generate as much energy as a typical home would need on annual basis, in what can be referred as a net zero energy solar home [252]. The life cycle costs of such homes is also an important topic to discuss, and has been investigated in different studies [253]. Another study by Iqbal investigated the feasibility of using wind energy in a net-zero-energy home, taking into account critical parameters such as wind speed [254]. Some studies have even tried to combine different types of renewable energy sources to design a NZEB. For instance, Melissa et al. investigated the power generated through solar thermal energy and wind power to supply the energy demand of a building [255], while Noori et al. investigated the socio-economic and environmental impacts of producing electricity for buildings using wind power plants [212].

In addition to renewable energy sources, the role of vehicles in supplying the energy demand of buildings is now yet another possibility to be investigated. With the help of newly introduced technologies, it is possible to use vehicles (esp. household vehicles) as potential energy sources for buildings. These technologies and their applications are discussed in further detail in the next section.

7.1.2 Vehicle to Home (V2H) Technology

In addition to renewable energy sources (solar panels, wind turbines, etc.), alternative-fuel vehicles can also be considered as viable energy sources to supply the power demand of a building. Existing bi-directional charging technology allows intelligent charging to be taken to a new level; with the help of vehicle-to-home (V2H) and vehicle-to-grid (V2G) technologies, the use of electric vehicles (EVs) can be considered an opportunity to use EV networks as power sources in and of themselves [256]. Using this technology in conjunction with other renewable energy sources makes the overall system more energy-efficient by storing excess energy generation during off-peak hours for use whenever the available power generation is not sufficient to meet the energy demand. Moreover, V2H technologies use idle EV battery power as a grid storage unit with which to handle fluctuating renewable electric power supply.

Different studies in this regard have examined this technology from different perspectives. One such study conducted by Haines et al. developed a simple V2H model for a home’s daily energy demand [256]. Another study by Liu et al. introduced different methodologies for using V2H, V2G, and vehicle-to-vehicle (V2V) technologies [257]. Cvetkovic et al. presented a small grid-interactive distributed energy resource system consisting of photovoltaic sources, plug-in hybrid electric vehicles (PHEVs), and various local loads [258]. Moreover, Noori et al. investigated the regional net revenue and emission savings that may be possible with the use of V2G technology [259]. The life cycle cost (LCC), environmental impacts, and market penetration of EVs are also important areas to consider when performing a thorough life cycle analysis of the system as a whole [94,260].

V2H technology enables users to connect a variable number of vehicles to a building's power distribution board, making it possible to supply the building's power demand at nighttime (when the building's electricity usage is usually at its peak). This is accomplished by depleting the stored power in the batteries of electric vehicles and then charging the battery when the power demand is low, using electricity from the power grid or from other renewable energy sources (solar panels, wind turbines, etc.). This system can also be used as a reliable energy source in case of an emergency such as a power outage. In this regard, government incentives can be implemented to compensate individuals and businesses for the increased initial costs of this technology. From the consumer's viewpoint, this means that cars are usable for mobile energy storage and not just for transportation purposes, being able to provide power to a building and thereby alleviate the corresponding stress on the conventional power grid. A schematic of the overall concept considered in this study is shown in Figure 7.1 below.

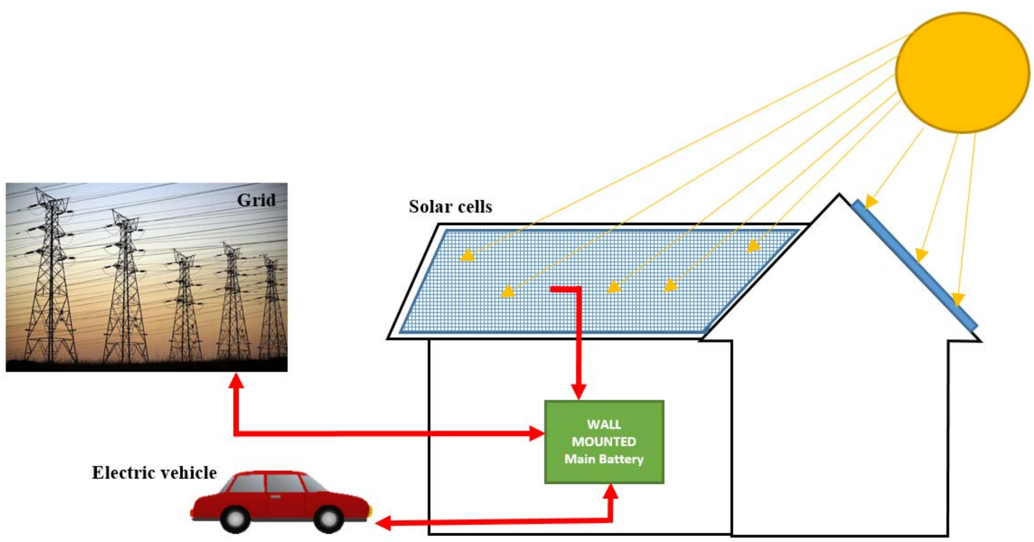

Figure 7.1 Net Zero Energy Building.

7.2 Methodology

The general methodology of this study is illustrated in Figure 7.2 below, which summarizes the different steps taken to achieve a completed NZEB design. The overall process starts with modeling the building itself, followed by an energy analysis and an optimization analysis in order to design an energy efficient building. Next, solar power and an EV battery are integrated in conjunction with the main energy source of the designed building (grid electricity), and the resulting interactions within this system as a whole are controlled using the developed algorithm.

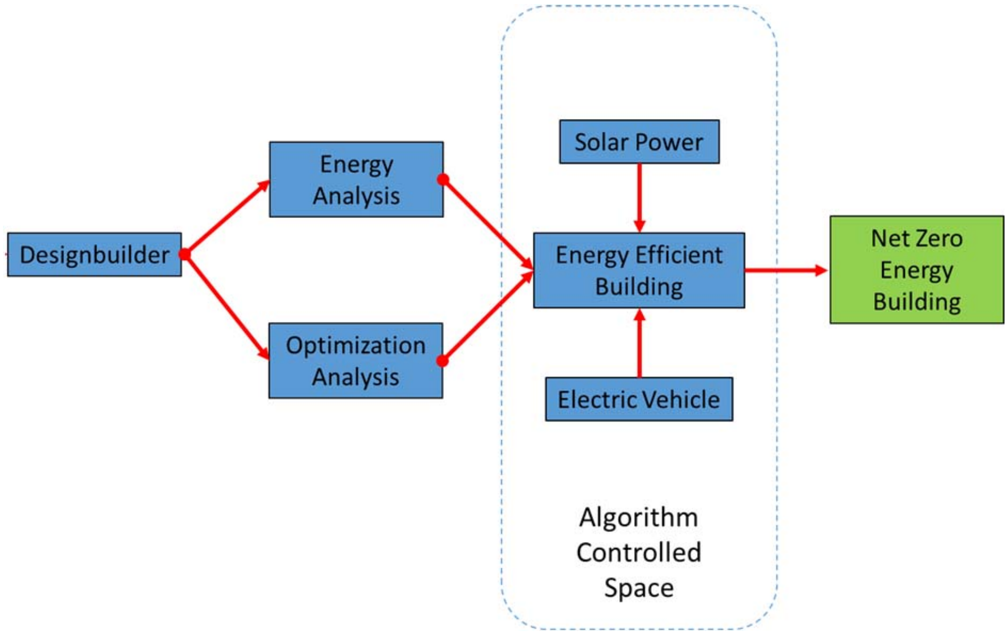

Figure 7.2 Developed Methodology

7.2.1 Model Development

For modeling purposes, the building modeled in this study is a two-story residential building with a total area of 1,184 square feet and a net conditioned building area of 1,074 square feet. This model can be seen in Figure 7.3. The detailed specifications of the modeled building are summarized in Table 7-1.

Table 7-1 Modeled Building's Specifications

Parameters	Values and types
Gross Wall Area	1,239 sq ft [115 sq m]
Window Opening Area	295 sq ft [27.4 sq m]
Gross Window-Wall Ratio [%]	23.80
Gross Roof Area	632.60 sq ft [58.77 sq m]
Skylight Area	50.30 sq ft [4.67 sq m]
Skylight-Roof Ratio [%]	7.95
Weather File	Orlando Sanford Airport FL USA TMY3 WMO#=722057
Latitude [deg]	28.78
Longitude [deg]	-81.3
HVAC system	Ground Source Heat Pump (GSHP)
Lighting system	Fluorescent, Compact (CFL)

In the next step, the developed model is used to evaluate the energy performance of the building. The Department of Energy (DOE) recommends a complex variety of tools and software for different design purposes, and one of the most comprehensive software programs currently available is EnergyPlus, which is designed to simulate and assess the energy consumption of the entire building [261]. Architects, engineers, and researchers have been able to use EnergyPlus to model the energy consumption of a designed building, (including energy consumption from heating, cooling, ventilation, lighting, and water usage) while also providing users with a broad range of alternatives for each component [262]. However, EnergyPlus reads inputs and writes outputs to text files, which can make it somewhat difficult and time-consuming to work with. In order to increase the usability of this software and make it more understandable for ordinary engineers, several graphical interfaces for EnergyPlus have been introduced. The graphical interface for EnergyPlus used in this study is Designbuilder, which accounts for the weather conditions of a particular region when performing an energy performance analysis, allowing the analysis in this study to account for average annual sunshine, wind speed, temperature, and all weather-related situations in addition to the other factors previously discussed [263].

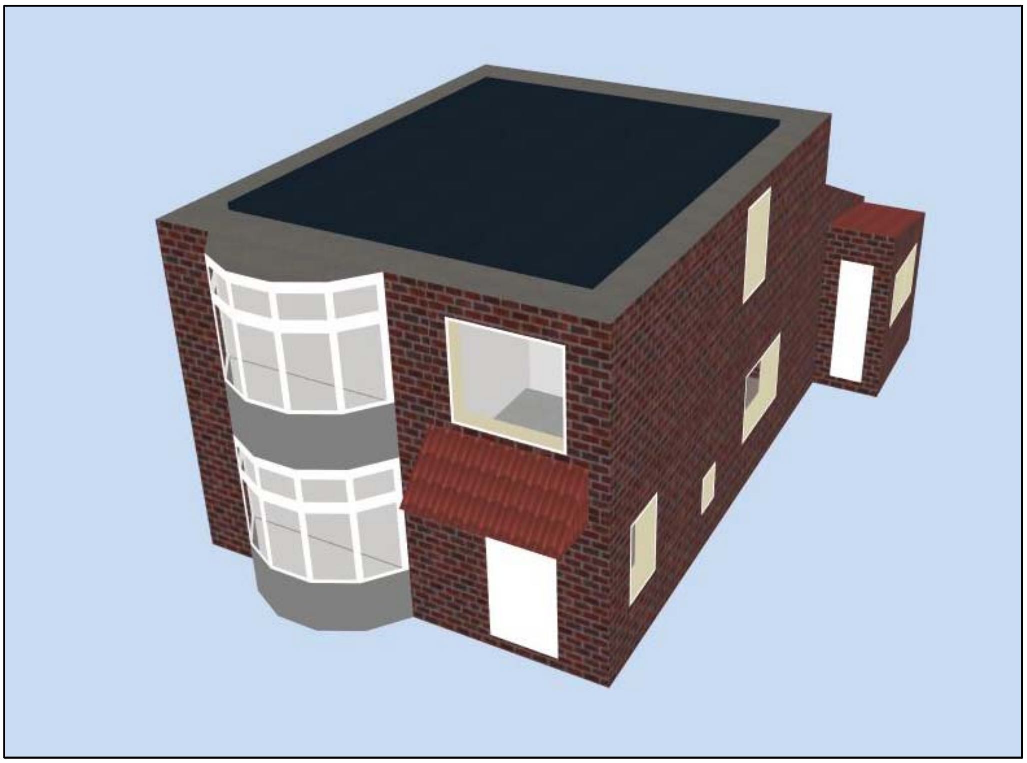

Figure 7.3 Developed Model in Designbuilder

7.2.2 Optimization of the Building's Energy Performance

Once the model is defined and the applicable weather database file is imported, the next step is to analyze the building's energy performance. As mentioned earlier, the process of choosing the best design options is a time-consuming process that requires a powerful database to enable designers to choose the best design alternative, while also considering relevant design constraints during the search for an optimal solution. Regarding the energy performance of a building, many different factors should be considered simultaneously in order to find an optimal solution; for purposes of this study, an optimal design should provide a high-quality, comfortable building fully compliant with the applicable standards and codes while also reducing the initial cost, operational energy usage, and environmental impacts of the building [264]. In this regard, an optimization analysis is performed in order to select the best building design options with which to minimize the energy consumption of the building in question without compromising any more than necessary in terms of cost, environmental impacts, and (more importantly) the comfort of the residents.

The process of finding the best design alternatives can be very difficult, especially with respect to conflict areas such as those related to economic and environmental performance levels [265]. The method used for this purpose should be chosen in a way that allows for a multi-objective optimization and also works relatively well given the non-explicit nature of the applicable objective functions [266]. Designbuilder provides a user-friendly interface that enables engineers to compare a set of different alternative design options for building envelopes (wall insulation, glazing type, etc.) as well as different heating and cooling systems, using the Genetic Algorithm (GA) multi-objective optimization method to select the best design alternatives. It is worth mentioning, however, that the Genetic Algorithm method does not guarantee the optimal solution, but instead finds an approximate solution to the optimization problem [42,43].

In this regard, more than 66% of the energy consumption of residential buildings is related to HVAC and lighting systems [222]. In this specific case study, considering the weather conditions in Orlando, cooling and lighting loads are expected to have dominant shares in the overall energy consumption of the building, which would match with the preliminary results of the energy analysis of the building in question. Therefore, in order to optimize the energy consumption of the building, more emphasis is placed on testing different HVAC and lighting systems to find an optimal solution that reduces energy consumption as much as possible. Figure 7.4 shows the results of this optimization analysis with different design variables and objective functions. In this figure, the results of the GA optimization method are shown as a set of optimal solutions, but the best design method with the least amount of energy consumption and the lowest cost can still be derived as a result of the aforementioned optimization analysis.

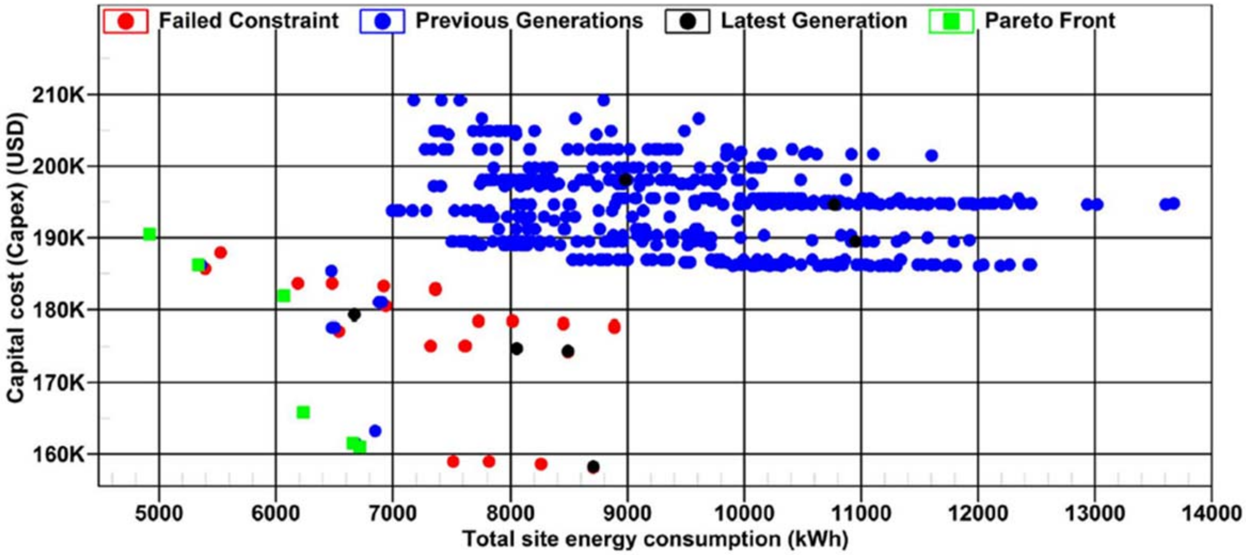

Figure 7.4 Optimization Analysis Results

As seen in Figure 7.4, a set of different colorful points is illustrated in this graph, with each point representing a separate design method with different HVAC and lighting systems. In general, three main areas must be considered when optimizing the energy consumption of the building: total site energy consumption, capital cost, and comfort level. For this purpose, the parameter values of the optimization analysis are set in a way that minimize the capital cost and total onsite energy consumption of the building. Clearly, as the system becomes more efficient, the energy consumption of the building decreases, but the capital cost may increase. On the other hand, ASHRAE Standard 55-2013 states that, for thermal comfort, the temperature in the building may range between 67°F and 82°F (approximately 19°C and 27°C, respectively) [268]. In order to ensure an acceptable level of comfort in the building, the comfort level is considered as a constraint in the optimization analysis, meaning that the only acceptable design methods are those that can ensure a comfortable temperature within the specified ranges; the green points in Figure 7.4 indicate the solutions corresponding to these designs. The red points represent the design methods that are optimal in terms of both capital cost and energy consumption, but fail to provide the desired comfort level.

During the optimization analysis, approximately 1,990 design set points were tested, and based on the results, 6 of these points are found to be acceptable for consideration as the optimal design methods. The specifications and optimization results for these 6 designs are summarized in Table 7-2.

Table 7-2 Optimization Analysis Iterations

HVAC template	Lighting template	Cooling system (COP)	Onsite energy consumption (kWh)	Capital cost (Capex) (USD)	Comfort Temp (°C) in building
Air to Water Heat Pump (ASHP), Convectors, Nat Vent	T8 Fluorescent - triphosphor - with STEPPED dimming daylighting control	2.63	5,336	186,203	27.75
Natural ventilation - No Heating/Cooling	T8 Fluorescent - triphosphor - with STEPPED dimming daylighting control	3.58	6,659	161,514	27.69
Natural ventilation - No Heating/Cooling	T8 (25mm diam) Fluorescent - triphosphor - with ON/OFF dimming daylighting control	3.32	6,719	170,000	27.71
Electric Convectors, Nat Vent	LED with linear control	2.76	6,069	181,917	27.6
Air to Water Heat Pump (ASHP), Convectors, Nat Vent	LED with linear control	2.69	4,918	190,489	27.6
Natural ventilation - No Heating/Cooling	LED with linear control	3.12	6,235	165,800	27.54

The above table describes the most optimal design points, such that their respective capital costs and energy consumption levels are both optimized while also ensuring that the basic requirements in terms of thermal comfort are met. In order to select the most efficient system among these 6 designs, the results of a separate energy analysis have first been derived for each design. Afterward, by comparing the discomfort hours of different systems based on ASHRAE 55-2004, the system with the lowest amount of total discomfort hours has been selected as the final optimal design. Now, after reducing the energy consumption of the building, the next step is to devise a system with which to supply the required power to the building.

7.2.3 . Power Supply System

In the following two sections, each of the energy sources chosen for the hypothetical building in this research (solar power and electric vehicles) are described in further detail.

7.2.3.1 Solar Power

The sun has produced energy for billions of years, and the energy in the sun's rays as they reach the earth can be converted into electricity through Photovoltaic (PV) cells, often better known as solar cells [269]. Solar energy is no longer viewed as a minor contributor to the nationwide energy grid mixture of the U.S., as it used to be in previous years due to high costs and other practical constraints [270]. Photovoltaic (PV) systems are like any other electrical power generation system, with some differences in the equipment used as opposed to the standard equipment for conventional electromechanical generation systems [271]. A basic diagram of PV systems is presented in Figure 7.5 below.

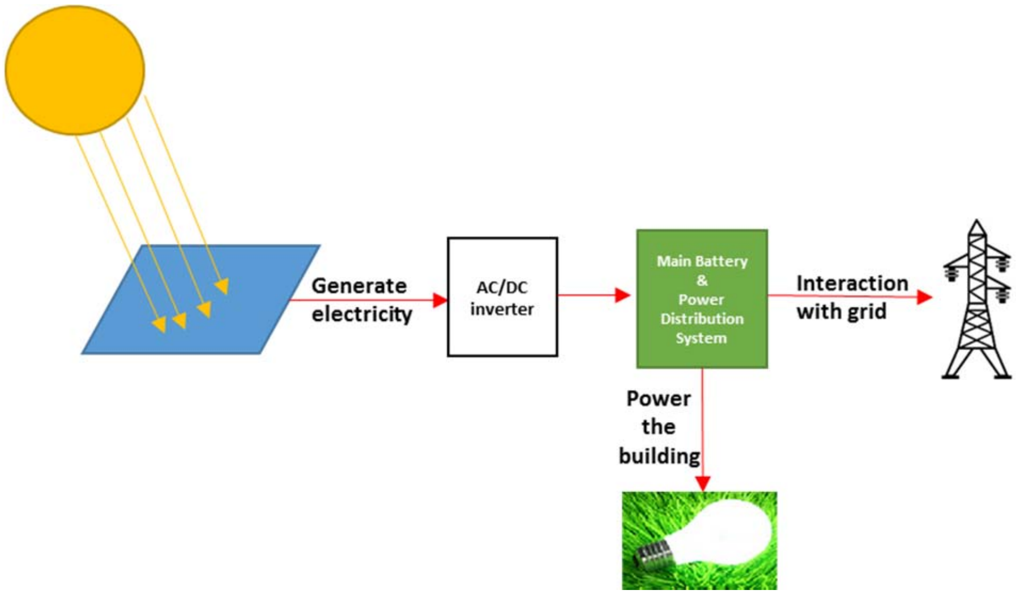

Figure 7.5 PV System Components

In order to convert solar energy to base-load power, excess power that is produced during sunny hours of a day must be stored for use during nighttime (on-peak) hours [270]. In this study, in order to consider solar energy as a part of a power supply system, a series of solar panels with a total area of 108 square feet is modeled on the roof of the building, as indicated by the dark blue areas in Figure 7.3, and each solar panel works as a separate electricity generator. The modeled solar panels generate DC electricity, which must be converted to AC electricity so that the generated power can be used for the building's appliances and stored in a battery designed to store AC power, which is the most widely available battery type for consumers. In short, the operation scheme of the solar panels is designed to generate electricity regardless of the energy demand at any particular time, while any excess amount of this generated electricity can be transferred to an EV battery and then stored in the main battery.

In this study, the solar panels are placed on top of the roof of the building in order to simulate the worst-case scenario in which the building in question is surrounded by other buildings, although it must be noted that, in many cases, it is possible to use the backyard and/or the front yard of the building to install these panels and generate electricity. The amount of solar energy generated with the solar panels depends on the properties of the modeled solar panels; detailed specifications for the solar panels in this study are presented in Table 7-3.

Table 7-3 Solar Panel Characteristics

Parameter	Characteristics
Solar collector type	Photovoltaic
Performance type	Simple
Performance model	PV with constant efficiency of 0.15
Heat transfer integration mode	Decoupled
Material	Bitumen felt
Area	108 sq ft [10 sq m]

Moreover, the amount of generated solar energy depends on the time of day, the amount of incoming solar radiation, and the angle of the solar panels with respect to the sun. All of these parameters have been considered when analyzing the solar power generation for the building. In order to better understand the way that the modeled system interacts with the position of the sun, a schematic view of the analysis is shown in Figure 7.6. In the example illustrated in the figure, the position of the sun (sun-path diagram) is shown for July 15th at 11 A.M.

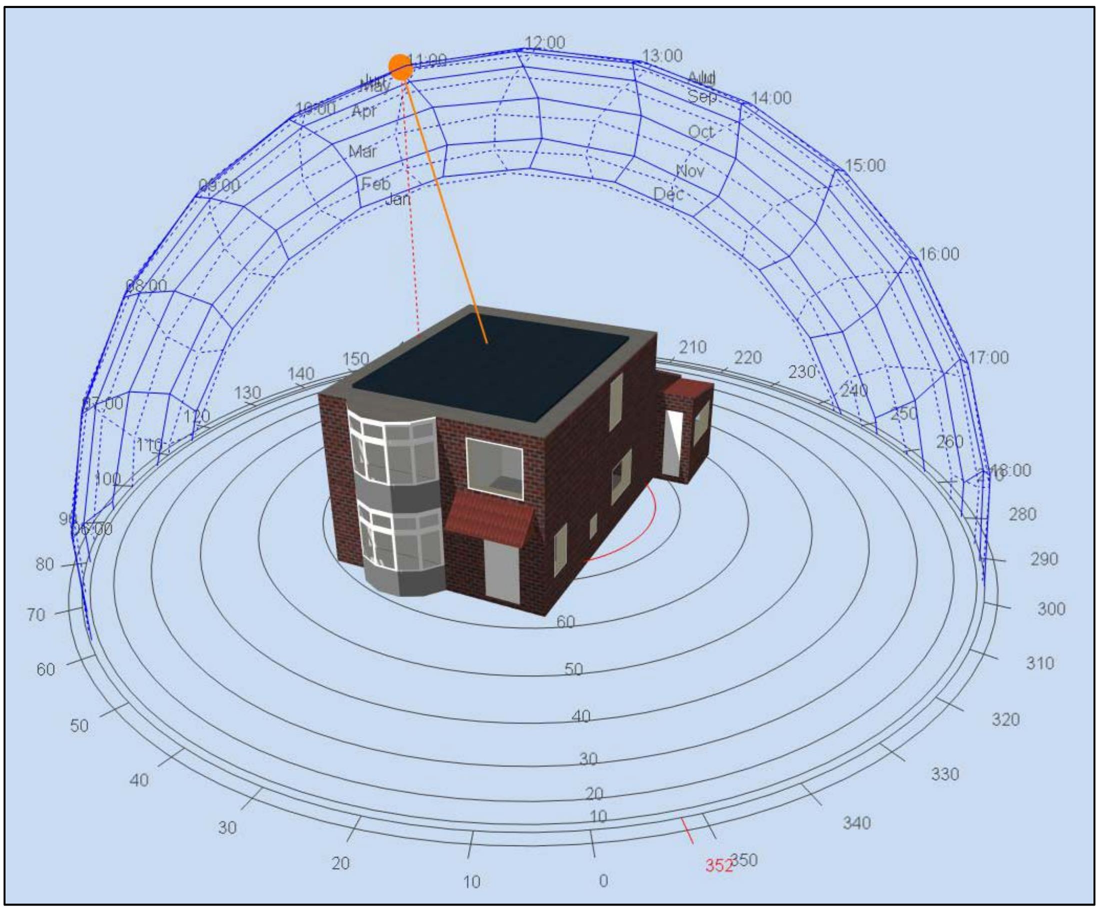

Figure 7.6 Schematic View of Sun-Path Diagram

Cost-related issues pertaining solely to solar power are beyond the scope of this study, and are not included in the results because the results can vary significantly depending on the boundaries of the cost analysis, and so a separate study is needed to fully investigate costs specific to solar electricity. That said, it is worth mentioning that the production price of solar energy has continuously decreased over the past few years, having dropped from 21.4 cents/kWh in 2010 to 11.2 cents/kWh in 2013 [272]. In order to make solar power more cost-competitive with traditional energy sources, a target has been set to reduce this price to 6 cents/kWh, which is now an achievable target given the current decreasing trend in prices as observed from 2010 to 2013 [272]. However, generating solar power can also have direct economic benefits in addition to the indirect economic advantage of reducing utility bills. For example, in Orlando, FL, some utility companies offer a credit to customers who generate solar energy ($0.05 per kWh of solar power generated), and if any such electricity can be transferred to the main power grid, utility companies typically buy this electricity for the same retail price.

7.2.3.2 Electric Vehicle

As discussed earlier, EVs are included in this study as part of the energy supply system for the modeled NZEB. The EV is modeled as a battery that can be connected to the home during certain hours of the day and certain days of the week. This study assumes that the vehicle is used to go to work between 9:00AM to 5:00PM, and is then connected to the building for the rest of the day. For modeling purposes, some specifications with respect to the EV in this study should be defined before starting the analysis, including EV battery capacity, state of charge, hourly EV charge (EV battery charging rate per hour), and other specifications as applicable.

EV battery capacity is highly dependent on the characteristics of the vehicle, and can range from 19 kWh for a mid-sized sedan to 30 kWh for a full-sized SUV [273]. This study assumes that the lithium–ion batteries is used as described for a Nissan EV, the EV batteries of which are said to be able to store up to 24 kWh [274]. The hourly EV charge depends on the battery size, the charging level, and other important factors. Assuming an average vehicle range, it generally takes 4 to 8 hours for an EV battery to be fully charged [275], so the hourly EV charge in this study is assumed to range from 3 kW/hr to 6 kW/hr.

The electricity that can be transferred to the building from the EV battery and vice versa is highly dependent on the amount of electricity that is left in EV battery when it reaches home. In this analysis, the state-of-charge (SOC) variable is used to determine how much electricity is still in the EV battery when the EV returns home. The SOC when the vehicle returns home depends on the distance that the vehicle needs to travel to reach home, which in turn may vary depend on the specific characteristics of each region. This study therefore uses the average returning SOC value as a starting point, and different ranges are applied to the analysis afterward to see the effect of this parameter on the required electricity from the power grid. All of the EV-related data and assumptions used in this study are summarized in Table 7-4 below.

Table 7-4 Model Parameters

Parameter	Source	Values & Ranges
EV Battery Capacity (kWh)	[273]	19-30
Hourly EV Charge (kW/hr)	[275]	3-6
Solar Photovoltaic Production Incentive ($/kWh)	[276]	0.05
Electricity to Grid Price ($/kWh)	[277]	0.0757

7.3 Power Distribution System

The role of Building Energy Management Systems (BEMS) is becoming more significant as the importance of providing the necessary thermal comfort, visual comfort, and indoor air quality is receiving more attention, especially in situations where fossil fuel consumption, GHG emissions, and price fluctuations are major obstacles to meeting the need for an energy-efficient building [278]. While the concept of BEMS generally applies to controlling HVAC systems and determining the operation times in order to reduce energy consumption without compromising comfort [278], this study attempts to use this management tool to establish a connection between different energy sources within the building and determine the flow of electricity between the main battery, the EV battery, and the power grid. In a NZEB, different types of energy sources should be used in conjunction with each other and with the conventional power grid. This study assumes that all of the power generated through the solar panels and the electricity from the EV battery are stored in a main battery already designed for this purpose. However, the specific technological advancements to be used in such a power distribution system are beyond the scope of this study.

This study attempts to develop an algorithm in which different energy sources interact with the grid in order to provide enough electricity to meet the energy demand of the building, while also transferring any surplus generated electricity to the grid and obtaining any additional required electricity from the grid during off-peak hours. In this algorithm (Figure 7.7), two possible situations are considered:

a) **The EV is connected to the building.** In this case, the EV is considered as part of the energy supply system of the building. This study assumes that the vehicle is used to drive the owner to work every day at 9:00AM and then return home by 5:00PM; during this time, the vehicle is therefore disconnected from the building. When the EV is connected to the building and is not fully charged, the algorithm checks whether or not the amount of onsite renewable generated electricity is greater than the amount of energy consumption for that specific hour of the day, in which case the excess amount of generated electricity is used to charge the connected EV. This process continues until the EV battery is fully charged.

   The next step is to see whether or not the main battery is fully charged. If not, then the onsite generated electricity is used to charge the main battery so that it can be used during on-peak hours, when the price of electricity is higher. After the EV battery and the main battery are both fully charged, if there is still any excess of generated electricity, it is transferred to the grid. In all of these steps, the algorithm checks if the generated renewable electricity is enough to supply the energy usage of the building.

If at any point the amount of onsite generated electricity is not enough to supply the energy demand of the building (especially during on-peak hours), then the system checks to see if there is any available electricity stored in the main battery. If there is, then the stored power in the main battery is used to power the building until it is fully depleted, after which the system checks if there is any electricity in the EV battery. Any stored power available in the EV battery is also used to power the building until the EV battery is also depleted, and if there is still insufficient power to meet the energy demand, then the remaining required electricity is taken from the grid.

b) **The EV is disconnected from the building.** In this case, the main battery and the power grid are considered as the only available energy sources. Like in the previous scenario, the system checks to see whether or not the amount of electricity generated is greater than the energy consumption of the building. If not, then the system checks the main battery to see if there is enough electricity available in the main battery to power the building. If at any point the main battery is depleted, the power grid is used to provide the remaining electricity demand.

If at any time the onsite generated electricity is greater than the energy consumption of the building, the excess of generated electricity stores in the main battery for use during on-peak hours. Once the main battery is fully charged, any remaining surplus energy transfers to the grid.

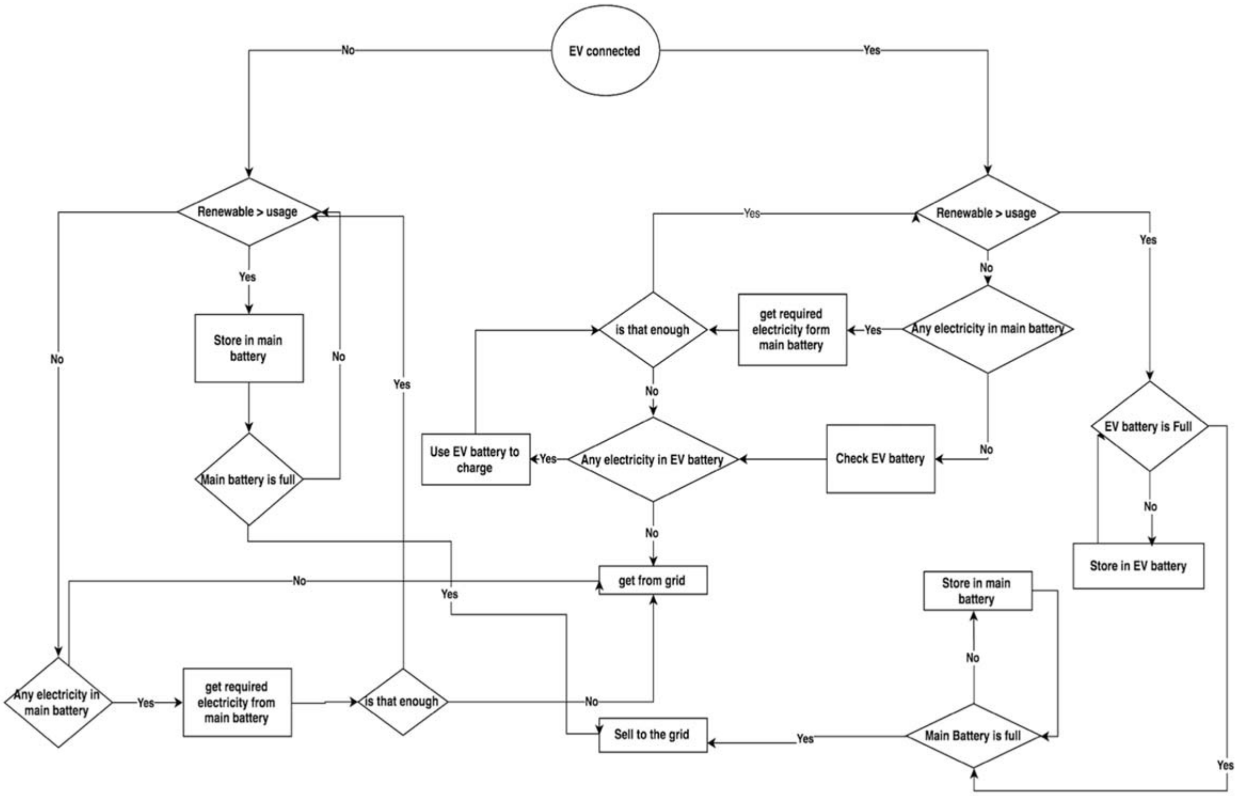

Figure 7.7 Power Distribution System Algorithm

7.4 Time-Based Electricity Pricing

Time-based electricity pricing is a pricing strategy in which power companies charge their customers extra for using electricity during certain time periods of the day ("on-peak hours") and offer credits to their customers who consume electricity during any other time period ("off-peak hours"). Utility companies have introduced this strategy to their customers to save money by reducing peak power demand [279]. For this purpose, a flat rate is applied to electricity consumption regardless of the time of usage, and then (depending on the usage hour and season) an extra charge is added to the total bill for using electricity during on-peak hours, while bonus credits are subtracted from the total bill for using electricity during off-peak hours [280]. Different electricity rates used in this study for different hours of the day are presented in Table 7-5 below for different seasons; in this study, these seasons have been separated into "summer" from April to October and "winter" from November to March.

Table 7-5 Hourly Electricity Pricing

	Summer (April-October)	Winter (November-March)
Flat rate ($/kWh)	0.0757	0.0757
On-peak charge ($/kWh)	0.06124	0.03316
Off-peak credit ($/kWh)	-0.01125	-0.01125

7.5 Results and Discussion

7.5.1 Energy Analysis Results

The results of the energy analysis are summarized in Table 7-6, including the monthly energy consumption of each type of power usage within the building (lighting, heating, cooling, etc.), as well as different sources of energy and/or energy savings, such as heat gain through windows and power generated through solar panels. Different parameters affecting the energy consumption of the building (outside temperature, humidity, building envelope, occupancy, heat gain through interior and exterior windows, etc.) have also been considered in this analysis, while Table 7-7 also summarizes the temperature and dry-bulb temperature for each month of the year. In Table 7-6, zone-sensible cooling and heating are defined as the sensible cooling and heating effect of any air introduced into the conditioned zone through the HVAC system [281]; for example, the heating effect of fans can be considered as a zone-sensible cooling load. Looking at Table 7-6, the results make sense in that, as the temperature increases from January to September (Table 7-7), the cooling load increases and reaches its maximum value in July, after which the temperature begins to decrease as the weather gets colder; although the month of February does not seem to follow this trend, this could be due to unusual weather conditions. The same trend can be seen in reverse for the heating load; as the number of cold days per month increases relative to the corresponding number of hot days, the heating load increases. The amount of electricity generated via the installed solar panels also can be tracked on a monthly basis (Table 7-6). This analysis shows that, as the number of sunny hours per day and/or the number of sunny days per month increase, the solar panels receive more sunlight and can therefore generate more and more electricity. This amount, as seen in Table 7-6, has an increasing trend until the end of July, after which it gradually starts to decrease until a sharp reduction us observed at the beginning of October. These differences in energy consumption trends are easily justifiable based on intuitive deductions from the surrounding environment. On the other hand, other contributors to the energy consumption of the building (room electricity, lighting and equipment components, etc.) have a nearly constant energy consumption rate with minimal variations during different months of the year, regardless of temperature changes or weather conditions.

Table 7-6 Energy Analysis Results

Energy analysis results (kWh)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Room Electricity	196.6	178.0	197.6	190.4	196.6	191.4	196.6	197.1	190.9	196.6	190.9	197.1
Lighting	133.4	117.1	123.2	117.4	115.3	106.9	113.6	117.4	117.5	129.5	125.1	132.2
Heating (Electricity)	28.7	24.5	34.7	1.4	0.0	0.0	0.0	0.0	0.0	1.8	5.2	25.9
Cooling (Electricity)	22.5	13.1	26.3	134.9	303.6	433.1	661.3	510.0	386.2	245.8	36.4	17.3
DHW (Electricity)	89.0	80.4	89.0	86.2	89.0	86.2	89.0	89.0	86.2	89.0	86.2	89.0
Generation (Electricity)	1,280	1,010	1,797	2,302	2,509	2,119	2,336	2,298	2,221	1,441	1,446	1,305
Computer + Equipment	196.6	178.0	197.6	190.4	196.6	191.4	196.6	197.1	190.9	196.6	190.9	197.1
Solar Gains Exterior Windows	811	564	831	1,003	1,046	920	977	972	990	731	868	864
Zone Sensible Heating	57.4	49.0	69.4	2.7	0.0	0.0	0.0	0.0	0.0	3.5	10.4	51.8
Zone Sensible Cooling	51.5	29.5	59.5	312.9	675.1	941.3	1,392	1071	827.8	519.3	81.1	39.4

Table 7-7 Temperature Data for Different Months of the Year

Temperature	Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec
Air temperature (C)	19	21	22	24	25	25	25	25	25	24	23	21
Outside dry-bulb temperature (C)	14	17	18	21	24	26	26	26	26	23	20	16.3

Figure 7.8 is presented below to better understand the results of the energy analysis of the building in question. In this graph, the energy consumption and generation for different months of the year can be observed for a quick visual comparison. The most significant variations occur for cooling load and electricity generation through solar panels during different months of the year, because unlike many areas in the U.S., heating load does not contribute significantly to the energy consumption of the building. As seen in this graph, as the hotter days of the year approach, the cooling load begins to increase significantly, while the opposite trend can be seen in the heating load. Except for the colder days in December, January and February, the heating load then becomes insignificant for the rest of the year. All other components (room electricity, lighting, hot water, etc.) have a relatively steady rate of variation for different months of the year. The negative values in the graph indicate the electricity generated via solar panels, which decreases the overall daily energy consumption.

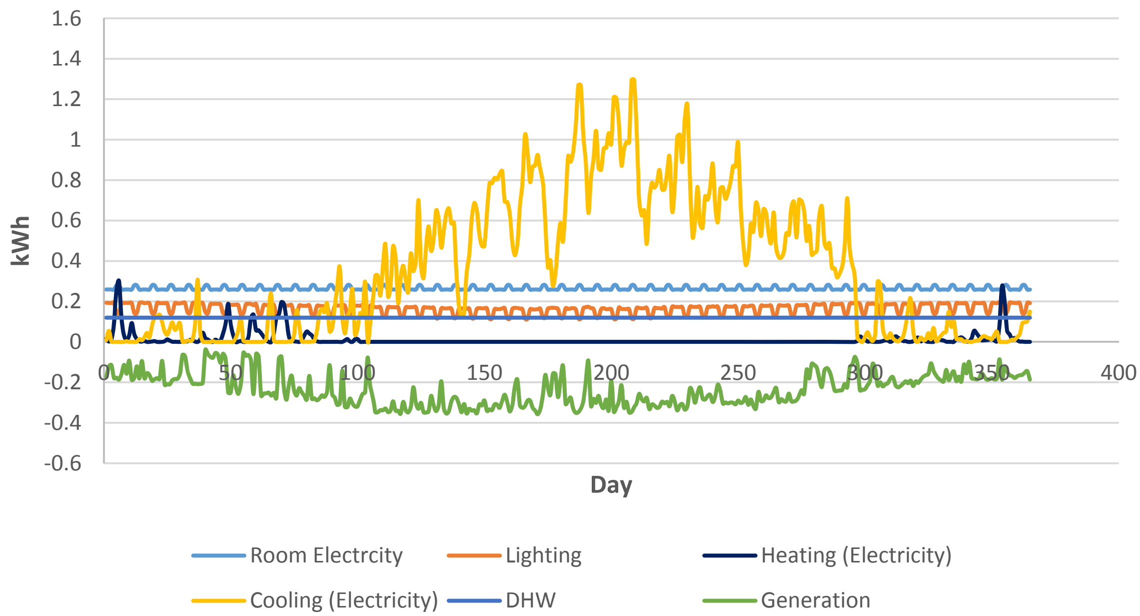

Figure 7.8 Daily Energy Consumption of The Building

7.5.2 Electricity Consumption

The hourly and cumulative rates of purchased electricity from the grid for the studied building are presented in Figures 7.9 and 7.10, respectively, each comparing the purchased electricity of the building with and without the integration of solar panels and the EV battery ("NZEB" and "conventional", respectively).

The purchased electricity drops significantly in the NZEB scenario compared to the conventional scenario, with the average hourly decrease in grid reliance being roughly 61% year-round, while the most visible hourly decrease (93%) was in September. The gap in purchased electricity between the two scenarios is greatest during the summer due to increased solar power generation from longer sunny periods compared to other months of the year. From Figure 7.9, the overall year-round energy savings with the NZEB scenario is 66%.

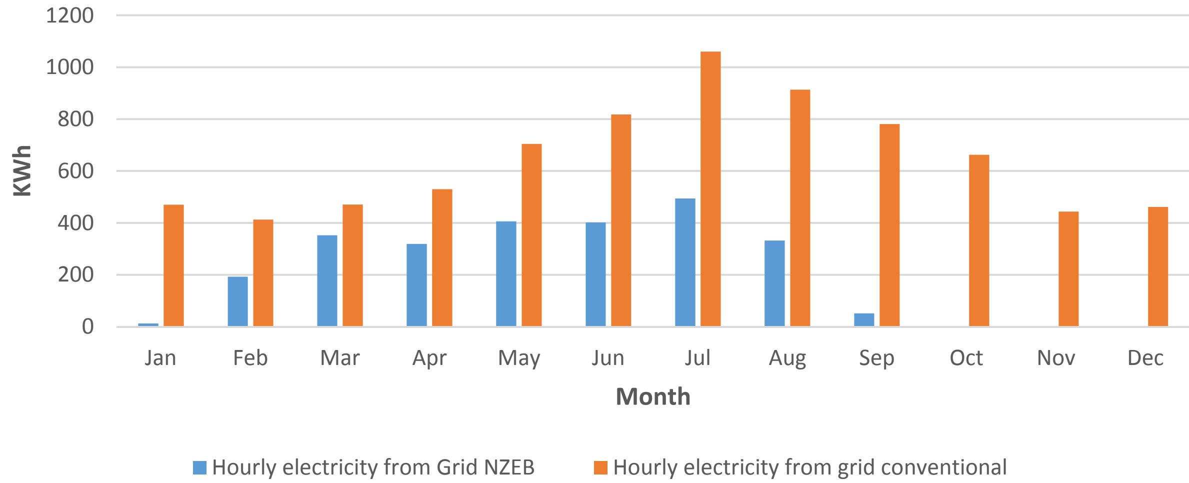

Figure 7.9 Comparison of Hourly Energy Consumption of the Building for Conventional and NZEB Scenarios

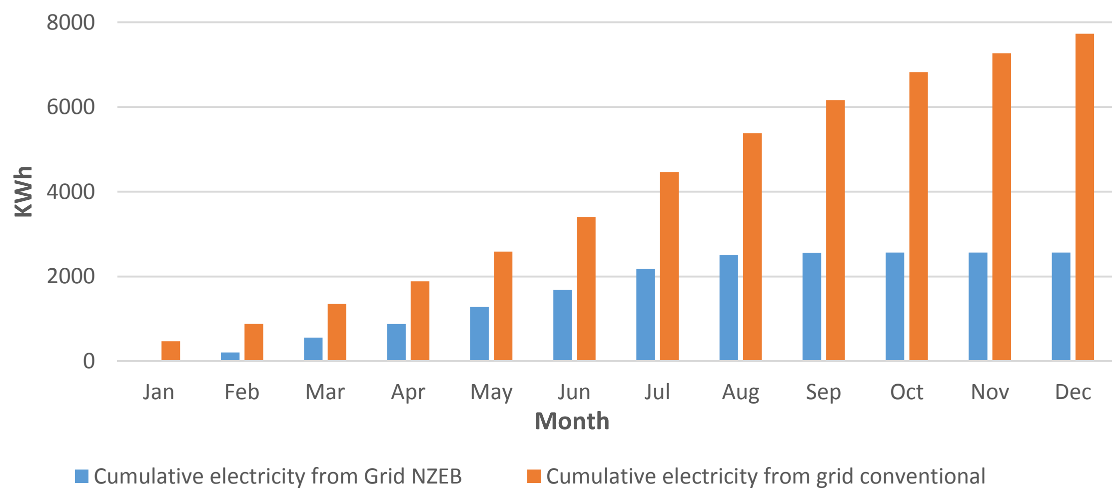

Figure 7.10 Comparison of Cumulative Energy Consumption of the Building for Conventional and NZEB Scenarios

7.5.3 Electricity to Grid

Any remaining excess amount of onsite generated electricity from the solar panels and from the stored electricity provided through the EV battery can be transferred to the power grid. Figure 7.11 presents the amount of electricity that can be transferred to the grid in different months of the year. The amount of electricity transferred to the grid in each month is highly dependent on the electricity consumption of the building, as well as the monthly electricity generation rate from the solar panels, so finding a constant trend in this case is not possible on a yearly basis. However, jumps in the amount of electricity transferred to the grid from month to month can be better understood by looking at the electricity consumption of the building (Figure 7.9) and the amount of solar energy generated. In general, less electricity is transferred to the grid when the monthly energy consumption is higher and/or when the amount of generated solar energy is lower, in which case the main priority of the system is to supply the energy demand of the building first and then transfer any excess amount of generated energy to the grid. For example, the amount of electricity to grid is higher in September than October, November, or December, but looking at Figure 7.9 and comparing electricity consumption rate in September with those in each of the last three months of the year, this may sound confusing. This confusion may be clarified by following the trend of electricity generation and analyzing the solar energy generation in each of the latter months.

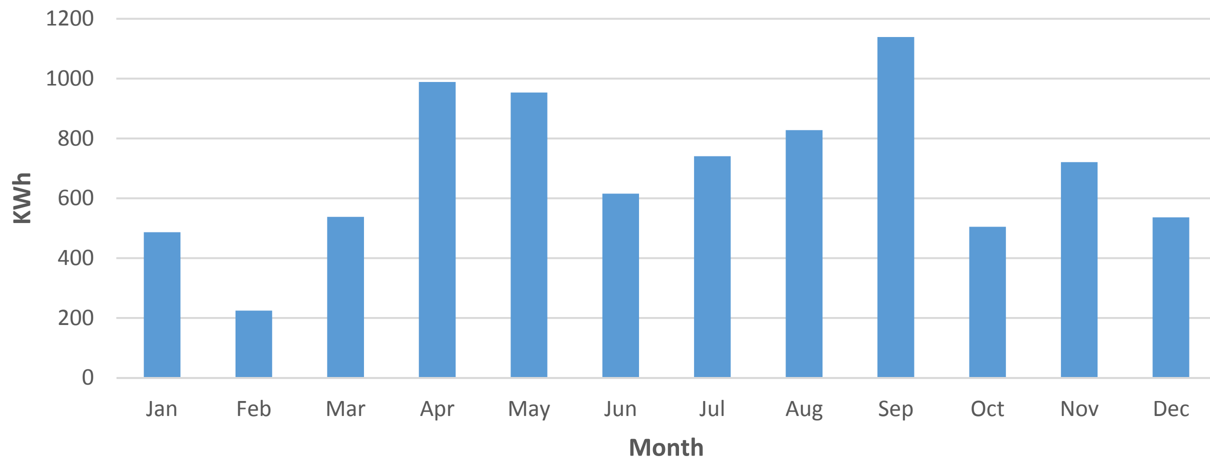

Figure 7.11 Monthly Amount of Electricity Transferred to the Grid

7.5.4 Price Comparison

A very important incentive for a NZEB is the potential economic advantages of such a building, as a true NZEB would effectively reduce its utility bills to zero. In the process, it is also possible to earn money to compensate for the installation costs of solar panels and other technologies required for the NZEB. Calculations regarding the monetary value of energy in this study are divided into two parts. The first part investigates how much in savings may be possible by reducing the energy consumption of the building, assuming that no credit is given to the customer for selling electricity to the grid or for producing renewable energy from solar panels or other energy sources. In the second part, however, a production credit is provided to customers who generate solar energy and then sell the excess amount of onsite generated electricity to utility companies such as the Orlando Utility Commission (OUC) [276].

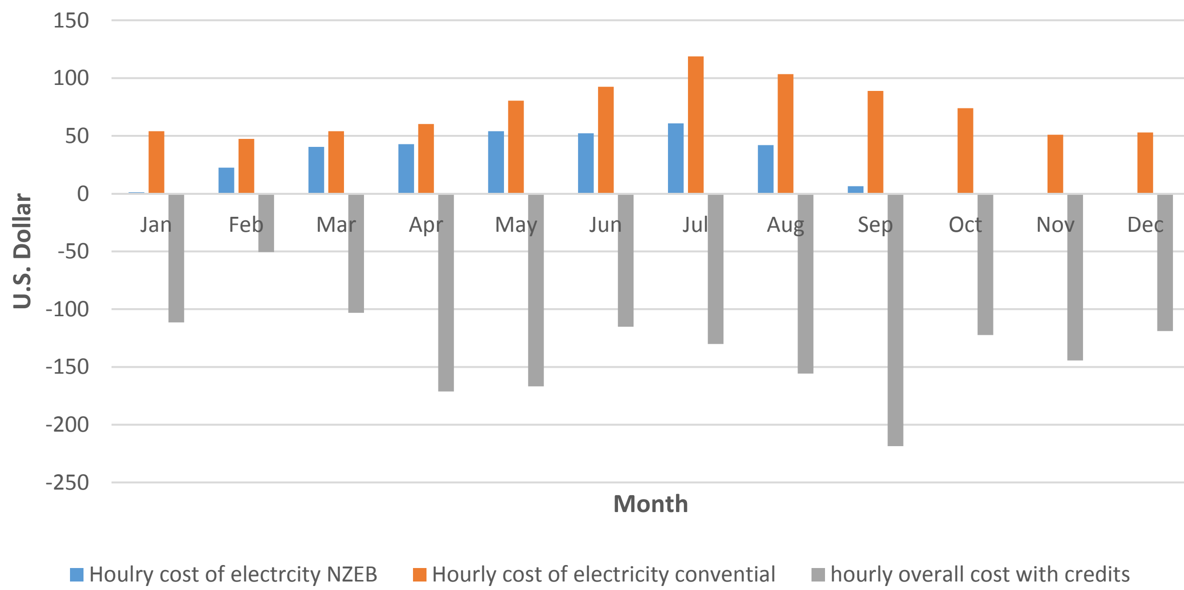

Figure 7.12 Monthly Electricity Bill Price Comparison

The differences in conventional and NZEB electricity costs (with and without credits) are presented in Figure 7.12, where it becomes immediately clear how much can be saved in electricity costs with an NZEB. Many utility companies provide incentives for their customers to encourage the integration of renewable energy sources into their energy portfolios. Considering all of these credits together, the final electricity price for the NZEB in this study with all of the above-mentioned considerations and energy sources taken into account is shown in Figure 7.12. This graph shows that, when the aforementioned credits are taken into consideration, the net electricity price is negative throughout the year, meaning that customers can effectively pay nothing for electricity and can even earn money as a result.

7.5.5 Sensitivity Analysis

We demonstrate the effect of these parameters (more specifically, the main battery capacity and the SOC) on the required electricity from the power grid and on the transferred electricity to the grid, and then compares the results as appropriate. For this purpose, two maximum and minimum ranges and three median values for main battery capacity (10 kWh to 90 kWh) and SOC (0.1 to 0.9) are tested, and the results are presented in Figures 7.13 and 7.14. The values of the aforementioned parameters and the corresponding results are presented in Tables 7-8 and 7-9 for comparison.

Table 7-8 Required Electricity from the Grid for Different Values of SOC

State of Charge	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0.1	95.8	487.4	767.2	693.8	841.3	776.8	851.1	619.8	106.6	160.5	13.9	41.8
0.3	32.5	392.4	622.2	568.8	696.3	651.8	725.9	512.1	81.2	127.6	0.0	6.3
0.5	17.7	325.7	497.2	443.8	551.3	526.8	609.4	422.1	66.2	37.6	0.0	0.0
0.7	12.7	192.7	352.2	318.8	406.3	401.8	494.4	332.1	51.2	2.1	0.0	0.0
0.9	7.7	90.3	203.6	194.8	262.0	278.5	380.0	242.1	36.2	0.0	0.0	0.0

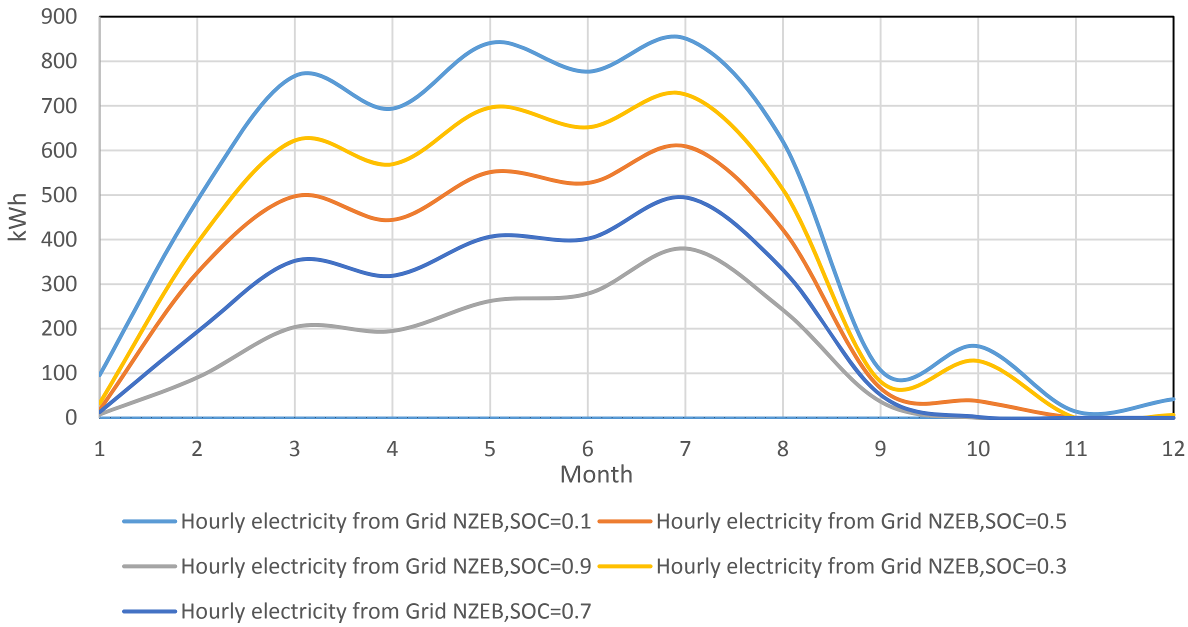

Figure 7.13 Electricity from the Grid for Different Ranges of SOC

Table 7-9 Amount of Electricity Transferred to the Grid for Different Values of Main Battery Capacity

Main battery capacity (kW)	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
10	786.2	574.4	1,303	1,799	1,858	1,415	1,542	1,582	1,620	906.8	962.1	813.1
30	353.4	278.7	771.9	1,233	1,248	845.3	943.2	970.2	1,071	426.7	573.9	387.6
50	331.7	118.7	306.7	733.6	670.2	378.2	507.1	600.2	981.0	366.5	573.9	381.3
70	311.7	66.6	25.0	281.5	165.6	37.5	175.3	338.6	908.0	354.4	573.9	381.3
90	291.7	46.6	5.0	86.5	26.2	3.5	78.1	217.2	866.2	354.4	573.9	381.3

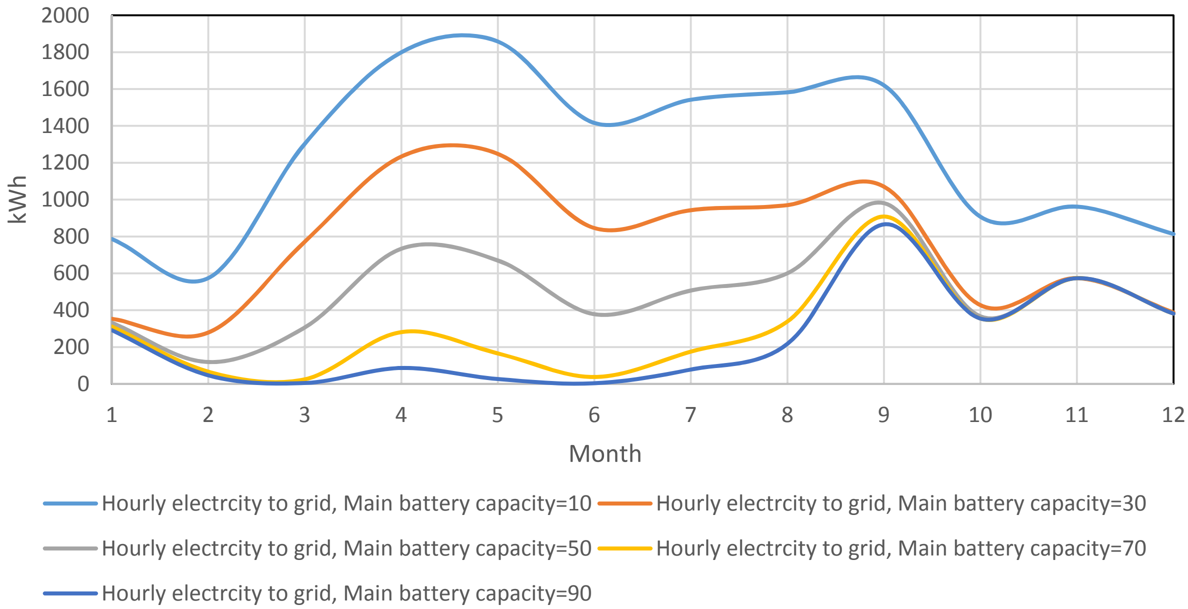

Figure 7.14 Electricity Transferred to the Grid with different ranges of main battery capacity.

The graph above (Figure 7.14) shows that the lowest grid electricity demand is evident whenever the SOC is at its highest value. For instance, in January, the required electricity from grid is reduced by 92% as the SOC increases from 0.1 to 0.9, which shows how significant the effect of state of charge is on demand from the power grid. On a year-round basis, an average reduction of 80% in the required electricity from the grid is observed for the two maximum and minimum assigned values of SOC. This is because, based on the defined algorithm, after supplying the energy demand of the building and before storing any electricity in the main battery, the system stores the surplus onsite generated electricity in the EV battery. Having more electricity available in the EV battery when the vehicle returns home for the day means that less electricity can be stored in the EV battery afterward, meaning that more energy is available to be stored in the main battery and/or used to supply the energy demand of the building. The same rule also applies for the EV battery capacity; as the EV battery capacity increases, more electricity can be stored in the EV battery, and so more electricity is required from the grid to fully charge the EV battery. In other words, decreasing EV battery capacity has the same effect as increasing the state of charge.

The results from Figure 7.14 match the stated expectations as well, in that more capacity to store the surplus onsite generated electricity can justify less transferred electricity to the grid. As seen in Figure 7.14, the highest amount of electricity supplied to the grid is observed when the capacity of the main battery is at its lowest value; hence, as the capacity of the main battery increases, the amount of electricity supplied to the grid decreases. For instance, as seen in Table 7-9 for the month of May, the observed reduction in electricity transferred to the grid is over 98%. On average, a 77% reduction in the amount of electricity transferred to the grid is observed for different months of the year as the main battery capacity increases from 10 kWh to 90 kWh. This is understandable because, based on the algorithm used, fully recharging the main battery is given priority over transferring electricity to the grid.

7.6 Conclusion

This study investigated the role of electric vehicles and renewable energy sources (e.g. solar power) as potential featured in a net-zero-energy building (NZEB). The main parts of the system analyzed included solar panels for generating electricity, a main battery that interacts with these solar panels, an EV, and the main power grid. Using an inverter, the generated solar power was stored in the main battery, while the EV contributed to the overall system by providing electricity during on-peak hours and receiving electricity from the main battery and/or from the grid during off-peak hours. The mechanics of the system as a whole were based on a unique algorithm, which assigned the energy sources to be used in the NZEB during any given hour of the day. The results showed that, with the help of this system, it is possible to reduce the amount of electricity required from the grid by up to 68% on average. The monetary value of reducing this grid reliance was also evaluated, and showed that the resulting electricity bill can be reduced by up to 62% without considering any of the various incentives and credits offered by different utility companies and government organizations; when these credits and incentives are taken into account, the resulting overall savings can increase drastically to as much as 2.83 times on average (Figure 7.12). In fact, throughout the year, the net electricity price when credits are included is shown as a negative value, representing a net profit to customers from selling electricity to the grid. The relevant emission factor indicates that reducing 1 kWh of electricity consumption can reduce CO_2 emissions by 6.89551×10^{-4} metric tons [282], meaning that it is possible for this system to reduce overall GHG emissions by 3.56 metric tons by the end of any given year. From this perspective, the large-scale environmental impacts of reducing reliance on grid electricity can be significant.

In the last phase of this analysis, a sensitivity analysis was performed to investigate the effect of the different modeled parameters (specifically the capacity of the main battery and the EV battery's state-of-charge value) on the overall performance of the system. It is worth noting that this study was an attempt to apply V2H technology and solar power to a possible NZEB scenario; the results of this analysis showed that the net cost of electricity is negative by the end of the year, which can be interpreted as a net revenue for homeowners, but it should also be noted that having an energy-efficient building and installing solar panels can significantly increase the total capital cost. Even though the cost of solar panel installation has reduced noticeably in recent years, such costs should still be included in any complete life cycle cost analysis. Nevertheless, the significant reduction in electricity cost shows that this research can be used as a starting point for future efforts to design a NZEB. In the continuation of this study, efforts will be made to modify this algorithm and the applicable ranges for different variables to more adequately reflect regional differences, as each region of the U.S. has its own driving behaviors and weather patterns that can affect the energy consumption of a particular building. This study also attempted to discuss and present the potential feasibility of this system by developing an algorithm that can connect the different components of the system (the EV battery, the main battery, the power grid, and the building itself), although investigating the life cycle cost of the building and the related technical aspects were both beyond the scope of this study.

In future research, different pricing ranges will be also tested using an Agent Based Modeling (ABM) approach where, by applying different pricing scenarios, the life cycle cost of the system and the payback period will be simulated in a real-time analysis. Moreover, more focus will be given to a life cycle cost comparison between a standard code-compliant building and a NZEB by considering the payback period of increased costs incurred from making the system more energy-efficient and from the integration of photovoltaic solar panels into the building's energy portfolio.

8.0 Socio-economic analysis of alternative fuel-powered Class 8 heavy-duty trucks

8.1 Introduction

8.1.1 Overview

Diesel-powered HDT technology has been the dominant fuel of choice for HDTs for decades, and HDTs on U.S. highways have likewise been highly dependent on fossil fuels [283]; a recent study by the American Transportation Research Institute (ATRI) showed that more than 92% of trucks currently run on fossil fuels [284][6]. Furthermore, despite accounting for only approximately 1% of on-road vehicles in 2013 [285] and a relatively tiny share of the total national Vehicle Miles Travelled (VMT) at slightly over 5% in 2013 [286], Class 8 HDTs consumed almost 29 billion gallons of fuel (17% of the total fuel consumption by highway vehicles) in 2013 [285]. Additionally, including distributed energy-related emissions, HDTs were responsible for almost the one-fourth of the U.S. transportation sector GHGs emissions in 2013 [287].

On one hand, the total global market share of hybrid-electric, plug-in-hybrid-electric, and battery-electric (BE) trucks were predicted to be 10 times larger by 2020 compared to 2013 [288]. Furthermore, the U.S. Environmental Protection Agency (U.S. EPA) projected that 3% of U.S. HDTs would be electrified by 2025 [289]. On the other hand, the U.S. Energy Information Administration (EIA)'s (2014) forecasts estimate that the growth in the U.S. economy between 2013 and 2040 will cause an increase in diesel consumption with an annual average rate of 0.8% until 2040, with trucking responsible for a large share of this increase. Hence, emissions from HDTs are expected to substantially increase by 2040.

This outlook with respect to the U.S. Class 8 HDTs raises significant concerns regarding the environmental and social impacts of such trucks [291]. Therefore, HDTs must be considered more thoroughly, taking into account the current status and future predictions related to the U.S. HDTs [292]. Furthermore, alternative fuel technology must be given special consideration for HDTs, and significant amount of upstream, downstream, and tailpipe emissions as well as high life-cycle costs (LCCs), including externalities.

8.1.2 Objective of the Study

Given the slow pace of alternative fuel technology adoption by HDTs in the U.S., as well as the relative infancy of some alternative fuel technologies such as BE HDTs, there has not been a sufficiently thorough comparison of conventional and alternative fuel-

[6] The contents of this section were partly published in Sen, B., Ercan, T., and Tatari, O. (2017). "Does a battery-electric truck make a difference? – Life cycle emissions, costs, and externality analysis of alternative fuel-powered Class 8 heavy-duty trucks in the United States." *Journal of Cleaner Production, Elsevier,* 141, 110-121, 2015 IF: 4.959. DOI: 10.1016/j.jclepro.2016.09.046

powered HDTs in the U.S. with respect to their life-cycle emissions, costs, and externalities.

This study attempts to fill this research gap by looking at alternative fuel-powered Class 8 HDTs from a life-cycle perspective in order to support all of the efforts put into increasing sustainability of new HDT technologies. The alternative fuel types considered in this analysis are hybrid, CNG, biodiesel (B20 – powered by 20% biodiesel and 80% conventional diesel), and BE. Additionally, this study separates hybrid and BE trucks more specifically into mild hybrid and full hybrid trucks, and 270 kWh motors- and 400 kWh motors-sizes, respectively. Therefore, these trucks are analyzed and compared separately. The alternative-fuel HDTs are all compared to conventional HDTs with respect to their life-cycle GHGs, costs, air pollutants emissions, and air pollution externalities (APE). The emissions considered in this study are CO_2, CO, NO_X, PM_{10}, $PM_{2.5}$, SO_2, and VOC emissions. Furthermore, the objectives of this study specifically include making a regional analysis of the environmental impacts of BE HDTs operated in each of the U.S. NERC regions as defined by North American Electric Reliability Corporation (NERC). The life-cycle analysis carried out in this study includes the manufacturing and use phases. Additionally, this study analyzes the APE costs, and compares these costs with respect to each HDT. This study makes a significant additional contribution to the literature especially in two important ways; firstly, by comprehensively analyzing BE trucks based on regional electricity generation and price forecasts, and secondly, by incorporating the APE costs of these trucks' lifecycle and tailpipe emissions into the analysis.

8.2 Methods and Materials

8.2.1 Hybrid Life-Cycle Assessment

LCA is a well-known, well-established tool [293] to analyze the direct and indirect upstream and downstream environmental, social, and economic impacts of processes and products that previously could not be accounted for, using complementary impact assessment methods. Process-LCA coined by Haes et al. (2004) and EIO-LCA have recently become more widely used in academia and industrial practice [83,295]. For the analysis of this study, both EIO-LCA and process-LCA are hybridized to account for both the upstream and the downstream environmental impacts of HDTs.

Almost all of the upstream environmental impacts are obtained using the Carnegie Mellon University Green Design Institute's publicly available online EIO-LCA tool [296]. The EIO-LCA tool uses EIO tables based on transactions in 2002 (Noori et al., 2015). Downstream environmental impacts are obtained using the EIO model and a variety of process-based models and databases, such as the *Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET)*, *Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET)*, and the U.S. EPA's *Motor Vehicle Emissions Simulator (MOVES)*. The EIO-LCA tool uses a linear model based on the EIO matrix developed by Leontief (1970). The monetary value of the product in question, in 2002 dollars, is used as input into the model embedded in the tool. The matrix used in this model consists of economic transactions between 428 sectors of the

U.S. economy. The North American Industry Classification System (NAICS) is used to categorize the data used in the model [298]. Hence, the input values needed to calculate the upstream life-cycle environmental impacts are the purchase prices of each HDT and, if any, those of their additional parts. As for the downstream emissions from fuel consumption during the use phase, the AFLEET and GREET models are used, both of which were developed by the Argonne National Laboratory.

Since its introduction in the literature, the LCA tool has been widely used by many scientific fields, although the hybrid LCA has not yet been used as widely. Egilmez et al. (2013) and Egilmez et al. (2016) used the EIO-LCA method in order to assess the sustainability of 53 U.S. manufacturing sectors and 33 U.S. food manufacturing sectors, respectively. Using the EIO-LCA method, Kucukvar et al. (2014a) carried out an analysis with regard to the sustainability of U.S. consumption and investment activities. Similarly, Kucukvar et al. (2014) and Kucukvar et al. (2014b) incorporated the EIO-LCA method into their studies to assess the sustainability of different asphalt pavement systems. Onat et al. (2014b) identified sustainability hotspots of U.S. residential and commercial buildings throughout their lifecycle, using hybrid-LCA. Furthermore, Onat et al. (2014b) also analyzed carbon footprint of U.S. buildings, using the same method. Facanha and Horvath (2006) applied a hybrid LCA method to analyze air pollutant emissions from freight transportation in the U.S. Jiang et al. (2014) likewise conducted an EIO-based hybrid LCA study for the manufacturing of a diesel engine. Ercan and Tatari (2015) analyzed the life-cycle emissions, LCCs, and total water withdrawal rates for alternative fuel-powered transit buses in the U.S., while Zhao and Tatari (2015) performed a hybrid LCA of the vehicle-to-grid applications for LDVs.

8.2.2 Monte Carlo Analysis

HDTs have a wide range of configurations, and thus a wide variety of possible Life-Cycle Inventory (LCI) components. Furthermore, the currently limited degree of deployment for alternative-fuel HDTs means that the number of available data points for such HDTs is limited. A probabilistic method should be integrated with the LCA methods in order to accommodate this uncertainty and the applicable value ranges. One such probabilistic method is the Monte Carlo method, which simulates point values with variable distributions, allowing the LCA analysis results to be presented within a range instead of being limited to only using average values [212,304,305]. The Monte Carlo simulation method is widely utilized in many scientific areas, and numerous examples of combining LCA with Monte Carlo uncertainty analyses are available from the literature [306–308]. Within the considered ranges, inputs are regenerated for one thousand iterations and linked with their corresponding hybrid-LCA components.

8.2.3 Life-Cycle Inventory

In the inventory analysis phase of a typical LCA, inputs to and outputs from a product system are quantified to assess the impacts in the next step. Process-LCA requires process-specific data inputs, while EIO-LCA requires the monetary values of products as inputs. The vehicle characteristics for the HDT considered in this study are presented in Table 8-1. Based on the goal and scope of the study, the life-cycle assessment phases for this study are divided into two primary parts, as shown in Figure 8.1.

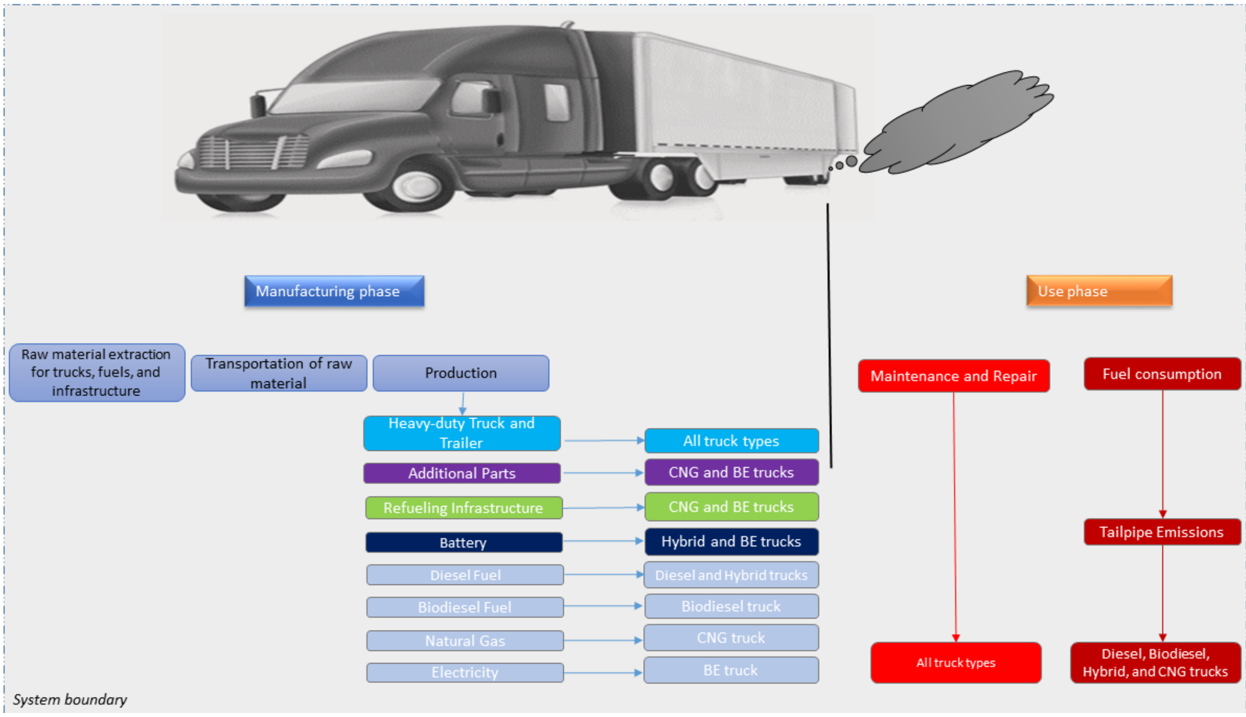

Figure 8.1 System boundary for hybrid-life cycle assessment

The baseline truck considered in the study is made of the essential components for a truck, including the truck's body, shell, engine, other required miscellaneous parts, and a trailer. The purchase price for such a truck, given in Table 3, is converted to 2002 US dollars using the U.S. Bureau of Labor Statistics' CPI Inflation Calculator, and used as an input to run the EIO model and obtain the environmental impact results from the relevant NAICS economic sector. The hybrid, CNG, and BE trucks each require additional parts during the manufacturing phases, and these additional parts come with additional costs to the baseline truck manufacturing.

Table 8-1 Vehicle characteristics and battery specifications

Characteristics	**Value**	**Source**
Lifetime	6.6 – 10 years	[309,310]
Average annual mileage	109,226 – 170,000 miles	[310,311]
Physical features	Class 8 heavy-duty trucks with 53' truck-trailer; >33,001 lbs.	[312]
Battery specifications (BE)	270kWh, 400kWh, 150Wh/kg, Li-ion batteries	[313]
Battery specifications (Hybrid)	5 kWh, 25 kWh, 150Wh/kg, Li-ion batteries	[314]

According to the California Air Resources Board (2015), BE trucks additionally require power electronics, an electric motor, and battery system. Likewise, CNG trucks require the installation of a metal tank and a heavy gauge [315]. For battery system manufacturing, the GREET tool's Vehicle-Cycle Model is used to calculate the environmental impacts of battery manufacturing based on the battery specifications.

CNG and BE trucks also necessitate refueling/recharging stations. The U.S. Department of Energy estimates the cost of a natural gas refueling station (NGRS) with the daily supply capacity of 1,500-2,000 gasoline-gallon-equivalents of fuel to range between $911,901.87 and $1,367,852.80 (both in 2002 dollars) [316]. As in Ercan and Tatari's (2015) study, it is assumed that 45.75%, 39%, and 15.25% of the total cost of a unit of NGRS consists of investment, labor, and installation costs for miscellaneous electrical equipment installed in the NGRS, respectively. The relevant NAICS sectors for the environmental impacts of the CNG refueling infrastructure are given in Table 8-2. Based on De Filippo et al.'s (2014) study as well as a report by the NREL (2012), charging stations used for HDTs are assumed to adopt conductive charging technique. Therefore, like in Ercan and Tatari's (2015) study, and also based on additional cost information from Proterra, this study assumes that BE HDTs are charged using Level 3 charging stations, each with a charging capacity of 250 kW. Also, it is assumed based on Kempton et al. (2001) that each charging station has an efficiency of 90%. It is assumed that the existing diesel infrastructure is suitable to refuel hybrid and B20 trucks.

In this study, the load-specific fuel economy (LSFE) is taken into account, thereby assuming that a truck's fuel economy decreases by 1% for each 1,000-lb increase in payload [314]. The truck fuel economy values are assumed to be for trucks with empty trailers, and that the maximum payload capacity of truck-trailers is 54,000 lbs. [314]. Based on these assumptions, the fuel economies of each truck type relative to their payload is first calculated in decreasing order, and the resultant fuel economies are normally distributed for each truck type. The load-specific fuel consumption of each type of truck is then randomized based on the relevant statistical parameters (mean, standard deviation, etc.). To calculate the environmental impacts of biodiesel production, the emissions produced by per gallon of B20 are taken from the GREET tool's process-LCA model.

Changing diesel prices are also reflected in this analysis, as are the various environmental impacts of regional electricity production and electricity prices. Based on a study by the EIA (2015), it is assumed that diesel prices follow a steady 30% increase from 2015 to 2025. Additionally, the MOVES analysis results for HDTs indicate that tailpipe emissions deteriorate over the HDT lifetime for each emission type. These deterioration factors are thus considered in the analysis, and the values of these factors for the overall impacts and costs of tailpipe emissions are taken from the AFLEET database.

As for battery manufacturing and replacement**,** it is assumed that the lithium-ion batteries are used in BE and hybrid HDTs, based on Transportation Research Board

(2010). This study used the same approach as Zhao et al. (2013), and assumed that the battery of a hybrid truck lasts for 3 years. Therefore, a hybrid truck replaces its battery 2 or 3 times during its entire lifespan, depending on its average lifetime, which is randomized between 6.6 and 10 years. It is also assumed, based on a study by Ozdemir (2012), that BE truck batteries are replaced approximately every 4 years. The GREET tool's Vehicle-Cycle Model is used to obtain the emissions from battery replacement. The future projections of battery price declines are reflected, applying a 2% annual inflation rate to this initial battery price, based on data from the EIA (2015). With regard to the maintenance and repair of trucks, it is possible to assume based on the NREL (2012), that hybrid and BE trucks have lower M&R costs than conventional trucks, because conventional trucks have more fluids to change and far more moving parts. Based on M&R cost and relevant NAICS Sector data for each of the studied truck types, given in Table 8-1, the environmental impacts of M&R activities are calculated, using the applicable M&R LCCs as inputs in the EIO-LCA tool. The details of the specific data for each of the aforementioned tools as applicable to each relevant part are given in Table 8-2.

Table 8-2 Inputs for hybrid life-cycle assessment

Vehicle technology	LCA component		Cost (2015$)	EIO-LCA tool NAICS sector	Process-LCA data	Source
Common for all types of trucks	Truck manufacturing		$107,362	#336120	n.a.	[313] [322]
	Trailer manufacturing		$32,500	#336212	n.a.	
Diesel	Diesel fuel production		$1,030,445	#324110	n.a.	[323]
	Maintenance		$224,873	#81111	n.a.	[315]
Biodiesel (B20)	Biodiesel fuel production		$867,976	#324110	GREET's biodiesel production	[315,323]
	Maintenance		$223,020	#81111	n.a.	[315]
CNG	Natural gas manufacturing		$855,785	#325120	n.a.	
	Metal tank, Heavy gauge manufacturing		$60,495	#332420	n.a.	[315]
	Infrastructure		$58,278	#332420, #237100, #335999	n.a.	[316]
	Maintenance		$224,873	#81111	n.a.	[315]
Hybrid	Diesel fuel production	Mild	$757,262	#324110	n.a.	[323]
		Full	$803,928			
	Battery system manufacturing	Mild	$3,000	n.a.	GREET's Battery Model based on specifications on Table 1.	[314,315]
		Full	$15,000			
	Battery replacement	Mild	$4,960	n.a.		
		Full	$24,802			
	Maintenance		$211,314	#81111	n.a.	[315]
BE	Power generation		$380,211	#221110	n.a.	[313]
	Battery system manufacturing	270kWh	$162,000	n.a.	GREET's Battery Model based on Table 1.	[313,315]
		400kWh	$240,000			
	Battery replacement	270kWh	$160,885	n.a.	GREET's Battery Model based on Table 1.	[313,315]
		400kWh	$238,350			
	Motor		$9,290	#335212	n.a.	[313]
	Power electronics		$12, 388			
	Maintenance		$202,715	#81111	n.a.	[315]

8.2.3.1 Regional Electricity Generation and Prices

A regional approach is used to evaluate electricity generation-related environmental impacts of BE trucks. More specifically, this study uses the North American Electric Reliability Corporation (NERC) regions for further analysis, as listed below:

1. Texas Regional Entity – TRE
2. Florida Reliability Coordinating Council – FRCC
3. Midwest Reliability Organization – MRO
4. Northeast Power Coordinating Council – NPCC
5. Reliability First Corporation – RFC
6. SERC Reliability Corporation – SERC
7. Southwest Power Pool – SPP
8. Western Electricity Coordinating Council - WECC

Similarly, the regional variations in electricity generation and prices are also considered in the fuel-LCCs of BE trucks. based on data from the EVRO tool (Noori, 2015; Noori et al., 2015a). To account for electricity price projections, the commercial electricity rate is assumed to be equal to the levelized cost of electricity. More detailed information on regional electricity prices and on the environmental impacts of power generation can be found in Ercan et al.'s (2016) study.

8.2.3.2 APE Costs

A few studies have included the externalities from vehicles' emissions during operation [66,193,325]. In general, the operation and maintenance costs calculations for trucks typically do not include these externalities [326]. With this in mind, the externality costs considered in this study are estimated based on the APEEP model by Muller and Mendelsohn (2007b) and Michalek et al. (2011)'s model of the adoption of electric vehicles.

APE costs of electricity generation are accounted for to cover the total externality costs of BE trucks. The energy consumption of a CNG truck was calculated to be 0.028 GJ/mile, and the total APE costs of natural gas are obtained based on this value. Regarding the externality costs of fuel consumption for conventional, hybrid, and B20 trucks, the APE costs provided for diesel production (in $/ton) are used. APE costs related to manufacturing (including batteries) and maintenance are considered within the same category, and are likewise applied to each truck type on a dollar-per-ton basis. Finally, the APE costs of tailpipe emissions are obtained for each type of truck on a dollar-per-ton basis, except for BE trucks.

8.3 Results

8.3.1 Life-Cycle Cost (LCC) Analysis Results

The use phase is the main driver of the LCCs of HDTs. As shown in Figure 8.2, BE and mild-hybrid trucks have the best overall performances out of all of the considered truck types in terms of their LCC impacts. The dominant contributor to the LCCs of all types of HDTs is the cost of fuel consumption followed by their M&R costs, except for BE HDTs.

Although there is a slight difference between the LCCs of conventional and CNG trucks, there is a noticeable difference between the fuel-LCCs of these two truck types. The fuel-consumption cost of a B20 truck is slightly higher than that of a CNG truck; however, a B20 truck performs better overall in terms of economic impacts.

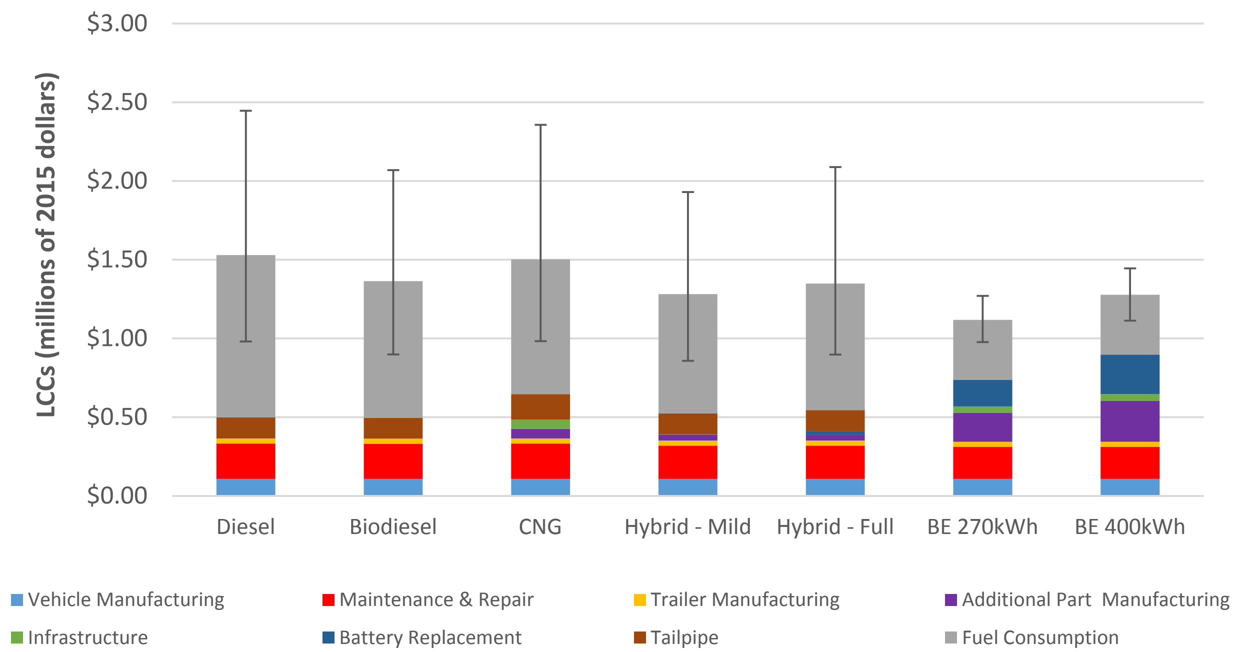

Figure 8.2 Life cycle costs of heavy-duty trucks

Unlike Lajunen's (2014) study, which found hybrid buses to be performing almost the same as diesel city bus with respect to LCCs, the results indicate that hybrid trucks may have moderately less LCCs than conventional trucks, and favor the hybrid configuration for trucks. Individual fuel-LCCs and battery replacement costs were the two primary differences in the respective LCCs of both hybrid truck types. The fuel economy of mild-hybrid trucks is considered to be better than that of full-hybrid trucks, resulting in lower fuel-LCCs for mild-hybrid trucks. For BE HDTs, additional part manufacturing was found to be the second largest driver of the LCCs of BE HDTs. The greatest portion of these incremental costs of BE HDTs stems from battery system manufacturing.

An important portion of the LCCs of trucks comes from M&R activities, with conventional trucks being costlier, as expected. Overall, the M&R LCCs of BE trucks are the lowest out of all truck types, which is consistent with the findings from the NREL (2012), which clearly highlights the lower maintenance requirements of battery-electric vehicles due to fewer fluids to change and fewer moving parts in such vehicles.

8.3.2 Environmental Emissions Results

Fuel consumption and tailpipe emissions are the predominant contributors to total life-cycle GHGs emissions, to the point where all other factors are practically negligible.

Overall, CNG trucks produced the largest amount of lifetime GHGs emissions compared to other trucks, with BE trucks emitting the least amount of GHGs emissions at 53% less than the GHGs emissions of CNG trucks. Like in the LCCs results, fuel consumption played a major role in the total amount of GHGs emissions from each truck type. In terms of GHGs emissions from fuel consumption, mild-hybrid trucks were found to outperform full-hybrid trucks and CNG-powered trucks by more than 6 percent and 121 percent, respectively, due to their better fuel economy.

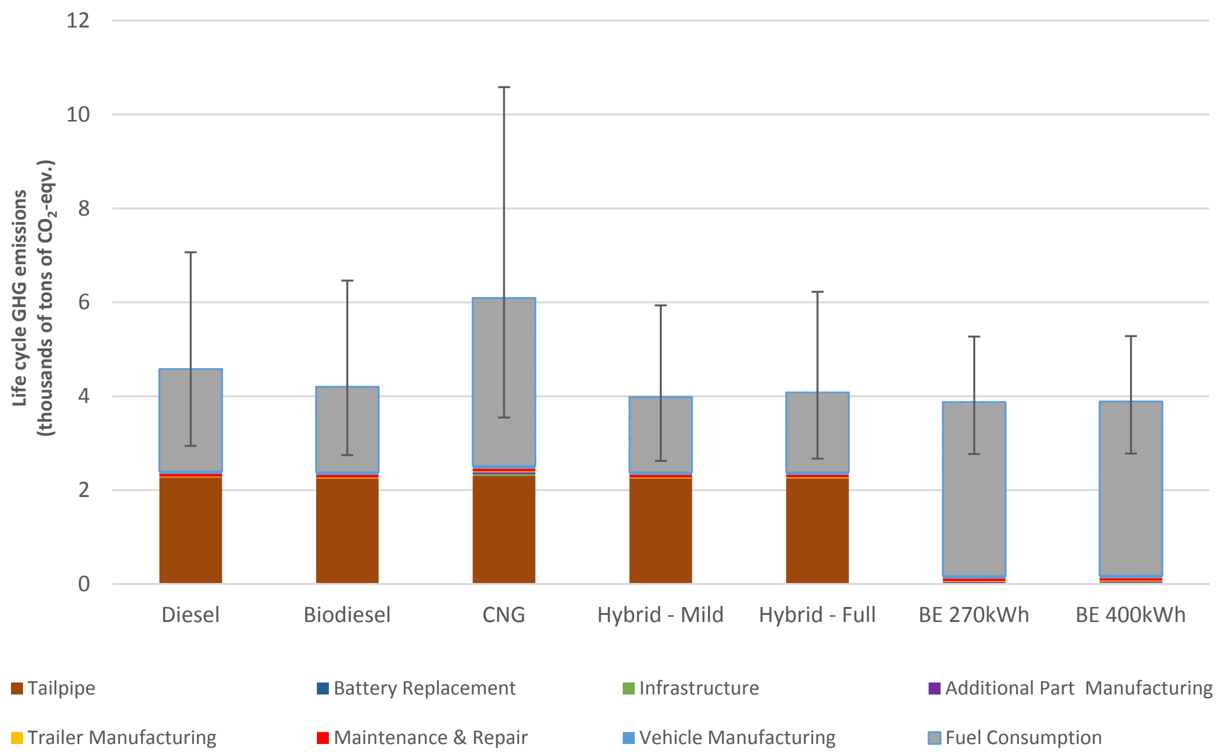

Figure 8.3 Life-cycle greenhouse gas emissions of heavy-duty trucks

Unlike Sharma et al.'s (2013) study, in which BE passenger vehicles were found to have higher life-cycle CO_2 emissions than diesel-fueled passenger vehicles, the results of this study found that BE trucks performed better (albeit slightly) than conventional trucks in terms of life-cycle GHGs emissions. An immense amount of GHGs emissions from electricity generation negated the zero-tailpipe emission advantage of BE HDTs. In fact, the amount of GHGs emissions from electricity generation from BE trucks are 70 percent and almost 5 percent greater, compared to the two largest GHGs emitters out of the considered truck types (conventional and CNG trucks), respectively.

Similarly, conventional and CNG trucks yielded the greatest amounts of air pollutant emissions compared to other trucks, as shown in Figure 8.4. Air pollutants emissions from CNG trucks are twice as much as those from conventional trucks. This is consistent with the findings in Tong et al.'s (2015) study, which also found that CNG trucks did not yield any emission improvements compared to diesel trucks. The main driver of this significant difference is CO emissions, which accounts for 68% of the tailpipe emissions from CNG trucks. NO_x and SO_x emissions are also significant contributors to total air pollutants emissions, largely due to fuel consumption and tailpipe emissions. Natural gas manufacturing is the biggest contributor to SO_x emissions, followed by electricity generation and diesel manufacturing. Mild-hybrid trucks had the lowest SO_x emissions at nearly 90 percent less than those of CNG trucks.

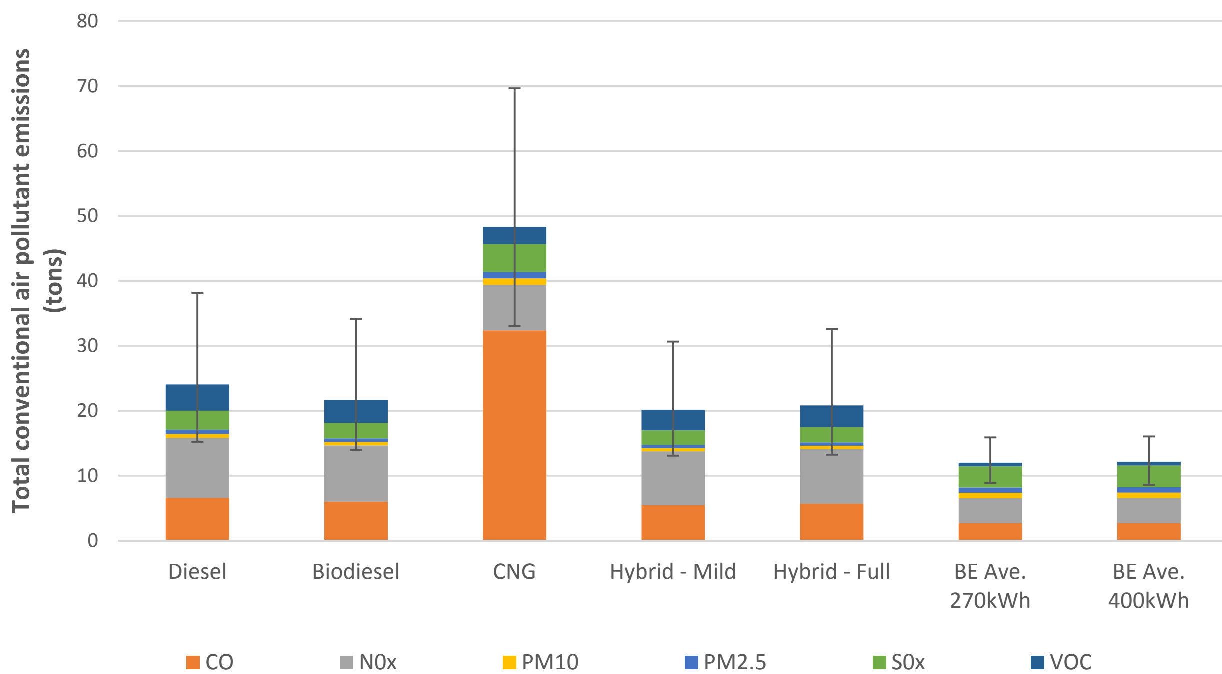

Figure 8.4 Life-cycle air pollutants emissions of heavy-duty trucks

From a life-cycle perspective, biodiesel-fueled trucks cause almost as much PM, CO, VOC, and NOx emissions as do diesel-fueled trucks. The main reason behind the difference between these emissions produced by biodiesel trucks and diesel trucks is that the emissions from maintenance and repair, fuel consumption, and tailpipe of biodiesel trucks are slightly less than diesel trucks. The emission factors for Heavy Duty Vehicle Manufacturing, Trailer Manufacturing, and Tailpipe Emissions are the same for both types of trucks.

8.3.3 APE Cost Results

Compared to the baseline truck, all of the alternative fuel-powered truck types, except CNG trucks, performed better with respect to APE LCCs. As expected, fuel consumption and tailpipe emissions are the two main contributors to APE LCCs, respectively yielding the largest and second-largest APE damages out of all of the analyzed modules. According to the results presented in Figure 8.5, the life-cycle externalities for each HDT type (except for BE trucks) ranged between \$280,000 and \$340,000 (in 2015 dollars), with GHGs and SO_x emissions as the main drivers of APE LCCs for such trucks.

Contrary to Michalek et al. (2011) results regarding BE vehicles' APE costs, the results of this study show that BE trucks significantly outperformed all other truck types in spite of the U.S. electricity generation sector's high dependency on fossil fuels. This is mainly because of that BE trucks have no tailpipe emissions, thereby eliminating one of the two main drivers of APE costs. This result is consistent with Feng and Figliozzi's (2013) study in that BE trucks are found to be more competitive when indirect costs are taken into account. On the other hand, CNG trucks are found to have the highest overall APE costs, with BE trucks' APE LCCs at 85% less than those of CNG trucks.

The life-cycle fuel consumption related APE costs of alternative-fuel trucks ranged between $140,000 and $160,000 (in 2015 dollars). Hybridization and electrification of trucks lowered the APE LCCs by 36% and 20% compared to conventional trucks, respectively. This is fact due on a large extent to several factors, including a projected increase in diesel prices over the lifetime of a truck, hybrid trucks' (especially mild-hybrid) relatively improved fuel economy, and a predicted decrease in electricity prices. Conventional, B20, and hybrid trucks all produced nearly the same amount of APE costs from tailpipe emissions, mainly because these trucks still run largely on diesel fuel, and because the tailpipe emission values collected from AFLEET and the tailpipe-related APE cost values collected from APEEP for these trucks are identical. In terms of damages from tailpipe emissions, CNG trucks incurred 22% higher APE costs than conventional trucks, largely because of the additional APE costs from tailpipe CO emissions from CNG trucks, as well as the higher SO_x emissions from natural gas manufacturing.

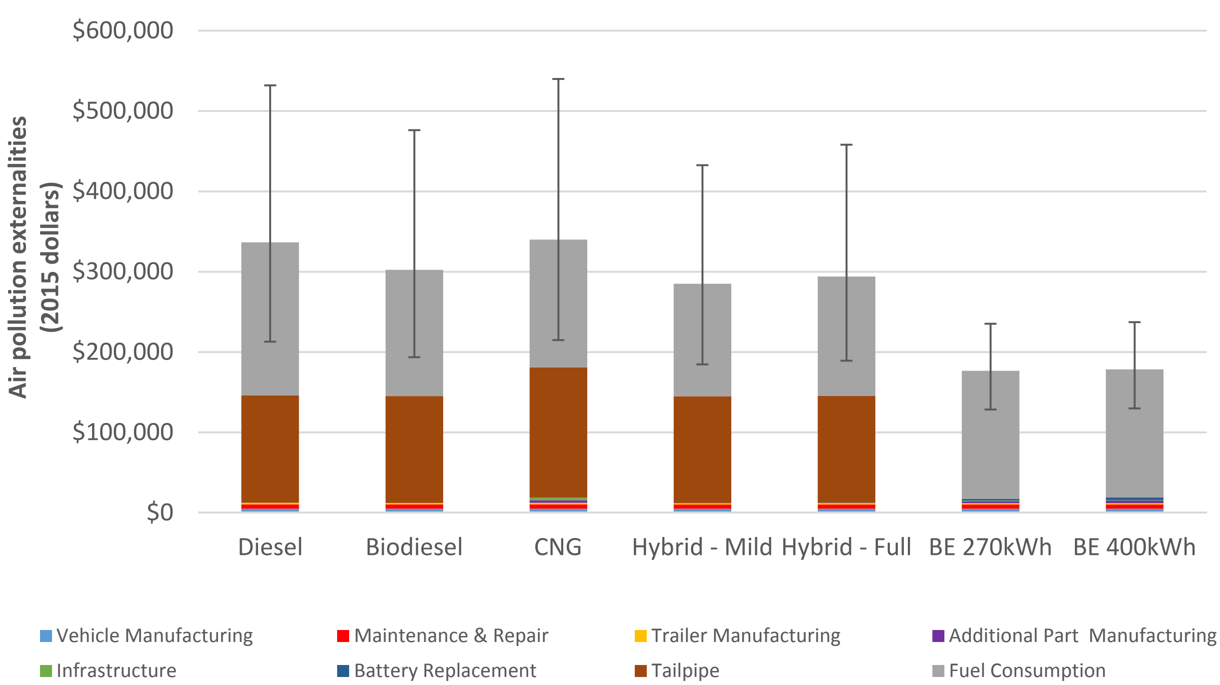

Figure 8.5 Life-cycle air pollution externalities

8.3.4 Cost and GHG Emissions Results for Regional Electricity Consumption

The regional analysis for BE HDTs is based only on the electricity consumption of such vehicles, which varies significantly among regions. Special emphasis is placed on electricity generation, and thus fuel consumption, taking into account the regional differences in life-cycle emissions and costs. Although BE trucks generally produced lower amounts of GHGs emissions than all other truck types, electricity generation alone was still responsible for a considerable amount of GHGs emissions. The results for BE trucks are based on a national average of the regional electricity grid mixes calculated based on NERC regions, but it must not be forgotten that different regions made varying contributions to this average. With respect to regional GHGs emissions from fuel consumption, the NPCC region produced substantially less emissions than other regions. The NPCC region's emissions from electricity generation were found to be 106% less than those of the SPP region. This difference is so significant that, if BE trucks nationwide are to be charged using the electricity grid mix of NPCC region, the fuel-consumption-related GHGs emissions of these trucks would decrease by over 70%, and overall GHGs emissions would decrease by over 63%. As previously noted in Ercan and Tatari's (2015) study, this is due in large part to the relatively small share of coal use in the electricity grid mix of the NPCC region.

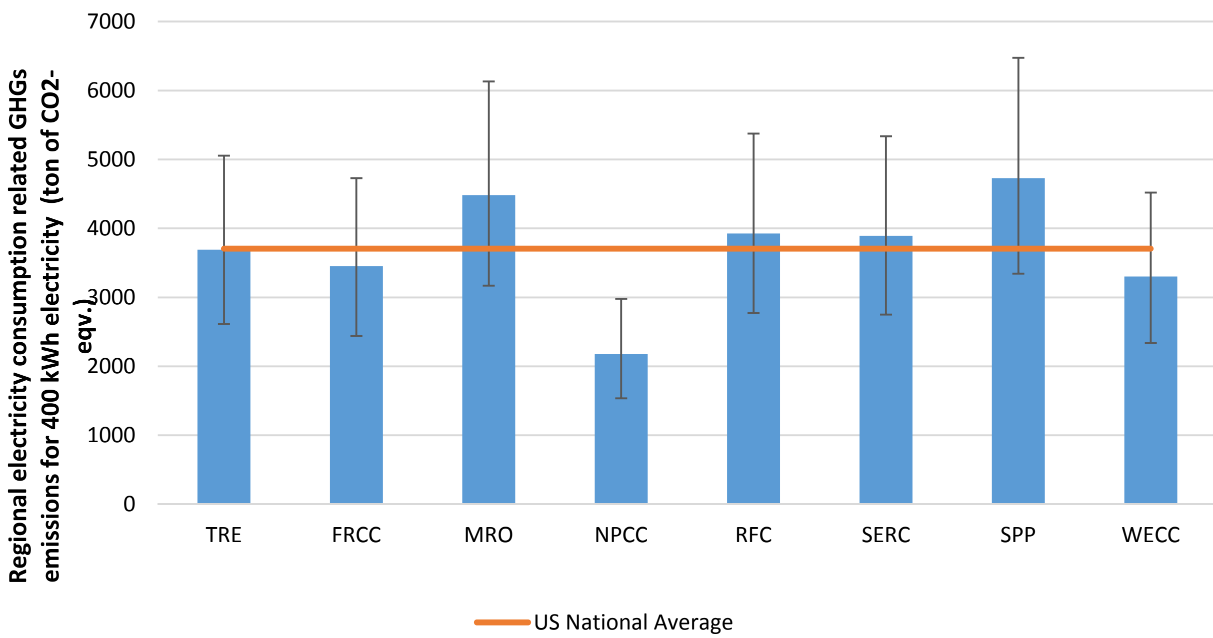

Figure 8.6 Regional electricity-consumption-related greenhouse gas emissions for 400 kWh electricity

Another significant impact driven largely by fuel consumption is the overall LCCs. That said, with respect to the LCCs of electricity-generation-related activities, though not as vastly different from region to region as GHGs emissions are, the differences in LCCs are still considerable. The electricity grid mix of the SERC region is found to have the greatest fuel-LCCs for BE trucks at almost 30% higher than the LCCs for the U.S. national average grid mix. On the other hand, it is seen that the use of the electricity grid mix in the NPCC region would improve the fuel-LCCs of BE trucks by 12% compared to the U.S. national average grid mix.

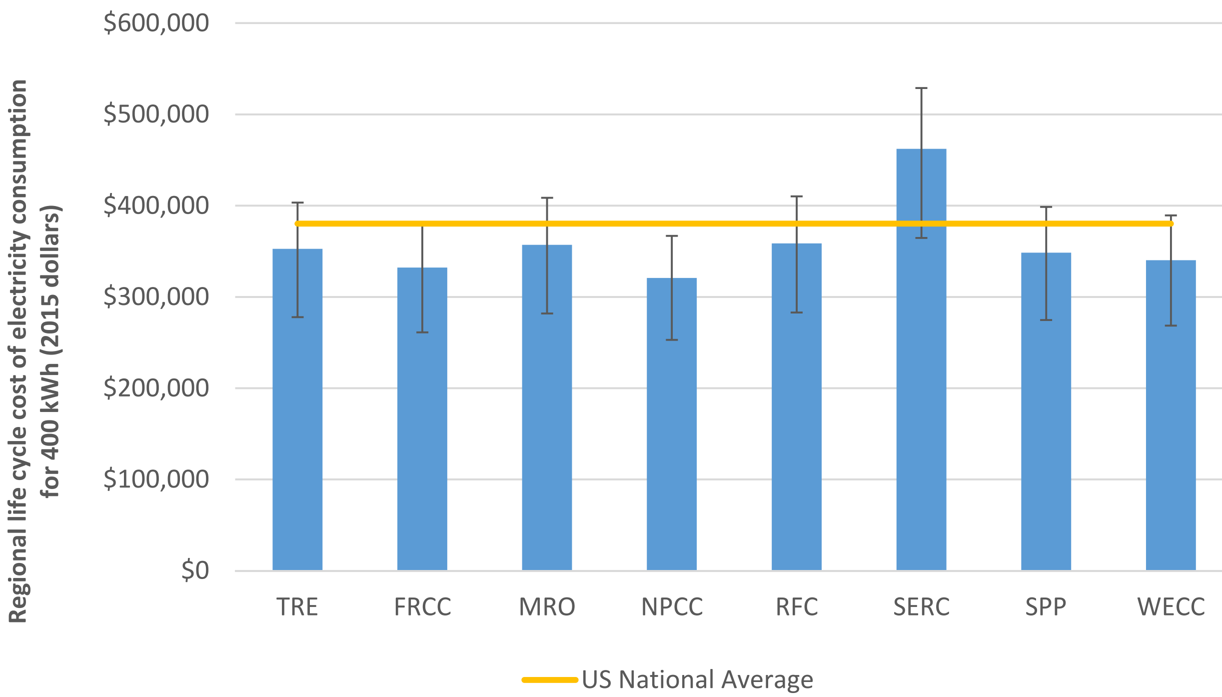

Figure 8.7 Regional life cycle cost of electricity for 400 kWh electricity

8.4 Conclusions and Discussions

The study presents a holistic analysis and comparison of the life-cycle emissions and costs, and air pollution externality costs of different types of alternative-fuel Class 8 heavy-duty truck-trailers. The alternative fuels analyzed in this study were biodiesel (B20), compressed natural gas (CNG), hybrid (mild and full), and battery electric (270kWh and 400kWh), with special attention to BE HDTs as an emerging technology, the life-cycle performance of which (as this study also shows) is heavily dependent on electricity-generation-related activities. The dynamism of the changing circumstances of trucks, i.e. account the estimated projections for future diesel and electricity prices and the effect of payload on the fuel economy of a truck, and the effect of tailpipe emissions deterioration factors, throughout their lifetimes are also reflected in this study.

To the authors' knowledge, this study has been the first comprehensive study that, in addition to life-cycle assessment for alternative fuel-powered HDTs, accounted for air pollution externalities in the form of APE costs incurred from the life-cycle of a truck. The inclusion of APE costs for different HDTs in a life-cycle assessment is an important feature in this study and a significant contribution to current literature. Another important feature of this study is the inclusion of a specific analysis and comparison of BE trucks based on the regional differences in electricity grid mixes and in the cost of electricity. Major differences have been observed between different NERC regions with respect to the emissions and costs from electricity generation. This study concludes that, if BE trucks are to be charged using the NPCC region's electricity grid mix, which only contains slightly over 10% of coal, the fuel consumption related emissions and life-cycle fuel costs of BE trucks could improve by over 70% and by over 63%, respectively. This important finding means that removing coal from the U.S. national electricity grid mix (or at least substantially reducing it by as much as possible) would achieve considerable emission reductions from the road transportation sector.

As expected, battery-electric HDTs outperformed all other truck types overall, despite having the greatest incremental costs and producing the largest amount of GHGs emissions due to the current use of the U.S. national grid mix. However, in an unexpected finding from this study, CNG trucks performed worse overall than the baseline truck considered in this study, mainly due to additional emissions for CNG trucks from CNG fuel production, additional infrastructure needs, and tailpipe emissions, as well as the underperforming fuel economy of CNG trucks which, in turn, increases CNG fuel production and consumption even further. This study therefore confirms that the fuel economy (the total miles driven per diesel-equivalent gallon of fuel) is very important for any emerging truck technology to improve the economic and environmental performances of HDTs. In light of the fact that trucks have the highest VMT among all on-road vehicles, improvements in truck fuel economy can therefore lead to greater benefits with regard to their total impacts, as fuel economy has a direct influence on both fuel consumption and tailpipe emissions, which are the two dominant drivers of all of the impacts analyzed in this study.

Overall, it can be concluded that BE trucks are a very promising truck alternative for sustainable trucking and road transportation, and that their substantial air quality improvements would, in turn, greatly improve environmental and human health nationwide. This holds true providing that electricity used to charge a BE truck is generated from renewable energy sources, which produce far lower life-cycle environmental impacts than fossil fuel-based generation. It should be kept in mind that, once the incremental costs of BE HDTs are decreased thanks to future technological advancements, BE HDTs would substantially outcompete all other HDT types. This study also shows that CNG trucks did not significantly improve either life-cycle emissions or costs compared to their conventional counterparts. Hence, the authors suggest that future policy efforts be directed primarily toward advancing BE HDTs as an emerging technology as opposed to HDTs with other alternative fuel sources.

EIO-LCA model used in this study is based on matrixes of transactions between sectors of a single country. The use of single-region I-O model leads to the fact that the impacts that are embedded in the domestic trade are better reflected in the results of this study. However, as also mentioned by Hertwich and Peters (2009), Kucukvar and Samadi (2015), Kucukvar et al. (2016, 2015), and Zhao et al. (2016), environmental impacts of production at global scale can be obtained through Multi Region Input-Output (MRIO) model. Therefore, a future study can extend the scope of this study including the environmental impacts of U.S. HDTs embedded in international trade using MRIO model as a complementary method in order to see the role of economic globalization, and minimize related uncertainties.

As observed during the literature review, the data regarding BE trucks is currently more limited than that of other alternative-fuel HDTs. For example, specific data on recharging infrastructure for BE HDTs could not be found, and was therefore assumed to be the same as that for BE bus charging infrastructure. Hence, it must be noted that the charging infrastructure for BE trucks may not be convenient for the extensive operation of long-haul trucks, so the deployment of BE trucks should consider charging infrastructure investments for DC charging. Moreover, the lack of data on APE costs per gram of emissions from electricity generation meant that the authors could not compare the APE costs of BE trucks on a regional basis. As more data on BE HDTs becomes available, future studies can focus specifically on the overall performance of BE trucks fueled with electricity generated from different renewable energy sources, and a scenario analysis in this regard can be carried out on a regional basis. Furthermore, future studies can focus on battery technology, specifically with respect to battery chemistry, by analyzing and comparing how each of the different types of battery chemistry can influence the performance of BE HDTs. However, despite these limitations, it can still be concluded that BE technology has a great deal of potential for significant economic, environmental, and social improvements to the transportation sector.

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