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Integrated Sustainability Assessment Framework for the U.S. Transportation

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INTEGRATED SUSTAINABILITY ASSESSMENT FRAMEWORK FOR THE U.S. TRANSPORTATION

by

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ABSTRACT

This dissertation aims to investigate the sustainability impacts of alternative vehicle technologies and develop comprehensive sustainability assessment frameworks to analyze potential impacts of these vehicles in the U.S. In order to assess sustainability impact of vehicle alternatives, life-cycle based models has been extensively used in the literature. Although life cycle-based models are often used for environmental impacts of alternative vehicles, analysis of social and economic impacts of these vehicles has gained a tremendous interest. In this regard, there is a growing interest among the international platform and academia to use the Life Cycle Sustainability Assessment framework to have more informed sustainable products, material and technology choices by considering the environmental, as well as social and economic impacts. The Life Cycle Sustainability Assessment framework is still under development and there is an ongoing research to advance it for future applications. In this dissertation, current and future needs of sustainability assessment frameworks and the U.S. transportation are identified and addressed. The major research gaps are identified as follows: (1) there has been small emphasis on effects of spatial and temporal variations on the sustainability impacts of alternative vehicle technologies, (2) no national research efforts as of now have been directed specifically toward understanding the fundamental relationship between the adoption of electric vehicles and water demand, (3) there has been a lack of understanding the dynamic complexity of transportation sustainability, encompassing feedback mechanisms, and interdependencies, for the environmental, social, and economic impacts of alternative vehicles, and (4) there is no

emphasis on addressing uncertainties inherent to the U.S. transportation and its complex relationships with the environment, society, and economy.

The environmental, economic, and social impacts of alternative vehicles are highly critical for truly assessing and understanding the long-term sustainability of vehicles and propose economically viable, socially acceptable, and environmentally-friendly transportation solutions for U.S. passenger transportation. This dissertation provides a more comprehensive sustainability assessment framework by realizing following objectives: (1) inclusion of spatial and temporal variations when quantifying carbon, energy, and water footprints of alternative vehicle technologies, (2) quantifying environmental, social, and economic impacts of alternative vehicle technologies, (3) capturing the dynamic relations among the parameters of U.S. transportation system, environment, society, and the economy, (4) dealing with uncertainties inherent to the U.S. transportation sector considering the complexity of the system and dynamic relationships.

The results of this dissertation reveal that the results with consideration of uncertainties, temporal and spatial variations, and dynamic complex relationships among the system variables can be significantly different than those of without consideration of those. Therefore, when developing policies the robustness of proposed scenarios should be valuated with consideration of uncertainties, temporal and spatial variations as well as the dynamic feedback mechanisms. The outcomes of this study can pave the way for advancement in the state-of-the-art and state-of-the-practice in the sustainability research by presenting novel approaches to deal with uncertainties and complex systems.

Dedicated to my family and friends

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TABLE OF CONTENTS

LIST OF FIGURES x
LIST OF TABLES xiv
CHAPTER 1. INTRODUCTION 1
1.1. The U.S. Transportation 1
1.2. General Overview of Alternative Vehicle Technologies 2
1.3. Problem Statement and Research Objectives 4
1.4 Organization of the Dissertation 8
CHAPTER 2. METHODOLOGY 11
2.1. Life Cycle Assessment 11
2.2. System Dynamics 13
CHAPTER 3: STATE-BASED ENERGY AND CARBON FOOTPRINTS OF ALTERNATIVE VEHICLE TECHNOLOGIES: INCLUSION OF SPATIAL AND TEMPORAL VARIATIONS 17
3.1. Literature review 17
3.2. Research Motivation and Objectives 25
3.3. Methodology 27
3.3.1. Vehicle Production 30
3.3.2. Battery Production 35
3.3.3. Vehicle Operation Phase 39
3.4. Results 55
3.4.1. State-based Average Electricity Generation Mix Scenario 57
3.4.2. State-based Marginal Electricity Generation Mix Scenario 59
3.4.3. Solar Energy Scenario 60
3.4.4. Sensitivity of Important Parameters 61
CHAPTER 4: A MISSING GAP IN THE ENVIRONMENTAL ASSESSMENT OF ALTERNATIVE VEHICLE TECHNOLOGIES: STATE-BASED WATER FOOTPRINT ANALYSIS 65
4.1. Background 66
4.2. Literature review 68
4.3. Methodology 70
4.3.1. Well-to-Tank (“WTT”) Calculations 73

4.4. Results 83
4.4.1. Water Withdrawal and Consumption of ICVs, HEVs, and BEVs with Solar Charging Infrastructure 84
4.4.2. Water Withdrawal and Consumption of BEVs and PHEVs 85
CHAPTER 5: DYNAMIC SUSTAINABILITY ASSESSMENT FRAMEWORK FOR ALTERNATIVE VEHICLE TECHNOLOGIES 92
5.1. Life cycle sustainability assessment 94
5.2. Broadening and deepening the LCSA framework 97
5.3. System dynamics modeling in transportation research 100
5.4. Motivation and research objectives 104
5.5. Methodology 105
5.5.1. Problem statement 106
5.5.2. Identification of parameters 107
5.5.3 System conceptualization 111
5.5.4. Model formulation 116
5.5.5. Model validation 130
5.5.6. Comparison of alternative vehicle technologies 133
5.6. Results and discussion 135
5.6.1. Environmental impacts 135
5.6.2. Economic Impacts 140
5.6.3. Social Impacts 142
CHAPTER 6. UNCERTAINTY-EMBEDDED DYNAMIC SUSTAINABILITY ASSESSMENT FRAMEWORK FOR ALTERNATIVE VEHICLE TECHNOLOGIES 147
6.1. Uncertainty in LCSA 147
6.2. Research Motivation and Objectives 148
6.3. Methodology 151
6.4. Results 157
6.4.1. Environmental Impacts 158
6.4.2. Economic impacts 174
6.4.3. Social Impacts 184

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS 195
REFERENCES 209

LIST OF FIGURES

Figure 1. Hierarchical outline of the research objectives 7

Figure 2. System Boundary of the Analysis 28

Figure 3. NERC Regions of EIA's Electricity Sector Model 52

Figure 4. Life cycle impacts of each vehicle type; a) GHG emissions, b) Energy consumption 56

Figure 5. State level vehicle preference results according to scenario 1; a) GHG emissions, b) Energy consumption 58

Figure 6. State level vehicle preference in the terms of GHG emissions for scenario 2 59

Figure 7. LCA impacts as a function of GHG and energy intensity, a) GHG emissions, b) Energy consumption per kilometer vehicle travels 62

Figure 8. LCA impacts as a function of UF varying from 0 to 1, a) GHG emissions, b) Energy consumption per kilometer vehicle travels. 63

Figure 9 Overview of Chapter 4 70

Figure 10. System boundary of this analysis (Note: Regions with dashed lines are excluded from the analysis) 72

Figure 11. Percentage Distribution of Average Electricity Generation Mix in U.S. (abbreviations: Geotherm: Geothermal; Hydro: Hydropower) 77

Figure 12. Water Withdrawal and Consumption of ICVs, HEVs, and BEVs with 100% solar-powered charging options (gal/mil) 85

Figure 13. Water withdrawal and consumption amounts for BEVs (gal/mil) (a) average electricity generation mix (b) marginal electricity generation mix 89

Figure 14. Water withdrawal and consumption amounts for PHEV40s (gal/mil) average electricity state-mix (b) 100% solar power (c) marginal electricity state-mix 90

Figure 15 Water withdrawal and consumption amounts for PHEV20s (gal/mil) a) average electricity state-mix, b) 100% solar power, c) marginal electricity state-mix.......................... 91

Figure 16. Atmospheric temperature change between 1980 and 2014....................................107

Figure 17. Causal loop diagram of the model...112

Figure 18. Fuel economy module for internal combustion vehicle 119

Figure 19. Stock and flow diagram for population module 120

Figure 20. Stock and flow diagram for climate change module 125

Figure 21. Stock and flow diagram of GDP module 128

Figure 22. CO_2 emissions from vehicle transportation a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle Emissions 136

Figure 23. PMF from vehicle transportation a) Manufacturing Phase, b) Operation Phase, c) 137

Figure 24. POF from vehicle transportation a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle...139

Figure 25. Annual vehicle ownership costs a) Operation Phase, b) Total Life Cycle.............141

Figure 26. Contribution to GDP a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle 142

Figure 27. Contribution to employment a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle...144

Figure 28. Human health impacts a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle 145

Figure 29. Total life cycle CO_2 emissions based on deterministic values........ 159

Figure 30. The multivariate dynamics of total annual CO_2 emissons (tonCO_2) a) BAU, b) S-HEV, c) S-PHEV, d) S-EV. 160

Figure 31. Histogram of the total CO_2 emissions based on Monte Carlo simulations: a) in 2030, b) in 2050. 162

Figure 32. Total life cycle PMF based on deterministic values. 163

Figure 33. The multivariate dynamics of total annual PMF emissions (kgPM10-eq) a) BAU, b) S-HEV, c) S-PHEV, d) S-EV. 165

Figure 34. Histogram of the total PMF based on Monte Carlo simulations: a) in 2030, b) in 2050. 167

Figure 35. Total life cycle POF based on deterministic values. 169

Figure 36. The multivariate dynamics of total annual POF (kgNMVOC-eq) a) BAU, b) S-HEV, c) S-PHEV, d) S-EV. 170

Figure 37. Histogram of the total POF based on Monte Carlo simulations: a) in 2030, b) in 2050. 173

Figure 38. Annual vehicle ownership costs based on deterministic values........ 175

Figure 39. The multivariate dynamics of total annual vehicle ownership cost (2013$) a) BAU, b) S-HEV, c) S-PHEV, d) S-EV. 176

Figure 40 Histogram of the vehicle ownership costs based on Monte Carlo simulations: a) in 2030, b) in 2050. 178

Figure 41 Annual contribution to GDP based on deterministic values 180

Figure 42 The multivariate dynamics of the contribution to GDP (2013$) a) BAU, b) S-HEV, c) S-PHEV, d) S-EV. 181

Figure 43 Histogram of the contribution to GDP based on Monte Carlo simulations: a) in 2030, b) in 2050. 183

Figure 44. Total life cycle employment generation based on deterministic values 185

Figure 45. The multivariate dynamics of the employment generation (#of people) a) BAU, b) S-HEV, c) S-PHEV, d) S-EV. 186

Figure 46. Histogram of the employment generation based on Monte Carlo simulations: a) in 2030, b) in 2050. 189

Figure 47. Total life cycle human health impacts based on deterministic values 190

Figure 48. The multivariate dynamics of the human health impacts (DALY) a) BAU, b) S-HEV, c) S-PHEV, d) S-EV. 191

Figure 49. Histogram of the human health impacts based on Monte Carlo simulations: a) in 2030, b) in 2050. 194

LIST OF TABLES

Table 1. Overview of Environmental LCA studies addressing alternative vehicle technologies 20

Table 2. Comparison of physical features of the vehicles types 30

Table 3. Conversions of vehicle producer prices 31

Table 4. Vehicle weight with and without batteries 33

Table 5. Vehicle material composition by weight in kg 33

Table 6. Producer prices of vehicle materials ($2002) and corresponding sector multipliers from EIO-LCA 34

Table 7. GWP and energy consumption from vehicle and material production per km of vehicle travel 34

Table 8. Properties of Li-ion batteries 36

Table 9. Properties of the Ni-MH battery 37

Table 10. GHG emissions and energy consumption from battery production 37

Table 11. Comparison of GWP (kgCO_2 eq.) and Energy use (MJ) per kg of battery production 38

Table 12. Key input parameters to calculate impacts from gasoline use 40

Table 13. Data for fuel economy of vehicles 41

Table 14. GHG emission and Energy consumption factors of various energy generation sources 43

Table 15. State-based GHG emission and energy consumption factors per kWh of electricity generation 45

Table 16. State-based GHG emission and energy consumption factors per kWh of marginal electricity generation in 2020 49
Table 17. Gasoline and electricity consumption (fuel economy) of the studied vehicles (Onat et al. 2015a) 73
Table 18. Water withdrawal and consumption factors of different fuel sources (gal/kWh) 75
Table 19. State-Specific Average Electricity Generation Mix (Scenario 1) 77
Table 20. State-specific Marginal Electricity Generation Mix (Scenario 2) 80
Table 21. State-specific water withdrawal and consumption factors for Scenario 1 and 2 (gal/kWh) 82
Table 22. Table of model boundary 108
Table 23. Summary of model parameters 109
Table 24. Results of the ANOVA analysis 131
Table 25. Results of Normality Tests 132
Table 26. Results of Two Sample Kolmogorov Smirnov 132
Table 27. Summary of the extreme scenarios 134
Table 28. Distribution types and parameters of the model variables 154
Table 29. $C0_2$ emission distribution parameters 160
Table 30. PMF distribution parameters 166
Table 31 POF distribution parameters 172
Table 32 Vehicle ownership cost distribution parameters 177
Table 33 Contribution to GDP distribution parameters 182
Table 34. Employment generation distribution parameters 187

Table 35. Human health impact distribution parameters....192

CHAPTER 1. INTRODUCTION

1.1. The U.S. Transportation

The need for sustainable and more efficient transportation systems is emerging in the U.S. owing to increasing concerns about global climate change, national energy security, and rising oil prices. Transportation sector has been one of the most significant sources of greenhouse gas emissions (GHG) and energy consumption in the U.S. Energy consumption and GHG emissions of transportation sector account for approximately 28% of the U.S. total. Additionally, the transportation sector is responsible for 67% of total U.S. petroleum consumption and 141% of the total U.S. petroleum production. The majority of the energy used in the transportation sector, about 93% of the total energy consumption mix, is provided through petroleum. On the other hand, light duty vehicles (LDVs) comprise 63% of the total petroleum use, 59% of total energy use, and 60% of the total GHG emissions of the U.S. transportation sector (Oak Ridge National Laboratory, 2013). Furthermore, LDVs compromise about 85% of the passenger miles traveled in the United States and it is a rapidly growing transportation mode in the world as well as in the developed countries (Committee for a Study of Potential Energy Savings and & Greenhouse Gas Reductions from Transportation, 2011; Sager, Apte, Lemoine, & Kammen, 2011).

As the U.S. transportation sector heavily relies on petroleum and it is a major contributor of the nation's GHG emissions, various alternative vehicle technologies such as hybrid, plug-in hybrid, and electric vehicles have been developed to minimize these impacts. Furthermore, federal governments, national agencies in the U.S. as well as the international organizations promote adoption of alternative vehicle technologies and support the efforts aiming to develop environmentally friendly and economically viable policies (DOT, 2013; Executive Office of the President, 2013; IPCC, 2007; WBCSD, 2004). According to the President Obama's climate action plan in 2013, increasing fuel economy standards and developing advanced transportation technologies are prioritized strategies to reduce environmental impacts of the U.S. transportation sector (Executive Office of the President, 2013). In this regard, national laboratories, various institutions, and research centers evaluate these options comprehensively and try to develop effective policies towards minimizing the environmental impacts (Argonne National Laboratory, 2014b; Center for Electric Car and Energy Conversion, 2014; Florida Solar Energy Center, 2014; MIT Electric Vehicle Team, 2014; National Renewable Energy Laboratory, 2014; Oak Ridge National Laboratory, 2014; UC Davis Plug-In Hybrid & Electric Vehicle Research Center, 2014).

1.2. General Overview of Alternative Vehicle Technologies

Analyzing alternative vehicle technologies, energy sources, transportation fuels, and more efficient ways of using the resources have been a growing interest in the literature and industry. The alternative vehicle types have been one of the ways to eliminate impacts of the U.S. LDT. The vehicle types considered in this study presented as follows:

- The Internal Combustion Engine Vehicle (ICV): has an engine in which the combustion of a fuel occurs with air in a combustion chamber. In an internal combustion engine, the expansion of the high-temperature and pressure generated by combustion creates a direct force to component of the engine including pistons, turbine blades, or a nozzle. This force moves the vehicle over a distance (e.g. Toyota Corolla).

- The Electric Vehicles (EV): is a typical type of battery electric vehicles (BEV), has an electric motor which us powered by a battery. The battery capacity is the most important determinant for EV range. In EV's, batteries are charged using the electricity grid via a standard socket or a special connection providing higher voltage and current which allows faster charging. EVs have several advantages over vehicles with internal combustion engines (ICEs) such as energy efficiency, environmentally friendliness, reduces energy dependency, and better performance. In addition, there are several types of challenges in use of electric vehicles related with driving range, charging time, and battery cost. (e.g. Nissan Leaf).

- The hybrid electric vehicle (HEV): is a vehicle utilizing both an electric motor and an internal combustion engine. There are several types of HEV power trains, but all have one ICE, at least one EM (the Toyota Prius has for example two EMs), and a battery. Hybrid-electric vehicles (HEVs) have the benefits of both gasoline engines and electric motors. HEV's can be configured to obtain different objectives including improved fuel economy, increased power, or additional auxiliary power for electronic devices and power tools. Toyota Prius is a typical HEV type and it is ranked as the best-selling hybrid car in the U.S. in 2013.

- The Plug-in Hybrid Electric Vehicle (PHEV): which can be charged either from the electricity grid or using the internal combustion engine. By combining an electric motor and an internal combustion engine, an HEV allows the ICE to run more efficiently by driving nearer its ideal rpm. There are several types of PHEV power trains based on ranges such as PHEV11 and PHEV38 which represents the two common range distances in the United States. The portion of the distance that can be powered by electricity depends on several important factors such as all-electric range (AER), driving distance, and driving conditions (Raykin, MacLean, & Roorda, 2012). AER is defined as the total miles can be driven, after the battery is fully charged, in electric mode (engine-off) before the engine turns on for the first time (Markel, 2006). The newly introduced plug-in version of Toyota Prius is an example of PHEV11. Chevrolet Volt is a PHEV38, which has the highest AER among the commercially available counterparts.

1.3. Problem Statement and Research Objectives

Alternative vehicle technologies, as an option to reduce negative environmental impacts of the U.S. 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, there is a strong need for robust comprehensive sustainability assessment frameworks to be able to analyze their potential to contribute the transportation sustainability. There are mainly several major methodological and application gaps in the sustainability assessment of electric vehicles and the U.S. transportation. First, there has been small emphasis on effects of spatial and temporal variations on the sustainability impacts of alternative vehicle technologies. Second, no national research efforts as of now have been directed specifically toward understanding the fundamental relationship between the adoption of electric vehicles and water demand. Third, there has been a lack of understanding the dynamic complexity of transportation sustainability, encompassing feedback mechanisms, and interdependencies, for the environmental, social, and economic impacts of alternative vehicles. Fourth, there is little or no emphasis on addressing uncertainties inherent to the U.S. transportation and its complex relationships with the environment, society, and economy. In order to fill these methodological and application based gaps, this research proposes novel and comprehensive sustainability assessment frameworks depending on needs, scope, and system-specific research questions. In this regard, current research aims to fill research gaps by answering the following research questions;

1) How do differences in regional driving patterns and electricity generation mix (marginal and average) effect energy use and GHG emissions of alternative vehicle technologies?

2) How do these spatial variations should affect the vehicle technology policies at state level?

3) What are the relative impacts of battery and vehicle manufacturing on GHG emissions and energy consumption within the total life cycle of vehicles?

4) What is the water footprint of EVs/PHEVs compared to ICVs and other alternative vehicle technologies? Does adoption of EVs/PHEVs jeopardize the water sources?

5) How do differences in regional driving patterns and electricity generation mix (marginal and average) effect water footprint of alternative vehicle technologies?

6) Do current life cycle assessment methods capable of capturing the system behavior, feedback relationships, and the dynamic interdependencies among the system variables? How can the existing life cycle assessment methodologies improved to provide a more comprehensive sustainability assessment?

7) Why is there a need for dynamic LCA? Are traditional LCA methods sufficient to account for feedback relationships and dynamic system behavior?

8) What is the behavior of the U.S. transportation system considering the dynamic interactions among the variables of the system?

9) How the uncertainties inherent to the U.S. transportation system effect the sustainability impacts of alternative vehicle technologies in the U.S.?

10) What is the trend in the LCA research field? What are the future needs for LCA framework?

Fig, 1 shows the generalized outline of the research objectives in parts. This figure mainly summarizes the methodological contributions of each phase which is composed of the chapters of this dissertation.

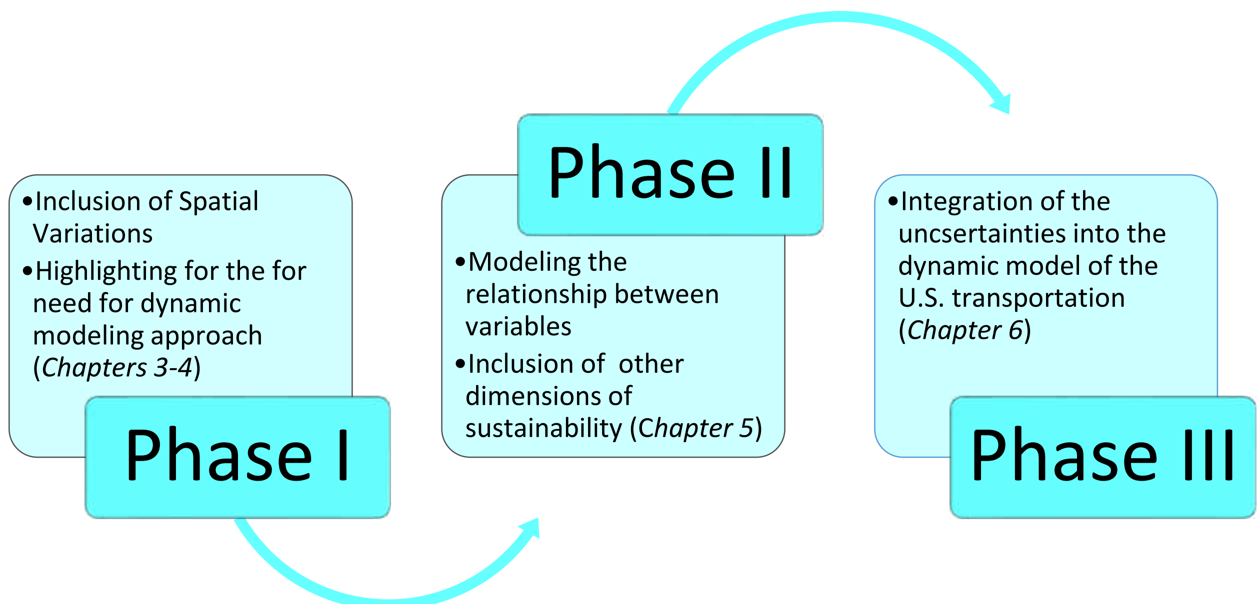


Figure 1. Hierarchical outline of the research objectives

1.4 Organization of the Dissertation

This dissertation composed of seven chapters. First two chapters is the introduction and generalized explanations of the methodologies utilized in the rest of the dissertation. The other chapters are self-standing sections, each has a literature review, details of the applied methodology, results, and conclusions. The summary of each section as follows:

Chapter 1: Introduction

This chapter presents background information about the U.S. transportation sector and their sustainability impacts in the U.S. Also, the alternative vehicle technologies are briefly introduced. This section includes the research problem statement, aims and objectives, and organization of the dissertation.

Chapter 2: Methodology

This chapter describes the methodologies applied in this dissertation. Considering that each section has its own specific methodology, in this section, a general overview of the applied methodologies are given rather than detailed methodology and calculations. Overall, the methodologies utilized in this dissertation are Life cycle Assessment (LCA), Life cycle Sustainability Assessment (LCSA), Economic Input-Output Life Cycle Assessment (EIO-LCA), Triple Bottom Line Life Cycle Assessment (TBL-LCA), The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation Model (GREET), eGRID database, system dynamics modeling.

Chapter 3: State-based Energy and Carbon Footprints of alternative Vehicle Technologies: Inclusion of Spatial and Temporal Variations

This chapter highlights how inclusion of spatial and temporal variations affect the carbon and energy footprint of alternative vehicle types. In addition, a comprehensive literature review is carried out to show major gaps in the literature. In this section, water and energy footprints of alternative vehicle technologies quantified for 50 states in the U.S. by utilizing life cycle assessment methodology.

Chapter 4: A Missing Gap in the Environmental Assessment of Alternative Vehicle Technologies: State-Based Water Footprint Analysis

This chapter points out an important gap in the literature about water footprint of EVs. Since the EVs are powered by electric power plants, the source of the electricity generation will have a big influence on the water consumption. This section will also include spatial variations and present a state-based water consumption and withdrawal of alternative vehicle technologies in each state in the U.S. This chapter also presents an application of life cycle assessment methodology. The methodological framework is same as in the previous chapter. However, the applied methodology is improved by presenting results in stochastic values rather than deterministic results presented in the previous chapter.

Chapter 5: Dynamic Sustainability Assessment Framework for Alternative Vehicle Technologies

This chapter includes a System Dynamic (SD) Model to quantify environmental, social, and economic impacts of alternative vehicle technologies in the U.S. considering different varying factors such as population, GDP, travel demand, public welfare, new vehicle sales, etc. In this chapter, a novel methodological contribution is presented to broaden and deepen existing life cycle sustainability assessment framework.

Chapter 6: Uncertainty-Embedded Dynamic Sustainability Assessment Framework for Alternative Vehicle Technologies

In this chapter, the dynamic sustainability assessment model developed in chapter 5 is improved by integrating uncertainties associated with the U.S. transportation sector. System dynamics methodology is utilized to deal with uncertainties, in which various distributions representing each variable assigned Monte Carlo simulations are run.

Chapter 7: Conclusions

This chapter summarizes the results of the proposed methodologies. Significance of the proposed frameworks for the U.S. Electric Vehicle applications will be discussed. Then, the limitations of the study will be explained and the conclusion of the dissertation will be made. Finally, the recommendations for the future studies will be indicated.

CHAPTER 2. METHODOLOGY

This proposal mainly utilizes two main methodology; Life Cycle Assessment and System Dynamics. Detailed calculations are subject to chapter content and therefore, will be given in the associated chapter.

2.1. Life Cycle Assessment

The necessity of life cycle thinking in sustainable vehicles' research is very crucial due to the fact that environmental loads are produced in various stages of the life cycle of vehicles such as material production, use and end-of-life. Life cycle thinking is "a way of thinking which will helps us recognize how our selections – such as buying electricity or a new computer – are one part of a whole system of events" (United Nations Envionment Program, 2004). To quantify the system of events associated with vehicle systems, life cycle assessment (LCA) models need to be developed and utilized. In this context, LCA is a well-known and widely used approach to quantifying the potential environmental impacts produced and natural resources used throughout a product's life cycle, including raw material acquisition, production, distribution, use, and end-of-life phases, which compromises the system of events (Finnveden et al., 2009). LCA was introduced in the early 1990s as a practical and robust tool to assess the potential environmental loads of industrial activities to help reduce the overall environmental impacts (Rebitzer et al., 2004). The most significant strength of LCA is that it considers the whole product life cycle so as to avoid problems associated with working with a narrowly defined, in other words limited scope (Curran, 1996). In LCA literature, three approaches have been used in the majority of the studies: process-based LCA (P-LCA), economic input-output LCA (EIO-LCA), and hybrid LCA (Suh & Huppes, 2005). P-LCA divides the product's manufacturing process into individual process flows to quantify the related direct environmental impacts (Onat, Kucukvar, & Tatari, 2014b). This LCA approach provides a methodological framework to estimate the environmental impacts of specific processes. Among the LCA methodologies, P-LCA has been often used to analyze the environmental implications of certain phases (e.g. manufacturing, transportation, use, etc.) without looking at the supply chain impacts. In P-LCA, due to the narrowly defined boundaries, some important environmental impacts in the extended supply chains might be overlooked since it is not possible to include the upstream suppliers for impact assessment using P-LCA (Facanha & Horvath, 2007). Additionally, P-LCA enables very detailed analysis, but can be very expensive, time-consuming, and inappropriate. To overcome these problems, EIO-LCA models initiated as robust methods in early 2000s (Guinée et al., 2011).

EIO-LCA, which is widely used in literature for quantifying the environmental impacts of products or processes, is able to quantify the overall environmental impacts considering the entire supply chain (C. T. Hendrickson, Lave, & Matthews, 2005; H. Scott Matthews, Hendrickson, & Weber, 2008; Minx et al., 2009). Today, EIO approach is utilized to assist in life cycle inventory (LCI) phase, as well as areas of LCA modeling and applications including dynamic modeling, environmental policy making, transportation, and life cycle cost analysis (Suh & Nakamura, 2007). EIO-LCA basically combines the environmental impact data with the economic input-output tables of a nation's economy to form a comprehensive system boundary. Using EIO-LCA model Matthews et al. (H.S. Matthews, Hendrickson, & Weber,

2008) analyzed different industrial sectors for carbon footprint analysis. The results of this study revealed that on the average, direct emissions from an industry accounts for only 14 percent of the total supply chain carbon emissions. Additionally, direct emissions plus industry energy inputs were found to be only 26 percent of the total supply chain-linked emissions. Therefore, using a comprehensive environmental LCA method like EIO-LCA is vital for tracking total emissions across the entire supply chain network. As employed in this research, Hybrid LCA combines both the P-LCA and EIO-LCA models to analyze process specific and supply chain related impacts (Guinée et al., 2011). Although, EIO-LCA was one of the most comprehensive LCA methods developed, due to its aging data and limited focus on only the environmental impacts, a new EIO-LCA model needs to be developed, one that covers TBL impacts and provides a more robust analytical framework, which can be used to conduct a broader LCA of products or systems (Murat Kucukvar, Noori, Egilmez, & Tatari, 2014; Wiedmann, Lenzen, & Barrett, 2009)

2.2. System Dynamics

Most of the problems of present are consequences of unforeseen side effects of the actions taken in the past, such as global climate change and depletion of resources. The policies implemented to solve significant problems mostly fail, make the problem even worse, or pave the way for other problems. Effective decision making requires a system thinking approach and understating behavior of the growing dynamic complexity of the systems. SD is a strong modeling approach to describe and understand the behavior of complex systems overtime (J. D. Sterman, 2000). The approach was introduced by Jay

Forrester in mid-1950s at Massachusetts Institute of Technology (MIT) (Jay Wright Forrester, 1961a). Since then, the SD approach has been employed to address critical problems from various fields of studies such as , engineering, economic, social and environmental sciences (Egilmez, Kucukvar, & Tatari, 2013b). Moreover, governmental organizations, many top companies, universities, and consulting firms use the system dynamic approach to solve critical problems and improve their decision making mechanism. The main difference between traditional conception of problem and system thinking is that the former focuses on the cause and effect relationship between the system components individually, while the latter considers system as a whole by covering all of the interactions among the components of the system. In other words, traditional approach is a narrower model, whereas the system dynamics is a board method which takes the elements of a system into account holistically.

In the SD approach, a dynamic system is modeled by feedback loops, stocks, flows, and auxiliary variables. Feedback loops represent the causal relationships between components (stocks) of a system. Feedbacks are expressed with flows. Direction of flows determines whether the feedback has a negative or positive relationship with the attributed variable or stock. Also, auxiliary variables are the rates that regulate flow values on a period of time. Stocks are accumulations of the flows which increase or decrease the amount of the stock based on the relationship between the stock and the flow. After the model is constructed based on the causal relationships including stocks, flows, and auxiliary variables, the model is simulated for a certain time period. Then, the simulation outputs are examined and validated in compliance with the initial base case conditions. Validation process is to test if the SD model can successfully represent the actual behavior of the system analyzed. This is done by comparing the values and trends of the past real data and the model results. After the validation of the model, different policies can be developed by altering certain variables such as retrofitting rate, energy efficiency, construction rate of new HPGBs and leave the rest as defined in the base model. Finally, the policies are compared to evaluate their impacts on the system behavior and to see their relative effects respect to the base case (J. D. Sterman, 2000), (Egilmez et al., 2013b).

SD approach has been widely used to conduct policy experiments by many researches and policy makers for over 30 years (Egilmez & Tatari, 2012; Trappey, Trappey, Hsiao, Ou, & Chang, 2012). SD models are also often used to address environmental issues and sustainability problems. For instance, Ford (Ford, 1999) studied wildlife population dynamics, air polluting, and vehicle emissions. Forrester et al.(J. W. Forrester, 1971a) and Meadows et al. (Meadows, Randers, & Meadows, 1993a) contemplated on global perspectives of environmental sustainability issues with a broader scope. Meadows et al. (Meadows, Randers, & Meadows, 2004a) and Randers (Randers, 2000b) utilized the SD approach to investigate the effects of increasing human population on the earth and natural resources. Several other studies utilized SD modeling approach includes the issues related to regional sustainable development (Saeed, 1994), environmental management (Mashayekhi, 1990), water resource planning (Ford, 1996), urban planning (White, Dajani, & Wright, 1974), and ecological modeling (Wu, Vankat, & Barlas, 1993). SD modeling has been also used for the areas of transportation, construction, building & environment. Egilmez and Tatari (Egilmez & Tatari, 2012) developed an SD model for U.S. highway system where the reference mode was considered as the increasing GHG emission trend between 1982 and 2007. Three policy areas including electric vehicles, public transportation and fuel efficiency are studied with quantitative policies for the period between 2012 and 2050. Results indicated that hybrid (hybrid) implementation of the selected policy areas can only lead to reduce the GHG emissions below the levels indicated by Liberman and Warner Climate Act.

In this proposal, system dynamics will be utilized for two main purposes; (1) to capture the dynamic relationships between environmental, economic, and social dimensions within the context of transportation, (2) to quantify social, economic, and environmental impacts of alternative vehicle technologies, (3) to deal with uncertainties inherent to the U.S. transportation and impacts of alternative vehicle technologies.

CHAPTER 3: STATE-BASED ENERGY AND CARBON FOOTPRINTS OF ALTERNATIVE VEHICLE TECHNOLOGIES: INCLUSION OF SPATIAL AND TEMPORAL VARIATIONS

Electric vehicles (EVs), plug-in hybrid electric vehicles (PHEVs), and hybrid electric vehicles (HEVs) are often considered as better options in terms of greenhouse gas emissions and energy consumption compared to internal combustion vehicles. However, making any decision among these vehicle options is not a straightforward process due to temporal and spatial variations, such as the sources of the electricity used and regional driving patterns. In this study, we compared these vehicle options across 50 states, taking into account state-specific average and marginal electricity generation mixes, regional driving patterns, and vehicle and battery manufacturing impacts. Furthermore, a policy scenario proposing the widespread use of solar energy to charge EVs and PHEVs is evaluated.

3.1. Literature review

A comprehensive literature review is undertaken to compare scope and main focus of various studies addressing environmental impacts of ICVs, HEVs, PHEVs, and EVs. In total, 38 different peer-reviewed articles, mainly LCA studies, are evaluated based on their scope, investigated vehicle technologies, and selected environmental impact categories. A detailed evaluation of these papers is shown in table 1. Of the 38 studies, 16 of them covered driving patterns and only 8 of them considered marginal electricity mix scenario. Studies containing both marginal electricity scenarios and driving patterns are mostly well-to-wheel studies in which only fuel-cycle is taken into consideration. 14 of the reviewed studies covered both battery and vehicle production phases, while only 11 of them investigated environmental impacts associated with end-of-life phase of vehicles. As a common finding in these studies, end-of-life phase is found to have a minimal impact compared to vehicle and fuel cycle. Majority of the studies made a comparison between environmental or energy performance of ICVs with those of other vehicle technologies. On the other hand, FCEVs are compared with other vehicle technologies in 7 studies only. HEVs are the most studied vehicle type compared to PHEVs, EVS, and FCEVs. Almost all of the studies, 37 articles, included GWP as an environmental impact category. Additionally, energy consumption is one of the most interested topics for researchers with 21 studies out of 38. On the contrary, other impact categories are significantly lower compared to GWP and energy consumption. For instance, water footprint of electric and conventional vehicles is only studied by King and Weber (King & Webber, 2008) using a process-based life cycle a. In addition, the majority of studies reviewed are mainly focused on mid-point life cycle inventory results such as energy, water and greenhouse gas emissions rather than end-point indicators such as damage to human health and ecosystems. Most of the studies reviewed here used the P-LCA methodology and only a limited number of studies employed a combination of P-LCA and EIO-LCA, which is also known as hybrid LCA (Cooney, Hawkins, & Marriott, 2013; Samaras & Meisterling, 2008).

Apart from the studies benchmarked in this study, there are many other studies mainly focusing on life cycle cost, vehicle-to-grid electricity transfers, market penetration, aged charging, and battery exchanging, etc. However, we limit the scope of literature review mainly to environmental LCA studies. Overall, use phase represents the most dominant phase compared to other life cycle components in most of the environmental impact categories. Therefore, marginal electricity mix and driving patters have significant effects on overall life cycle impacts of EV technologies. M&R of vehicles and battery production are responsible for lower amount of total environmental effects compared to operation phase. In general, the majority of the studies have primarily focused on either national scale impacts or very specific local regions, and none of the studies have analyzed the 51 U.S. states with driving patters and marginal electricity mix profiles. As a common conclusion, EVs are found to be sustainable from an environmental perspective; however three main factors are emphasized in the literature to improve the performance of EVs: battery technology improvement, eco-driving behavior, and environmentally benign electricity mix through use of renewable energy sources.

Table 1. Overview of Environmental LCA studies addressing alternative vehicle technologies

		Scope								Vehicle Types					Environmental Impact and resource category											
Author(s)	**Year**	**Vehicle Cycle**	**Battery**	**Fuel Cycle**	**Maintenance**	**Marginal Electricity**	**Driving Conditions**	**Driving Patterns**	**End of Life**	**ICVs**	**HEVs**	**PHEVs**	**EVs**	**FCEV**	**GHG/GWP**	**Energy**	**Water**	**AP**	**ADP**	**EP**	**HTP**	**ET**	**ODP**	**POFP**	**MDP**	**FDP**
Wang et. al.	1997	✓		✓			✓		✓	✓	✓				✓	✓										
Hackney and Neufville	2001			✓						✓	✓		✓	✓	✓	✓										
Schexnayder et. al.	2001	✓	✓	✓					✓	✓	✓				✓	✓		✓		✓	✓					
Plotkin et. al	2002			✓			✓	✓		✓	✓	✓	✓		✓	✓										
McCleese and LaPuma	2002	✓	✓	✓	✓					✓			✓		✓	✓										
Lave and Mclean	2002			✓						✓	✓				✓											
Daniel and Rosen	2002			✓						✓	✓	✓	✓		✓	✓										
Van Mierlo et. al.	2004			✓						✓	✓		✓		✓			✓			✓					
Brinkman et. al.	2005			✓			✓			✓	✓		✓	✓	✓	✓										
Mohamadabadi et. al.	2009			✓						✓	✓				✓	✓										
Stephan and Sullivan	2008			✓		✓				✓	✓	✓			✓	✓										
Kintner-Meyer et. al.	2007			✓	✓							✓			✓											
Samaras and Meisterling	2008	✓	✓	✓				✓		✓	✓	✓			✓											
Bandivadekar	2008	✓		✓			✓		✓	✓	✓	✓	✓	✓	✓	✓										

		Scope								Vehicle Types					Environmental Impact and resource category											
Author(s)	**Year**	**Vehicle Cycle**	**Battery**	**Fuel Cycle**	**Maintenance**	**Marginal Electricity**	**Driving Conditions**	**Driving Patterns**	**End of Life**	**ICVs**	**HEVs**	**PHEVs**	**EVs**	**FCEV**	**GHG/GWP**	**Energy**	**Water**	**AP**	**ADP**	**EP**	**HTP**	**ET**	**ODP**	**POFP**	**MDP**	**FDP**
Fontaras et. al.	2008						✓	✓		✓	✓	✓			✓											
Letendre et. al.	2008			✓		✓		✓		✓	✓	✓			✓											
King and Webber	2008			✓				✓		✓		✓	✓				✓									
Elgowainy et. al.	2009			✓		✓		✓				✓			✓	✓										
Boureima et. al.	2009	✓	✓	✓	✓				✓	✓					✓			✓			✓					
Baptista et. al.	2009	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓										
Jaramillo et. al.	2009	✓	✓	✓				✓		✓	✓	✓		✓	✓											
Shiau et. al.	2009	✓	✓	✓				✓	✓	✓	✓	✓			✓	✓										
Notter et. al.	2010	✓	✓	✓	✓				✓	✓			✓		✓	✓										
Huo et. al.	2010			✓						✓	✓		✓		✓	✓										
Axsen et. al.	2011			✓		✓		✓		✓	✓	✓			✓											
Ma et. al.	2012	✓	✓	✓	✓	✓	✓		✓	✓	✓		✓		✓											
Bartolozzi et. al.	2012			✓						✓			✓	✓	✓			✓	✓	✓	✓	✓	✓	✓		
Faria et. al.	2012			✓			✓	✓		✓	✓	✓	✓		✓	✓										
Sharma et. al.	2013	✓	✓	✓	✓		✓			✓	✓	✓	✓		✓											

		Scope								Vehicle Types					Environmental Impact and resource category												
Author(s)	**Year**	**Vehicle Cycle**	**Battery**	**Fuel Cycle**	**Maintenance**	**Marginal Electricity**	**Driving Conditions**	**Driving Patterns**	**End of Life**	**ICVs**	**HEVs**	**PHEVs**	**EVs**	**FCEV**	**GHG/GWP**	**Energy**	**Water**	**AP**	**ADP**	**EP**	**HTP**	**ET**	**ODP**	**POFP**	**MDP**	**FDP**
Hawkins et. al.	2012	✓	✓	✓	✓				✓	✓			✓		✓			✓			✓	✓		✓	✓	✓
MacPherson et. al.	2012	✓	✓	✓		✓		✓	✓			✓			✓	✓										
Thomas et. al.	2012			✓		✓				✓	✓	✓	✓	✓	✓											
Raykin et. al.	2012			✓			✓	✓		✓	✓	✓			✓	✓										
Kelly et. al.	2012			✓				✓				✓			✓	✓										
Marshall et. al.	2013			✓		✓	✓	✓		✓		✓			✓	✓										
Faria et. al.	2013	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓		✓	✓										
Cooney et. al.	2013	✓	✓	✓	✓					✓			✓		✓											
Karabasoglu and Michalek	2013			✓			✓	✓		✓	✓	✓	✓		✓											
Onat et al. (Chapter 3)	***2014***	✓	✓	✓	✓	✓		✓		✓	✓	✓	✓		✓	✓										

In this chapter, the end-of-life impacts are not included due to their relatively low impacts on GWP and energy consumption. Also, FCEVs were not included in our analysis. This is because of that they are not likely to penetrate the in the market in near future (Jeong & Oh, 2002; Keith & Farrell, 2003). The infrastructure requirement for the hydrogen distribution has not been developed and there are still significant concerns about the material availability and high cost (Hawkins, Gausen, & Strømman, 2012; Råde, 2001).

Another important part that is not included in this study was the driving conditions. "Driving conditions" refers to factors influencing the fuel efficiency performance in real world, while "Driving patterns" represents the driving distance which determines the fraction of vehicle kilometers travelled in either electric or gasoline mode. We used the EPA's label values to reflect vehicles' fuel economy performances. EPA tests vehicles with 5-cycle test to label for their fuel economy. The test results from the phases of each of the 5 drive cycles (FTP, HWFET, US06, SC03, Cold FTP) are input to a set of formulae to produce final city and highway fuel economy label values. 5-cycle tests contain vehicle performance under different climate conditions where air condition is on. Also, fuel efficiency in congested roads and highways are calculated with these tests. For more information about these tests, please see following references (Gonder, Brooker, Carlson, & Smart, 2009; Meyer, 2011; U.S. Environmental Protection Agency Office of Transportation and Air Quality, 2006). EPA assigned some weights to these test results to represent typical U.S. driving conditions from the certification test cycles. We tried to develop a methodology to modify these fuel economy values representing each state and contacted with National Vehicle and Fuel Emissions

Laboratory regarding this issue. However, 5-cycle method was developed with no understanding of electric vehicles and the impact of cold, air conditioning, or other factors on these vehicles. EVs do not run all five cycles for fuel economy or emissions testing, and instead for fuel economy and other parameters (e.g., range), EPA applies an adjustment factor of 0.7. Currently, EPA is developing a way for EVs to better estimate efficiency and range using a 5-cycle process. Moreover, 5-cycle tests do not applied to most of the vehicles to determine their fuel economy. When EPA developed the regulation, they were aware of that requiring this for every model would be a huge testing burden on manufacturers. Especially, since tests like the air conditioning and cold temperature tests required specialized test facilities that are in short supply. Therefore, EPA developed a new approach called "derived 5-cycle" method. It is simply a mathematical adjustment to the standard city and highway tests. The derived 5-cycle equations adjusted the EVs by about 0.7 (a 30% reduction in fuel economy test results obtained from standard city and highway tests). In other words, If Nissan Leaf on city and highway tests gets about X mpg on a charged battery, but in the real world the experience seems to be pretty close, on average, to about 0.7mpg. Tests procedure for PHEVs has completely different test methodology. They are tested both with a full battery (charge depleting mode) and with a discharged battery (charge-sustaining mode). The charge-sustaining mode is an all-gasoline mode, and the charge-depleting can be all-electric (e.g., the Chevrolet Volt) or a mix of electricity and gasoline (the Prius PHEV). In charge-depleting mode, EPA does not require 5-cycle testing. They rather run the city and highway driving cycles to full battery depletion. In the charge-sustaining mode a vehicle might run all 5 cycles, or might use the derived 5-cycle adjustment if they qualify. On the other hand, HEVs are tested same as ICVs, standard highway and city tests. However, they are usually more sensitive to hot or cold conditions, usually because of the impact on engine-off at idle (U.S. Environmental Protection Agency Office of Transportation and Air Quality, 2006). All in all, there is no widely accepted methodological framework to modify fuel economy values of each vehicle type to account based on regional variations such as temperature, road density, and congestion rates, etc.. EPA's fuel economy label values are used in the calculations. In the literature, researchers generally conduct laboratory tests to calculate the impacts of different driving conditions.

3.2. Research Motivation and Objectives

Although there are a wide range of studies evaluating environmental performance of EVs and PHEVs, studies covering spatial variations are relatively lower. The importance of electricity generation mix and driving patterns has been stressed in previous studies(Faria et al., 2013; Faria, Moura, Delgado, & de Almeida, 2012; Huo, Zhang, Wang, Streets, & He, 2010; Karabasoglu & Michalek, 2013; Kelly, MacDonald, & Keoleian, 2012; Ma, Balthasar, Tait, Riera-Palou, & Harrison, 2012; Marshall, Kelly, Lee, Keoleian, & Filipi, 2013; Raykin et al., 2012; Samaras & Meisterling, 2008; Sharma, Manzie, Bessede, Crawford, & Brear, 2013; Stephan & Sullivan, 2008). Samaras & Meisterling (2008) analyzed life cycle GHG emissions of PHEVs considering various electricity mix scenarios and the U.S. average driving patterns. Kelly et al. (2012) investigated the impacts of U.S driving patterns, demographic variations, and different charging scenarios on GHG emissions of PHEVs at national scale. Ma et al. (2012) conducted a full life cycle assessment of EVs considering marginal electricity mixes and driving conditions for the United Kingdom and California. One of the most comprehensive studies found in the literature was conducted by Faria et al. (2013), in which country scale temporal and spatial variations for France, Portugal, and Poland are taken into consideration and their impact on GHG emissions and energy use of EVs and PHEVs were highlighted. Raykin et al. (2012) examined how driving patterns influence the GHG emissions of PHEVs under various electricity generation mix scenarios in Ontario, Canada. Huo et al. (2010) investigated energy use and GHG emissions of EVs considering the various regional electricity generation mixes in China and their analysis revealed that EVs are not the best option to reduce GHG emissions in China due to high GHG intensity of China's current electricity generation mix. However, all of these studies are either at national level or for a specific region and most of them did not include marginal electricity mix scenario. Also, majority of the studies focused on use phase only, known as well-to-wheel analysis. This study differs from previous LCA studies by making comparisons across 51 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. The objectives of this chapter as follows:

1) to investigate impacts of regional driving patterns and electricity generation mix scenarios (marginal and average) on energy use and GHG emissions of alternative vehicle technologies,

2) to highlight how these spatial and temporal variations influence the vehicle technology preference at state level,

3) to show relative impacts of battery and vehicle manufacturing on GHG emissions and energy consumption within the total life cycle of vehicles,

4) to evaluate impacts of the possible policy implications.

3.3. Methodology

LCA is a widely accepted method to quantify the environmental impacts of products or processes throughout production, use, and end of life phases (Finnveden et al., 2009). Traditionally, there are two main methodologies to utilized in LCA literature: process based (P-LCA) and input-output based (IO-LCA). In this study, both of the approaches were used. Production and maintenance of vehicles, and the upstream emissions from gasoline supply were analyzed with Economic Input-Output Life Cycle Assessment model (EIO-LCA) (Carnegie Mellon University Green Design Institute, 2008), while electric power supply and battery manufacturing were analyzed with P-LCA. Additional information about LCA methods are provided in Chapter 2. Data used in this study is collected from publicly available sources such as the U.S. Life Cycle Inventory (LCI) database(National Renewable Energy Laboratory, 2013), GREET vehicle cycle model(Burnham, Wang, & Wu, 2006), eGRID database(EPA, 2009), and National Household Travel Survey (NHTS) (National Household Travel Survey, 2009). Fig. 2 shows the system boundary of the analysis.

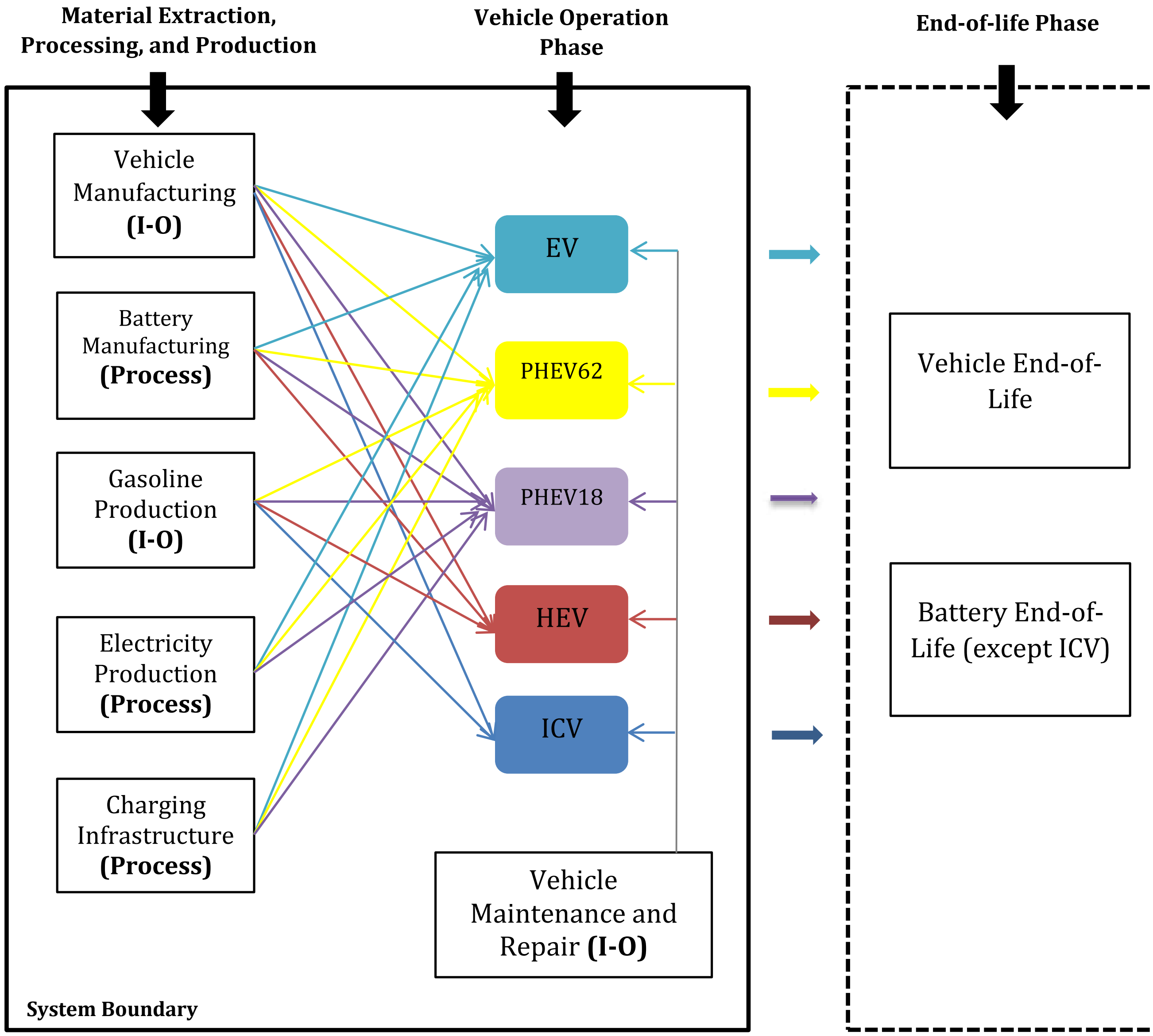


Figure 2. System Boundary of the Analysis

In this chapter, five vehicle types representing different vehicle technologies have been comparatively evaluated based on their energy consumption and GHG emissions for 51 states in the U.S. All vehicles are ranked based on their GHG emission amount and energy consumption for each state. To account for variability in the electricity generation profiles across 51 states, three different electricity generation scenarios are considered. These scenarios are as follows:

1) State-based average electricity generation mix: Based on state level electricity power generation profiles in 2009, derived data from the most recent eGRID database (EPA, 2009).

2) State-based marginal electricity generation mix: Estimated state-based marginal electricity mix profiles in 2020, derived data from National Oak Ridge Laboratory's estimations (Hadley W. & Tsvetkova, 2008) and literature(Thomas, 2012).

3) 100% solar powered charging stations: a futuristic scenario where there are solar charging stations and roof-top solar panels to charge electric vehicles are common in residential and commercial buildings.

The vehicle technologies considered are ICVs, HEVs, PHEVs, and EVs. Toyota Corolla (ICV), Toyota Prius (HEV), plug-in Toyota Prius (PHEV-AER18), Chevrolet Volt (PHEV-AER62), and Nissan Leaf (EV) has been selected to represent each vehicle technology. The physical features of the vehicles are presented in table 2.

Table 2. Comparison of physical features of the vehicles types

Vehicle Types	Weight (kg)	height (cm)	Width (cm)	Length (cm)	Coefficient of drag	EPA Size Class
ICV-Toyota Corolla-L 2014	1255	146	178	464	0.29	Midsize
HEV-Toyota Prius 2014	1380	149	174	448	0.26	Midsize
PHEV-Toyota Prius 2014	1436	149	174	448	0.26	Midsize
PHEV- Volt 2014	1717	144	157	450	0.28	Compact
EV-Nissan Leaf 2014	1493	155	177	445	0.28	Midsize

The useful life time for all vehicles is assumed to be 240,000 kilometers (150,000 miles). The functional unit of this study is 1 kilometer (km) of vehicle travel. GHG emissions are reported in grams CO_2 equivalent (g CO_2-eq.) based on 100 years of time horizon Global Warming Potential values recommended by the Intergovernmental Panel on Climate Change (IPCC Working Group I, 2001).

3.3.1. Vehicle Production

Energy consumption and GHG emissions from automobile manufacturing are calculated for each vehicle type by utilizing the EIO-LCA model (Carnegie Mellon University Green Design Institute, 2008), which consists of identical sectors and their interactions 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. Since the EIO-LCA model developed based on economic activities and interrelations of sectors in 2002, based on latest available data form the U.S. Department of Commerce, the input values (2013$) are converted into 2002$ by using the producer price indexes. It is assumed that the producer price of vehicles are 80% of the retail price (Samaras & Meisterling, 2008). Table 3 summarizes this conversion for each vehicle type. The battery cost is deducted from the vehicle costs, since impacts from battery production is calculated separately. Also, the vehicle manufacturing impacts, excluding the batteries, of HEV Prius and PHEV Prius are assumed to be same since both of the vehicles are identical and have exactly same vehicle body. The battery cost for Nissan Leaf was not available in the manufacturer's web site, and therefore, we have scaled its price by using weights of Volt's and Leaf's Li-ion batteries.

Table 3. Conversions of vehicle producer prices

	ICV-Toyota Corolla-L-2014	**HEV-Toyota Prius 2014**	**PHEV- Volt-2014**	**EV-Nissan Leaf-2014**
Purchaser price ($) (MSRP)	16,800	24,200	26,685	28,800
Producer price ($)	13440	19360	21348	23040
Battery cost ($)	0	2589	2,995	3160
PPI 2013	142.7	142.7	142.7	142.7
PPI 2002	134.9	134.9	134.9	134.9
Price for 2002 ($)	12705	15854	17350	18793

The automobile manufacturing sector multipliers corresponding to $1M dollars output for GWP and energy consumption are 563 tons of CO_2-eq and 8.33 Terajoule (TJ), respectively (Carnegie Mellon University Green Design Institute, 2008). The total impacts from vehicle manufacturing can be obtained by multiplying these multipliers with the corresponding input value for each vehicle type.

Additionally, the impacts from material production are separately calculated with EIO-LCA model after determining the material component of each vehicle. The material component of each vehicle type is estimated with GREET 2.7 vehicle cycle model by using their real weights. The EIO-LCA is preferred at this stage as well considering its ability capture impacts from entire supply chain and avoid of truncation error. In the GREET model, the material composition of each vehicle part is calculated by using the total weight of vehicles. After calculating weight of each material, their costs are determined and entered as an input to the relevant sector in the EIO-LCA model to calculate impacts from vehicle material production separately. These values are buried in the total vehicle production impacts However, it was not possible to track the source of the impacts from different phases of manufacturing. Therefore, vehicle manufacturing impacts are calculated separately. Table 4 and 5 show the vehicle weights for each vehicle type and their material compositions by weights. Weight of the batteries are obtained through GREET model by using their charge capacity values obtained from manufacturer's web sites. When calculating the impacts from vehicle manufacturing, the impacts of battery manufacturing is excluded since the price premium for HEVs, PHEVs, and EVs over a conventional vehicle mainly stems from the additional battery and electronics (Samaras & Meisterling, 2008).

Table 4. Vehicle weight with and without batteries

Weight (kg)	ICV-Toyota Corolla-L-2014(Toyota, 2014a)	HEV-Toyota Prius 2014(Toyota, 2014b)	PHEV- Volt-2014(Chevrolet, 2014)	EV-Nissan Leaf-2014(Nissan, 2014)
Weight (total)	1255	1380	1717	1493
Weight (excluding the batteries)	1255	1307	1456	1226

Table 5. Vehicle material composition by weight in kg

Vehicle Materials	ICV-Toyota Corolla-L-2014	HEV-Toyota Prius 2014	PHEV- Volt-2014	EV-Nissan Leaf-2014
Steel	753.340	859.316	965.717	813.992
Cast Iron	131.756	75.435	76.776	24.443
Wrought Aluminum	26.603	22.970	25.957	12.681
Cast Aluminum	56.066	66.061	69.087	67.109
Copper/Brass	22.626	55.855	62.707	57.390
Magnesium	0.213	0.237	0.269	0.262
Glass	34.683	38.492	43.709	42.627
Average Plastic	134.516	137.406	153.756	148.516
Rubber	27.288	22.813	25.046	21.542
Platinum	0.006	0.004	0.005	0.000
Others	22.859	28.662	32.472	37.225

Producer unit prices ($/kg) for each material type are multiplied with each weight of the each material to obtain their costs. Then, the relevant sector multipliers from the EIO-LCA are derived to calculate the GWP and energy consumption associated with vehicle material production. Table 6 indicates producer prices and sector multipliers for each material type. Unit prices of each material are obtained from the U.S. Geological Survey database(U.S. Geological Survey (USGS), 2014).

Table 6. Producer prices of vehicle materials ($2002) and corresponding sector multipliers from EIO-LCA

Material	ICV	HEV	PHEV	EV	NAICS sector ID	GWP (ton CO_2eq./$M)	Energy (TJ)
Steel	163.1	186.1	209.1	176.2	331110	3660	43.3
Cast Iron	3.4	1.9	2.0	0.6	212210	3660	43.3
Wrought Aluminum	38.0	32.8	37.1	18.1	33131A	3340	49
Cast Aluminum	80.2	94.5	98.8	96.0	33131A	3340	49
Copper	37.8	93.3	104.8	95.9	331420	906	15.1
Glass	3.9	4.3	4.9	4.8	327211	2050	37.1
Average Plastic	243.7	249.0	278.6	269.1	325211	2510	42
Rubber	13.3	11.1	12.2	10.5	325212	894	14.4
Platinum	108.5	77.5	79.2	0.0	339910	746	8.68

GWP and Energy consumption from vehicle and material manufacturing are represented in table 7. The impacts are represented per km of vehicle travel.

Table 7. GWP and energy consumption from vehicle and material production per km of vehicle travel

		ICV	HEV	PHEV	EV
Vehicle Production	GWP (gram of CO_2-eq.)	29.63	36.98	40.46	43.83
	Energy consumption (MJ)	0.44	0.55	0.60	0.65
Material Production	GWP (gram of CO_2-eq.)	7.25	7.87	8.70	7.50
	Energy consumption (MJ)	0.10	0.11	0.12	0.11

These results are also compared with other studies from literature. In the literature, the GWP impacts from vehicle production ranges between 27 to 62.4 gCO_2-eq/km depending on the assumed useful life for vehicles and vehicle characteristics (Hawkins et al., 2012).

Impacts from battery production is calculated with the P-LCA and explained in the following subsection. Impacts from vehicle and battery production are assumed to be independent from the regional variations since majority of the vehicles are manufactured in specific places and driven in the entire country. GHG emissions and energy consumption from end of life phase are found to be quite small compared to other life cycle phases and therefore neglected in this analysis (Schmidt et al., 2004). However, as the 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 emissions and energy consumption associated with vehicle production stage. Furthermore, the recycling of these materials can be more important (Geyer, 2008; Kim, McMillan, Keoleian, & Skerlos, 2010; Stephan & Sullivan, 2008).

3.3.2. Battery Production

The choice of battery for the vehicle technologies depends on cost, lifetime, performance characteristics such as depth of discharge, behavior under high and low temperature, energy density, and their environmental impacts. EVs and PHEVs typically use lithium ion (Li-ion) batteries, while nickel–metal hydride battery (Ni-MH) is mostly preferred to power HEVs due to its relatively lower cost (Burke, 2007). A major advantage of Li-ion batteries is that they provide a high power and energy density. Additionally, they require little maintenance and there is no scheduled cycling to prolong the battery's life, small self-discharge, and no memory effect (Notter et al., 2010). Considering that Ni-MH batteries has lower energy density (Wh/kg), they can increase the weight of the vehicle considerable, which is not desirable since increased weight generally result in loss in fuel efficiency. Li-ion batteries are expected to be the most common battery technology in EVs in the near future owing to their higher energy density and decreasing cost (Hawkins et al., 2012). The HEV in our analysis uses Ni-MH battery, while others (PHEVs, EVs) have Li-ion batteries as an electricity storage device. GREET 2.7, vehicle cycle model, were utilized to calculate GHG emissions and energy use from battery production. The weights of the batteries are determined by equations in the GREET 2.7 model using peak battery power and battery energy values, which were obtained from manufacturer's websites. These values are presented in Table 8 and 9.

Table 8. Properties of Li-ion batteries

Vehicle Type	Battery Type	Peak battery energy(kWh)	Battery Specific Energy (Wh/kg)	Battery weight (kg)
EV- Leaf	Li-Ion	24.0 (Nissan, 2014)	102.0	235
PHEV-Prius	Li-Ion	4.4 (Toyota, 2014c)	55.1	80
PHEV-Volt	Li-Ion	16.5 (Chevrolet, 2014)	74.0	223

Table 9. Properties of the Ni-MH battery

Vehicle Type	Battery Type	Peak battery power (kW)	Battery Specific Power (W/kg)	Battery weight (kg)
HEV- Prius	Ni-MH	27 (Toyota, 2014b)	800	34

The GHG emissions and energy consumption from each battery are presented per vehicle km travel in table 10 bellow. The lifetime of the batteries are assumed to be same and 150,000 km, which is also life time of the vehicles.

Table 10. GHG emissions and energy consumption from battery production

Impact Category	HEV	PHEV-Prius	PHEV-volt	EV
GHG emissions (gCO_2-eq./km)	1.00	1.98	5.68	5.59
Energy (MJ/km)	0.017	0.029	0.079	0.077

According to the analysis results, GHG emissions from li-ion batteries 5.68, 5.59, and 1.98 gCO_2-eq./km for PHEV-AER62, EV, and 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 stems from battery lifetime assumptions. The life time is generally defined as a certain amount of charge-discharge cycles. However, there is no certain agreement regarding the unit of lifetime of batteries because of the uncertainties in use patterns and consumer behavior directly effecting the charge-discharge cycles (Hawkins et al., 2012). Another important source of the variability is that the studies compared are within the last 15 years and the battery technology significantly improved in recent years. Therefore, some recent studies were selected to make comparison between the results, which is presented in table 11. In this analysis, the lifetime of batteries are assumed to be same as the vehicle lifetimes and they are not replaced during the vehicles' operation phase. In the case of that battery is replaced in the future, the impacts from battery production may not be doubled since the battery industry is improving rapidly and energy requirement and GHG emissions intensity may possibly be lower than it is today. Impacts from battery production are assumed to be independent from the regional variations to be consistent with the same assumptions made for vehicle production.

Table 11. Comparison of GWP (kgCO_2 eq.) and Energy use (MJ) per kg of battery production

Battery Type	**Analysis Results**		**(Notter et al., 2010)**		**(Samaras & Meisterling, 2008), (Rydh & Sandén, 2005)**		**(Majeau-Bettez, Hawkins, & Strømman, 2011)**	
	GWP	Energy	GWP	Energy	GWP	Energy	GWP	Energy
Li-Ion	6.2	85.8	6.0	103.6	9.6	136.7	21.6	-
Ni-MH	7.2	118.2	-	-	8.4	116.8	20.1	-

Developments in battery technologies have the greatest potential towards widespread adoption of EVs (Cooney et al., 2013). On the other hand, they also have certain technological limitations, environmental and economic concerns associated with battery production and adoption. Although scope of this analysis is limited with GHG emissions and energy consumption, there are other concerns associated with battery production such as rare earth metals use and end of life treatment of batteries. Production capacity and material reserves for producing EV batteries mainly depends on rare earth metals (Nd, La, Ce, Pr) in NiMH batteries and cobalt in both NiMH and Li-ion batteries. However, resource availability concerns related to li-ion batteries are relatively much less significant than that of NiMH batteries (Hawkins et al., 2012; RYDH & SVARD, 2003). According to the USGS, rare earth metals are relatively abundant globally (USGS, 2009). Gaines and Nelson (Gaines & Nelson, 2010) investigated the issues related to li-ion batteries and concluded that even if 90% of the U.S. light duty vehicle compromise of PHEVs and EVS by 2050, the demand for lithium production would not surpass the current production capacity until and after 2030 if these batteries containing lithium are recycled.

3.3.3. Vehicle Operation Phase

Use phase is the most carbon and energy intensive phase in the life cycle phases of all vehicles (Hawkins, Singh, Majeau-Bettez, & Strømman, 2013; Ma et al., 2012; Samaras & Meisterling, 2008). The vehicles compared in this analysis are either powered with gasoline or electricity. Hence, analyzing the impacts of electricity generation, gasoline combustion, and their upstream are the most influential parts of this study.

Maintenance and Repair: GHG emissions and energy consumption associated with maintenance and repair (M&R) are also quantified, which has generally lower impacts compared to fuel supply. 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 is obtained from the U.S. Transportation Energy Data book (Transportation Energy Data book, 2012). The M&R cost for an ICV was approximately 5 U.S. cents per km in 2012. This cost is converted into 2002 dollars in value by using the consumer price indexes. The total life time M&R for an ICV is calculated as $8970. The M&R cost for an EV is approximately is 65-80% of an ICV due to fewer components and moving parts, and less maintenance requirement of electric motor in EVs (M. A. Delucchi & Lipman, 2001; Faria et al., 2013). In this analysis, the M&R cost of the EV are assumed to be 70% of and the ICV, while M&R cost of the PHEVs is assumed to be 80% of the ICV (M. A. Delucchi & Lipman, 2001). The cost for the HEV is assumed to be same as the ICV's.

Gasoline Supply: The upstream emissions and energy use associated with gasoline supply are also calculated with the EIO-LCA tool by using NAICS sector 324110, Petroleum Refineries. The producer price for a litre (L) was $0.76 in 2002, after deducting taxes and profit (C. T. Hendrickson, Lester, & Matthews, 2006). Upstream GHG emissions to produce 1 L of gasoline are calculated as 0.56 kgCO_2-eq., whereas the upstream energy consumption is calculated as 6.37 MJ per L of gasoline. Direct tailpipe emissions resulted from burning 1 L of gasoline is 2.26 kg kgCO_2-eq. (EPA, 2013). The key input parameters are presented in Table 12.

Table 12. Key input parameters to calculate impacts from gasoline use

Key input parameters	
Gasoline Producer Price per L ($2002) (C. Hendrickson, Lave, & Matthews, 2006)	0.20
Upstream emissions for production of 1 L gasoline (kgCO_2-eq)(Carnegie Mellon University Green Design Institute, 2008)	560. 20
Upstream energy consumption for production of 1 L gasoline (MJ)(Carnegie Mellon University Green Design Institute, 2008)	6.37
Direct emissions per L (kgCO_2-eq) (EPA, 2013)	2.26

The GHG emission amounts and energy consumption for ICV, HEV, and the gasoline operation mode of PHEV are calculated by determining the energy requirement of each vehicle type to travel 1 km. The energy delivered to the wheels through burning 1 L of gasoline is 8.9 kWh (U.S. Environmental Protection Agency Office of Transportation and Air Quality, 2006). Fuel economy labels reported by EPA are utilized to calculate energy consumption and GHG emissions from vehicle operation phase in gasoline mode. The fuel economy values for each vehicle are provided in table 13. Data for fuel economy values are obtained from the manufacturer's websites(Chevrolet, 2014; Nissan, 2014; Toyota, 2014a, 2014b, 2014c).

Table 13. Data for fuel economy of vehicles

	ICV	**HEV**	**PHEV-AER18**		**PHEV-AER62**		**EV**
			Electricity	Gas only	Electricity	Gas only	
Kilometers per Liter (KM/L)	13.2	21.3	40.4	21.3	37.8	15.7	48.5
Miles per gallon (MPG)	31	50	95	50	89	37	114

In order to calculate GHG emissions per vehicle kilometer traveled, gasoline consumption amount per kilometer needed to be determined. By using the impacts associated with production and combustion of 1 L of gasoline presented in table 12, impacts per km can be easily calculated. For instance, the ICV requires 1/13.2 L (0.076) to travel 1 km. Hence, the tail pipe emissions from combustion and production of the gasoline consumed can be calculated as follows;

GHG (gCO_2-eq/km) = Gasoline consumed (L)* [Direct emissions + Indirect emissions] (gCO_2-eq/L) (3.1.)

= 0.076* [2260+560.2]

= 214.34 gCO_2-eq/km

The energy delivered to the wheels through burning 1 L of gasoline is 8.9 kWh.

Similarly, the energy consumption of the ICV to travel 1km can be calculated as follows;

Energy use (MJ/km) = Gasoline consumed (L) * [Direct energy use + Indirect energy use] (3.2.)

= 0.076* [8.9 kWh*3.6 MJ/kWh+ 6.37 MJ]

= 2.92 MJ/km

The same methodology can be applied to the HEV and gasoline operation mode of the PHEVs. 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, which are explained in the following subsection.

Electricity Supply: Although electricity use in EVs and PHEVs does not cause tailpipe emissions, the way the electricity generated plays a crucial role in determining the GHG emissions and energy consumption resulted from operating vehicles in electric mode. The GHG emissions and energy consumption from electric power generation sector is calculated for each state using the electricity generation mix profiles in 2009 published by eGRID(EPA, 2009) database. The eGRID database also provides the GHG emissions for each state. However, upstream emissions such as 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 by using data from the U.S. LCI database(National Renewable Energy Laboratory, 2013). Both upstream and onsite GHG emission factors and energy consumption to generate electric power for each type of resource are given in Table 14.

Table 14. GHG emission and Energy consumption factors of various energy generation sources

Energy Source	GHG emission factors (gCO_2-eq/kWh)		Energy Consumption (kWh/kWh)	
	Direct	Indirect	Fuel	Feedstock
Natural gas	588	60	0.22	2.38
Coal	1050	61	0.06	3.10
Residual fuel oil	806	99	0.39	3.26
Nuclear	0	11	0.05	1.07
Hydro	0	8	0.00	0.00
PV	0	60	0.00	0.00
Biomass	43	2	0.24	5.14
Wind	0	15	0.00	0.00
Geothermal	0	122	0.00	0.00

Fuel and feedstock energy consumption values are obtained from GREET 2.7 model (Burnham et al., 2006). Indirect emission values are obtained from former literature (MacPherson, Keoleian, & Kelly, 2012). On the other hand, indirect GHG emission values for geothermal power plants and hydropower are also obtained from former literature (Samaras & Meisterling, 2008; Sullivan, Clark, Han, & Wang, 2010). All of these values are utilized to calculate impacts from electricity consumption for scenarios 1 and 2. In the first scenario, state-based electricity generation mix profiles taken from eGRID data base are used. Average GHG emission and energy consumption values per output of 1 kWh of electricity are calculated by using state based energy mix profiles, which is presented in Table 15.

On the other hand, it was assumed that the existing electricity generation capacity in the U.S. could support additional energy demand from use of PHEVs and EVs up to 50% of conversion of the U.S. light duty automobile fleet (Cooney et al., 2013; Denholm & Short, 2006; Stephan & Sullivan, 2008). For the third scenario which proposes widespread use of solar charging station, upstream emissions and energy consumption to construct required infrastructure for solar charging stations are also included (Engholm, Johansson, & Persson, 2013).

Scenario 1: Average electricity generation mix: As stated previously, Scenario 1 utilizes the state based average energy generation mixes. On the other hand, it is important to note that there are imports and exports among some states, which may influence the GHG emission factors calculated for each state. There were ten states importing 25% or more of its energy demand from surrounding states in 2000 (Marriott & Matthews, 2005). The import and export values are published by the department of Energy routinely. However, this published data does not indicate the importers and exporters and the amount of the interstate trade. They simply subtract the gross electricity consumption from the gross electricity generation. In this regard, Marriot and Matthews estimated the consumption mix of each state as of the year 2000 by utilizing a distance based optimization model (Marriott & Matthews, 2005). They assumed that electricity sales will follow the shortest distance. According to their model, imported electricity were assumed to be having the same generation mix of the state importing that electricity. On the other hand, a large coal-based power plant might be establish next to the border of an importing state which might possibly purchasing 100% coal based generated electricity, rather than generation mix of the exporting state. The complexity of finding consumption based electricity mix profiles for states were stressed by Marriot and Matthews. Considering the abovementioned facts, we did not use consumption based mixes. It should be noted that the calculated GHG intensity for states can be significantly different for the states that have high export or import.

Table 15. State-based GHG emission and energy consumption factors per kWh of electricity generation

States	GHG emission factor (gCO_2-eq/kWh)	Energy consumption for power generation (kwh/kwh)
AK	602.12	2.32
AL	553.13	2.25
AR	586.67	2.34
AZ	574.70	2.25
CA	394.96	1.86
CO	834.95	2.71
CT	300.73	1.82
DC	905.56	3.65
DE	846.04	2.93
FL	650.31	2.60
GA	673.65	2.53
HI	828.91	3.32
IA	774.63	2.46
ID	96.65	0.54
IL	505.57	2.10
IN	993.16	3.05
KS	764.05	2.55
KY	993.02	3.06
LA	598.73	2.48
MA	613.70	2.53
MD	612.31	2.32
ME	326.55	2.47
MI	748.63	2.68
MN	631.81	2.37
MO	872.31	2.80
MS	590.68	2.50
MT	631.83	1.94

States	GHG emission factor (gCO_2-eq/kWh)	Energy consumption for power generation (kwh/kwh)
NC	605.75	2.33
ND	909.17	2.75
NE	713.66	2.48
NH	335.56	1.97
NJ	313.99	1.85
NM	909.16	2.90
NV	659.89	2.42
NY	327.62	1.64
OH	902.87	2.92
OK	774.26	2.65
OR	251.10	0.99
PA	595.40	2.33
RI	636.73	2.65
SC	432.93	2.04
SD	429.10	1.29
TN	554.63	2.11
TX	687.61	2.52
UT	950.09	2.98
VA	512.48	2.30
VT	11.29	1.14
WA	159.55	0.68
WI	722.56	2.60
WV	1006.04	3.05
WY	959.99	2.91
U.S. Avg.	663.3832	2.37

The geographic uncertainty regarding GHG emission factors from electricity generation were also highlighted by Weber, Jiaramillo, Marriott, & Samaras, (2010). They have compared 7 different estimation of GHG emission factors for states including the state consumption mixes calculated by Marriot and Matthews and concluded that there are high variations between the GHG emission factors from various datasets. Although some of the dataset they compared were from different years and some of them were reported emissions by companies, there are variations among different reports for state based GHG emission factors. To overcome this problem, GHG emission rate and energy consumption values are varied within a certain range to show its effect on the vehicle preference, which is presented in the results section.

Scenario 2: Marginal electricity generation: Since GHG intensity of the electricity generation highly depends on the energy source, the generation mix of the incremental electricity demand, known as marginal electricity, from EVs and PHEVs should be also taken into account. Inclusion of marginal electricity to calculate associated GHG emission intensity is suggested by many researchers(Chen, Sijm, Hobbs, & Lise, 2008; Dotzauer, 2010; Elgowainy, Han, Poch, & Wang, 2010; Hawkes, 2010; McCarthy & Yang, 2010). Marginal electricity demand is usually provided through fossil fuels which have significantly higher GHG intensity and therefore causes higher operation phase emissions for EVs and PHEVs. The reason behind is that the low GHG intensity power generation sources such as nuclear, solar, and wind are generally 100% in use and remained fluctuating electricity demand provided through nonrenewable sources such as natural gas, coal, and petroleum due to their relatively lower short-run marginal costs(Ma et al., 2012). The utilized production capacity of renewable energy sources are generally not restricted or driven by the change in electricity demand. They are rather influenced by the availability of sunlight for solar, wind for wind turbines, weather conditions for hydropower, and security reasons for nuclear power plants (Dotzauer, 2010). The marginal electricity mix scenario is developed to account for impacts from different generation costs, demand patterns over the day and season. Due to the need for instantaneously meeting the electricity demand, electricity power generation operators rely on different generation sources to secure the grid stability. For example, while nuclear power and hydroelectric power plants usually provide steady supply to meet the base electricity load demand, natural gas or coal power plants provide the supply for some portion of the base load and mostly peak demand above the base load. Estimating the marginal electricity generation profiles of states is quite complex due to demand load that varies significantly by time (Weber et al., 2010). Marginal generation mix depends on both temporal and spatial variations.

The marginal electricity mix profiles are obtained from a study conducted by Hadley and Tsvetkova at the Oak Ridge National Laboratory (Hadley W. & Tsvetkova, 2008). They estimated regional marginal mixes by using the Oak Ridge Competitive Electricity Dispatch (ORCED) computer model. This model utilizes data from National Energy Modeling System containing information about 21,000 electrical generation plants in the U.S. The study conducted by Hadley and Tsvetkova is based on the North American Electricity Reliability Corporation (NERC) regions specified in 2007 Annual Energy Outlook (AEO). The projections of AEO for possible electricity generation mixes were utilized to calculate marginal electricity mixes for 2020 and 2030. There were 6 scenarios which combines two charging periods (Evening charging from 5 pm to 6 pm and Night-time charging from 10 pm to 11 pm) and three charging rates (1.4 kW, 2 kW, 6 kW). They have compared the base case (without any PHEV) and these six scenarios and determined which electric plants need to generate more electricity to supply additional load resulted from charging PHEVs. They assumed that 25% of the existing fleet is replaced by the PHEVs in 2020 through 2030. Sandy (Sandy Thomas, 2012) simplified the analysis conducted by Oak Ridge Laboratory and averaged the marginal grid results of 6 scenarios. Additionally, Sandy calculated marginal electricity mix profiles for Alaska and Hawaii, which were not included in the Oak Ridge'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 base marginal emissions are calculated for each region associated with these states and multiple results are provided. State based marginal GHG emission and energy consumption factors are presented in table 16. In addition to inclusion of marginal electricity mix profiles, electricity transmission loss factors for each region are also taken into consideration for both scenarios.

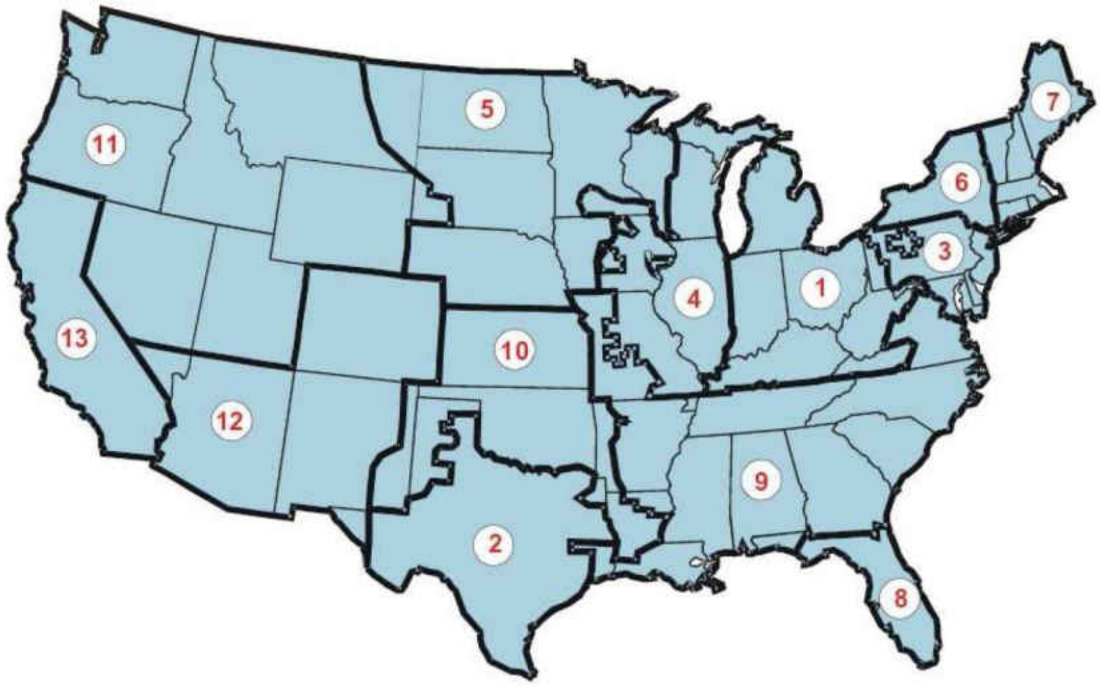
Table 16. State-based GHG emission and energy consumption factors per kWh of marginal electricity generation in 2020

States	NERC Region Abbreviation	GHG emission factor (gCO_2-eq/kWh)	Energy consumption for power generation (kwh/kwh)
AK	N/A	724.86	2.82
AL	SERC	770.94	2.75
AR	SPP	674.47	2.65
AZ	WECC-RMP/ANM	676.85	2.64
CA	WECC-CA	645.77	2.59
CO	WECC-RMP/ANM	676.85	2.64
CT	NPCC-NE	770.81	2.93
DC	MAAC	774.20	2.85
DE	MAAC	774.20	2.85
FL	FRCC	683.37	2.75
GA	SERC	770.94	2.75

States	NERC Region Abbreviation	GHG emission factor (gCO_2-eq/kWh)	Energy consumption for power generation (kwh/kwh)
HI	N/A	911.30	3.65
IA	MAIN	892.70	2.95
	MAPP	751.54	2.76
ID	WECC-NW	648.46	2.60
IL	MAIN	892.70	2.95
IN	ECAR	864.73	2.90
KS	SPP	674.47	2.65
KY	ECAR	864.73	2.90
LA	SERC	770.94	2.75
MA	NPCC-NE	770.81	2.93
MD	MAAC	774.20	2.85
ME	NPCC-NE	770.81	2.93
MI	ECAR	864.73	2.90
MN	MAIN	892.70	2.95
	MAPP	751.54	2.76
MO	SERC	770.94	2.75
	MAIN	892.70	2.95
MS	SERC	770.94	2.75
MT	WECC-NW	648.46	2.60
	MAPP	751.54	2.76
NC	SERC	770.94	2.75
ND	MAPP	751.54	2.76
NE	MAPP	751.54	2.76
NH	NPCC-NE	770.81	2.93
NJ	MAAC	774.20	2.85
NM	WECC-RMP/ANM	676.85	2.64
NV	WECC-RMP/ANM	676.85	2.64
	WECC-NW	648.46	2.60
NY	NPCC-NY	699.22	2.77
OH	ECAR	864.73	2.90
OK	SPP	674.47	2.65
OR	WECC-NW	648.46	2.60
PA	MAAC	774.20	2.85
RI	NPCC-NE	770.81	2.93
SC	SERC	770.94	2.75

States	NERC Region Abbreviation	GHG emission factor (gCO_2-eq/kWh)	Energy consumption for power generation (kwh/kwh)
SD	MAPP	751.54	2.76
	WECC-NW	648.46	2.60
TN	SERC	770.94	2.75
TX	ERCOT	644.57	2.58
UT	WECC-NW	648.46	2.60
VA	SERC	770.94	2.75
	ECAR	864.73	2.90
VT	NPCC-NE	770.81	2.93
WA	WECC-NW	648.46	2.60
WI	MAPP	751.54	2.76
WV	MAIN	892.70	2.95
	ECAR	864.73	2.90
WY	WECC-NW	648.46	2.60

The NERC electricity generation regions defined by the Energy Information Administration for their 2007 AEO are shown in the Figure 2.



*NERC regions abbreviations: 1) East Central Area Reliability Coordination Agreement (ECAR), 2) Electric Reliability Council of Texas (ERCOT), 3) Mid-Atlantic Area Council (MAAC), 4) Mid-America Interconnected Network (MAIN), 5) Mid-Continent Area Power Pool (MAPP), 6) Northeast Power Coordinating Council/New York (NPCC-NY), 7) Northeast Power Coordinating Council/New England (NPCC-NE), 8) Florida Reliability Coordinating Council (FRCC), 9) Southeastern Electric Reliability Council (SERC), 10) Southwest Power Pool (SPP), 11) WECC/ Northwest Power Pool Area (WECC-NW), 12) WECC/Rocky Mountain, Arizona, New Mexico, S. Nevada Power Area (WECC-RMP/ANM), 13) WECC/California (WECC-CA).

Figure 3. NERC Regions of EIA's Electricity Sector Model

Scenario 3: Scenario 3 proposes a widespread use of solar power to charge EVs. The use of solar power is provided through roof-top solar panels in residential and commercial buildings and solar charging stations. In the scenario 3, the life cycle emission and energy values for solar charging station are derived from Engholm et. al.(Engholm et al., 2013). They calculated the LCA impacts of a solar charging station, which consists of a steel frame standing on a concrete ground. The station has two solar PV modules; each has 7 m2 surface area and mounted on the top of the steel frame. Additionally, the system contains several electronic components such as an inverter, cables, and transformers. The GHGs emitted from construction of this system including the emissions from manufacturing the PVs, are calculated as 72 gCO_2-eq per 1 kWh of electricity output. The energy consumption to generate 1 kWh of electricity is estimated as 0.11 kWh. In this scenario state-based ranking for each vehicle type is affected by the driving patterns only, since the power generation scenario were assumed to be identical for each state.

Driving Patterns: Another important source of the variability among the states is the driving patterns, which refers to actual daily vehicle km travel patterns in this study. Since PHEVs use both of the energy sources, gasoline and electricity, determining the portions of total vehicle travels in each mode is a significant parameter in calculating their impacts. The percentage of the distance traveled in electric mode is represented as a parameter, known as utility factor (UF). The UF depends on the AER of PHEVs. A longer AER capability will provide a greater share of the kilometers travelled in electric mode, which means 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 less than a given distance per day. For instance, 35% of the vehicle km travels are less than 18 km in the state of Florida, which means the utility factor of the PHEV-AER18 (Prius) is 0.35. .In order to account for regional variability, specific UFs for each state are calculated using the online table designer tool developed by NHTS (National Household Travel Survey, 2009). It should be noted that the PHEVs are assumed to be fully charged once in a day. The data for daily vehicle kilometers travelled are collected for each from National Household Travel Survey database (National Household Travel Survey, 2009). The main objective was to find what percentage of daily travel can be powered by PHEVs depending on their AER features. Basically, vehicle kilometer traveled data are collected for some distance intervals and it is converted into a cumulative table which shows the total vehicle kilometer travelled less than a given distance. It should be noted that the given values are based on average daily values. Therefore, any vehicle trip that is more than 3090 km is omitted considering that a vehicle can travel maximum 3090 km (1920 miles) with 129 km (80 mph) in 24 hours (MacPherson et al., 2012)

After calculating state-based UFs, the GHG emission of PHEVs can be calculated as follows;

$$GHG/km= UF*[(kWh/km) * (GHGpower\ generation/kWh)] + (1-UF) * [(Lgasoline/km) * (GHG\ gasoline\ production/\ Lgasoline)] \quad (3.3)$$

Basically, Eq. 3.3 has two main parts, where the emissions from electricity consumption are calculated in the first part. The second part is used to calculate the emissions from gasoline consumption. Similar methodology is applied to calculate energy consumption of PHEVs.

3.4. Results

The results for the U.S. average case (at national scale) are given as a base scenario to compare its results with Scenarios 1, 2, and 3. Also, contribution of each life cycle phase is calculated. According to the results at national scale, the PHEV18 reduces the GHG emissions by 29% compared to ICVs, while the GHG emissions for EV, HEV, and PHEV18 are relatively similar. Emissions from vehicle and material manufacturing range from 11% to 23% of the total life cycle emissions and these emissions are highest for the EVs. GHG emissions from battery manufacturing are found to be insignificant compared to total life cycle emissions and it is the highest for production of li-ion batteries for EV and PHEV62. Operation phase is the most dominant phase for both GHG emissions and energy consumption. Figure 4 shows the total life cycle impacts and contribution of each phase per vehicle kilometer travel.

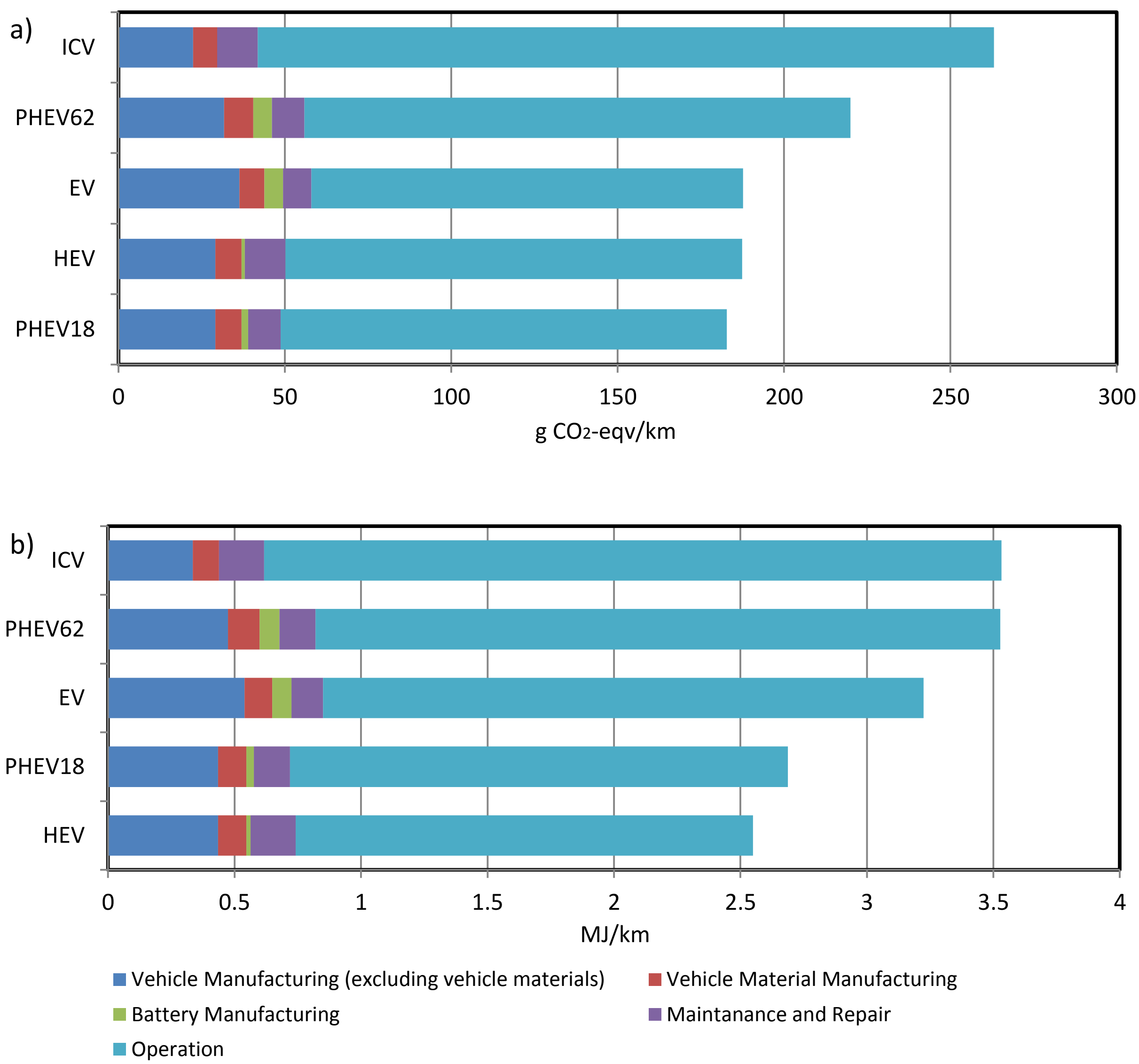


Figure 4. Life cycle impacts of each vehicle type; a) GHG emissions, b) Energy consumption

Form energy consumption perspective, the best option is found to be HEVs. EVs and longer range PHEVs are found to be less energy efficient. This might be stemming from the losses during the transmission, distribution, and generation of electric power, which decrease the efficiency of the energy utilization. Based on 2009 electricity generation mix in the U.S., 2.37 kWh (Feedstock+ fuel) of energy is required per kWh of electricity generation(Burnham et al., 2006; EPA, 2009). The contribution of each phase to the total life cycle impacts are similar to that of GHG emissions. Since the energy consumption and GHG emission impacts highly depend on electricity generation mix, the results for each state will vary significantly.

3.4.1. State-based Average Electricity Generation Mix Scenario

When state specific average electricity generation mix and driving patterns are taken into account, the results for each state are quite different compared to U.S. average results at national scale. Figure 5 shows the best vehicle option for each state in the terms of GHG emission and energy consumption. According to the results of the scenario 1, EVs are the least carbon-intensive vehicle option in 24 states which account for the 56% of the number of registered light duty vehicles (LDVs) in the U.S. In other words, 56% of the LDVs in U.S. have a significant GHG reduction potential if they are replaced with EVs. On the other hand, 10 states (23% of the total number of LDVs) favor the PHEV18 option based on spatial characteristics from GHG emission perspective. HEVs are better options for 17 states (21% of the total number of LDVs). PHEV62 and ICV were not ranked as a best option in any state.

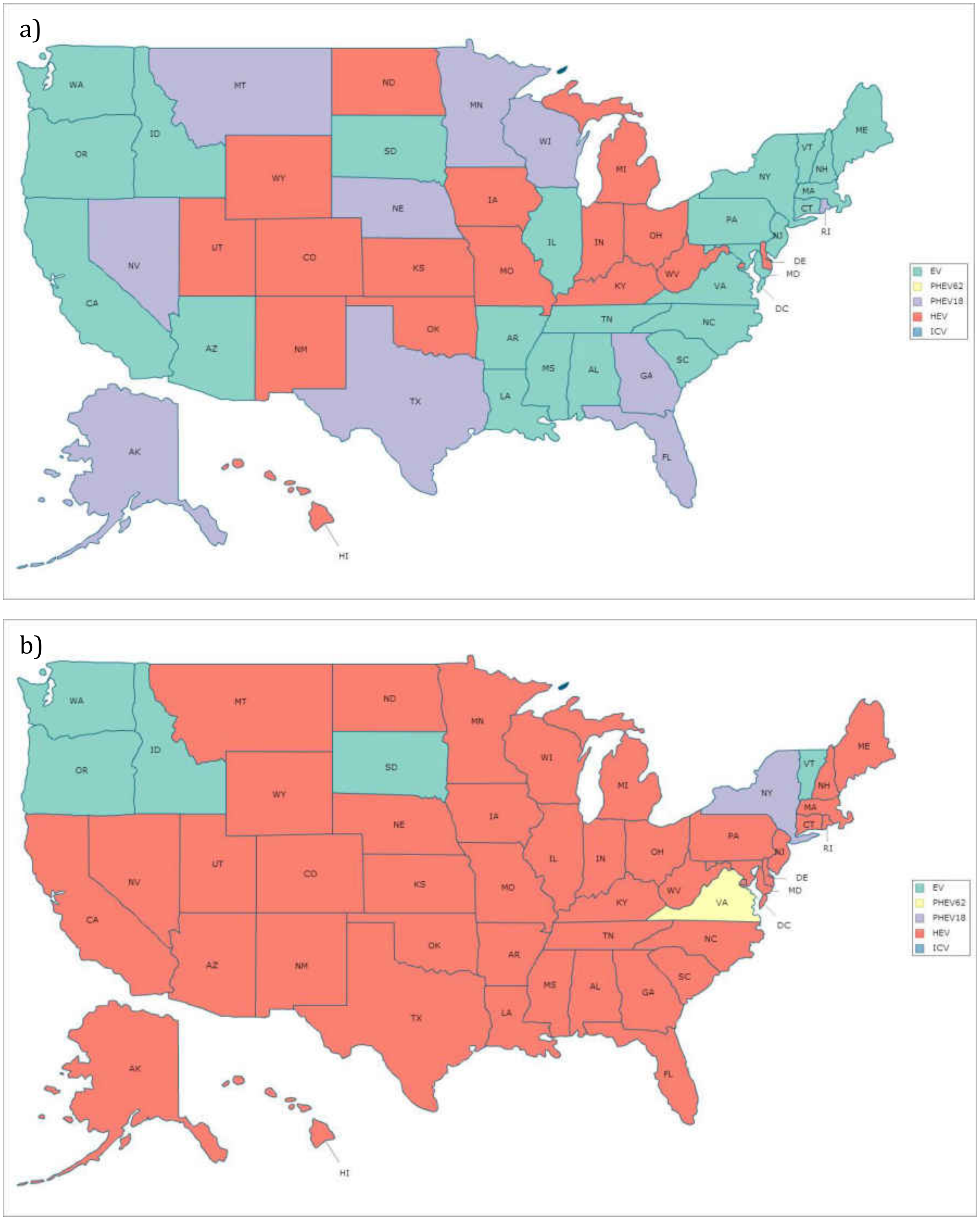


Figure 5. State level vehicle preference results according to scenario 1; a) GHG emissions, b) Energy consumption

Energy consumption results are relatively homogenies compared to GHG emission results. HEVs are ranked as the best option in the majority of the states, 45 states (91% of the total number of LDVs). On the other hand, EVs found to be better option in only 5 states. The rest of the states favor PHEV18 as a best option in the terms of energy consumption.

3.4.2. State-based Marginal Electricity Generation Mix Scenario

According to marginal electricity generation mix scenario, HEV is the least GHG intensive option in most of the states. The state-level preference based on GHG emissions is presented in Figure 6. Although scenario 2 is calculated based on NERC regions which are not bounded with the state borders, the states that are in multiple regions indicate the same result.

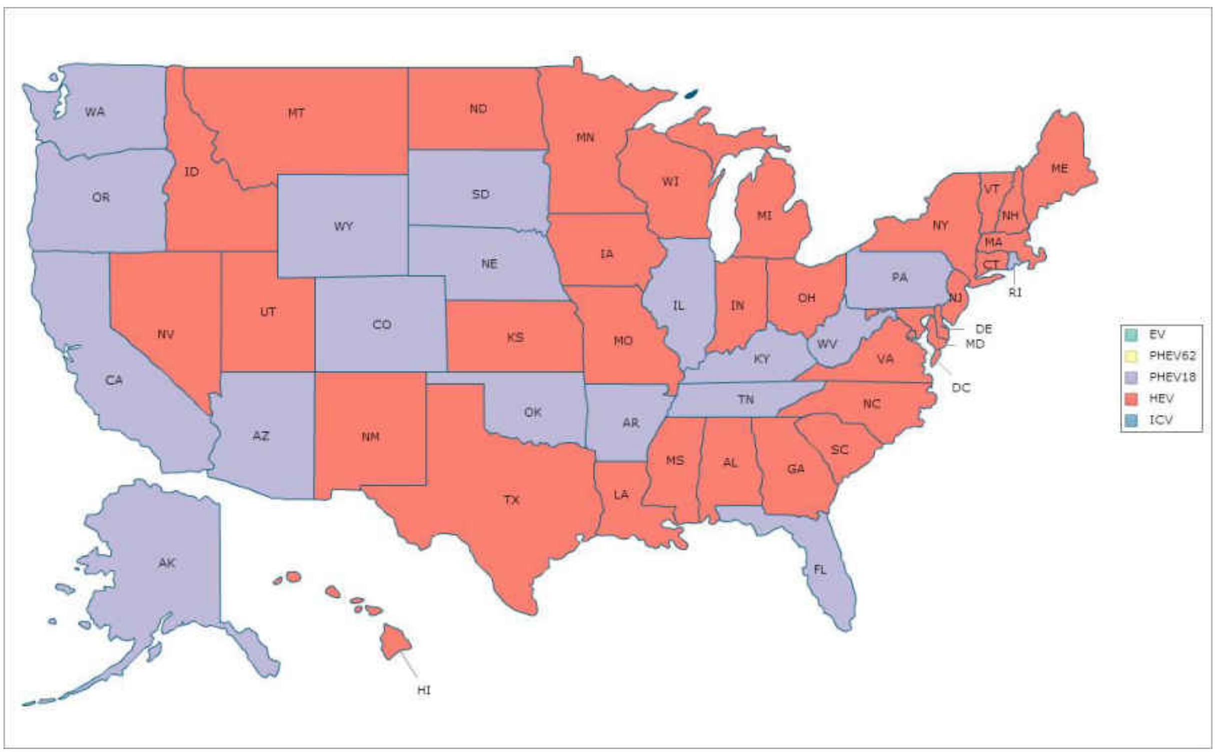


Figure 6. State level vehicle preference in the terms of GHG emissions for scenario 2.

According to Scenario 2, only two vehicle types are selected based on state-specific life cycle GHG emissions. There is significant change in GHG emission results of EVs compared to previous scenario. EVs are not ranked as the best vehicle option in any states. HEVs are ranked as the best option in 33 states (58% of the total number of LDVs), while PHEV18 are selected for 18 states (42% of the total number of LDVs). On the other hand, PHEV18 and ICVs are not favored by any of the states.

HEVs are found to be best option based on energy consumption performance of vehicle types in every state. Therefore, the state-specific results were not shown in a separate map. The second best option is PHEV18 for all of the states as well. The rest of the ranking order (3rd, 4th, and 5th) might be different based on state specific marginal electricity mix and driving pattern characteristics.

3.4.3. Solar Energy Scenario

As scenario 3 proposes widespread use of solar power to charge EVs, the GHG intensity and energy required to produce electricity is 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 very low carbon electricity source (72 gCO_2-eq / kWh) and quite low energy requirements (0.11 kWh/kWh) to generate electricity. These values are assumed to be identical for every state and hence, only spatial variation stems from the different driving patterns of the states. Additionally, the transmission and distribution losses are also saved compared to the previous scenarios. The total life cycle GHG emissions and energy consumption per kilometer an EV travels is calculated as approximately 72 gCO_2-eq. and 1.59 MJ, respectively. According to scenario 3, the GHG emission reduction that can be achieved by utilization of EVs is 73%, while the energy consumption reduction is calculated as 55% compared to ICVs. These are the highest reduction rates compared to other scenarios.

3.4.4. Sensitivity of Important Parameters

The behavior of LCA impact trends of the vehicle options are also analyzed to account for variability in the GHG energy emission factors and energy consumption rates. LCA impacts of vehicle options are presented as a function of GHG and energy intensity in Figure 7. The UF values for PHEV18 and PHEV62 are assumed as U.S. average values. As can be seen from the figure, the PHEV62 has more GHG emission rate than ICVs when the GHG intensity of the electricity supply is above 950 gCO_2-eqv/kWh. Any GHG emission factor below 600 gCO_2-eqv/kWh makes EVs the least carbon intensive option. From energy consumption perspective, EVs are better option until the point where the required energy to produce 1 kWh of electricity is 1.25 kWh. Any power generation scenario above 1.75 kWh/kWh of energy consumption rate makes the HEVs the most energy efficient option, while the PHEV18 are the least energy intensive option in the range between 1.25 and 175 kWh/kWh.

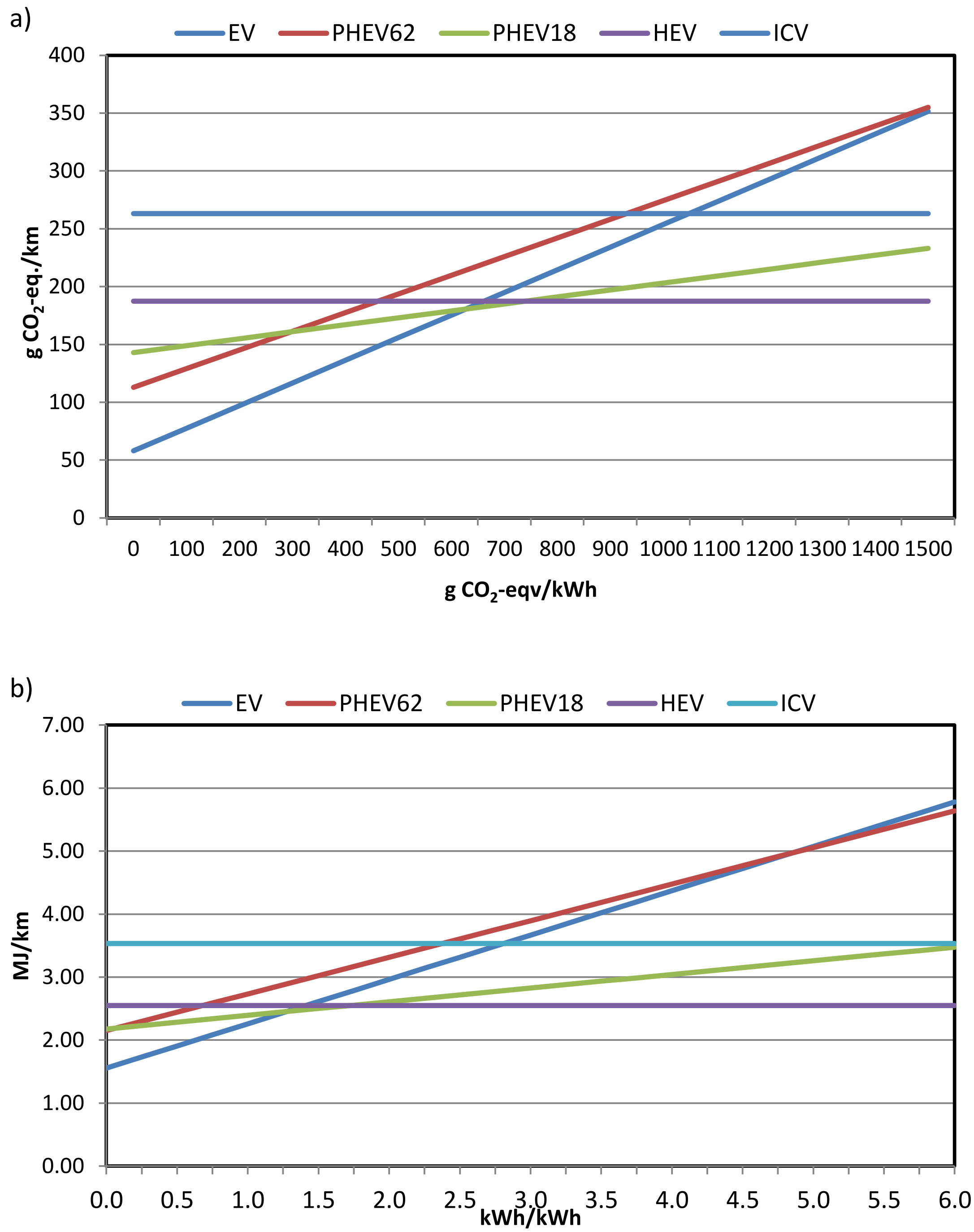


Figure 7. LCA impacts as a function of GHG and energy intensity, a) GHG emissions, b) Energy consumption per kilometer vehicle travels.

Similarly, 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 8.

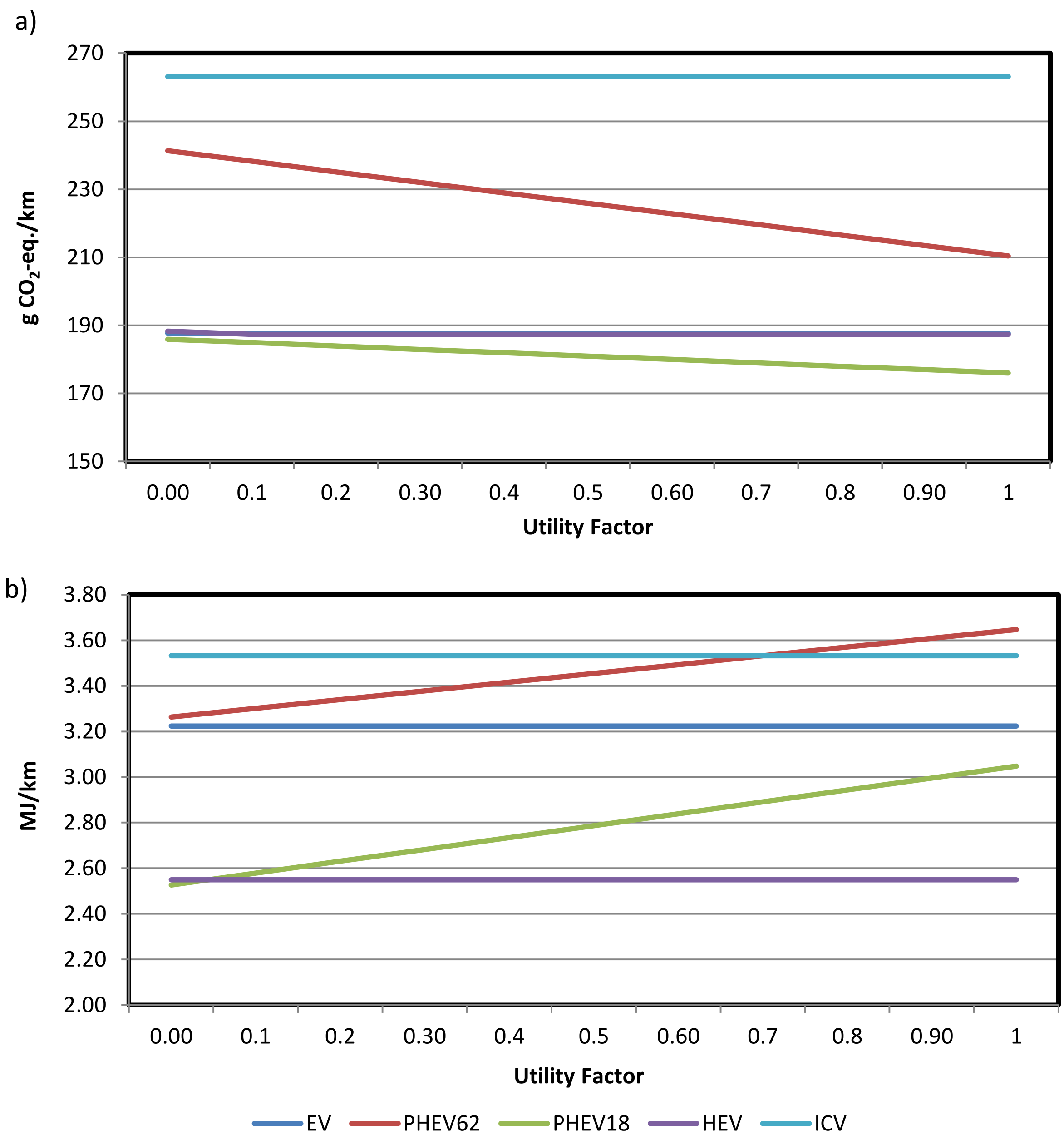


Figure 8. LCA impacts as a function of UF varying from 0 to 1, a) GHG emissions, b) Energy consumption per kilometer vehicle travels.

The sensitivity of GHG emissions and energy consumption are investigated under varying UFs. 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. As can be seen from Figure 7, 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.

CHAPTER 4: A MISSING GAP IN THE ENVIRONMENTAL ASSESSMENT OF ALTERNATIVE VEHICLE TECHNOLOGIES: STATE-BASED WATER FOOTPRINT ANALYSIS

Although electrical vehicles are receiving support from the United States federal government to achieve energy-efficient and carbon-neutral transportation, increasing levels of water demand become a particularly serious challenge for many states, especially since water is essential for producing petroleum and electricity as a transportation fuel. Unfortunately, no national research efforts as of now have been directed specifically toward understanding the fundamental relationship between the adoption of electric vehicles (EVs) and water demand. In this regard, this research aims to fill this knowledge gap and provide a practical decision-making platform with which to analyze the potential water impacts resulting from the increased usage of alternative vehicle technologies in the United States. In this chapter, 5 vehicle types - Internal Combustion Vehicles (ICVs), Hybrid Electric Vehicles (HEVs), Plug-in Hybrid Electric Vehicles (PHEV20, PHEV40) and Battery Electric Vehicles (BEVs) - are analyzed across 50 U.S. states with 3 different electric power generation mix profiles: the state-based average electricity generation mix, the state-based marginal electricity generation mix, and a hypothetical electricity generation mix consisting entirely of solar-powered charging stations. With respect to the water footprint of each vehicle type, water consumption and water withdrawal are separately analyzed using what is known as a Well-to-Tank (WWT) analysis. State-specific variations related to electricity production and driving patterns are incorporated into the analysis in order to quantify the water footprints of electric vehicle usage on the national scale and on each specific regional scale.

4.1. Background

The United States (U.S.) has one of the largest transportation networks in the world with its immense fuel consumption and travel characteristics (Egilmez and Tatari 2012). While the U.S. transportation sector's energy consumption was observed to be 27.8% of the total energy consumption in the U.S., the petroleum-based share of the transportation energy consumption mix was 92.8% (Transportation Energy Data Book 2012). In the U.S. passenger transportation system, approximately 90% of the total vehicle miles travelled (VMT) was attributed to light-duty vehicles (National Transportation Statistics 2013). Combustion emissions from U.S. automobiles and light-duty trucks accounted for approximately 60% of greenhouse gas (GHG) emissions from the U.S. transportation sector, or 17% of total U.S. carbon emissions (Samaras and Meisterling 2008). Due to the aforementioned statistics, energy consumption and global climate change have become topics of considerable interest for sustainable vehicle transportation, and there is now a growing trend in use of electric cars in U.S. highways (Onat et al. 2014a; Onat et al. 2015a). However, vehicle water footprints are also becoming increasingly important due to the fundamental connection between water consumption/withdrawal and electricity production, as well as the adoption of energy- and carbon-efficient electric vehicle technologies, which have a direct impact on regional water demand levels.

Furthermore, the expected increase in the U.S. population will significantly boost the demand for light-duty vehicles, in turn simultaneously increasing domestic energy and water consumption levels. According to the 2001 National Energy Policy, the growing U.S.

population and economy will require 393,000 MW of new energy generating capacity by the year 2020, which in and of itself will put additional pressure on domestic water resources. Electricity production from fossil fuels and nuclear energy requires a total of 190 billion gallons of water per day, accounting for 39% of all freshwater withdrawals in the U.S., 71% of which goes to fossil-fuel electricity generation alone. Additionally, coal plants account for nearly 52% of the total U.S. electricity generation mix, requiring 25 gallons of water withdrawal per kWh of electricity generated from these coal plants (Sandia National Laboratories 2015). Overall, coal, nuclear and biomass energy are responsible for the largest water withdrawal levels in the U.S. (Fthenakis and Kim 2010). Among these energy sources, coal-based power generation is responsible for approximately 50% of the total water withdrawal, followed by irrigation, municipal water usage, and other categories.

Although the number of electric vehicles on U.S. highways has demonstrated an increasing trend, many concerns regarding the regional water footprint of electric vehicles must still be discussed. To better assess the energy-use-related water footprints of emerging electric vehicle technologies, this research aims to quantify the water consumption and withdrawal levels of ICVs, PHEVs, and BEVs in the United States. To that end, the scopes of the current research primarily focused on the water footprints of the vehicle operation phase and excluded other vehicle life-cycle phases, including the vehicle part manufacturing phase(s), the vehicle maintenance and repair phases, and the vehicle end-of-life phase. This assumption is made based on past studies showing that the vehicle operation phase is responsible for the highest energy consumption, whereas the contributions of other life-cycle phases were found to be considerably lower compared to the operation phase (Onat et al. 2014a; Onat et al. 2015a).

4.2. Literature review

Although past studies assessed the environmental performance of BEVs, no study has yet been performed covering spatial variations for water footprint analysis. The importance of the electricity generation mix and driving patterns has been stressed in previous studies (Huo et al. 2010), but no national research effort in the U.S. has yet been directed specifically at understanding the intimate relationship between the adoption of EVs and water usage. Similarly, no currently available study compares the total water footprints of ICEV, PHEV, and BEV technologies to investigate the impacts of regional driving patterns and electricity generation mix scenarios (marginal and average) on the water consumption and withdrawal of alternative vehicle technologies. The most important goal of this research is to address this vital knowledge gap, and so, in this research, ICEVs, PHEVs, and BEVs will be comparatively evaluated based on their water footprints for 50 U.S. states, with all vehicle types evaluated based on their water consumption and withdrawal levels in each state. To account for variability in the electricity generation profiles across the 50 states, three different electricity generation scenarios are considered. For clarity, a general overview of the steps used in this research is illustrated in Fig. 9.

Three policy scenarios were applied in Chapter 3, and are summarized as follows:

- ❖ State-Based Average Electricity Generation Mix: Based on state level electricity power generation profiles in 2009 and derived data from the most recent eGRID database (EPA 2009).
- ❖ State-Based Marginal Electricity Generation Mix: Based on estimated state-based marginal electricity mix profiles in 2020 and derived data from the National Oak Ridge Laboratory's estimations (Hadley and Tsvetkova 2008), as well as applicable literature (Thomas 2012).
- ❖ 100% Solar Powered Charging Stations: An extreme scenario in which electric vehicles are charged only through solar charging stations.

According to definitions cited by King and Weber (2008) and Blackhurst et al. (2010), the consumption and withdrawal of water are differentiated in this work and defined as follows:

- ❖ Water Consumption is the amount of water obtained from a surface water or groundwater source that is not directly returned to its original source. For example, water evaporation from cooling at a thermoelectric steam power plant is an example of water consumption.
- ❖ Water Withdrawal is the amount of water obtained from a surface water or groundwater source that is used in a process and then sent back to system. For example, the abstracted water used for cooling at a coal power plant and then

returned to the catchment that it was originally withdrawn from is an example of water withdrawal.

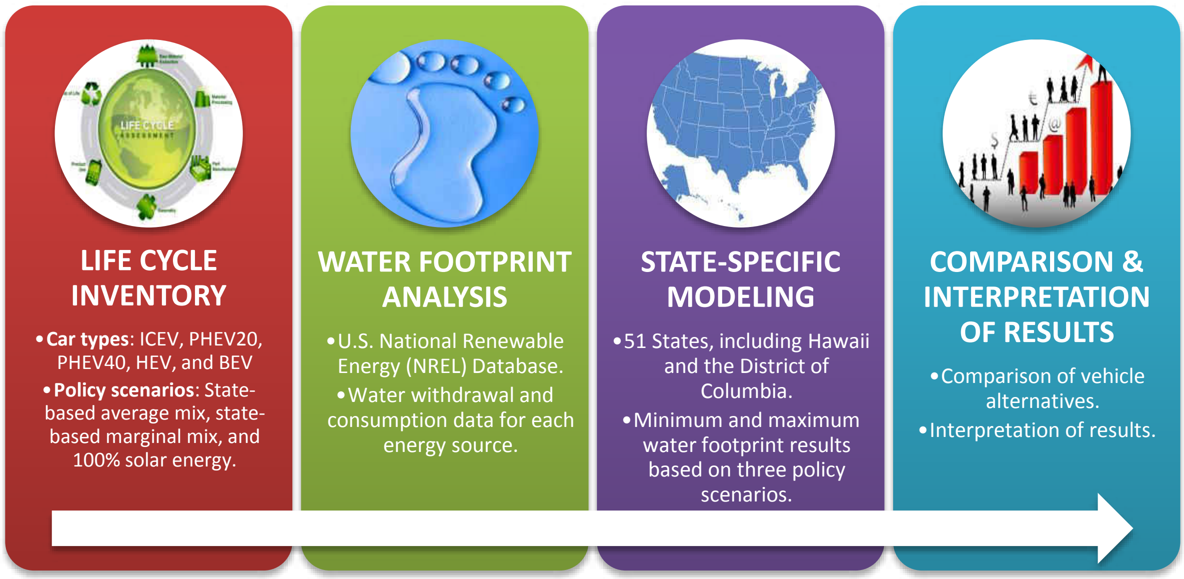


Figure 9 Overview of Chapter 4

4.3. Methodology

A Well-to-Wheel (WTW) analysis is a specific type of life cycle assessment used for transportation fuels and vehicles. There are two main stages in a WTW analysis, which consist of "well-to-tank (WTT)" and "tank-to-wheel (TTW)" analyses. The former (WTT) covers upstream impacts, including raw material extraction, fuel production, and fuel delivery, while the latter (TTW) is used for direct impacts such as tailpipe emissions during vehicle operation (Elgowainy et al. 2009). Since there is no direct water consumption in the vehicle operation phase except for car washing, the water footprint impacts of a car typically stem from the WTT part of the vehicle operation phase. Fig. 10 depicts the system boundary of this analysis. In this study, five types of vehicles (ICEVs, HEVs, PHEV20, PHEV40, and

BEVs) are analyzed, and their respective water withdrawal and consumption impacts are quantified across 50 states in the U.S. with three different electric power generation mix profiles in each state. Among the alternative vehicle technologies mentioned above, PHEVs have both an electric motor and an internal combustion engine, the former of which is powered via high capacity power-grid-based battery charging, allowing PHEVs to reduce their petroleum consumption to an extent by using electric power. The portion of the distance that a PHEV can travel by electricity alone depends on several important factors, including the all-electric range (AER) of the vehicle, the driving distance, and driving conditions (Raykin et al. 2012). AER is defined as the total miles that can be driven in electric mode ("engine-off") after the battery is fully charged, before the engine turns on for the first time (Markel 2006). The useful lifetime for all vehicles is assumed to be 150,000 miles. In addition to state-specific driving patterns obtained from the National Travel Household Survey (National Household Travel Survey 2009), three different electricity generation scenarios are considered to account for variability in the available power generation source(s). These electricity generation scenarios are based on the average and marginal electricity generation mixes, as well as a hypothetical scenario consisting of 100% solar electricity generation. For the average electricity generation mix, the average mixes provided by the eGRID 2009 database were utilized to calculate water withdrawal and consumption factors per kWh of electricity generation for each state (EPA 2009), and water withdrawal and consumption data for each fuel source is obtained from the National Renewable Energy Laboratory (NREL 2011). These factors are quantified in a similar manner for the marginal electricity generation scenario for 2020, using marginal electricity mix data from the National Oak Ridge Laboratory's estimations and literature (Hadley and Tsvetkova 2008; Thomas 2012). The third scenario proposes widespread use of solar charging stations, and assumes the use of 100% solar energy to power EVs and PHEVs. The life cycle inventory for a typical solar charging station is derived from Engholm et al. (2013). The functional unit of this analysis is 1 mile of vehicle travel.

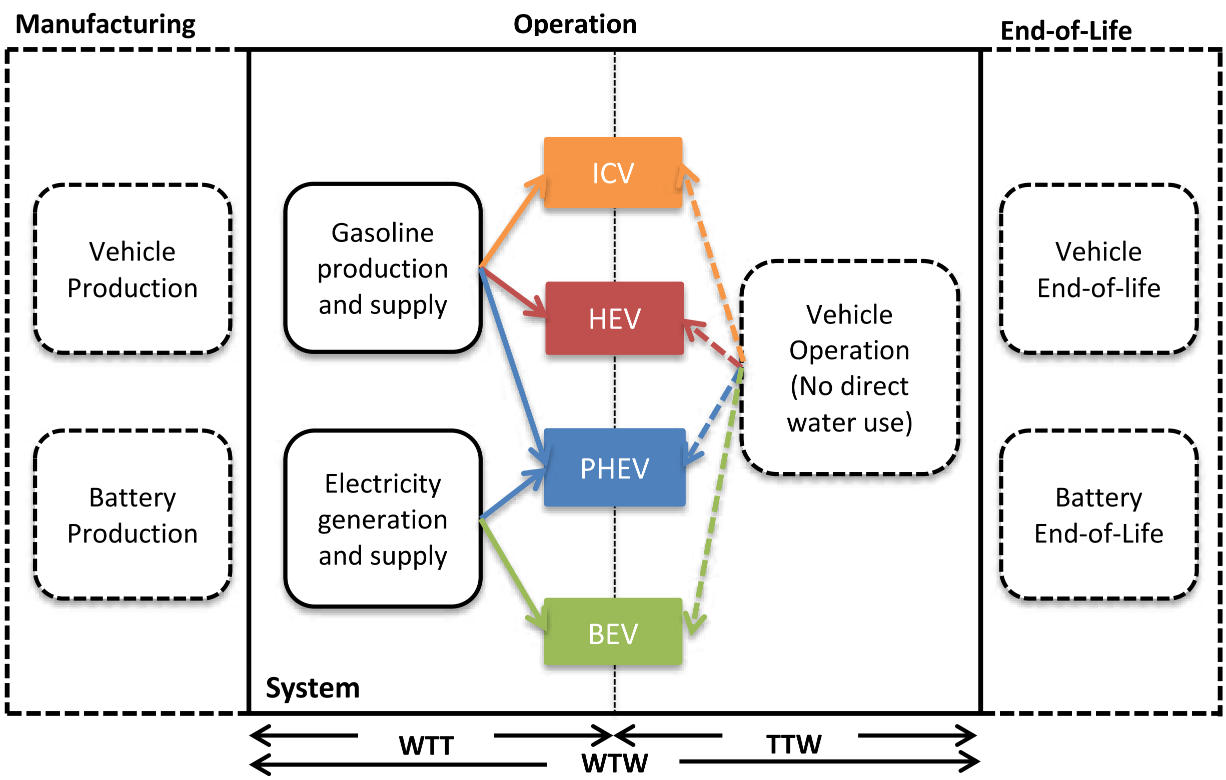


Figure 10. System boundary of this analysis (Note: Regions with dashed lines are excluded from the analysis)

4.3.1. Well-to-Tank ("WTT") Calculations

A WTT analysis is conducted for gasoline production and supply as well as for electricity generation and supply. Gasoline is consumed by ICVs, HEVs, and PHEVs, and the impacts associated with each vehicle type are quantified by determining how much gasoline they consume per vehicle mile traveled (VMT). The fuel economy (FE) of ICVs and HEVs is assumed to be 30 and 50 miles per gallon (mpg), respectively, whereas the FE of PHEVs is assumed to be 50 mpg in gasoline mode and 0.29 kWh/mile in electric mode. Finally, the FE of BEVs is assumed to be 0.30 kWh/mile, which is similar to the FE of the Nissan Leaf. Although these vehicles as modeled in this research are generic, the fuel economy values described above are relevant to their counterparts currently available in the market (Nissan 2014; Toyota 2014a,b,c). The gasoline and electricity consumption rates (FE values) of these vehicles are presented in Table 17. The electricity required to travel a mile includes regenerative braking benefits and efficiency losses in the battery, charger, and electric motor. Additionally, the transmission and distribution losses for each region that covers the corresponding states are taken into account when calculating WTT impacts.

Table 17. Gasoline and electricity consumption (fuel economy) of the studied vehicles (Onat et al. 2015a)

Vehicle Type	Gasoline (mpg)	Electricity (kWh per mile)
ICV	30	N/A(*)
HEV	50	N/A
PHEV20	50	0.29
PHEV40	50	0.29
BEV	N/A	0.3

N/A(*): Not available

After calculating the amount of gasoline required to travel 1 mile for each vehicle, the resultant amount is multiplied by applicable stochastic water consumption and withdrawal factors for petroleum production and supply, as presented in Table 18. Since HEVs and ICEVs only consume petroleum, their impacts are calculated by multiplying the amount of petroleum consumed to travel 1 mile by the associated water consumption and withdrawal factors, which indicate the amount of water consumed or withdrawn to produce and supply 1 gallon of gasoline. Eq. 4.1 below shows how the water consumption and withdrawal per mile are calculated for HEVs or ICEVs.

$$(\text{WTT impacts})_{\text{ICV or HEV}} = (1/\text{FE})_{\text{ICV or HEV}} * (\text{impact factor}_{\text{petroleum supply}}) \qquad (4.1)$$

On the other hand, since PHEVs use gasoline and electricity, their total impacts are the accumulation of impacts from both of these fuel supply sources. To estimate the portion of the VMT powered by electricity, the driving patterns of each state must be considered. In this study, the driving patterns in each state are considered for two AER options for PHEVs (PHEV20 and PHEV40) to calculate the regional impacts associated with PHEVs compared to internal combustion vehicles (ICVs). These driving patterns determine what portion of the VMT can be powered by electricity for various PHEV AER ranges. For instance, vehicles traveling less than 30 miles comprise approximately 63% of the daily VMT in the U.S. (The U.S. Department of Transportation 2009), but this percentage can vary from state to state, and hence the associated environmental impacts of PHEVs may vary significantly from one state to another. The driving patterns of each state determine what fraction of the total VMT is driven in gasoline mode and in electric mode; the fraction of the VMT driven in electric mode is defined with an indicator called the Utility Factor (UF). To calculate state-specific UFs, the daily cumulative VMT distribution for each state is constructed, thereby presenting the total portion of the VMT less than a given distance. The main objective is to estimate what percentage of daily travel can be powered by PHEVs in electric mode when their AER features are considered; a longer AER provides a greater share of the VMT in electric mode, which is represented by a higher UF. It is assumed that the PHEVs are fully charged once daily. VMT data for the U.S. states considered in this analysis (including Hawaii and the District of Columbia) are collected from 2009 National Household Travel Survey (NHTS) data using their online table design tool (National Household Travel Survey 2009).

Table 18. Water withdrawal and consumption factors of different fuel sources (gal/kWh)

	Withdrawal		Consumption	
Fuel Type	**Min**	**Max**	**Min**	**Max**
PV	0.026	0.033	0.026	0.033
Wind	0	0.001	0	0.001
Hydro	N/A(*)	N/A(*)	1.425	18
Oil	0.3	0.6	0.3	0.48
Nuclear	1.1	2.6	0.672	0.845
Natural gas	0.253	0.283	0.198	0.3
Coal	1.005	1.2	0.687	1.1
Bio power	0.878	1.46	0.553	0.965
Geothermal	1.796	1.796	1.796	1.796
Petroleum**	2.6	7.15	2	5.5

N/A(*): Not available

**The unit for petroleum is gal/gal indicating that gallons of water consumption/withdrawal to produce a gallon of petroleum

Electricity supply is another important component of the WTT analysis of this study, and is the main source of the observed regional variations owing to different electricity generation mixes from state to state. Each energy source utilized to generate electricity has different water withdrawal and consumption rates per kWh, as shown in Table 19 for each energy source type. It should be noted that the applicable water withdrawal factors can vary significantly based on the cooling method used in a particular power plant (Meldrum et al. 2013; World Energy Outlook 2012), so in this study, we used the minimum, maximum, and average values for each fuel type. Fig. 11 shows the percentage distribution of the electricity generation mix of each state based on Scenario 1 (S1), which, as explained previously, includes the average electricity generation profiles. It is important to note that the electricity consumption and generation mixes can vary significantly depending on each state's electricity imports and exports. Export and import data for 2009 has not yet been released, and even though these values are available for previous years, the exporter and importer states involved and the degree of interstate trade are not known, making the estimation of consumption mixes complicated and uncertain (Marriott and Matthews 2005).

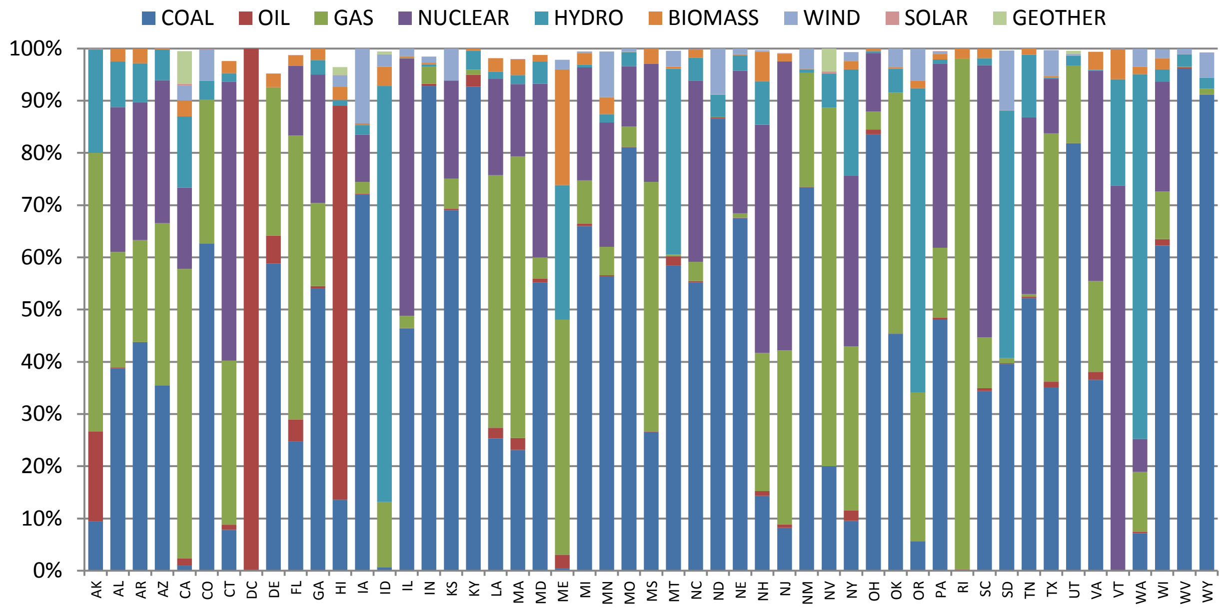


Figure 11. Percentage Distribution of Average Electricity Generation Mix in U.S. (abbreviations: Geotherm: Geothermal; Hydro: Hydropower)

Table 19. State-Specific Average Electricity Generation Mix (Scenario 1)

States	Coal	Oil	Gas	Nuclear	Hydro	Biomass	Wind	Solar	Geother
AK	0.09	0.17	0.53	0.00	0.20	0.00	0.00	0.00	0.00
AL	0.39	0.00	0.22	0.28	0.09	0.02	0.00	0.00	0.00
AR	0.44	0.00	0.20	0.26	0.07	0.03	0.00	0.00	0.00
AZ	0.35	0.00	0.31	0.27	0.06	0.00	0.00	0.00	0.00
CA	0.01	0.01	0.55	0.16	0.14	0.03	0.03	0.00	0.06
CO	0.63	0.00	0.28	0.00	0.04	0.00	0.06	0.00	0.00
CT	0.08	0.01	0.31	0.53	0.02	0.02	0.00	0.00	0.00
DC	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DE	0.59	0.05	0.28	0.00	0.00	0.03	0.00	0.00	0.00
FL	0.25	0.04	0.54	0.13	0.00	0.02	0.00	0.00	0.00
GA	0.54	0.01	0.16	0.25	0.03	0.02	0.00	0.00	0.00
HI	0.14	0.75	0.00	0.00	0.01	0.02	0.02	0.00	0.02
IA	0.72	0.00	0.02	0.09	0.02	0.00	0.14	0.00	0.00
ID	0.01	0.00	0.13	0.00	0.80	0.04	0.02	0.00	0.01
IL	0.46	0.00	0.02	0.49	0.00	0.00	0.01	0.00	0.00
IN	0.93	0.00	0.03	0.00	0.00	0.00	0.01	0.00	0.00
KS	0.69	0.00	0.06	0.19	0.00	0.00	0.06	0.00	0.00
KY	0.93	0.02	0.01	0.00	0.04	0.00	0.00	0.00	0.00
LA	0.25	0.02	0.48	0.18	0.01	0.03	0.00	0.00	0.00
MA	0.23	0.02	0.54	0.14	0.02	0.03	0.00	0.00	0.00
MD	0.55	0.01	0.04	0.33	0.04	0.01	0.00	0.00	0.00
ME	0.00	0.03	0.45	0.00	0.26	0.22	0.02	0.00	0.00
MI	0.66	0.00	0.08	0.22	0.01	0.02	0.00	0.00	0.00
MN	0.56	0.00	0.05	0.24	0.02	0.03	0.09	0.00	0.00
MO	0.81	0.00	0.04	0.12	0.03	0.00	0.01	0.00	0.00
MS	0.27	0.00	0.48	0.23	0.00	0.03	0.00	0.00	0.00

States	Coal	Oil	Gas	Nuclear	Hydro	Biomass	Wind	Solar	Geother
MT	0.58	0.02	0.00	0.00	0.36	0.00	0.03	0.00	0.00
NC	0.55	0.00	0.04	0.35	0.04	0.02	0.00	0.00	0.00
ND	0.87	0.00	0.00	0.00	0.04	0.00	0.09	0.00	0.00
NE	0.68	0.00	0.01	0.27	0.03	0.00	0.01	0.00	0.00
NH	0.14	0.01	0.26	0.44	0.08	0.06	0.00	0.00	0.00
NJ	0.08	0.01	0.33	0.55	0.00	0.01	0.00	0.00	0.00
NM	0.73	0.00	0.22	0.00	0.01	0.00	0.04	0.00	0.00
NV	0.20	0.00	0.69	0.00	0.07	0.00	0.00	0.00	0.04
NY	0.10	0.02	0.31	0.33	0.20	0.02	0.02	0.00	0.00
OH	0.84	0.01	0.03	0.11	0.00	0.00	0.00	0.00	0.00
OK	0.45	0.00	0.46	0.00	0.05	0.00	0.04	0.00	0.00
OR	0.06	0.00	0.28	0.00	0.58	0.01	0.06	0.00	0.00
PA	0.48	0.00	0.13	0.35	0.01	0.01	0.00	0.00	0.00
RI	0.00	0.00	0.98	0.00	0.00	0.02	0.00	0.00	0.00
SC	0.34	0.01	0.10	0.52	0.01	0.02	0.00	0.00	0.00
SD	0.40	0.00	0.01	0.00	0.47	0.00	0.11	0.00	0.00
TN	0.52	0.00	0.01	0.34	0.12	0.01	0.00	0.00	0.00
TX	0.35	0.01	0.48	0.10	0.00	0.00	0.05	0.00	0.00
UT	0.82	0.00	0.15	0.00	0.02	0.00	0.00	0.00	0.01
VA	0.37	0.02	0.17	0.40	0.00	0.03	0.00	0.00	0.00
VT	0.00	0.00	0.00	0.74	0.20	0.06	0.00	0.00	0.00
WA	0.07	0.00	0.11	0.06	0.70	0.01	0.03	0.00	0.00
WI	0.62	0.01	0.09	0.21	0.02	0.02	0.02	0.00	0.00
WV	0.96	0.00	0.00	0.00	0.02	0.00	0.01	0.00	0.00
WY	0.91	0.00	0.01	0.00	0.02	0.00	0.05	0.00	0.00

On the other hand, power plants generally rely on fossil fuels due to the need to instantaneously meet fluctuating electricity demands. A steady power supply to meet base electricity loads is usually provided through nuclear power and hydroelectric power plants, while natural gas or coal power plants usually provide for some portion of the steady demand and mostly for the peak demand above the base load. Hence, the additional unsteady demand from the use of BEVs and PHEVs is more likely to be provided by nonrenewable energy sources. Therefore, the regional marginal mixes estimated by the Oak Ridge National Laboratory are also taken into consideration as Scenario 2 (S2). As solar power is currently one of the most promising renewable energy technologies in terms of energy efficiency and environmental impacts, a fully solar electricity generation mix is also evaluated to highlight its benefits in Scenario 3 (S3). Table 20 shows the marginal electricity generation mix of each state.

After defining the electricity generation mixes and impact factors by energy source, state-specific impact factors can be calculated by using the values presented in Tables 18, 19, and 20; these calculated factors for this study are presented in Table 21. As the impacts per kWh of electricity generation in each state are determined, the WTT impacts from each vehicle type can be calculated by multiplying the electricity required from the grid to travel 1 mile (including transportation and distribution losses) by the calculated state-specific water consumption and withdrawal factors, depending on the state in question and the scenario being considered.

Since PHEVs can operate in either electric mode or gasoline mode, Eq. 4.1 is not sufficient to calculate its impacts. Using the data presented in Tables 18 through 21 and the UFs derived from 2009 NHTS data, the per mile water consumption and withdrawal of PHEVs can be calculated as follows.

$$(\text{WTT impacts})_{\text{PHEV}} = \text{UF}*[(1/\text{FE}_{\text{on electric mode}}) * (\text{impact factor}_{\text{electricity supply}}) + (1-\text{UF}) * [(1/\text{FE}_{\text{on gasoline mode}})*(\text{Impact factor}_{\text{gasoline supply}})] \quad (4.2)$$

Eq. 4.2 has two parts, the first part representing electric mode impacts and the second part representing gasoline mode impacts. Since BEVs only use electric power, the per mile water consumption and withdrawal of BEVs can be calculated by using only the first part of Eq. 4.2 (UF = 1), thereby eliminating the gasoline related impacts in Eq. 4.2.

Table 20. State-specific Marginal Electricity Generation Mix (Scenario 2)

State		Coal	Oil	Gas	Nuclear	Hydro	Bio	Wind	Solar	Geother
AK	N/A	0.09	0.16	0.75	0.00	0.00	0.00	0.00	0.00	0.00
AL	SERC	0.33	0.00	0.65	0.00	0.00	0.00	0.00	0.02	0.00
AR	SPP	0.05	0.02	0.93	0.00	0.00	0.00	0.00	0.00	0.00
AZ	WECC-RMP/ANM	0.07	0.00	0.93	0.00	0.00	0.00	0.00	0.00	0.00
CA	WECC-CA	0.00	0.00	0.99	0.00	0.00	0.00	0.00	0.01	0.00
CO	WECC-RMP/ANM	0.07	0.00	0.93	0.00	0.00	0.00	0.00	0.00	0.00
CT	NPCC-NE	0.16	0.23	0.61	0.00	0.00	0.00	0.00	0.00	0.00
DC	MAAC	0.25	0.11	0.64	0.00	0.00	0.00	0.00	0.00	0.00
DE	MAAC	0.25	0.11	0.64	0.00	0.00	0.00	0.00	0.00	0.00
FL	FRCC	0.00	0.17	0.82	0.01	0.00	0.00	0.00	0.01	0.00
GA	SERC	0.33	0.00	0.65	0.00	0.00	0.00	0.00	0.02	0.00
HI	N/A	0.02	0.97	0.02	0.00	0.00	0.00	0.00	0.00	0.00
IA	**MAIN**	0.62	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.00
	MAPP	0.25	0.02	0.73	0.00	0.00	0.00	0.00	0.00	0.00
ID	WECC-NW	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
IL	MAIN	0.62	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.00
IN	ECAR	0.56	0.00	0.43	0.00	0.00	0.00	0.00	0.01	0.00
KS	SPP	0.05	0.02	0.93	0.00	0.00	0.00	0.00	0.00	0.00
KY	ECAR	0.56	0.00	0.43	0.00	0.00	0.00	0.00	0.01	0.00
LA	SERC	0.33	0.00	0.65	0.00	0.00	0.00	0.00	0.02	0.00
MA	NPCC-NE	0.16	0.23	0.61	0.00	0.00	0.00	0.00	0.00	0.00
MD	MAAC	0.25	0.11	0.64	0.00	0.00	0.00	0.00	0.00	0.00
ME	NPCC-NE	0.16	0.23	0.61	0.00	0.00	0.00	0.00	0.00	0.00
MI	ECAR	0.56	0.00	0.43	0.00	0.00	0.00	0.00	0.01	0.00
MN	**MAIN**	0.62	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.00
	MAPP	0.25	0.02	0.73	0.00	0.00	0.00	0.00	0.00	0.00
MO	**SERC**	0.33	0.00	0.65	0.00	0.00	0.00	0.00	0.02	0.00
	MAIN	0.62	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.00
MS	SERC	0.33	0.00	0.65	0.00	0.00	0.00	0.00	0.02	0.00
MT	**WECC-NW**	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
	MAPP	0.25	0.02	0.73	0.00	0.00	0.00	0.00	0.00	0.00
NC	SERC	0.33	0.00	0.65	0.00	0.00	0.00	0.00	0.02	0.00
ND	MAPP	0.25	0.02	0.73	0.00	0.00	0.00	0.00	0.00	0.00
NE	MAPP	0.25	0.02	0.73	0.00	0.00	0.00	0.00	0.00	0.00
NH	NPCC-NE	0.16	0.23	0.61	0.00	0.00	0.00	0.00	0.00	0.00
NJ	MAAC	0.25	0.11	0.64	0.00	0.00	0.00	0.00	0.00	0.00
NM	WECC-RMP/ANM	0.07	0.00	0.93	0.00	0.00	0.00	0.00	0.00	0.00
NV	**WECC-RMP/ANM**	0.07	0.00	0.93	0.00	0.00	0.00	0.00	0.00	0.00
	WECC-NW	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
NY	NPCC-NY	0.04	0.14	0.82	0.00	0.00	0.00	0.00	0.00	0.00
OH	ECAR	0.56	0.00	0.43	0.00	0.00	0.00	0.00	0.01	0.00
OK	SPP	0.05	0.02	0.93	0.00	0.00	0.00	0.00	0.00	0.00
OR	WECC-NW	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
PA	MAAC	0.25	0.11	0.64	0.00	0.00	0.00	0.00	0.00	0.00
RI	NPCC-NE	0.16	0.23	0.61	0.00	0.00	0.00	0.00	0.00	0.00
SC	SERC	0.33	0.00	0.65	0.00	0.00	0.00	0.00	0.02	0.00
SD	**MAPP**	0.25	0.02	0.73	0.00	0.00	0.00	0.00	0.00	0.00
	WECC-NW	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
TN	SERC	0.33	0.00	0.65	0.00	0.00	0.00	0.00	0.02	0.00
TX	ERCOT	0.00	0.00	0.99	0.00	0.00	0.00	0.00	0.00	0.00
UT	WECC-NW	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
VA	**SERC**	0.33	0.00	0.65	0.00	0.00	0.00	0.00	0.02	0.00
	ECAR	0.56	0.00	0.43	0.00	0.00	0.00	0.00	0.01	0.00
VT	NPCC-NE	0.16	0.23	0.61	0.00	0.00	0.00	0.00	0.00	0.00

State		Coal	Oil	Gas	Nuclear	Hydro	Bio	Wind	Solar	Geother
WA	WECC-NW	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
WI	**MAPP**	0.25	0.02	0.73	0.00	0.00	0.00	0.00	0.00	0.00
	MAIN	0.62	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.00
WV	ECAR	0.56	0.00	0.43	0.00	0.00	0.00	0.00	0.01	0.00
WY	WECC-NW	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 21. State-specific water withdrawal and consumption factors for Scenario 1 and 2 (gal/kWh)

States	Scenario 1						Scenario 2					
	Withdrawal			Consumption			Withdrawal			Consumption		
	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg
AK	0.282	0.369	0.326	0.504	3.903	2.203	0.326	0.415	0.370	0.257	0.399	0.328
AL	0.772	1.284	1.028	0.635	2.325	1.480	0.500	0.585	0.542	0.358	0.563	0.460
AR	0.803	1.307	1.055	0.638	2.134	1.386	0.292	0.337	0.315	0.225	0.345	0.285
AZ	0.738	1.228	0.983	0.574	1.777	1.175	0.307	0.349	0.328	0.233	0.358	0.295
CA	0.465	0.738	0.601	0.550	2.922	1.736	0.252	0.282	0.267	0.197	0.299	0.248
CO	0.700	0.832	0.766	0.536	1.406	0.971	0.307	0.349	0.328	0.233	0.358	0.295
CT	0.769	1.610	1.190	0.514	0.956	0.735	0.386	0.504	0.445	0.301	0.471	0.386
DC	0.300	0.600	0.450	0.300	0.480	0.390	0.446	0.546	0.496	0.331	0.519	0.425
DE	0.702	0.856	0.779	0.491	0.783	0.637	0.446	0.546	0.496	0.331	0.519	0.425
FL	0.563	0.852	0.707	0.392	0.604	0.498	0.269	0.355	0.312	0.219	0.335	0.277
GA	0.874	1.368	1.121	0.621	1.367	0.994	0.500	0.585	0.542	0.358	0.563	0.460
HI	0.413	0.680	0.546	0.376	0.748	0.562	0.315	0.610	0.463	0.308	0.492	0.400
IA	0.832	1.111	0.972	0.589	1.216	0.903	0.720	0.852	0.786	0.501	0.796	0.649
ID	0.081	0.107	0.094	1.195	14.427	7.811	0.253	0.283	0.268	0.198	0.300	0.249
IL	1.017	1.850	1.434	0.658	0.950	0.804	0.720	0.852	0.786	0.501	0.796	0.649
IN	0.945	1.130	1.037	0.653	1.113	0.883	0.672	0.795	0.734	0.471	0.746	0.608
KS	0.916	1.335	1.126	0.613	0.942	0.778	0.292	0.337	0.315	0.225	0.345	0.285
KY	0.945	1.135	1.040	0.700	1.696	1.198	0.672	0.795	0.734	0.471	0.746	0.608
LA	0.609	0.971	0.790	0.434	0.859	0.646	0.500	0.585	0.542	0.358	0.563	0.460
MA	0.554	0.847	0.701	0.406	0.881	0.644	0.386	0.504	0.445	0.301	0.471	0.386
MD	0.943	1.560	1.252	0.681	1.692	1.187	0.446	0.546	0.496	0.331	0.519	0.425
ME	0.321	0.472	0.397	0.590	5.003	2.797	0.386	0.504	0.445	0.301	0.471	0.386
MI	0.943	1.413	1.178	0.636	1.049	0.843	0.672	0.795	0.734	0.471	0.746	0.608
MN	0.872	1.361	1.116	0.599	1.151	0.875	0.720	0.852	0.786	0.501	0.796	0.649
MO	0.953	1.287	1.120	0.682	1.488	1.085	0.720	0.852	0.786	0.501	0.796	0.649
MS	0.663	1.085	0.874	0.446	0.655	0.550	0.500	0.585	0.542	0.358	0.563	0.460
MT	0.597	0.718	0.658	0.917	7.061	3.989	0.253	0.283	0.268	0.198	0.300	0.249
NC	0.960	1.598	1.279	0.692	1.724	1.208	0.500	0.585	0.542	0.358	0.563	0.460
ND	0.871	1.041	0.956	0.657	1.731	1.194	0.440	0.517	0.478	0.321	0.502	0.411
NE	0.983	1.525	1.254	0.692	1.508	1.100	0.440	0.517	0.478	0.321	0.502	0.411
NH	0.744	1.471	1.107	0.597	2.165	1.381	0.386	0.504	0.445	0.301	0.471	0.386
NJ	0.791	1.658	1.224	0.505	0.675	0.590	0.446	0.546	0.496	0.331	0.519	0.425
NM	0.794	0.944	0.869	0.558	0.997	0.778	0.307	0.349	0.328	0.233	0.358	0.295
NV	0.453	0.512	0.483	0.444	1.679	1.062	0.307	0.349	0.328	0.233	0.358	0.295
NY	0.555	1.088	0.822	0.653	4.170	2.411	0.290	0.363	0.326	0.231	0.357	0.294
OH	0.978	1.315	1.147	0.667	1.103	0.885	0.672	0.795	0.734	0.471	0.746	0.608
OK	0.576	0.680	0.628	0.470	1.465	0.967	0.292	0.337	0.315	0.225	0.345	0.285
OR	0.141	0.169	0.155	0.933	10.650	5.791	0.253	0.283	0.268	0.198	0.300	0.249
PA	0.914	1.548	1.231	0.613	1.038	0.826	0.446	0.546	0.496	0.331	0.519	0.425
RI	0.265	0.306	0.285	0.206	0.324	0.265	0.386	0.504	0.445	0.301	0.471	0.386
SC	0.961	1.824	1.392	0.636	1.111	0.874	0.500	0.585	0.542	0.358	0.563	0.460
SD	0.401	0.480	0.441	0.950	8.967	4.958	0.440	0.517	0.478	0.321	0.502	0.411
TN	0.909	1.526	1.217	0.765	3.033	1.899	0.500	0.585	0.542	0.358	0.563	0.460
TX	0.594	0.838	0.716	0.414	0.672	0.543	0.251	0.281	0.266	0.197	0.298	0.248
UT	0.872	1.037	0.954	0.631	1.303	0.967	0.253	0.283	0.268	0.198	0.300	0.249
VA	0.889	1.593	1.241	0.582	0.871	0.727	0.500	0.585	0.542	0.358	0.563	0.460
VT	0.860	1.998	1.429	0.817	4.350	2.584	0.386	0.504	0.445	0.301	0.471	0.386
WA	0.184	0.306	0.245	1.119	12.756	6.937	0.253	0.283	0.268	0.198	0.300	0.249
WI	0.903	1.360	1.132	0.636	1.334	0.985	0.440	0.517	0.478	0.321	0.502	0.411
WV	0.968	1.156	1.062	0.695	1.478	1.087	0.672	0.795	0.734	0.471	0.746	0.608
WY	0.919	1.097	1.008	0.659	1.384	1.021	0.253	0.283	0.268	0.198	0.300	0.249

In Scenario 3, withdrawal and consumption factors are assumed to be identical for every state. The maximum, minimum and average values are 0.033, 0.026, and 0.030 gal per kWh of electric power generation from solar panels.

4.4. Results

As discussed before, this chapter concentrated on three main policy scenarios based on three different electric power generation mix profiles: state-based average electricity generation mix, state-based marginal electricity generation mix, and 100% solar-powered charging stations. Using Eqn. 4.1 and Eqn. 4.2, the total amounts of water consumption and withdrawal are calculated in gallons per VMT (gal/mil). According to analysis findings, the aforementioned scenarios only demonstrated a change in the state-based water consumption and withdrawal amounts for PHEV20, PHEV40 and BEVs, while the applied policy scenarios did not change the water consumption or withdrawal of ICVs, HEVs, or EVs with solar charging options. In this regard, the results are presented in the following two subsections; subsection 4.4.1. presents the water consumption and withdrawal amounts of ICVs, HEVs, and HEVs with solar charging, and subsection 4.4.2. presents the maximum and minimum water consumption and withdrawal amounts for PHEVs and BEVs given the relevant variations in the 50 states (including Hawaii and the District of Columbia) considered in this study.

4.4.1. Water Withdrawal and Consumption of ICVs, HEVs, and BEVs with Solar Charging Infrastructure

Fig. 12 shows the minimum and maximum water withdrawal and consumption amounts for three vehicle types: ICVs, HEVs, and BEVs with solar charging infrastructure. Based on the functional unit (1 VMT), the results are presented in gallons of water required for 1 mile of vehicle travel. These findings show that BEVs with solar charging have the lowest water consumption and withdrawal compared to ICVs and HEVs, while ICVs are found to have higher maximum water usage rates than HEVs. The water withdrawal rates of ICVs ranged between 0.23 and 0.08 gallons of water per VMT, while the water consumption of ICVs ranged between 0.18 and 0.06 gallons of water per VMT. The HEV's maximum and minimum water withdrawal amounts were found to be 0.14 and 0.05 gallons of water per VMT, respectively, whereas its maximum and minimum water consumption values were found to be 0.11 and 0.04 gallons of water per VMT, respectively. These results revealed that, despite ICVs having the higher worst-case-scenario water consumption and withdrawal levels, it is still possible for HEVs to have higher water consumption and withdrawal values than ICVs, depending on relevant factors. For instance, the maximum water consumption of HEVs (0.11gal/mil) is found to be higher than the minimum water consumption of ICVs (0.06 gal/mil), while the water consumption and withdrawal rates of BEVs were found to be always less than those of ICVs and HEVs for all maximum and minimum values.

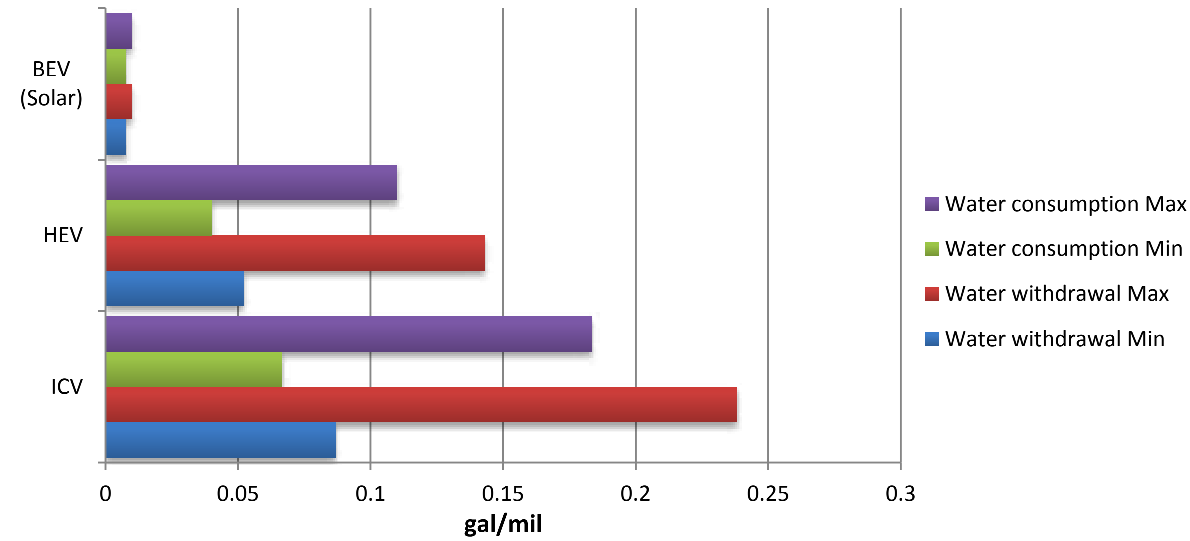


Figure 12. Water Withdrawal and Consumption of ICVs, HEVs, and BEVs with 100% solar-powered charging options (gal/mil)

4.4.2. Water Withdrawal and Consumption of BEVs and PHEVs

Figure 13 presents the water withdrawal and consumption rates, in gal/mil, of BEVs and PHEVs in different states, and shows large variations among these states. The results indicate that, for the average electricity generation mix scenario (Figure 6a), the water consumption and withdrawal rates generally range between 0.01 and 0.05 gallons of water per VMT. However, for some states, such as Idaho (ID), Oregon (OR), and Washington (WA), the corresponding water consumption rates are shown to reach as high as 4.6 gal/mil, because these states, as shown in Figure 4, are heavily reliant on hydropower plants, which have a high water consumption rate per kWh based on the NREL database (NREL 2011). On the other hand, the marginal electricity mix, which represents a more realistic electricity generation scenario, showed more clearly different results for the water footprint of BEVs.

In this scenario, the electricity requirement of BEVs is mostly supplied by fossil fuel sources, mainly coal and natural gas, and the findings (Figure 6b) showed that water withdrawal and consumption rates increased for the majority of states when compared to the average electricity mix scenario. For the marginal electricity scenario, the lowest water withdrawal and consumption values are observed for Wyoming (WY), Washington (WA), Utah (UT), Texas (TX), Oregon (OR), New York (NY), Idaho (ID), and California (CA); among these states, CA, NY and TX are among the most heavily populated states in the U.S., and water consumption values per VMT range between 0.06 gal/mil and 0.09 gal/mil for CA, 0.07 gal/mil and 0.11 gal/mil for NY, and 0.06 gal/mil and 0.09 gal/mil for TX. On the other hand, the largest observed water footprint is that of Illinois (IL), where a significant percentage of electricity generation comes from coal burning with approximately 62% of the total electricity production attributed to coal power plants under the marginal electricity mix scenario (S2).

Figures 13 and 14 show the water footprints of the PHEV40 and the PHEV20, respectively. For both PHEVs, Scenario S3 (100% solar-powered charging stations) tends to have the lowest water footprint as opposed to the average and marginal electricity mix scenarios. Upon analyzing the water footprints of PHEVs for the average electricity mix scenario (S1), it was discovered that the minimum and maximum water withdrawal values for the PHEV40 (Figure 7a) are 0.03 gal/mil in Idaho (ID) and 0.51 gal/mil in Vermont (VT), respectively. On the other hand, the minimum and maximum water consumption rates of PHEV40 were 0.06 gal/mil in Rhode Island (RI) and 3.59 gal/mil in Idaho (ID), respectively.

Likewise, based on the analysis results for the PHEV20 (Figure 8a), the minimum and maximum water withdrawal values for PHEV20 are 0.04 gal/mil in Oregon (OR) and 0.38 gal/mil in Illinois (IL), respectively. However, the minimum and maximum water consumption levels of the PHEV20 are found to be 0.06 gal/mil in Rhode Island (RI) and 2.39 gal/mil in Washington (WA), respectively.

In addition to the average electricity mix scenario, the impacts of the marginal electricity mix scenario on the overall water footprint of the PHEVs are also analyzed, and are presented in Figures 13b and 14b. The marginal electricity mix is the most realistic power supply scenario, and the largest portion of electricity demand of BEVs and PHEVs is supplied by fossil fuel sources. In this scenario, if the marginal electricity demand is supplied by coal, natural gas, or another highly water-intensive source, and the water efficiency of a PHEV or BEV is relatively low, then the all-electric driving mode of any such vehicle would increase said vehicle's water footprint when compared to an HEV. This is because, in some of the scenarios presented in this chapter, it is clearly shown that the total water footprints of BEVs under the marginal electricity mix scenario might be higher than the corresponding water footprints of HEVs.

After analyzing the water footprints of PHEVs under the marginal electricity mix scenario, the results showed that the minimum and maximum water withdrawal values for the PHEV40 (Figure 13b) are 0.03 gal/mil in Idaho (ID) and 0.51 gal/mil in Vermont (VT), respectively. On the other hand, the minimum and maximum water consumption values of the PHEV40 are 0.06 gal/mil in Wyoming (WY) and 0.24 gal/mil in Illinois (IL), respectively.

Likewise, based on analysis results for the PHEV20 under a marginal electricity mix scenario (Figure 14b), the minimum and maximum water withdrawal values for the PHEV20 are 0.06 gal/mil in Wyoming (WY) and 0.21 gal/mil in Illinois, (IL), respectively, while the corresponding minimum and maximum water consumption values are 0.05 gal/mil in Wyoming (WY) and 0.18 gal/mil in Illinois (IL), respectively. Overall, the results show that the PHEV40 has a smaller total water footprint than the PHEV20 for both average and marginal electricity mix scenarios, with a higher dependence on less water-intensive fossil-fuel energy sources. One of the most interesting finding of this study is that water consumption or withdrawal of electric vehicles (BEVs, PEHVs) are generally lower than those of ICVs and BEVs in average and marginal scenarios due to water-intensive processes involved in petroleum production (please see table 18). However, when electricity generation mix scenarios, covering temporal and spatial variations, and driving patterns are included in the estimations, there is no one right answer fits for all cases. Therefore, such comprehensive analysis provides very useful information for policy makers at both state and national level.

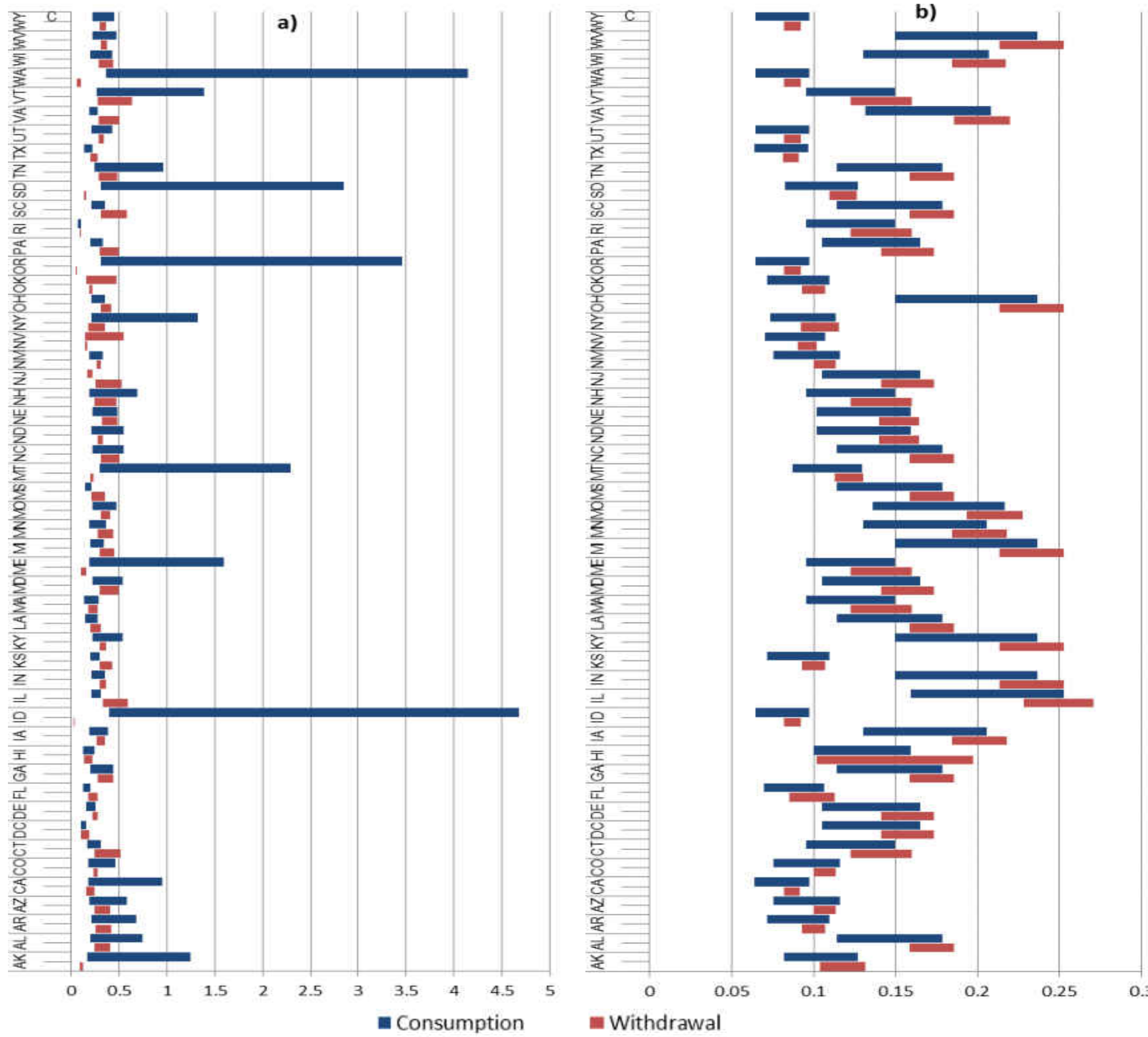


Figure 13. Water withdrawal and consumption amounts for **BEVs** (gal/mil) (a) average electricity generation mix (b) marginal electricity generation mix

(NOTE: for 100% solar energy charged BEVs, there is no variation per gallon of water used between states)

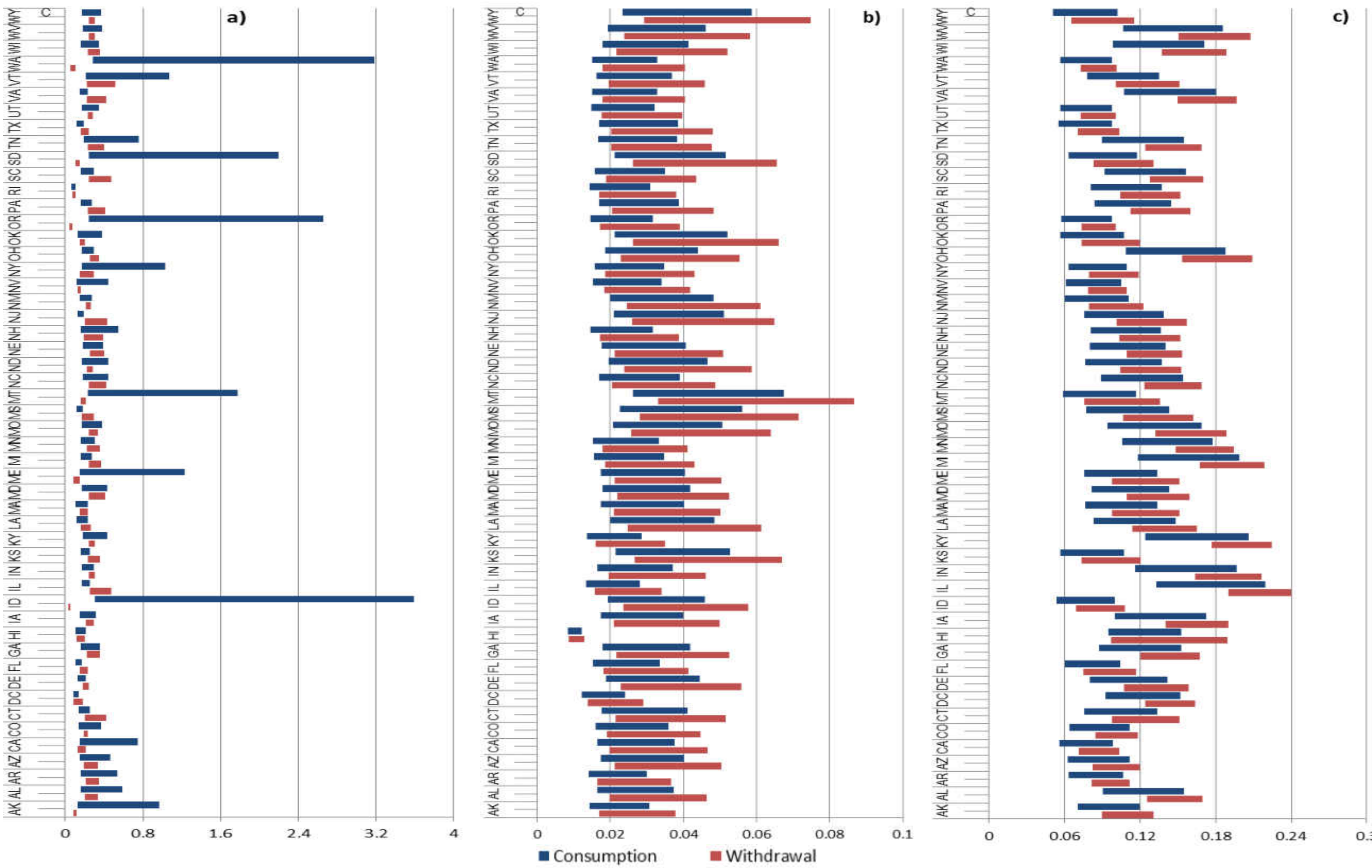


Figure 14. Water withdrawal and consumption amounts for **PHEV40s** (gal/mil) average electricity state-mix (b) 100% solar power (c) marginal electricity state-mix

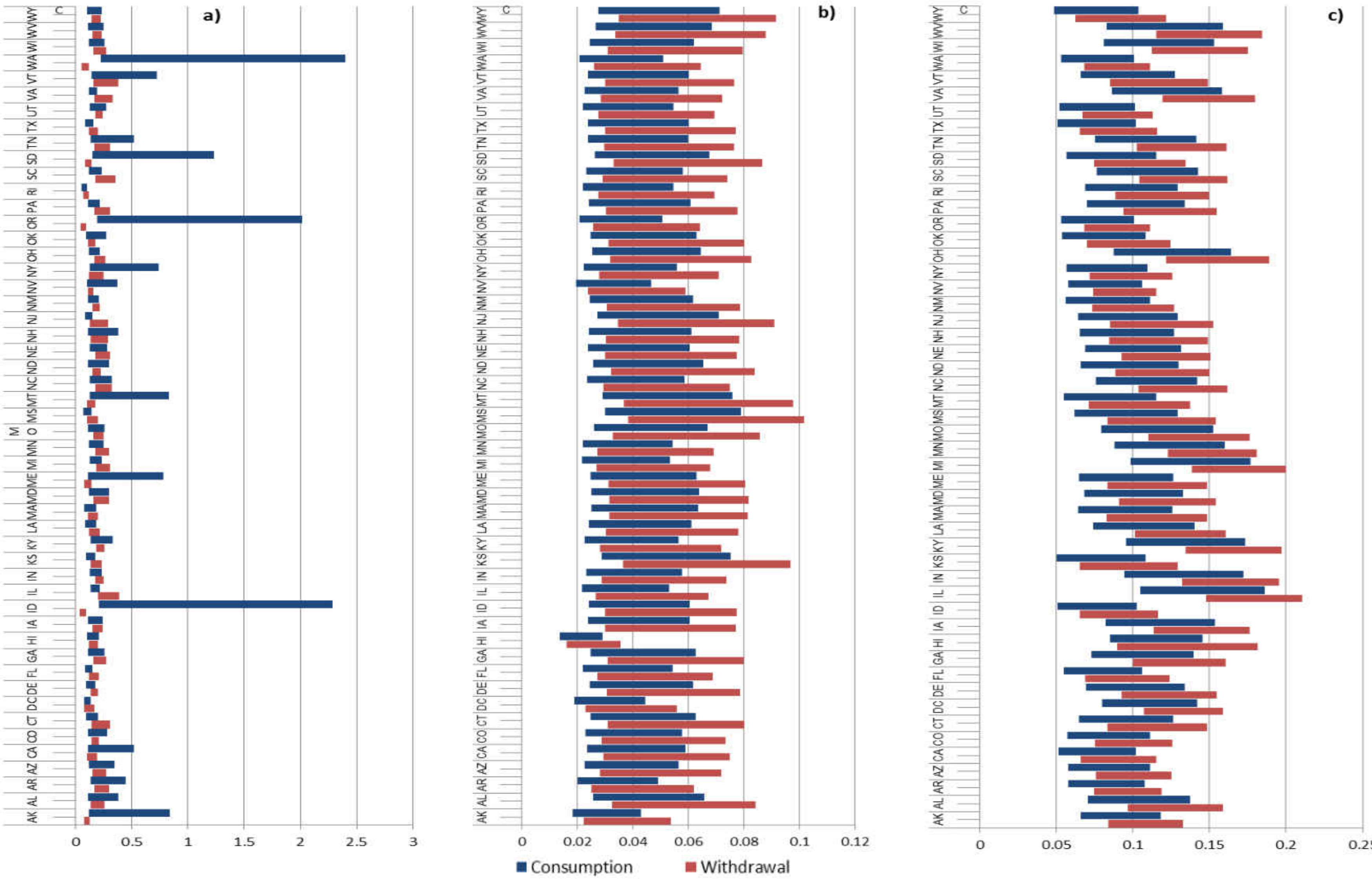


Figure 15 Water withdrawal and consumption amounts for **PHEV20s** (gal/mil) a) average electricity state-mix, b) 100% solar power, c) marginal electricity state-mix

CHAPTER 5: DYNAMIC SUSTAINABILITY ASSESSMENT FRAMEWORK FOR ALTERNATIVE VEHICLE TECHNOLOGIES

This Chapter aims to present a practical and novel approach for (1) broadening the existing Life Cycle Sustainability Assessment (LCSA) framework by considering macro-level environmental, economic and social impacts (termed as the triple bottom line), simultaneously, (2) deepening the existing LCSA framework by capturing the complex dynamic relationships between social, environmental, and economic indicators through causal loop modeling, (3) understanding the dynamic complexity of transportation sustainability for the triple bottom line impacts of alternative vehicles, and finally (4) investigating the impacts of various vehicle-specific scenarios as a novel approach for selection of a macro-level functional unit considering all of the complex interactions in the environmental, social, and economic aspects.

To alleviate these research objectives, we presented a novel methodology to quantify macro-level social, economic, and environmental impacts of passenger vehicles from an integrated system analysis perspective. An integrated dynamic LCSA model is utilized to analyze the environmental, economic and social life cycle impact as well as life cycle cost of alternative vehicles in the United States. System dynamics modeling is developed to simulate the U.S. passenger transportation system and its interactions with economy, the environment, and society. Analysis covers manufacturing and operation phase impacts of internal combustion vehicles (ICVs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs). In total, seven macro level indicators are selected; global warming potential, particulate matter formation, photochemical oxidant formation, vehicle ownership cost, contribution to gross domestic product, employment generation, and human health impacts. Additionally, contribution of vehicle choices to global atmospheric temperature rise and public welfare is investigated.

Environmental impacts related to U.S. transportation sector are growing steadily, and transportation-related environmental pressures are increasingly scrutinized because of concerns related to sustainability (M. Delucchi, 2003). 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. Furthermore, 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. Analysis of alternative vehicle systems needs a holistic sustainability accounting which requires a set of environmental, economic and environmental indicators (T. A. Litman, 2009). 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 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 (Hawkins et al., 2012). 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 (T. Litman & Burwell, 2006). At this point, 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 could only provide a snapshot analysis with an isolated view of all pillars of sustainability and neglecting the bigger picture as a system. In this study, we aim to develop 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, as well as the dynamic interdependencies, causal relationships among these impact categories, transportation system, and its components.

5.1. Life cycle sustainability assessment

Almost 12 years passed since Walter Kloepffer and his colleagues have 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) (Kloepffer, 2008; Alessandra Zamagni, 2012). This framework was then put into the conceptual formula (LCSA = LCA + LCC + SLCA) by Klöpffer (2007).

LCSA represents the state-of-the-art in the life-cycle assessment literature since it provides a system-based approach by combining three important pillars of sustainable development as environment, economy, and society (Finkbeiner, Schau, Lehmann, & Traverso, 2010; Murat Kucukvar, 2013). Consisting of these three pillars, LCSA framework seeks to achieve, in a balanced manner, economic viability, social cohesion and environmental protection. Today, there is a growing interest among the international platform and academia to methodologically advance the LCSA framework and use it to have more informed sustainable products, material and technology choices (Guinée et al., 2011; Halog & Manik, 2011; Heijungs, Huppes, & Guinée, 2010; Traverso, Finkbeiner, Jørgensen, & Schneider, 2012; S Valdivia, Ugaya, Sonnemann, & Hildenbrand, 2011; Sonia Valdivia et al., 2012). In a critical review article on the past, present and future of the LCA, the period between 2010 and 2020 is named as the "decade of life cycle sustainability assessment". Although LCSA is still a new concept within the LCA literature, it has gained a wide acceptance by LCA practitioners over the last decade. Based on the authors review, there have been numerous studies found in the literature that have used LCSA in a real case study. To name a few, life-cycle sustainability implications of various renewable and non-renewable electricity scenarios in UK are analyzed based on economic, social and environmental indicators (Santoyo-Castelazo & Azapagic, 2014; Stamford & Azapagic, 2012, 2014). Hu et al. (2013) presented an approach to put the LCSA framework into practice by analyzing the environmental, economic, and social life cycle implications of concrete recycling processes. In another paper, Traverso et al. (2012a) analyzed the manufacturing processes of photovoltaic modules and environmental, economic and social impacts of Italian and German polycrystalline silicon modules are quantified using the LCSA.

Although several studies emphasized the importance of system-based tools for LCA, the applications of LCSA for large systems are still rare. Guinée et al. (2011) 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 used in conjunction for a multi-criteria decision analysis of hot-mix and warm-mix asphalt mixtures. Onat et al. (2014c) also used the LCSA framework for a 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. In a recent work, 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. However, only a handful of studies addressed this issue and expand the system boundary of LCSA to economy-wide analysis.

5.2. 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 (Sala, Farioli, & Zamagni, 2012a, 2012b). The Coordination Action for innovation in Life Cycle Analysis for Sustainability (CALCAS) is a partnership-based project, funded by the European Commission under Sixth Framework Programme (Heijungs et al., 2010; A Zamagni et al., 2009). In general, this CALCAS project has the following two objectives to further improve the life-cycle modeling for sustainability assessment (Stefanova, Tripepi, Zamagni, & Masoni, 2014; Weidema, Ekvall, & Heijungs, 2009):

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

In current LCA framework, inclusion of social-economic metrics, linkage between social, economic and environmental indicators, and the effects of social choices to life-cycle impacts are not fully addressed. However, moving from LCA to LCSA absolutely requires a system-based approach since it emphasizes the consideration of all three pillars of sustainability, simultaneously. In a real world, the analysis environment-economy-society nexus makes the dynamic approach essential because of the fact that these metrics are fundamentally connected and there is a strong causal relationship between socio-economic and environmental indicators (Fiksel, 2006). Hence, to truly make LCSA an integrated approach and eliminate the shortcomings of the existing isolated modeling structure, a system dynamic modeling can be a novel and visionary modeling technique in a way that a ripple effects and dynamic relationships are embedded in the state-of-the art for the life cycle sustainability accounting.

In a Deliverable 17 Final Report of CALCAS project, several options and models are suggested to broaden and deepen the existing LCA framework (CALCAS, 2009). To name a few, 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 (Jeswani, Azapagic, Schepelmann, & Ritthoff, 2010). 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 (Alessandra Zamagni et al., 2013):

❖ The number of applications of LCSA is still limited and needs to be improved,

- ❖ 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.

Under the light the aforementioned comments that address critical points for future LCSA, broadened and deepened LCSA should go beyond the identifying the snapshot of sustainability hotspots (Alessandra Zamagni et al., 2013). Hence, LCSA requires the consideration of dynamic relationship between LCSA indicators and provide additional insights regarding the time-variant effects of products or systems' sustainability implications. At this point, system dynamics model can be a superior modeling approach to address the future research needs of advanced LCSA. The importance of system dynamics approach in LCSA is also highlighted in a comprehensive methodology paper 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 (Halog & Manik, 2011).

Even though the environmental dimension of sustainability is an important pillar of sustainable development, social and economic dimensions have to be integrated into a holistic sustainability assessment framework to make economically viable, socially acceptable, and environmentally benign policies towards achieving sustainability for many systems including manufacturing, construction, transportation, etc. (Egilmez, Kucukvar, & Tatari, 2013a; Murat Kucukvar, Egilmez, & Tatari, 2014; Onat, Kucukvar, & Tatari, 2015; Onat, Kucukvar, et al., 2014c). From a complex system perspective, triple bottom line consequences of the transportation impacts are inevitably interconnected, and therefore such complexity requires a novel system thinking approach in which all possible outcomes, ripple effects, and unforeseen impacts must be estimated (Lee, Geum, Lee, & Park, 2012).

5.3. System dynamics modeling in transportation research

The traditional approaches to LCSA often focus on understanding the behavior of a system based on the cause and affect relationships among system elements separately, which is generally termed “event oriented thinking.” However, in real life, causal relationships are often complex in a way that one stage or element can be the result of another and the cause of another simultaneously, which can be considered as series of interconnected causal relationships (J. D. Sterman, 2000). Majority of traditional modeling approaches fail to capture the feedback relationships among the variables in the system (Barlas, 1996). A systems-thinking perspective is vital for understanding and tackling sustainability problems (J. Sterman, 2012). From systems-thinking perspective, complex systems should be treated and studied as a whole structure (Akhtar, Wibe, Simonovic, & MacGee, 2013; Davies & Simonovic, 2011). Three pillars of sustainability that individually analyzed in LCSA framework might have a dynamic impact on each other over time. Therefore, a holistic LCSA modeling approach is required to observe, analyze and model the whole system considering complex feedback mechanisms among the models parameters and LCSA indicators. System dynamics (SD) modeling philosophy serves best to such objectives since it assists with defining the feedback mechanisms, potential delays and multi-dimensional causal relationships quantitatively (Onat, Egilmez, & Tatari, 2014).

Most of the problems of present are consequences of unforeseen side effects of the actions taken in the past, such as global climate change and depletion of resources. The policies implemented to solve significant problems mostly fail, make the problem even worse, or pave the way for other problems. Effective decision making requires a systems thinking approach and understanding behavior of the growing dynamic complexity of the systems. In this sense, SD is a strong modeling approach to describe and understand the behavior of complex systems overtime. SD is a computer aided dynamic simulation modeling approach to enhance the overall understanding of complex systems' behavior over time. The evolution of dynamic modeling was initiated by Forrester (1961). SD is a very robust research method which has been used to model complex socio economic systems to understand the pattern of behavior over time (Meadows, Randers, & Meadows, 1993b). SD models are also often used to address environmental issues and sustainability problems. Forrester (1971) investigated the global impacts of environmental sustainability issues with a broader scope. Meadows et al. (2004) and Randers (2000) utilized the SD approach to investigate the effects of increasing human population on the earth and natural resources. Several other studies utilized SD modeling approach includes the issues related to urban sustainability (Feng, Chen, & Zhang, 2013; Mirchi, Madani, Watkins, & Ahmad, 2012), product and service systems (Lee et al., 2012), water resource planning (Winz, Brierley, &

Trowsdale, 2008), urban planning (Yoshino, Fong, Matsumoto, & Lun, 2009), and highway sustainability (Egilmez & Tatari, 2012).

SD modeling has also been also used in transportation research as a well suited modeling approach for strategic policy analysis and decision making supporting tool. SD modeling can significantly contribute to understanding the relationships between elements of the transportation system and the environment it is interacting with (Abbas & Bell, 1994). Shepherd (2014) evaluated over 50 peer-reviewed journal papers that applied SD models in transportation research since 1994. The paper indicated that use of SD modeling in the transportation research has been focused on several major areas;

- Alternative fuel vehicles
- Supply chain management with transportation
- Highway/infrastructure construction and maintenance
- Strategic policy at urban, regional, and national scale
- Air transportation
- Other emerging areas such as safety, city bus systems, port security

To give some examples, Han and Hayashi (2008) built a system dynamics model for policy assessment and carbon dioxide (CO_2) mitigation potential analysis for inter-city passenger transportation in China. Wang et al. (2008) used a system dynamics approach urban transportation system in Dalian city of China by considering social, economic and environmental factors and their complex interactions. In other study, Jin et al. (2009) presented a system dynamics approach for integrating complex interactions between ecological footprint indicators for sustainable urban planning including future transportation systems. Egilmez and Tatari (2012) developed a system dynamic model in order to dynamically simulate CO_2 emissions of U.S. transportation system under three policy scenarios: fuel efficiency, public transportation and electric vehicle usage. Shepherd et al. 2012 also developed a system dynamics model in order to analyze the impact of CO_2 emissions under several scenarios including subsidies, range, charge point availability, emission rates and a revenue preserving tax. Schade and Schade (2005) modeled the transportation system, which consist of five sub-models, namely: the macroeconomic, the transport, the regional economic, the environmental and the policy model. Baldoni et al. (2010) studied the transportation sustainability and energy policy interactions. Majority of the transportation studies focused on either carbon footprint, energy, or economic aspects of the problem. Moreover, most of the studies focused on either GHG emissions or energy consumption associated with transportation sector. Similarly, SD studies focusing on energy consumption and climate change associated with transportation sector are limited within their system boundaries or at most the relationship between economy & energy, climate & energy, and the individual relationships between these sectors and their surrounding environment. There has been no effort to study the system of transportation as a whole and with its interactions of environment-economy-society nexus and understanding the dynamic complexity as it pertains to LCSA and transportation sustainability.

5.4. 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 objectives of this Chapter 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 attempt towards developing integrated and dynamic LCSA framework for sustainability assessment of new generation transportation systems.

5.5. Methodology

In this chapter, 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 (Triple-bottom-line, 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 useful life time is assumed to be 150,000 miles per vehicle. The comparison is made based on extreme scenarios for each vehicle such as %100 of market share for BEVs from now until 2050, which is explained in Section 3 in more detail. Therefore, the defined functional unit is unit impacts per extreme scenario.

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 sub-models, 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.

In the methodology section, following hierarchical framework is presented. First, the problem statement and reference more are explained. Second, system boundary, exogenous, endogenous, and excluded variables are introduced along with a brief explanation about each parameter. Third, causal relationships among the parameters and the sub-systems are explained. Fourth, mathematical relationships and formulations in the model are explained. Fifth, validation of the model is explained with graphical and statistical analyses.

5.5.1. Problem statement

As the U.S. transportation sector is an integrated part of economy, the environment, and society, it should be analyzed with a broader approach where all of these dimensions are dynamically captured. In this regard, the objective of this modeling effort is to develop a dynamic model that is capable of capturing dynamic behavior, feedback relations, interdependencies, side effects, and macro-level triple bottom line impacts of alternative vehicle technologies as well as conventional vehicles in the U.S. The proposed model investigates the long term behavior of each sub-system based on different alternative vehicle options to minimize their environmental impacts, while revealing the associated changes in the economy and society. The reference mode is selected as the change in temperature of the atmosphere and upper ocean compared to preindustrial levels. (°C) due to greenhouse gas emissions (NASA, 2014). However, validation of all of the sub-models are presented in Section 5.5.5.

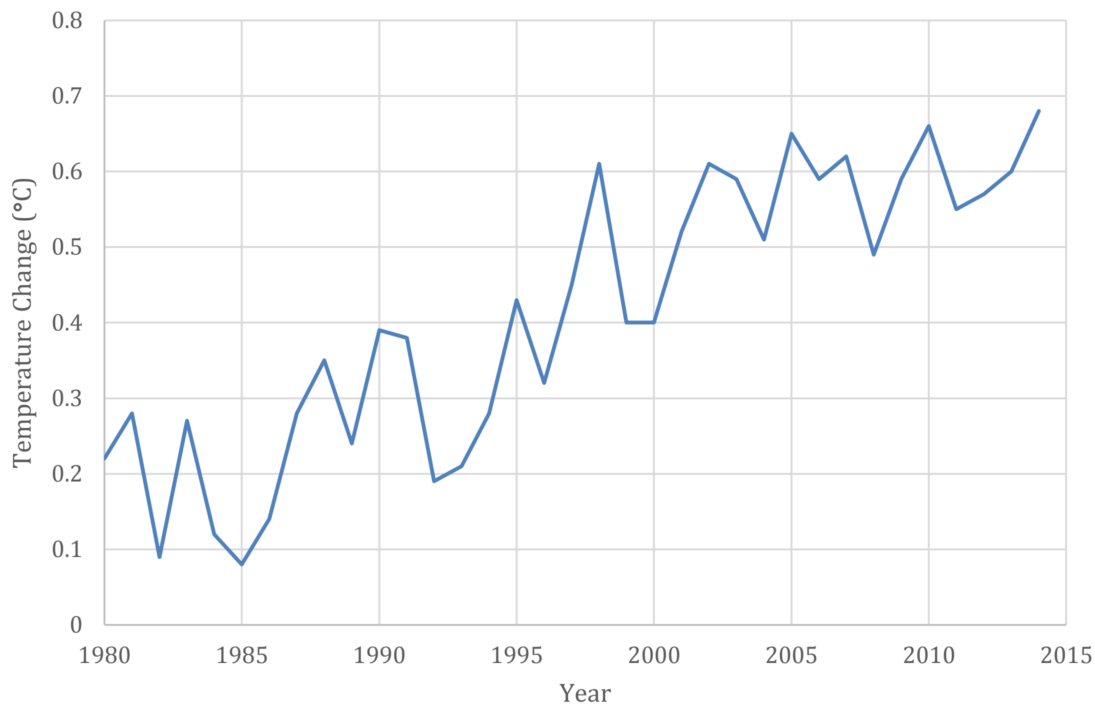


Figure 16. Atmospheric temperature change between 1980 and 2014

5.5.2. Identification of parameters

Model boundary is presented in Table 22 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 by the model based on the interactions and mathematical relationships among the variables.

Table 22. Table of model boundary

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

	Endogenous variables	Exogenous variables	Excluded variables
Social sub-model	Human health impacts from transportation	Life expectancy	
	Adjusted life expectancy	HH characterization factors	
	Employment from vehicle op.	Max life expectancy	
	Employment from vehicle man.	Life expectancy norm	
	Employment from rest of the U.S.		
	Public welfare		
	Education index		
	Income index		
	Life expectancy index		

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

Additionally, a brief description and units of the most critical parameters are presented in Table 23.

Table 23. Summary of model parameters

Model parameters	***Description***	***Unit***
New passenger vehicle sales	Number of vehicles sold in a year	#vehicles
Travel need index	Travel need as a function of employment, public welfare and population	Dmnl
Average annual VMT	Annual vehicle miles traveled	Miles
*On-road fuel efficiency**	Average fuel efficiency of vehicles on-road	Mpg
*Vehicle disposal**	Number of vehicles disposed each year	#vehicles
*Market share of vehicles**	Percentage share of vehicle type sold in a year	%
*Fuel efficiency of vehicles**	Gasoline or electricity consumption performance of vehicles	Mpg
Population	The total number of people in the U.S.	#people
Fertility rate	The average number of children that would be born to a woman over her lifetime	#people
Number of potential drivers	The number of people older than 16	#people

Model parameters	*Description*	*Unit*
Total number of vehicles on-road	The total number of vehicles on-road	#vehicles
*Emissions from vehicle manufacturing**	Total CO_2 emissions from vehicle manufacturing	tCO_2
*Emissions from vehicle operation**	Total CO_2 emissions during vehicles' operation phase	tCO_2
*PMF from vehicle manufacturing**	Particulate matter formation from vehicle manufacturing	kgPM10-eq
*PMF from vehicle operation**	Total PMF during vehicles' operation phase	kgPM10-eq
*POF from vehicle manufacturing**	Photochemical oxidant formation from vehicle manufacturing	kgNMVOC-eq
*POF from vehicle operation**	Photochemical oxidant formation from vehicle operation	kgNMVOC-eq
Deep ocean temp	Temperature of the deep ocean	C
Atmos. upper Ocean Temp	Temperature of the Atmosphere and Upper Ocean	C
Economic climate damage fraction	Economic impact of climate change on GDP increase rate	%
*Annual vehicle operation cost**	Total operation cost of vehicle including fuel and M&R cost	$
*Annual vehicle ownership cost**	Total vehicle ownership cost including vehicle operation and purchase	$
GDP contribution of manufacturing phase	Contribution of vehicle manufacturing to the U.S. gross domestic product	$
GDP contribution of operation phase	Contribution of activities during vehicle operation phase to the U.S. gross domestic product	$
GDP increase rate	Annual increase rate of the U.S. gross domestic product	%
Human health impacts from vehicle transportation	Human health impacts of air pollutants and CO_2 resulted from vehicles	DALY
Adjusted life expectancy	Average life expectancy after being exposed to air pollutants and CO_2	Years
Employment from vehicle operation	Employment generated due to activities during vehicle operation phase	#people
Employment from vehicle manufacturing	Employment generated due to vehicle manufacturing	#people
Employment from rest of the U.S. Economy	Employment trend from rest of the U.S. economy as a function of U.S. GDP	#people
Public welfare	Geometric average of education, income, and life expectancy index.	dmnl

Model parameters	*Description*	*Unit*
Education index	An index representing education status of the U.S.	dmnl
Income index	An index representing income status of the U.S.	dmnl
Life expectancy index	An index representing health status of the U.S.	dmnl

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

5.5.3 System conceptualization

System conceptualization is explained with the causal loop diagram (CLD) and a brief description of each loop. The CLD is presented in Fig. 17 in 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.

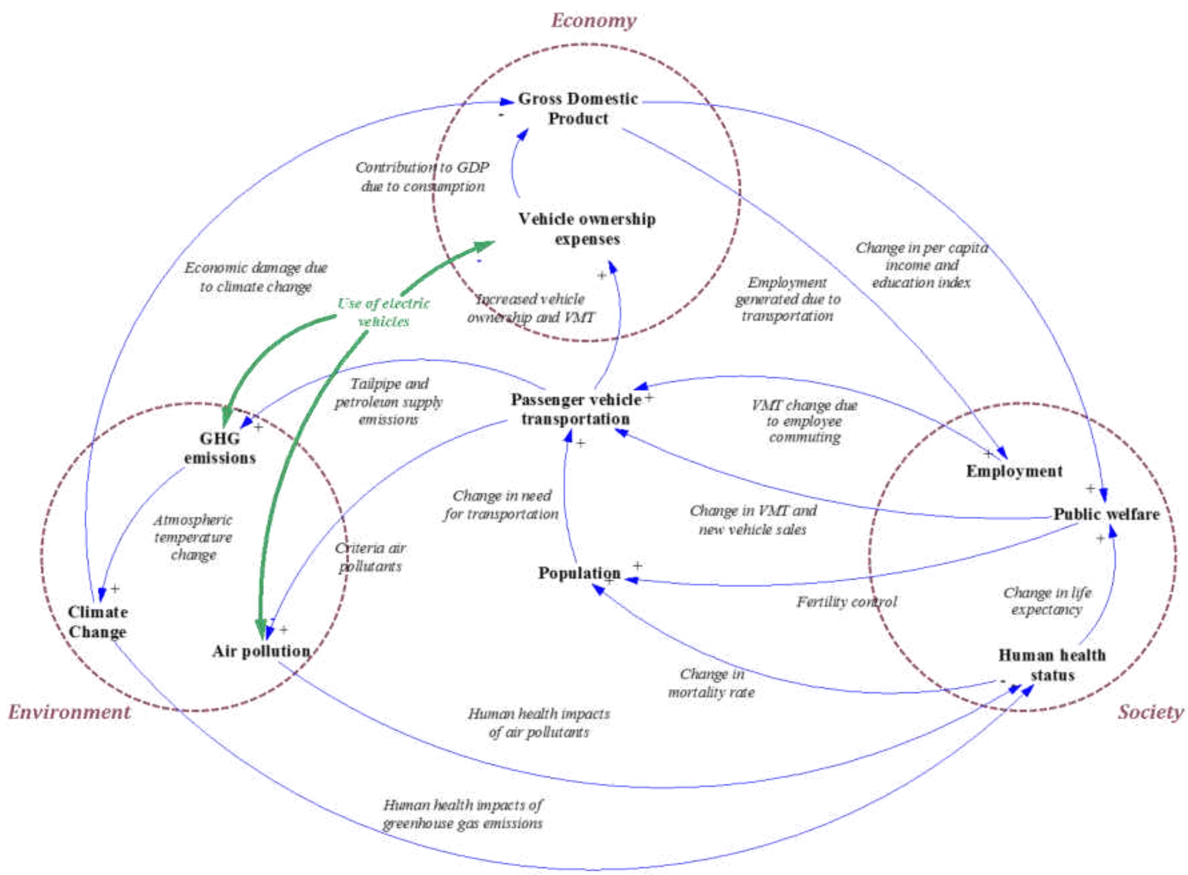


Figure 17. Causal loop diagram of the model

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 Fig. 17). In Figure 17, 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, accelerating 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. 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, 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, 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, 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. These sectorial outputs changes 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.

5.5.4. Model formulation

In this stage, mathematical relationships between major variables and the sub-models are explained in detail. The proposed SD model consists of 4 comprehensive sub-models as follows;

5.5.4.1. The U.S. transportation Sub-model:

The transportation sub-model is the focal point of this model, and includes indicators related to life cycle impacts of alternative passenger vehicles which depends on the estimated vehicle miles travelled (VMT) and on-road fuel efficiency. This sub-model receives feedbacks from the economy and social sub-models and population module which is adopted from the population module of WORLD3 model and modified for the U.S (Bossel, 2007; Meadows et al., 2004b). VMT increases as the travel need index increases, which is a function of public welfare, total employment, and population. Additionally, the number of vehicles on-road is an important parameter of this sub-model. The number of new vehicle sales increases as the income index and number of potential drivers increases. Mathematical formulations of the critical variables in the Transportation sub-model are as follows;

- *Average annual VMT:* This variable is a function of employment, public welfare, and population, which are endogenously calculated by the sub-models. An index is developed to represent the travel need in a single value by taking geometric average of the normalized values of employment, public welfare, and population. The relationship between the average annual VMT and travel need index is estimated by regression analysis (R^2=0.86). Eq. 5.1 shows the mathematical relationship between these two variables.

$$(\text{Average annual VMT})_{year}=1.54682e+012*LN((\text{Travel need index})_{year}) + 1.13085e+012 \tag{5.1}$$

- *New passenger vehicle sales:* This variable is a function of income index, number of potential drivers, and market share of passenger vehicles. A regression analysis conducted to estimate total number vehicle sales annually, which is multiplied by market share of passenger vehicles (automobiles). The market share data for automobiles is obtained from the U.S. Environmental Protection Agency (EPA, 2014) and the LAVE-Trans model (The National Research Council, 2013). Number of potential drivers are calculated endogenously through the population module, which refers to number of people above 16 years old. Income index is calculated endogenously via the Society sub-model. Future market share of each vehicle type is obtained from business as usual (BAU) case of the LAVE-Trans model, while past market shares are obtained from EPA (EPA, 2014). Annual new passenger vehicle sales are calculated as follows;

$$(\text{New passenger vehicle Sales})_{year} = (\text{Market share of passenger vehicles})_{year} * (138723* LOG((\text{number of potential drivers})_{year})+(\text{Income index})_{year}* 317195 + 883865)*1000 \tag{5.2}$$

- *On-road fuel efficiency:* This variable is calculated for each vehicle type. It is a function of the vehicle stuck, inflow of new vehicles with more efficient fuel economy, and outflow of disposed vehicles with less fuel economy. It is modeled via using a general density formula (mass=density*volume) in physics, where the stock is represented by multiplication of existing fuel economy and the number of vehicles. Inflow is the multiplication of new vehicle sales and the fuel economy of new vehicles, whereas outflow is the multiplication of the number of disposed vehicles each year and the fuel economy of the disposed vehicles. The same approach applied for each vehicle type. The fuel economy values between 1980 and 2014 of new vehicles are obtained from the transportation energy data book (Oak Ridge National Laboratory, 2013), while the future values are taken from the Vision model developed by Argonne National Laboratory (Argonne National Laboratory, 2014a). Fig. 18 shows the stock and flow diagram of the on-road fuel efficiency module for ICVs.

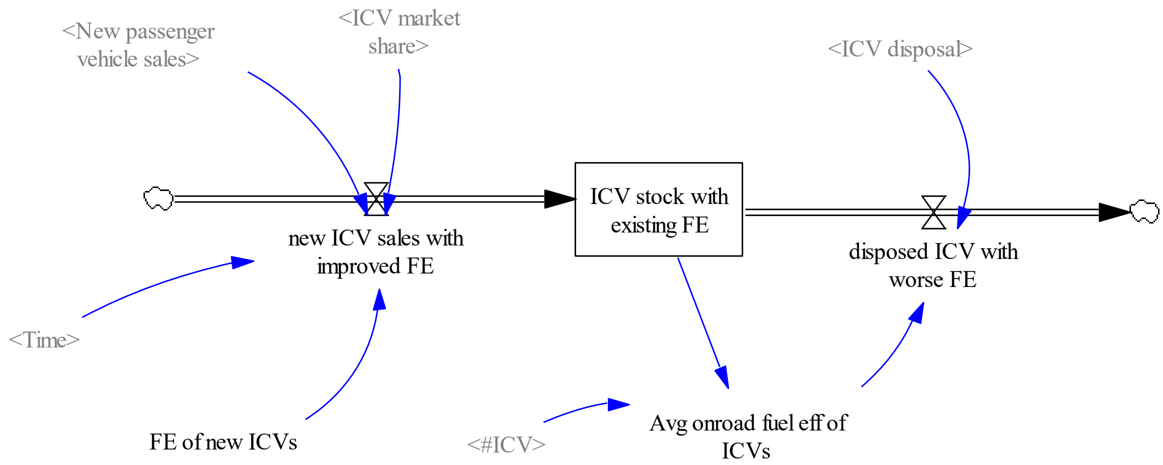


Figure 18. Fuel economy module for internal combustion vehicle

- *Population:* This module is adopted from the population module of WORLD3 model and modified for the U.S (Bossel, 2007; Meadows et al., 2004b). In this module, each age group is modelled as stocks and have different mortality rates based on the adjusted life expectancy which includes the human health impacts from air pollution and CO_2 emissions. Fertility rate is a function of public welfare. The studies in the literature confirm that the fertility-development relationship in the U.S. have a J-shaped relationship, where declining fertility rate was reversed after a threshold value of development (Furuoka, 2009, 2010; Myrskylä, Kohler, & Billari, 2009). In accordance with literature, the relationship between public welfare (as an indicator of development) and fertility rate is investigated. Eq. 5.3 shows the public welfare and fertility rate relationship (R^2=0.81). The equation shows the relationship after the threshold value where the fertility rate starts to increase. Fig. 19 shows the population module of the Transportation sub-model.

$$(\text{Fertility rate})_{year} = -38.9606*(\text{Public Welfare})_{year}\hat{}2 + 70.9836*(\text{Public Welfare})_{year} - 30.2566 \quad (5.3)$$

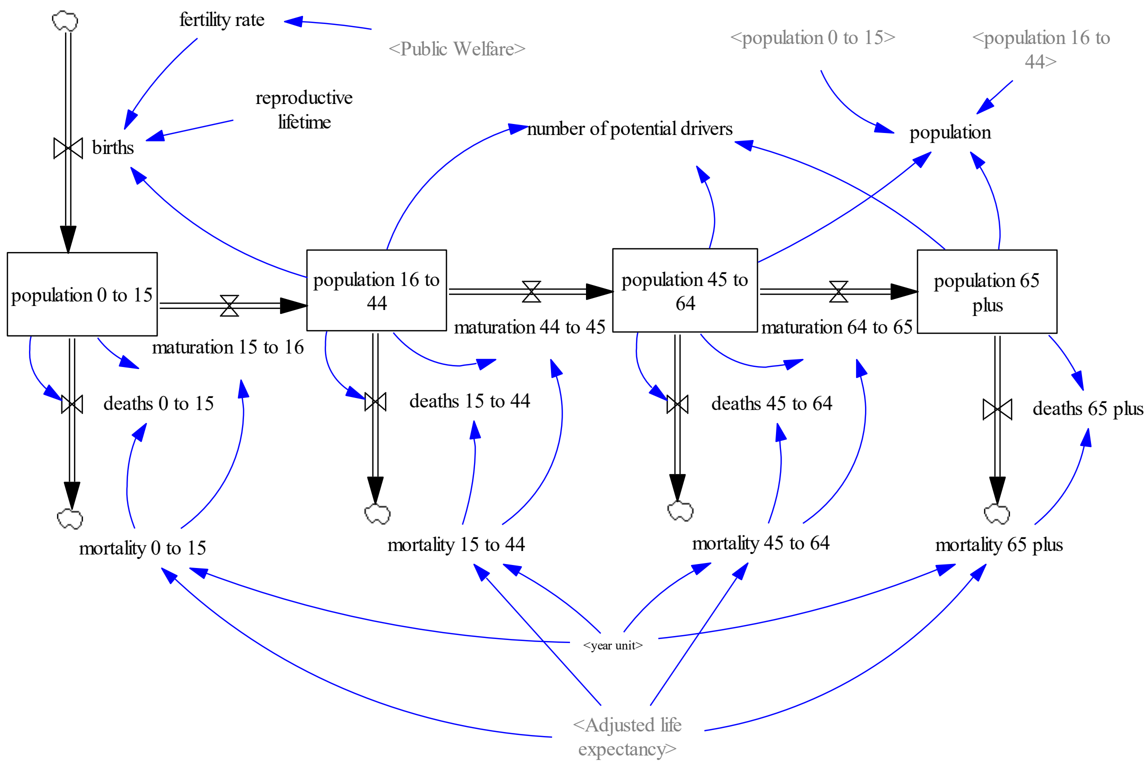


Figure 19. Stock and flow diagram for population module

5.5.4.2. The environment sub-model:

This sub-model calculates the environmental impacts, particularly CO_2, PM10-eq. (particulate matter less than 10 micrometers in diameter), and NMVOC-eq. (Non-methane volatile organic compound) emissions. These emissions are calculated for manufacturing and operation phases of passenger vehicles by considering transportation activities and upstream components such as petroleum supply and electric power generation. The Environment model also contains a climate change module where carbon cycle, atmospheric temperature change and associated economic damages are calculated based on the emissions from the U.S. transportation sector and exogenously defined systems including rest of the U.S. and the World. The climate model is a modified version of the Dynamic Integrated Climate-Economy model (DICE) developed in Yale University (Fiddaman, 2008; Nordhaus, 2006). Mathematical relationships in some of the critical parameters and modules are as follows;

- *CO_2 Emissions from vehicle manufacturing and operation:* Vehicle manufacturing emissions are calculated via emission multiplier obtained from literature (Onat, Kucukvar, et al., 2014c). The total emission is calculated by multiplying the emission multiplier per vehicle and the number of vehicle sale. This procedure applied for each vehicle type. Battery manufacturing impacts are included by the representative emission multipliers for each vehicle type, which are 6.96 and 7.52 tonCO_2 per ICV and HEV. The emission multipliers for PHEVs and EVs ranges between 7.49 and 11.2 tonCO_2, depending on the battery size and all-electric range (AER). The manufacturing emissions changes through time as the technology advances. These emissions are entered as exogenous lookup variables and this data is obtained from LAVE-trans model. On the other hand, operation emissions are calculated using multipliers from the TBL-LCA model. The phase emissions for ICVs and HEVs are calculated as follows;

$$(\text{ICV } CO_2 \text{ emission rate})_{year} = 1/(\text{Avg. on*road fuel eff. of ICVs})_{year} * (\text{Annual VMT per vehicle})_{year} * (\text{Petroleum supply emission per gallon of gasoline} + \text{Tail pipe emissions per gal of gasoline}) \quad (5.4)$$

Same methodology is applied for HEVs. Petroleum supply and tail pipe emissions are 2.11 $kgCO_2$ and 8.92 $kgCO_2$ per gal on gasoline, respectively (EPA, 2013; Onat, Kucukvar, et al., 2014c). On the other hand, operation phase emissions of PHEVs and EVs are calculated as follows;

PHEV CO_2 emission rate)$_{year}$ = (Annual VMT per vehicle)$_{year}$*(Utility factor*((Avg. on-road FE of PHEV on elect.)$_{year}$*Electricity supply emissions per kWh)+(1-Utility factor)*(1/(Avg. on-road FE of PHEV on gas)$_{year}$ *(Tail pipe emissions per gal of gasoline + Petroleum supply emission per gallon of gasoline))) (5.5)

(EV CO_2 emission rate)$_{year}$ =(Annual VMT per vehicle)$_{year}$ *(Avg. on-road FE of EVs)$_{year}$*Electricity supply emissions per kWh (5.6)

Where, the utility factor is a function of AER which is determined by battery size based on the equations provided by the VISON and LAVE trans models (Argonne National Laboratory, 2014a; The National Research Council, 2013). The utility factor is calculated as follows;

$$0.00049+0.0194148*AER-0.000214596*AER+0.00000130166*AER^3$$
$$0.00000000327902*AER^4 \quad (5.7)$$

- *PMF and POF from vehicle manufacturing and operations:* The same methodology is applied to calculate PMF and POF from vehicle manufacturing and operations. Manufacturing PMF multipliers are 16.38, 17.68, 17.9-20.9, 26 $kgPM_{10}$-eq per ICV, HEV, PHEV, and EV, respectively (Onat, Kucukvar, et al., 2014c). PMF and POF are calculated by using characterization factors from ReCiPe (ReCiPE, 2009), using emissions of CO, NO_x, PM_{10}, $PM_{2.5}$, SO_2, and VOC. Manufacturing POF multipliers are 31.1, 33.2, 32.7-38.3, 46.2 kgNMVOC-eq per ICV, HEV, PHEV, and EV, respectively (Onat, Kucukvar, et al., 2014c). Similarly, operation phase emissions are calculated using both sector and process level data, which is known as hybrid input-output life cycle assessment (C. T. Hendrickson et al., 2006; Huang, Weber, & Matthews, 2009; Onat, Kucukvar, et al., 2014b; Suh et al., 2004). Sector level data is obtained from the TBL-LCA model (Murat Kucukvar, Egilmez, et al., 2014; Onat, Kucukvar, et al., 2014a). Tail pipe PMF and POF per burning a gallon of gasoline is 0.0019343 kgPM10-eq. and 0.01152 kgNMVOC, respectively. Electric power generation and its upstream PMF and POF are 0.00135394 kgPM10-eq. and 0.00186 kgNMVOC, respectively, whereas gasoline supply PMF and POF values per gallon of gasoline are 0.00192721 kgPM10-eq. and 0.00688 kgNMVOC, respectively (Onat, Kucukvar, et al., 2014c).

- *Economic climate damage fraction:* Economic loss due to climate change is resented as damage to GDP, which is usually related to damages associated with agricultural productivity, dislocations resulting from higher sea levels, and dollar-equivalent costs such as increases in mortality, morbidity, and social disruption (Pindyck, 2011). In the literature, most of the quantification of climate related economic damages are expressed as direct impact temperature change to the levels of GDP and consumption. Similarly, the economic damage function of the DICE model relates the temperature change directly to level of GDP (Nordhaus, 2006). However, global warming can have a permanent impact on future GDP and consumption, and therefore should be related to the “growth rate of GDP” rather than directly affecting “level of

GDP" (Pindyck, 2011). Therefore, we combined the DICE model and the economic damage function proposed by Pindyck (2011). The atmospheric and upper ocean temperature change is calculated using DICE model, whereas the relationship between the temperature change and economy is formulized according to climate damage function of Pindyck (2011). Eq. 5.8 shows the climate damage function.

$$\gamma = \frac{1.79\beta\Delta T}{H} \tag{5.8}$$

where, ΔT is atmospheric temperature change, β is a variable follows gamma distribution (min= 0.000628, max=0.00321, order=4.5, shift= 0.0019, stretch= 0.00105), and H is 100 years. Hence, economic climate damage on GDP growth rate, the growth rate loss function, is calculated as follows;

$$g_t = g_0 - \gamma\Delta T_t \tag{5.9}$$

where, $g_t$and g_0 are the growth rates at time 0 and t. Fig. 20 shows he climate change module of the model.

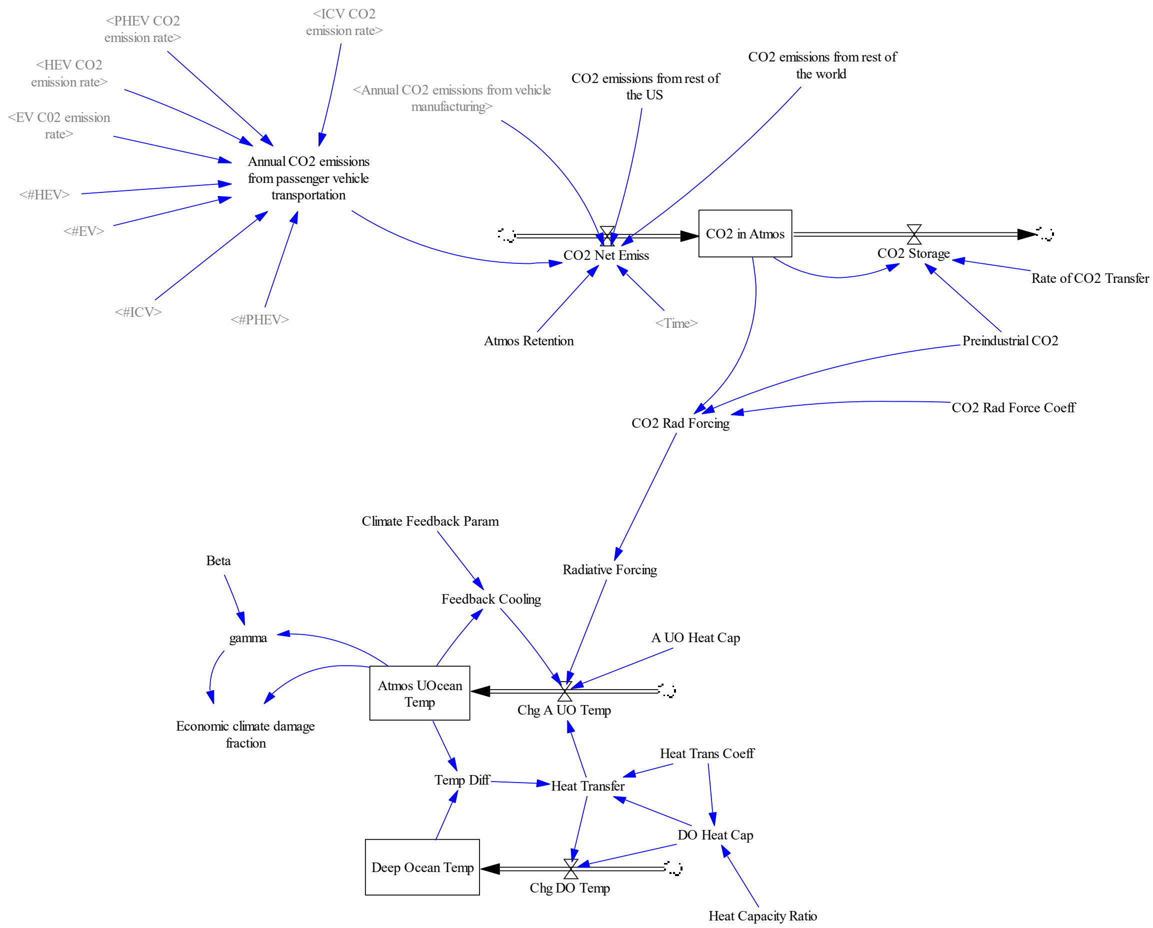


Figure 20. Stock and flow diagram for climate change module

5.5.4.3. The Economy sub-model:

This sub-model is primarily consist of two modules, which are vehicle ownership cost and gross domestic product (GDP). Vehicle ownership cost includes vehicle purchase, maintained and repair, battery costs (in the case of change), and fuel expenses. The vehicle related expenses increases the economic activity in transportation and related sectors and contribute GDP through increased consumption. Rest of the U.S. economy is modeled as exogenous variables by using Organisation for Economic Co-operation and Development (OECD) estimates of the U.S. economic growth for the period between 2015-2050 (Chateau, Rebolledo, & Dellink, 2011). Some of the key variables are as follows;

- *Annual vehicle operating and ownership costs*: These variable are calculated for each vehicle type and represented as different variables correspond each. Vehicle operating cost includes cost of gasoline, electricity, battery replacement, and maintenance and repair. Operating costs of HEVs and ICVs are calculated with the same formulation, represented in Eq. 5.10 for HEV.

$$(\text{HEV annual operating cost})_{time} = (\text{Annual VMT per vehicle})_{time} * (1/(\text{Avg. on-road fuel eff. of HEVs})_{time} * (\text{cost per gal of gasoline})_{time} + \text{per mile M\&R cost}) \quad (5.10)$$

Equations 5.11 and 5.12, shows the annual operating costs for PHEVs;

$$(\text{PHEV annual operating cost})_{time} = (\text{Annual VMT per vehicle})_{time} * [[\text{Utility factor} * (\text{electricity cost per kWh})_{time} * (\text{Avg. on-road fuel eff. of PHEV on elect.})_{time}] + [(1-\text{Utility factor}) * (1/\text{Avg. on-road FE of PHEV on gas})_{time} * (\text{cost per gal of gasoline})_{time}] + \text{per mile M\&R cost} * 0.85 + \text{Battery cost/Useful lifetime}] \quad (5.\ 11)$$

$$(\text{EV annual operating cost})_{time} = (\text{Annual VMT per vehicle})_{time} * [(\text{Avg. on-road fuel eff. of EVs})_{time} * (\text{electricity cost per kWh})_{time} + \text{per mile M\&R cost} * 0.8 * + \text{Battery cost for EV/Useful lifetime}] \quad (5.\ 12)$$

The future cost of electricity, batteries, and vehicles are taken from LAVE-Trans model (The National Research Council, 2013), while cost of gasoline are obtained from transportation energy data book (Oak Ridge National Lab., 2013) and annual energy outlook 2014 (The U.S. Energy Information Administration, 2014). The gasoline cost estimates was until 2040, and therefore, the rest of the data is extrapolated until 2050 based on department of energy's estimations. All of the costs are presented in 2013 constant dollars, using consumer price indexes where it is necessary.

- *GDP contribution of manufacturing and operation phases*: GDP contribution of transportation related expenses are calculated by using the ownership costs. Basically, retail prices are multiplied by a set of factors to estimate the producer price of items and processes. Producer price of vehicles are assumed to be 65% of the retail price of vehicles, while the producer price of the operation phase activities are assumed to be 80% of the retail prices. Fig. 21 shows a part of the GDP module where total GDP and contribution of transportation is calculated.

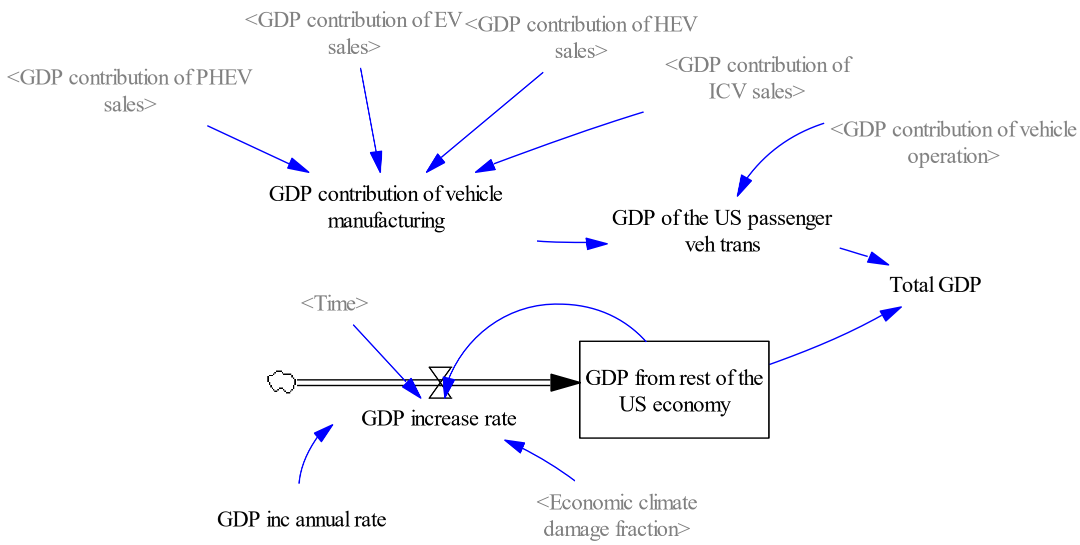


Figure 21. Stock and flow diagram of GDP module

5.5.4.4. The society Sub-model:

There are three important modules in this sub-model, which are human health, employment, and public welfare. Life expectancy data is obtained from the U.S. Social Security (the U.S. Social Security, 2014) and calibrated by including impacts of CO_2 and air pollutant emissions. The air pollutants and CO_2 emissions from transportation sector effects the life expectancy values of the U.S. The characterization factors to estimate health impacts of air pollutants and CO_2 are obtained from ReCiPe (ReCiPE, 2009). The adjusted life expectancy values affect the mortality rates at different age groups through population module. Employment in transportation sector is obtained by using the TBL-LCA model, where sector-specific employment per $M output are provided as a multipliers (M Kucukvar & Tatari, 2013; Onat, Kucukvar, et al., 2014c). Public welfare is a function of income, health, and education indexes, which indicates the human development index developed by United

Nations Human Development Programme (United Nations, 2014). These indexes are calculated based on the guidelines provided by UN and endogenous data calculated by the model variables.

- *Employment from vehicle operation and vehicle manufacturing*: Employment is calculated as a function of economic activity in relevant sectors. Employment multipliers (#of people per $ of contribution to GDP) is multiplied by GDP contribution of vehicle operation. These multipliers are obtained from the TBL-LCA model (Murat Kucukvar & Tatari, 2013; Onat, Kucukvar, et al., 2014a, 2014c)

- *Employment from rest of the U.S. Economy*: This variable is a function of GDP from rest of the economy (excluding the transportation sector). The relationship is defined by a regression analysis (R^2=0.996) and formulated as follows;

Employment from rest of the U.S. Economy = e^(-0.206976*LN(GDP from rest of the US economy)^2+12.9031*LN(GDP from rest of the US economy)-182.284) (5.13)

- *Public welfare*: Calculation of this variable is based on human development index developed by United Nations Human Development Programme (United Nations, 2014). Public welfare is geometric average of income, education and life expectancy indexes. Income and life expectancy indexes are calculated as follows;

Income index = LN((GDP per capita in $2011)-LN(100))/(LN(75000)-LN(100)) (5.14)

Life expectancy index = (Adjusted life expectancy-Life expectancy norm)/(Max life expectancy-Life expectancy norm) (5.15)

where, life expectancy norm and max life expectancy are 25 and 85 years, respectively. On the other hand, education index is calculated as a function of GDP per capita via a regression analysis (R^2=0.90);

Education index=0.15321*LN(GDP per capita in $2011)-0.783541 (5.16)

5.5.5. Model validation

Model validation, the accuracy of the model behavior's compared to the existing system behavior (Barlas, 1996), is a critical phase in SD modeling. There are two types of modeling techniques from model validation perspective, namely: causal descriptive and black-box (Barlas, 1996). 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 (Egilmez and Tatari, 2012).

Mainly, 9 variable sets are considered to be used in the validation analysis, namely: 1) Atmospheric temperature change, 2) New passenger vehicle sales, 3) New passenger vehicle sales , 4) Population, 5) On-road fuel efficiency of ICVs, 6) GDP, 7) Life expectancy, 8) Employment, 9) Public Welfare The validation step is carried out by looking at the actual data and the 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. On the other hand, the nonparametric test, Two Sample Kolmogorov Smirnov, is used for the variables that the either of the datasets (model or real) does not hold the assumptions of the ANOVA test.

Analysis is done by using SPSS software. According to the analysis results, 7 out of 9 variables are 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 are not normal were found to be associated with 3rd and 5th variables, namely: new passenger vehicle sales and new passenger vehicle sales. Results of the ANOVA analysis are shown in Table 24. 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 24. Results of the ANOVA analysis

Variable number	Variable name	One Way ANOVA	
		F Value	Test Statistic
1	Atmospheric temperature change	1.794	0.185
2	New passenger vehicle sales	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 25, which indicate that at least one test statistic is less than 0.05. In Table 26, results of non-parametric two sample 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 25. 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 26. 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

5.5.6. Comparison of alternative vehicle technologies

The comparison of vehicle types (ICVs, HEVs, PHEVs, EVs) are made based on the defined function unit, which is 100% annual market share per vehicle type starting from 2016. These extreme scenarios are compared with the forecasts of the VISION model, developed by the U.S. Department of Energy (Argonne National Laboratory, 2014a). The rationale behind the selection of the functional unit is to capture the effect of all system and reveal the maximum available sustainability impacts from each vehicle type. It is very common that LCA studies that focus on quantifying impacts of vehicles are based on per kilometer or mile. Such functional units cannot capture the dynamic relationships and causal factors that may affect the performance of vehicles. For instance, if HEVs are sold with 100% market share starting from 2016, the number of new vehicle sales, population, economic parameters, etc. will be different 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 selected functional unit 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 more fair 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. Table 27 shows these extreme scenarios.

Table 27. 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%	5.720%	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%	5.720%	0.584%	0.001%
	2016	0.0%	100%	0.000%	0.000%
	2030	0.0%	100%	0.000%	0.000%
	2040	0.0%	100%	0.000%	0.000%
	2050	0.0%	100%	0.000%	0.000%
S-PHEV	2010	95.8%	4.2%	0.005%	0.001%
	2015	93.7%	5.720%	0.584%	0.001%
	2016	0.0%	0.0%	100%	0.000%
	2030	0.0%	0.0%	100%	0.000%
	2040	0.0%	0.0%	100%	0.000%
	2050	0.0%	0.0%	100%	0.000%
S-EV	2010	95.8%	4.2%	0.005%	0.001%
	2015	93.7%	5.720%	0.584%	0.001%
	2016	0.0%	0.0%	0.0%	100%
	2030	0.0%	0.0%	0.0%	100%
	2040	0.0%	0.0%	0.0%	100%
	2050	0.0%	0.0%	0.0%	100%

5.6. Results and discussion

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

5.6.1. Environmental impacts

Fig. 22 shows the CO_2 emissions impacts for each vehicle type compared the BAU scenario. Manufacturing impacts of S-EV and S-PHEV are much higher compared to other scenarios, which is mainly because of the battery manufacturing On the other hand, the CO_2 emissions are revered in the operation phase, in which the EVs are found to be the best option followed by the PHEVs. When total life cycle impacts are considered, the impacts of manufacturing phase is effective between 2016 and 2018. The total life cycle CO_2 emissions of EVs are found to be least after several years of worst performance due to manufacturing phase. Considering that the battery improvements and associated impacts are taken into account, the technological advances in battery technology favors EVs and PHEVs, while fuel efficiency improvements favors all of the vehicles at different degrees. BAU scenario, which contains much higher number of ICVs, has a declining trend than to fuel efficiency improvements of ICVS.

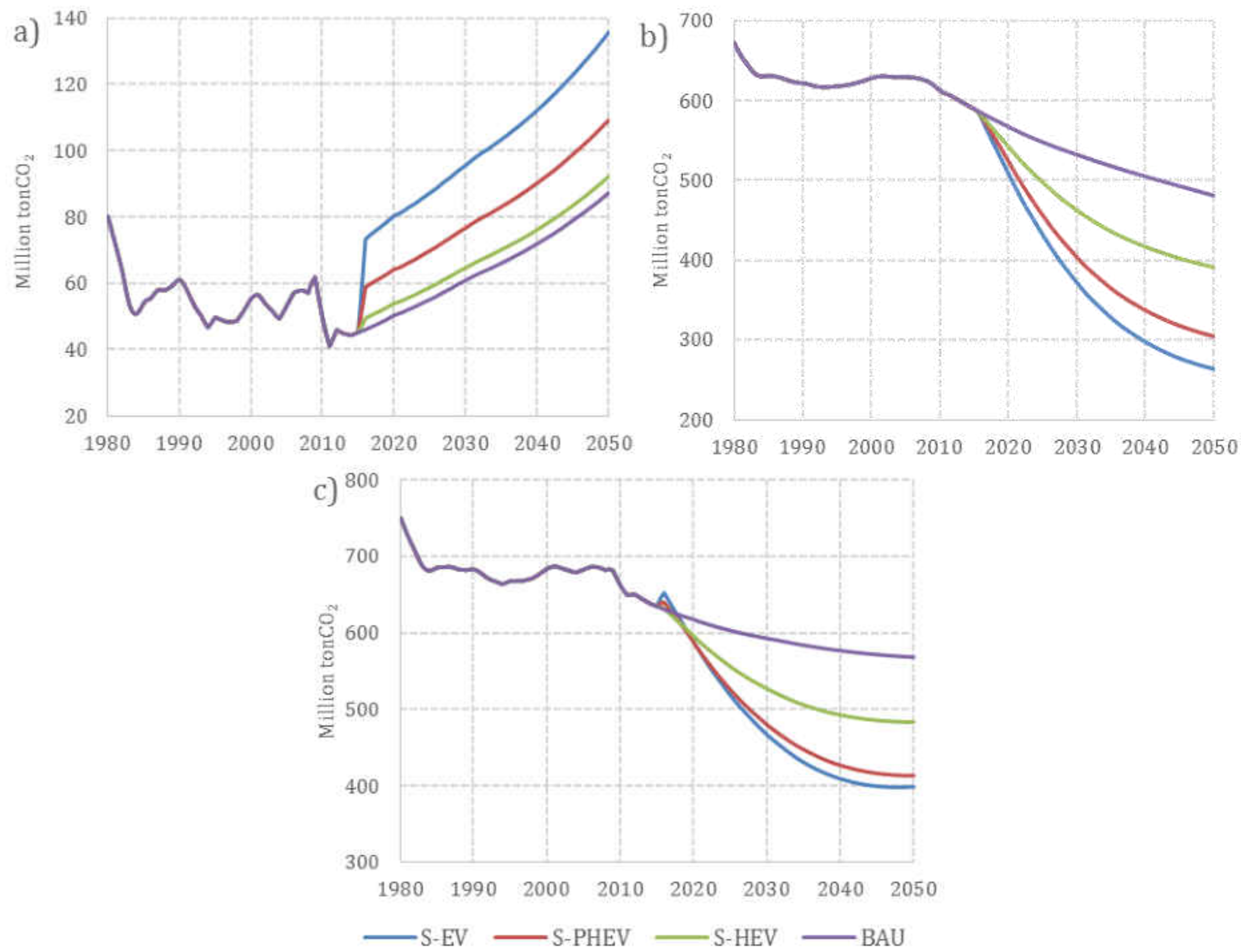


Figure 22. CO_2 emissions from vehicle transportation a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle Emissions

PMF impacts of vehicle options are presented in Fig. 23. PMF impacts have similar trends with those of CO_2 emissions. PMF of EVs are highest in the manufacturing phase, whereas it is lowest during the operation phase. PMF of PHEVs are very close to that of EVs in the operation phase. The maximum PMF reduction potential of EVs are 11% compared to BAU case. The effect of manufacturing phase 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 less reduction in operation phase compared to sharp increase in manufacturing phase.

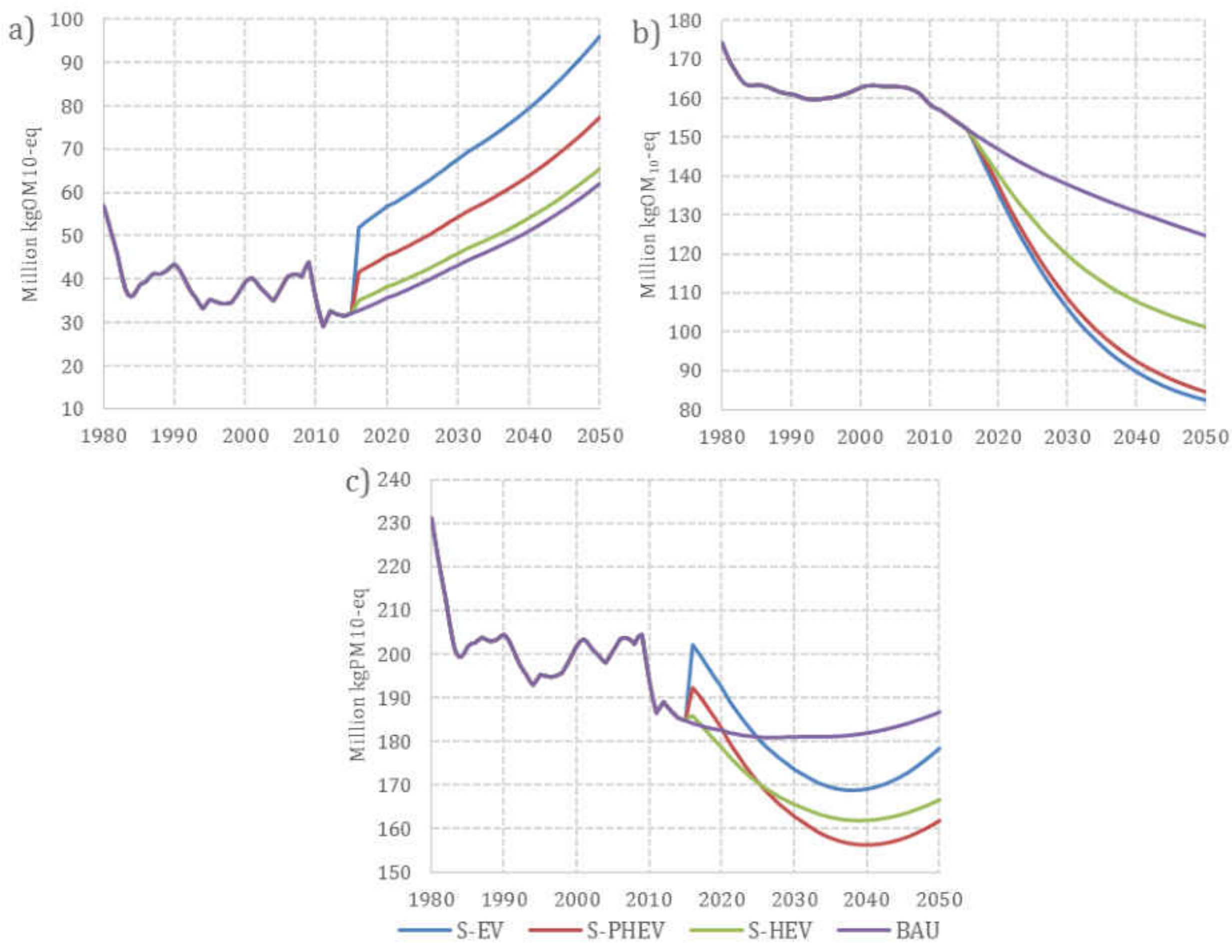


Figure 23. PMF from vehicle transportation a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle

Fig. 24 shows the POF impacts of vehicle options. The trend of manufacturing phase similar to that of PMF and CO_2 emissions. EVs perform the worst in manufacturing phase, while they are the second worst in operation phase with HEVs. 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 with a period of exemption between 2032 and 2043. Overall, HEVs and PHEVs are better options to reduce POF impacts from transportation.

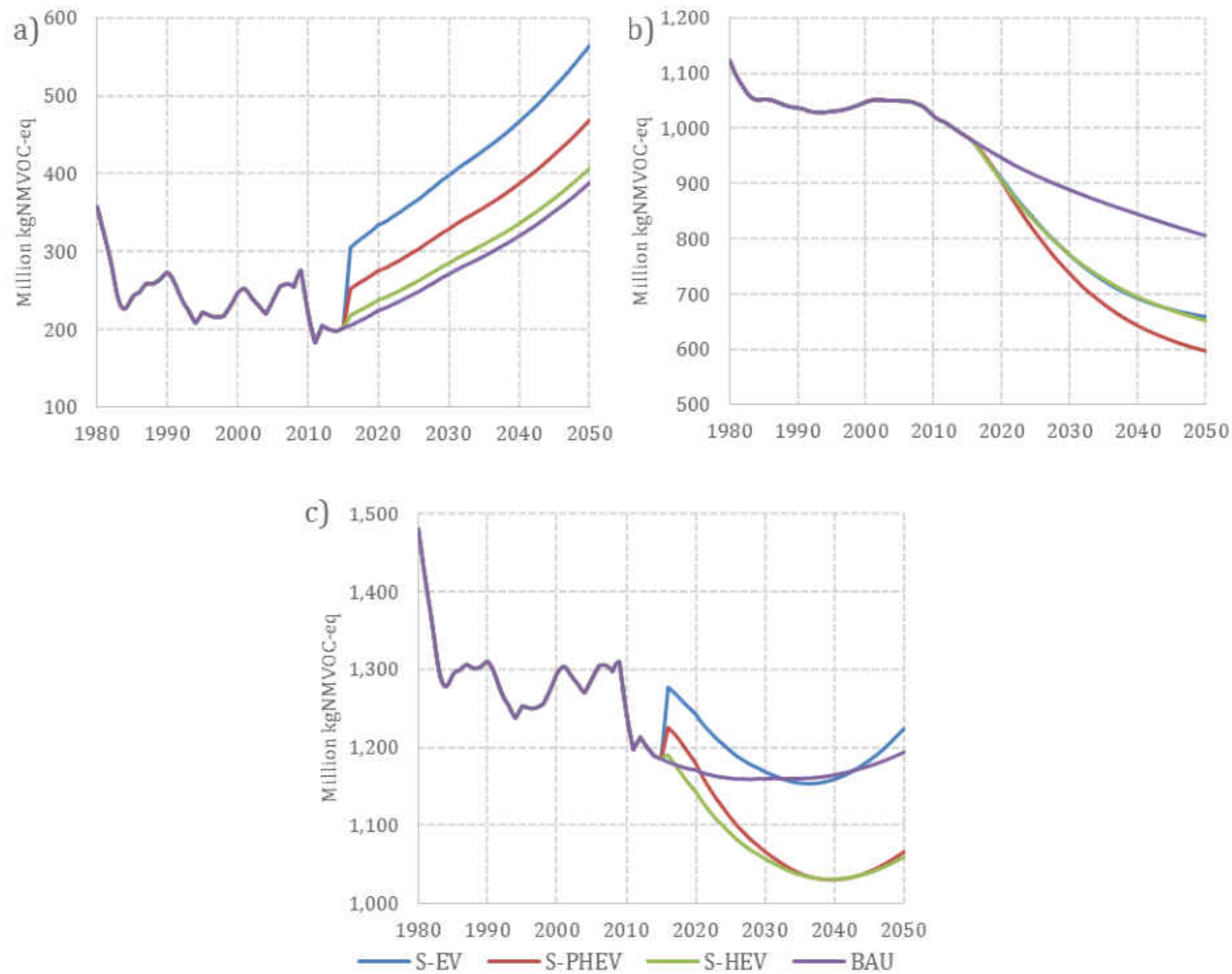


Figure 24. POF from vehicle transportation a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle

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 does not affect the atmospheric temperature significantly. Reducing the atmospheric climate change requires much more ambiguous 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.

5.6.2. Economic Impacts

Economic impacts are evaluated according to vehicle ownership costs to drivers and overall contribution to U.S. GDP. Fig. 25 shows the vehicle ownership costs during the operation phase and the total life cycle ownership costs. As shown in Figure 9, 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 are slightly lower than the BAU case that is composed of ICVS. Operation phase costs are lowers for PHEVs until 2029 where EVs became more favorable option afterwards. Another interesting result is that the total life cycle cost of ICVs became as low as PHEVs and slightly lower 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.

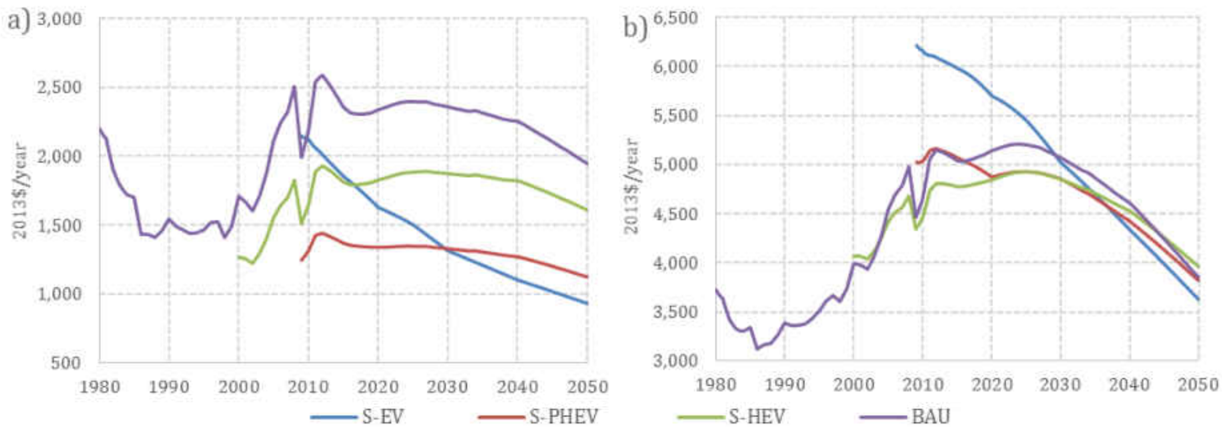


Figure 25. Annual vehicle ownership costs a) Operation Phase, b) Total Life Cycle

Fig. 26 shows the contribution of each life cycle phase to the U.S. GDP for each scenario. GDP contribution in manufacturing phase is dominated by EVs and PHEVs. All of the vehicle types have and increasing trend due to increased consumption. While economic size 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 HEVs, whereas the contributions PHEVs and BEVs decrease. Because, increasing VMT trend stimulated the contribution of HEVs and ICVs, while it couldn't 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. Overall, the contribution of HEVs became the largest in 2050 with an increasing trend since they are introduced to the market.

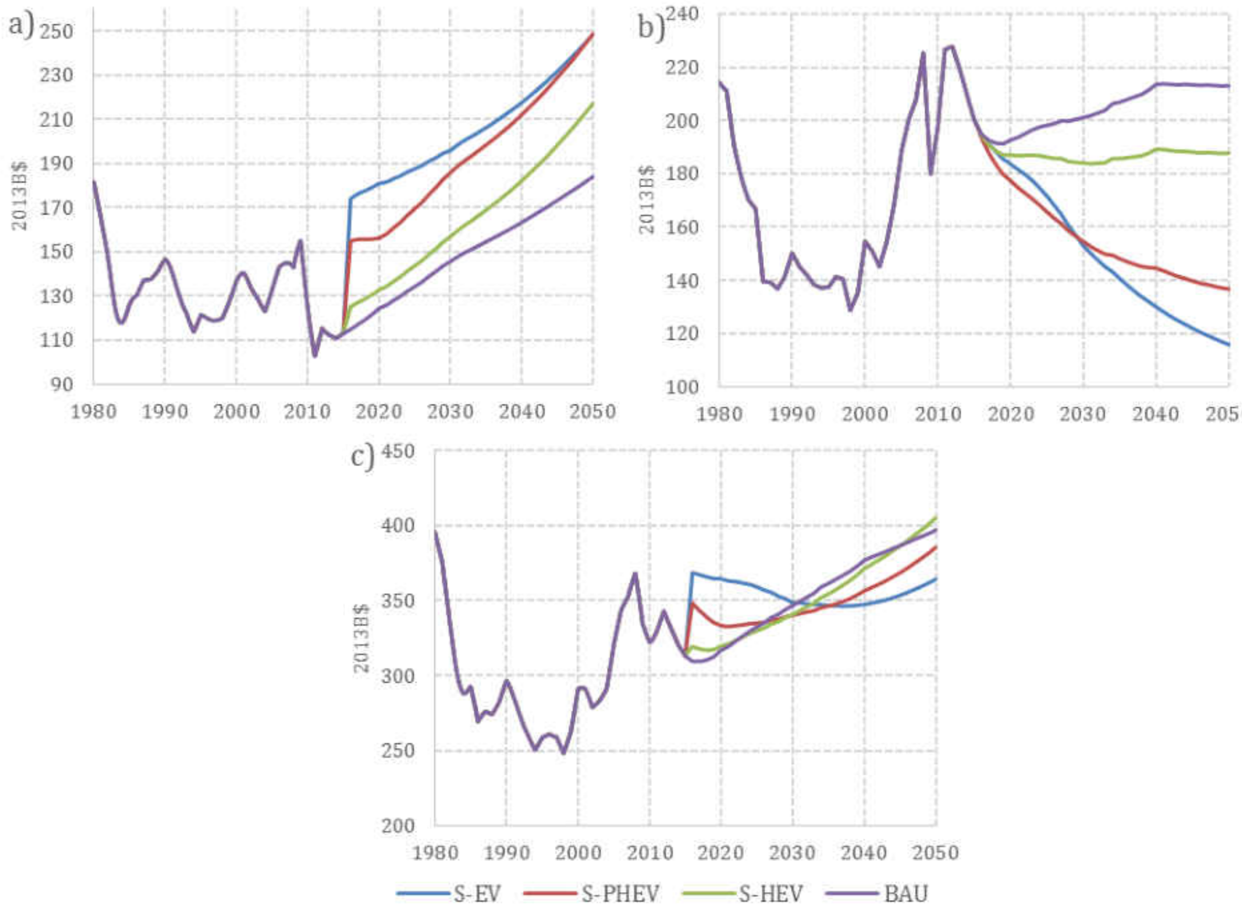


Figure 26. Contribution to GDP a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle

5.6.3. Social Impacts

Social impacts are represented by the indicators of employment and human health. Employment contribution of each life cycle phase and vehicles are presented in Fig. 27. 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 and reduced consumption. The total life cycle employment trends have a fluctuating structure where newly introduced technologies creates more employment at the beginning and reaches an equilibrium afterwards. Overall, the total life cycle employment contribution of HEVs and ICVs are more stable and increases with almost a constant slope mainly due to increased travel demand and developments in the associated sectors.

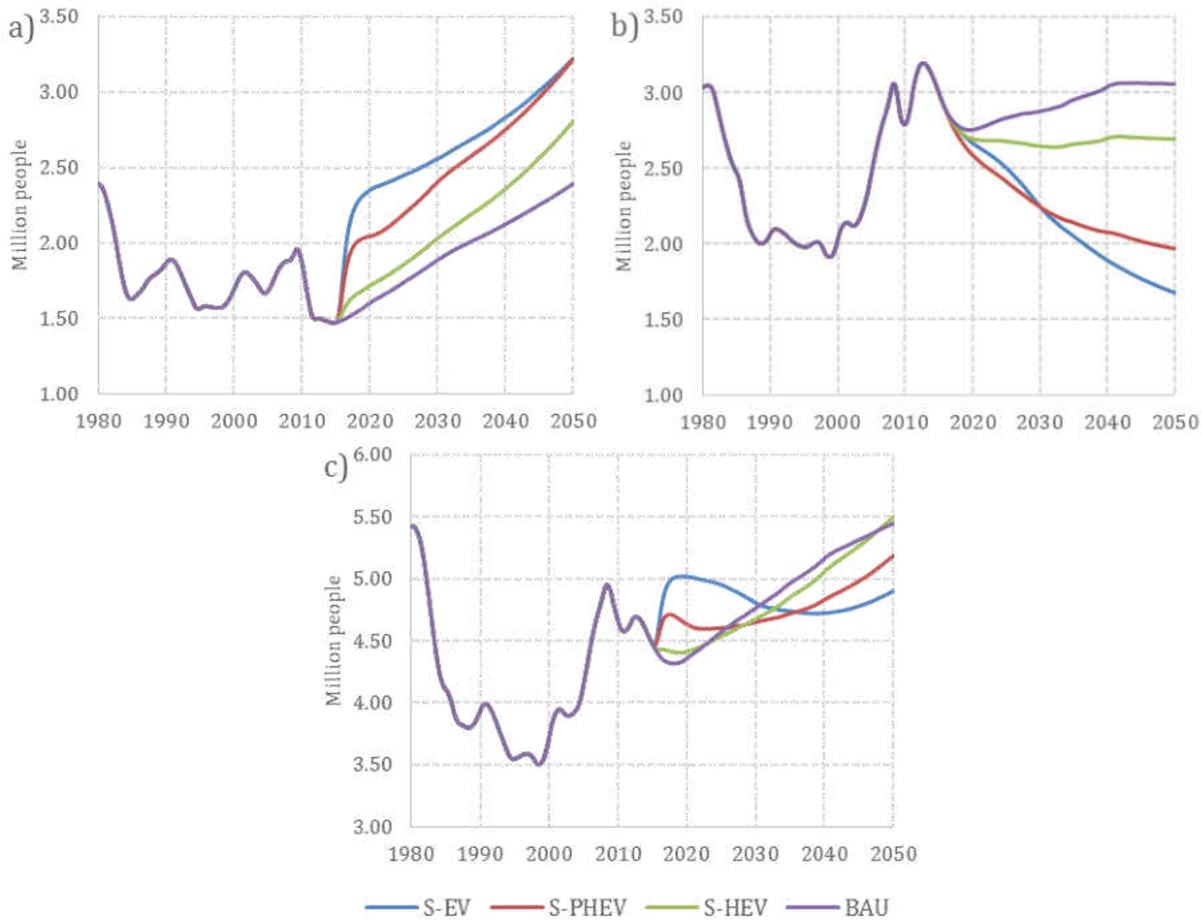


Figure 27. Contribution to employment a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle

Human health impacts resulting from PMF, POF, and the global warming are presented in Fig. 27. The human health impacts in manufacturing phase is much smaller than the operation phase in general. However, as the fuel efficient and battery technologies improved the relative impacts of operation phase become smaller. Human health impacts in manufacturing phase is dominated by EVs and PHEVs and have an increasing trend over time due to increased travel demand. On the other hand, 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. 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.

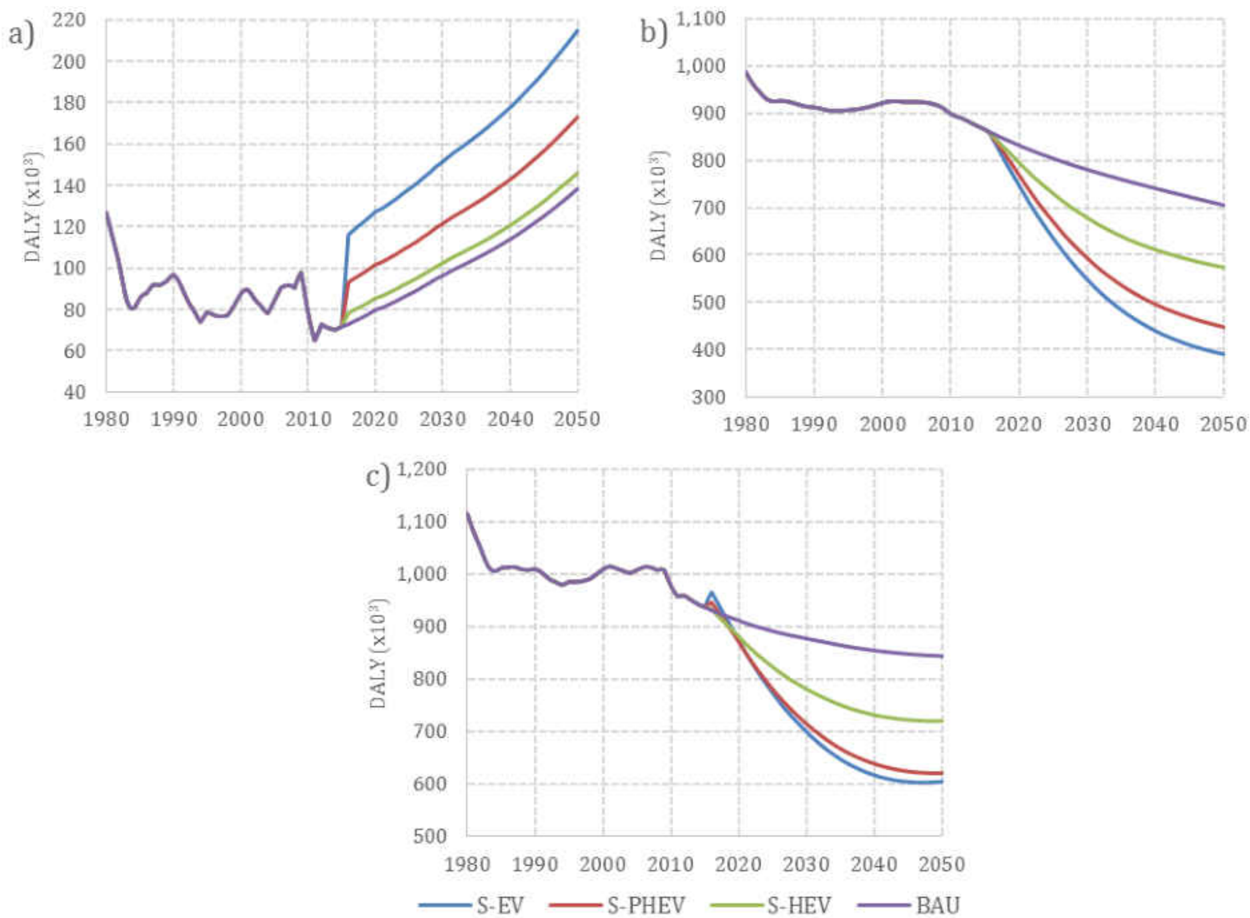


Figure 28. Human health impacts a) Manufacturing Phase, b) Operation Phase, c) Total Life Cycle

The use of different vehicle types has a negligible 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 reasons of this insignificant impact is that the determinants of public welfare does not change significantly as the vehicle preference changes. The effect of vehicle choices on income, education, and life expectancy indexes are very small and geometric average of these indexes are even smaller.

CHAPTER 6. UNCERTAINTY-EMBEDDED DYNAMIC SUSTAINABILITY ASSESSMENT FRAMEWORK FOR ALTERNATIVE VEHICLE TECHNOLOGIES

This Chapter mainly focuses on improving the model presented in Chapter 5 by considering behavioral uncertainties inherent in the system of transportation as well as its surrounding economic, social, and environmental systems.

6.1. Uncertainty in LCSA

The reliability of LCA results is highly dependent on the quality of data used. According to a review of unresolved problems associated with the LCA methodology, uncertainties in life-cycle inventory data is currently among the most critical of these problems and is therefore of paramount importance (Reap, Roman, Duncan, & Bras, 2008). The researchers also concluded that improper treatment of uncertain data can result in problematic decisions during the life cycle impact assessment and in the subsequent interpretation of LCA results. According to Finnveden the quality of the input data and the degree to which uncertainties are considered are both crucial considerations for any LCA analysis. Uncertainty analyses are of particularly great importance today because the majority of LCA studies in current literature have assigned a single value to each input parameter and then developed deterministic models to estimate the environmental impacts, even though using such deterministic models fails to adequately account for the inherent variability and uncertainty in any LCA analysis. To make more informed and accurate decisions, LCA practitioners need to understand and account for the uncertainty in input data used in LCA (Lloyd & Ries, 2008). Several approaches have been proposed and implemented in currently available literature for conducting LCA analyses under uncertainty, including Monte Carlo simulation, which has been applied in a handful of LCA studies as a promising technique to address data uncertainty and inaccuracy (M. A. J. Huijbregts et al., 2001; M. Huijbregts, 2002; Hung & Ma, 2008; M Kucukvar et al., 2014; Murat Kucukvar & Tatari, 2011; Lo, Ma, & Lo, 2005; Tatari, Nazzal, & Kucukvar, 2012). According to Ciroth et al. (Ciroth, Fleischer, & Steinbach, 2004), the evaluation of uncertainty is relatively new in environmental LCA and is not taken into account sufficiently in many LCA studies. On the other hand, uncertainty analysis provides useful information to assess the reliability of LCA-based decisions and to help to decision makers to reduce uncertainties in LCA. In this regard, this chapter used a Monte Carlo simulation technique to deal with inherent uncertainties in LCSA of electric vehicles. The distribution of each uncertain parameter and their corresponding data sources are presented in the following section.

6.2. Research Motivation and Objectives

LCSA framework is still under development and there is an ongoing research to advance the methodology of LCSA for future applications (Sala et al., 2012a, 2012b). According to the European Commission funded project, namely Coordination Action for innovation in Life Cycle Analysis for Sustainability (CALCAS), current LCA methodology should be advanced in two directions ((Stefanova et al., 2014). The first direction is to deepen the LCSA by considering the dynamic relationships among the LCA parameters and analyzing the complex causality mechanism between the system parameters. The second direction is to broaden the LSCA by including all pillars of sustainable development as environment, economy and society and extend the system boundary from micro-level analysis to macro-level discussed in Guinee et al. (Guinée et al., 2011).

In addition to the CALCAS project, a recent review study pointed out the potential limitations and future of LCSA. Based on this work, the following points are highlighted for the current LCSA framework (Alessandra Zamagni et al., 2013):

Point 1: The uncertainties in LCSA results not fully addressed and discussed,

Point 2: The social LCA (S-LCA) is not well-studied and understood,

Point 3: There is a mechanistic understanding without looking at the environmental LCA, social LCA and life cycle cost assessment results simultaneously, and

Point 4: there is a lack of understanding the complex and mutual interactions between the environmental, economic and social pillars of the sustainability.

In this regard, moving from LCA method to LCSA framework will require a system-based approach, as the LCSA methodology emphasizes the simultaneous consideration of all three pillars of sustainability. Most currently available published LCSA literature provide "snapshot" analyses that do not consider the dynamics of the relevant life cycle sustainability impacts over a period of time. Also, most LCSA studies looked at the life cycle inventories of products of systems from a very isolated perspective, thereby failing to properly address the inherent interdependencies between the environmental, social, and economic indicators associated with sustainability. Hence, a proper LCSA will require researchers to consider the dynamic relationships between LCSA indicators as well as the inherent uncertainties in LCA input parameters. At this point, a system dynamics modeling approach can be a superior modeling approach to address the future research needs of advanced LCSA. The importance of the system dynamics method with respect to LCSA is also highlighted in a comprehensive methodology paper addressing the need to develop a more integrative approach for LCSA, which would attempt to develop a more holistic sustainability assessment framework and link dynamic interrelations between LCSA indicators over a period of time(Halog & Manik, 2011).

Overall this dissertation is a first empirical work addressed all future research needs of LCSA for alternative vehicle's sustainability research. To do so, this work aims to fulfill three main research objectives. The first objective of this research is to provide a holistic comparison of electric vehicles and an internal combustion electric vehicles considering the time period between 2015 and 2050 over their entire life cycle. The second objective this research is to provide an uncertainty-embedded dynamic life cycle sustainability assessment framework that can be used for assessing alternative vehicle options considering their complex and interdependent environmental, economic and social impacts, simultaneously. The third objective of this research is to test several extreme scenarios in order to analyze the long-term sustainability of EVs, HEVs, PHEVs and ICVs in the United States. The results of this study are presented for seven relevant environmental, economic, and social impact categories, including (a) CO_2 emissions, (b) particulate matter formation (PMF), (c) photochemical oxidant formation (POF), (d) vehicle ownership cost, (e) contribution to gross domestic product (GDP), (f) employment generation, and (g) human health (HH) impacts of air pollution and climate change. To address uncertainties in life-cycle model parameters and the mutual cause-and-effect relationships between LCSA indicators, an uncertainty-based system dynamics modeling approach is employed using uncertain parameters with predetermined probabilistic distributions.

6.3. Methodology

System dynamics is often used to analyze more complex systems with greater degrees of uncertainty (Pruyt, 2007), and so this section will serve to explain these uncertainties as applicable to the parameters of this model. More specifically, the uncertainty analysis performed in this study will involve assigning appropriate distributions to each parameter and conducting simultaneous Monte Carlo simulation for each variable in what is known as a multivariate sensitivity analysis. Most of the distribution types shown in this study are derived from literature, and some distributions are estimated using raw data from publicly available resources. Table 1 shows an overview of the model parameters, their assigned distributions, and their relevant distribution parameters. The deterministic values calculated in the previous study (Onat, Kucukvar, Tatari, & Egilmez, 2015), are assumed to be mean values for the assigned distributions. Uncertainties related to environmental impacts (CO_2 emissions & air pollution), economic impacts (vehicle ownership costs depending on gasoline, electricity, M&R costs, etc.), and social impacts (human health characterization factors & employment multipliers) are addressed for each vehicle type with respect to its corresponding manufacturing and operation phase.

Automobile manufacturing emissions are assumed to be normally distributed. The standard deviations of these distributions are derived from a study by the Argonne National Laboratory, in which the researchers calculated the standard deviations and average values of emissions stemming from the manufacturing phase of a generic vehicle. The standard deviation values are derived proportionally in accordance with the proportions of the means and standard deviations derived from the referred study (Sullivan, Burnham, & Wang, 2010). The deterministic emission values including GHGs and air pollutants are obtained from (Onat, Kucukvar, et al., 2014c) and (Onat, Kucukvar, Tatari, & Egilmez, 2015). On average, the standard deviation of the manufacturing emissions is approximately 10% of the mean value, while the standard deviation of the petroleum supply and distribution emissions is higher at about 26% of the mean value (Venkatesh, Jaramillo, Griffin, & Matthews, 2011). The distribution for CO_2 emissions per kWh of electric power generation is assumed to be triangular and the proportions of worst, base, and average values are derived from (Michalek et al., 2011). Standard deviation of tail pipe CO_2 emissions is only 2% of the mean (Venkatesh et al., 2011). The distribution type and parameters of tail pipe air pollutant emissions are derived from the referred study (Zhang, Bishop, & Stedman, 1994). The distributions for air pollutant emissions for petroleum production and electric power generation are derived from the Argonne National Laboratory's study (Brinkman, Wang, Weber, & Darlington, 2005). For some variables, such as the fuel economy values of each vehicle type, a unit normal distribution with a mean of 1 and standard deviation of 0.07 is assigned (Wi & Park, 2013). These proportional values of the mean and standard deviation are derived from the referred values, and we assigned unit distributions for some variables because these variables were initially defined as lookup variables, each consisting of an exogenous table of inputs to the model such that the value changes independently of other variables over time. For instance, the fuel economy values and the standard deviation of new vehicles' fuel economy values are obtained from the BAU case of the VISION model, after which these lookup values are multiplied by the assigned unit distribution to obtain the fuel economy distribution for each year. The average costs per gallon of gasoline and per kWh of electricity are assumed to have triangular distributions, the data for which is obtained from the U.S. Energy Information Administration (Faron, Pagerit, & Rousseau, 2009; The U.S. Energy Information Administration, 2014, 2015a, 2015b). Using these data sets, the proportions of maximum and minimum values are obtained for each year, and their proportions to the corresponding mean values are estimated to construct the triangular distributions. The distributions for employment multipliers are estimated using raw data from the U.S. Bureau of Labor Statistics (the U.S. Bureau of Labor Statistics, 2015). Human health characterization factors are taken from ReCiPe (ReCiPE, 2009). In both cases, the distributions are assumed to be triangular, using minimum and maximum values derived from available literature (Michalek et al., 2011; AM De Schryver, 2011; Shah & Ries, 2009).

Table 28. Distribution types and parameters of the model variables

Variable Name	Deterministic values	Unit	Dist. type	Distribution parameters	References
CO_2 emission multiplier per ICV	6.960	$tonCO_2$-eq /vehicle	Normal	μ= 6.96, σ=0.668	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Onat, Kucukvar, et al., 2014c; Sullivan, Burnham, et al., 2010)
CO_2 emission multiplier per HEV	7.520	$tonCO_2$-eq /vehicle	Normal	μ= 7.52, σ= 0.723	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Onat, Kucukvar, et al., 2014c; Sullivan, Burnham, et al., 2010)
CO_2 emission multiplier per EV	11.10	$tonCO_2$-eq/vehicle	Normal	μ= 11.1, σ= 1.066	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Onat, Kucukvar, et al., 2014c; Sullivan, Burnham, et al., 2010)
Petroleum supply CO_2 emission per gallon of gasoline	2.11	$kgCO_2$-eq /gal	Normal	μ= 2.11, σ= 0.549	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Onat, Kucukvar, et al., 2014c; Venkatesh et al., 2011)
Electricity supply CO_2 emissions per kWh	0.696	$kgCO_2$-eq /kWh	Triangle	a= 0, b= 0.696, p= 1.067	(Michalek et al., 2011; Onat, Kucukvar, Tatari, & Egilmez, 2015)
Tail pipe CO_2 emissions per gal of gasoline	8.92	$kgCO_2$-eq/gal	Normal	μ= 8.92, σ= 0.1784	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Venkatesh et al., 2011)
PMF multiplier per ICV	16.38	$kgPM_{10}$-eq /vehicle	Normal	μ= 16.38, σ= 1.57248	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Onat, Kucukvar, et al., 2014c; Sullivan, Burnham, et al., 2010)
PMF multiplier per HEV	17.68	$kgPM_{10}$-eq /vehicle	Normal	μ= 17.68, σ= 1.69728	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Onat, Kucukvar, et al., 2014c; Sullivan, Burnham, et al., 2010)

Variable Name	Deterministic values	Unit	Dist. type	Distribution parameters	References
PMF multiplier per EV	26.00	$kgPM_{10}$-eq /vehicle	Normal	σ= 26, μ= 2.496	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Onat, Kucukvar, et al., 2014c; Sullivan, Burnham, et al., 2010)
Tail pipe PM_{10}eq emissions per gal of gasoline	1.93E-03	$kgPM_{10}$-eq /gal	gamma	α= 1.93E-03, β=0.14768	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Zhang et al., 1994)
Petroleum supply PM_{10}eq emission per gallon of gasoline	9.21E-04	$kgPM_{10}$-eq /gal	Normal	μ= 9.21E-04, σ= 8.84E-05	(Brinkman et al., 2005; Onat, Kucukvar, Tatari, & Egilmez, 2015)
Electricity supply PM_{10}eq emissions per kWh	2.26E-04	$kgPM_{10}$-eq/kWh	Beta	α= 0.38, β=1.3	(Brinkman et al., 2005; Onat, Kucukvar, Tatari, & Egilmez, 2015)
POF multiplier per ICV	31.10	kgNMVOC - eq/vehicle	Normal	μ=31.1, σ= 2.99	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Onat, Kucukvar, et al., 2014c; Sullivan, Burnham, et al., 2010)
POF multiplier per HEV	33.20	kgNMVOC - eq/vehicle	Normal	μ= 33.2, σ= 3.18	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Onat, Kucukvar, et al., 2014c; Sullivan, Burnham, et al., 2010)
POF multiplier per EV	46.20	kgNMVOC - eq/vehicle	Normal	μ= 46.2, σ= 4.44	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Onat, Kucukvar, et al., 2014c; Sullivan, Burnham, et al., 2010)
Tail pipe NMVOC emissions per gal of gasoline	1.15E-02	kgNMVOC -eq/gal	Gamma	α= 0.03196, β= 0.360413	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Zhang et al., 1994)
Petroleum supply NMVOC emission per	6.88E-03	kgNMVOC -eq/gal	Normal	μ=6.88E-03, σ= 6.6E-04	(Brinkman et al., 2005; Onat, Kucukvar, Tatari, & Egilmez, 2015)

Variable Name	Deterministic values	Unit	Dist. type	Distribution parameters	References
gallon of gasoline					
Electricity supply NMVOC emissions per kWh	1.86E-03	kgNMVOC-eq/kWh	Beta	α= 0.45, β=1.24	(Brinkman et al., 2005; Onat, Kucukvar, Tatari, & Egilmez, 2015)
Fuel economy distribution	lookup variable	dmnl	Normal	μ= 1, σ= 0.07	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Wi & Park, 2013)
AER	40.00	miles	Normal	μ= 40, σ=2.8	(Bastani, Heywood, & Hope, 2012; Onat, Kucukvar, Tatari, & Egilmez, 2015)
cost per gal of gasoline	lookup variable	dmnl	Triangle	a= 0.8496, b= 1.124 p= 1	(Faron et al., 2009; Onat, Kucukvar, Tatari, & Egilmez, 2015)
per mile M&R cost	0.05	$/mile	Triangle	a= 0.042, b= 0.0625 p= 0.05	(Barnes & Langworthy, 2003; Faron et al., 2009; Onat, Kucukvar, Tatari, & Egilmez, 2015)
Unit cost of EV battery	lookup variable	dmnl	Normal	μ= 1, σ=0.04	(Barnett et al., 2009; Onat, Kucukvar, Tatari, & Egilmez, 2015)
electricity cost per kWh	Lookup variable	dmnl	Triangle	a= 0.5439, b= 2.34 p= 1	(Faron et al., 2009; Onat, Kucukvar, Tatari, & Egilmez, 2015)
Battery replacement	1.00	#of replacement	Triangle	a= 0, b= 3 p= 1	(Onat, Kucukvar, Tatari, & Egilmez, 2015; Onat, Kucukvar, et al., 2014c)
EV range	100.00	miles	Normal	μ= 100, σ=7	(Bastani et al., 2012; Onat, Kucukvar, Tatari, & Egilmez, 2015)
Employment multiplier of vehicle operation	1.43E-05	#person/$	Beta	α= 5.15E-06 , β=1.65E-05	(Onat, Kucukvar, Tatari, & Egilmez, 2015; the U.S. Bureau of Labor Statistics, 2015)
Employment multiplier of vehicle manufacturing	1.32E-05	#person/$	Weibull	α= 3.45, β=1.62E-05	(Onat, Kucukvar, Tatari, & Egilmez, 2015; the U.S. Bureau of Labor Statistics, 2015)

Variable Name	Deterministic values	Unit	Dist. type	Distribution parameters	References
HH CF for PMF	2.60E-04	DALY/kgP M_{10}-eq	Triangle	a= 1.56E-05, b= 5.75E-04 p= 2.6E-04	(Michalek et al., 2011; Onat, Kucukvar, Tatari, & Egilmez, 2015; ReCiPE, 2009)
HH CF for POF	3.90E-08	DALY/kgNMVOC-eq	Triangle	a= 3.51E-08, b= 7.02E-08 p= 3.9E-08	(Onat, Kucukvar, Tatari, & Egilmez, 2015; ReCiPE, 2009; Shah & Ries, 2009)
HH CF for GWP	1.40E-06	DALY/kgC O_2-eq	Triangle	a=1.19E-06, b= 3.51E-06 p= 1.4E-06	(A. M. De Schryver, Brakkee, Goedkoop, & Huijbregts, 2009; Onat, Kucukvar, Tatari, & Egilmez, 2015; ReCiPE, 2009; An De Schryver, Van Zelm, Humbert, McKone, & Huijbregts, 2011)

After the uncertainties associated with the model parameters are defined, 1,000 iterations are run simultaneously for 31 different parameters. These iterations are run in each year from 1980 to 2050, thereby revealing the behavioral limits of the environmental, economic, and social impacts of alternative vehicle technologies. Additionally, we estimated the histogram distribution of each impact for every year and presented the parameters of these distributions for 2030 and 2050 in the following section.

6.4. Results

Results for seven different impact categories are presented within the subsections of environmental, economic, and social impacts. In the subsections of the results, deterministic and multivariate behaviors, as well as histogram distributions in 2030 and 2050 are presented.

6.4.1. Environmental Impacts

Results if the environmental impacts, including CO_2 emissions, particulate matter formation, and photochemical oxidant formation, are explained in the following subsections.

6.4.1.1. CO_2 emissions:

Fig. 29 shows the total life cycle CO_2 emissions of each vehicle type (scenario) based on the deterministic values of the relevant parameters. The initial peak observed in the 2016 is due to the sudden increase in vehicle manufacturing emissions, which is subsequently overwhelmed by the savings in operation-phase emissions in later years. The maximum CO_2 emission reduction potential of EVs is the highest in the long run, with that of PHEVs as a close second. It should be noted that technological improvements in battery technology and fuel efficiency improvements were taken into consideration in this study; while the former most strongly favored the emission reduction potential of PHEVs and EVs, the latter favored all vehicle types to some degree; since both of these factors were considered simultaneously, these overall improvements may have contributed to some extent to the superior performance of EVs and PHEVs in terms of CO_2 emissions. Likewise, the declining trend in the BAU scenario is mainly due to the fuel efficiency improvements of ICVs.

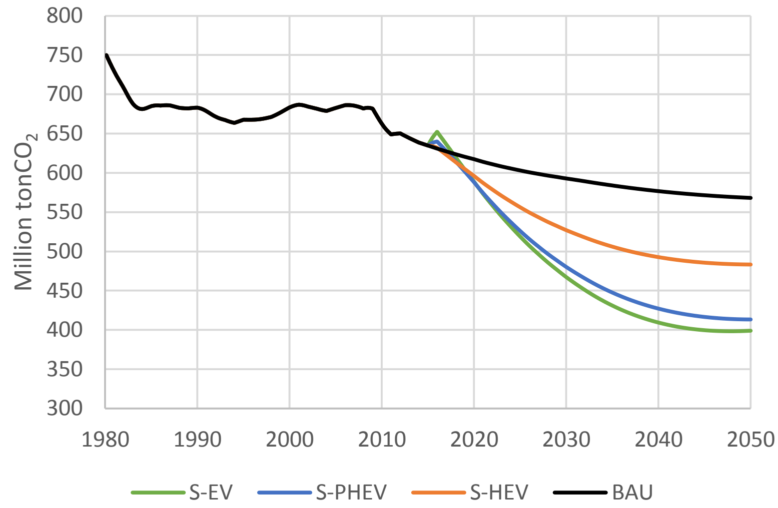


Figure 29. Total life cycle CO_2 emissions based on deterministic values.

Fig. 30 shows the stochastic results for each scenario and their behavioral limits in probabilistic terms. For instance, of 1000 iterations, 50% falls into the orange shaded area. Similarly, blue, green and grey areas are composed of the 75%, 95%, and 100% of the simulation results, respectively. The same representation is applied for each impact category in the following subsections. According to Fig.3, the uncertainty associated with EVs is higher than others and the span between maximum and minimum values of emissions has an increasing trend (Fig 3-d). All of the scenarios result in a decreasing CO_2 emission trend, while BAU scenario (Fig. 3-a) has the smallest decrease since 2015. Fig. 30 should be evaluated along with the values presented in Table 29 and Fig 31.

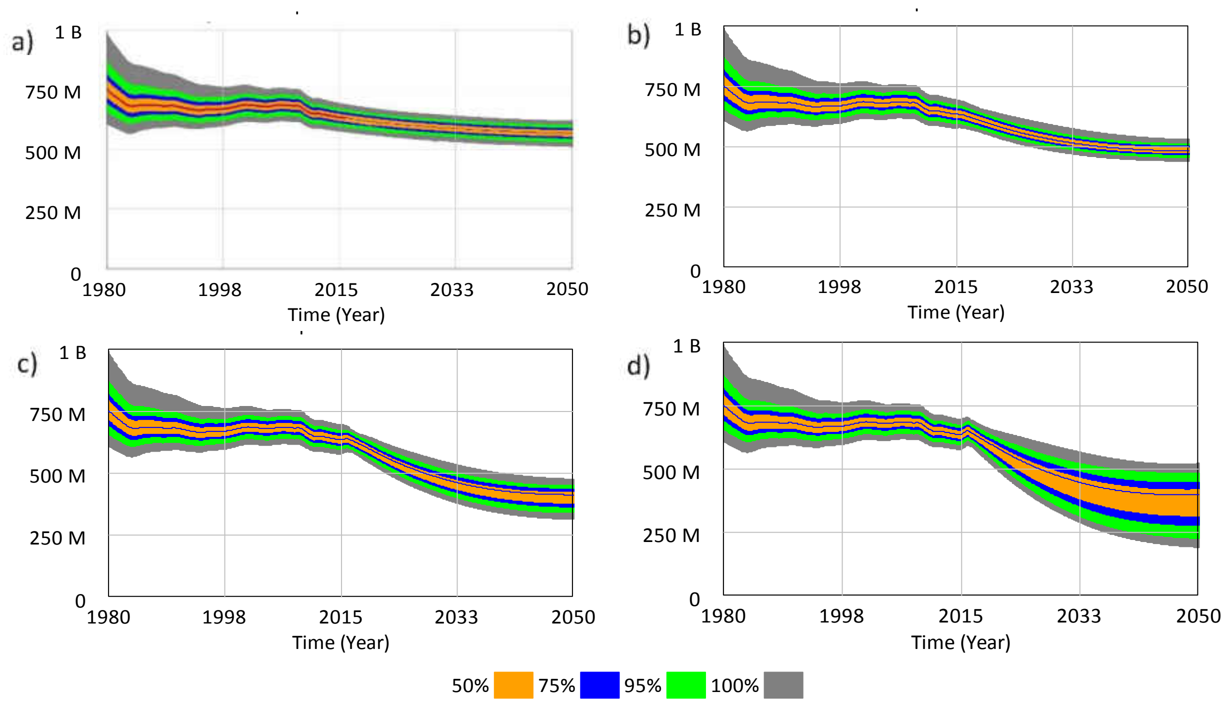


Figure 30. The multivariate dynamics of total annual CO_2 emissons (tonCO_2) **a)** BAU, **b)** S-HEV, **c)** S-PHEV, **d)** S-EV.

Table 29 shows the distribution parameters for the CO_2 emissions in 2030 and 2050. The standard deviation of the S-EV is 11% and 19% of the mean in years 2030 and 2050, respectively, while the corresponding percent values for the BAU and S-HEV scenarios are 3% in 2030 and 2050. The maximum CO_2 emissions value for the S-EV scenario is approximately 1.5 times greater than its mean value in 2050, while the corresponding minimum CO_2 emissions value is about half of the mean value in 2050. Hence, the estimated CO_2 emission reduction potential for EVs can be estimated within ±50% of the mean value, whereas the corresponding variations for the S-PHEV, S-HEV, and BAU scenarios in 2050 are approximately ±21%, ±11%, ±9%, respectively. Based on a 90% confidence interval, the maximum CO_2 emission reduction potentials of HEVs, PHEVs, and EVs are 3%, 11%, and 10% in 2030 compared to their respective 2015 emission levels. In 2050, these reduction potentials increase to 11%, 23%, and 20%, respectively. From the stochastic results, it is interesting to note that the CO_2 emission reduction potential of PHEVs is found to be slightly higher than that of EVs, which was found to be greater on average. On the other hand, based on a 90% confidence interval, the CO_2 emissions rate for the BAU scenario increases by 9% in 2030 and by 4% in 2050, compared to its corresponding CO_2 emissions rate in 2015.

Table 29. $C0_2$ emission distribution parameters

Year	Scenario	Min	Max	Mean	Median	StDev	50%	75%	90%
2030	BAU	5.37E+08	6.46E+08	5.93E+08	5.93E+08	1.80E+07	5.93E+08	6.05E+08	6.16E+08
	S-HEV	4.80E+08	5.88E+08	5.28E+08	5.27E+08	1.59E+07	5.27E+08	5.39E+08	5.49E+08
	S-PHEV	4.00E+08	5.51E+08	4.71E+08	4.70E+08	2.49E+07	4.70E+08	4.87E+08	5.03E+08
	S-EV	3.20E+08	5.83E+08	4.44E+08	4.46E+08	5.10E+07	4.46E+08	4.82E+08	5.11E+08
2050	BAU	5.11E+08	6.21E+08	5.68E+08	5.68E+08	1.80E+07	5.68E+08	5.81E+08	5.91E+08
	S-HEV	4.39E+08	5.32E+08	4.84E+08	4.84E+08	1.51E+07	4.84E+08	4.95E+08	5.04E+08
	S-PHEV	3.13E+08	4.75E+08	3.99E+08	4.01E+08	2.93E+07	4.01E+08	4.21E+08	4.37E+08
	S-EV	1.91E+08	5.20E+08	3.64E+08	3.68E+08	6.93E+07	3.68E+08	4.17E+08	4.53E+08

Fig. 31. shows the histogram of CO_2 emission results for each scenario in 2030 and 2050, whose parameters are given in Table 2. As can be seen from Fig. 4 (a) and (b), the uncertainty range of S-EV is much higher. Both of the distributions in 2030 and 2050 have similar shape.

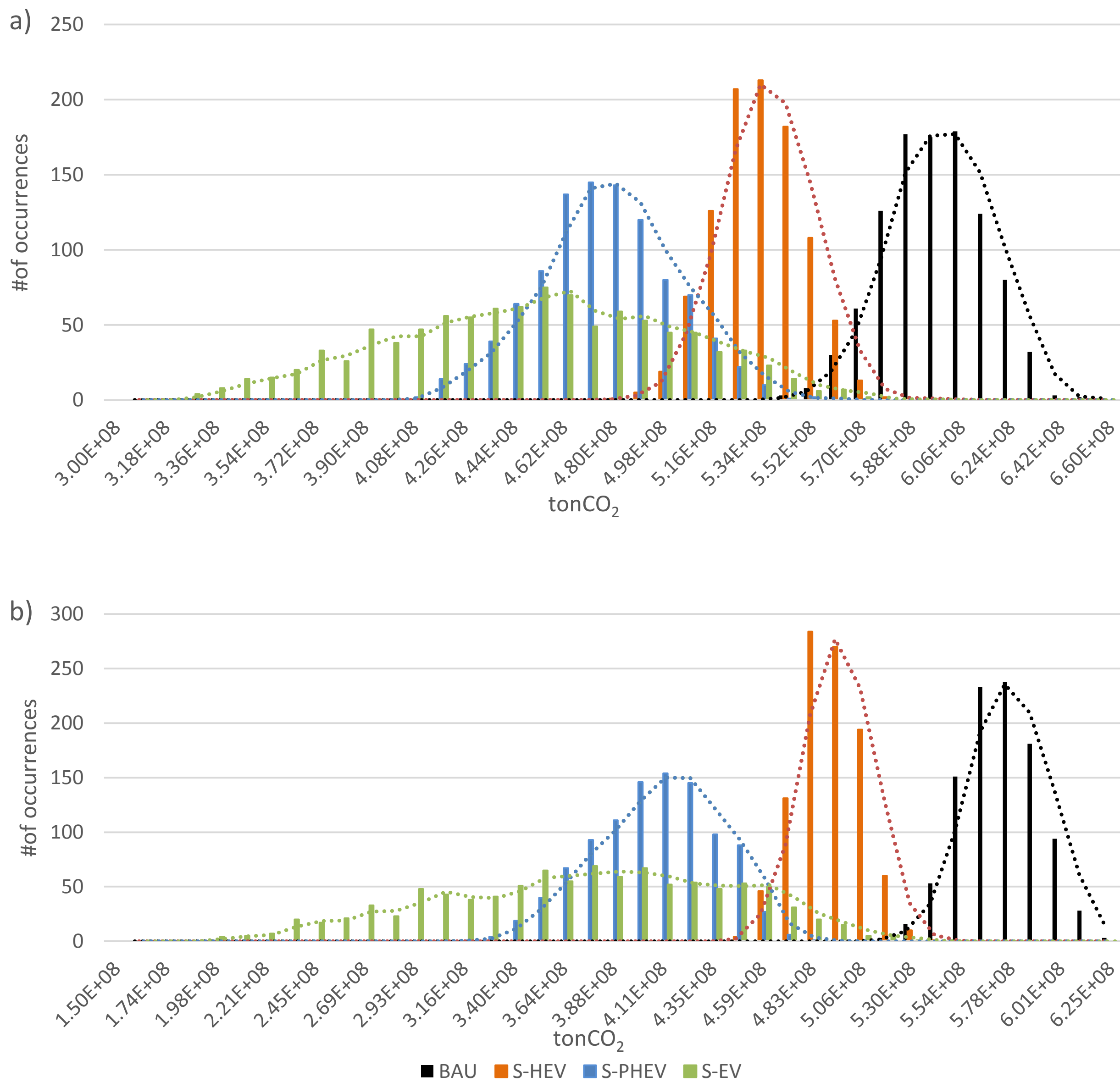


Figure 31. Histogram of the total CO_2 emissions based on Monte Carlo simulations: a) in 2030, b) in 2050.

6.4.1.2. Particulate matter formation:

Fig. 32 shows the PMF impacts of each scenario based on the deterministic values presented in Table 1. The initial jump observed for all scenarios in 2016 (except for the BAU scenario) is due to the PMF impacts of the manufacturing phase, which suddenly increases due to new vehicle sales. Consequently, the manufacturing impacts of HEVs, PHEVs, and EVs are greater than those of ICVs. Because the operation-phase savings are reduced over time, the decreasing trend of PMF is reveres after 2035 and 2036. Aside from these differences, PMF impacts demonstrate a similar trend to that of CO_2 emissions. PHEVs have the maximum PMF reduction potential, with 11% smaller PMF impacts compared to the BAU scenario, which is mostly composed of ICVs. EVs become a better option after 2025 compared to the PMF impacts of ICVs.

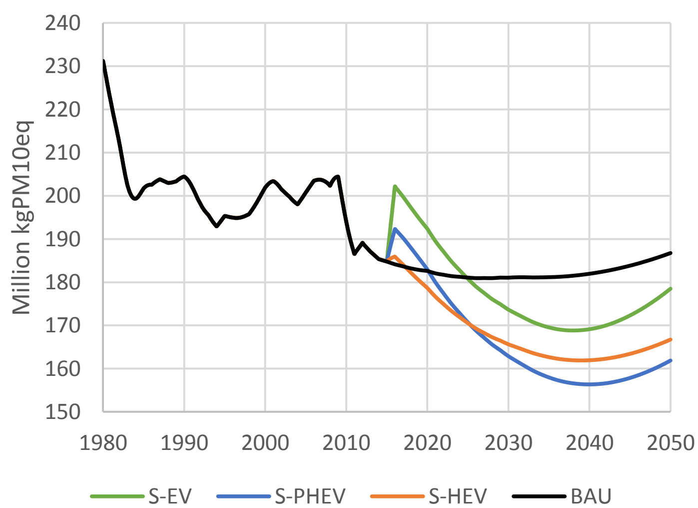


Figure 32. Total life cycle PMF based on deterministic values.

The stochastic results are presented in Fig. 33. The uncertainty ranges (the difference between maximum and minimum values of PMF impacts) are higher in BAU (Fig 33-a) and S-EV (Fig. 33-d). The smallest range is observed in S-PHEV (Fig 33-c). Considering that PHEVs had the maximum potential of reduction in the deterministic scenario, adoption of PHEVs is a more robust strategy to reduce PMF impacts. Furthermore, the uncertainty range associated with PMF impacts of PHEVs decreases overtime. Behaviorally, there has been no significant difference compared to deterministic trends. PMF impacts of all scenarios decreases until a certain time, then a slight increase is observed. For more detailed evaluation, it is necessary to look at the findings in Table 30 which shows the distribution parameters of PMF impacts in 2030 and 2050.

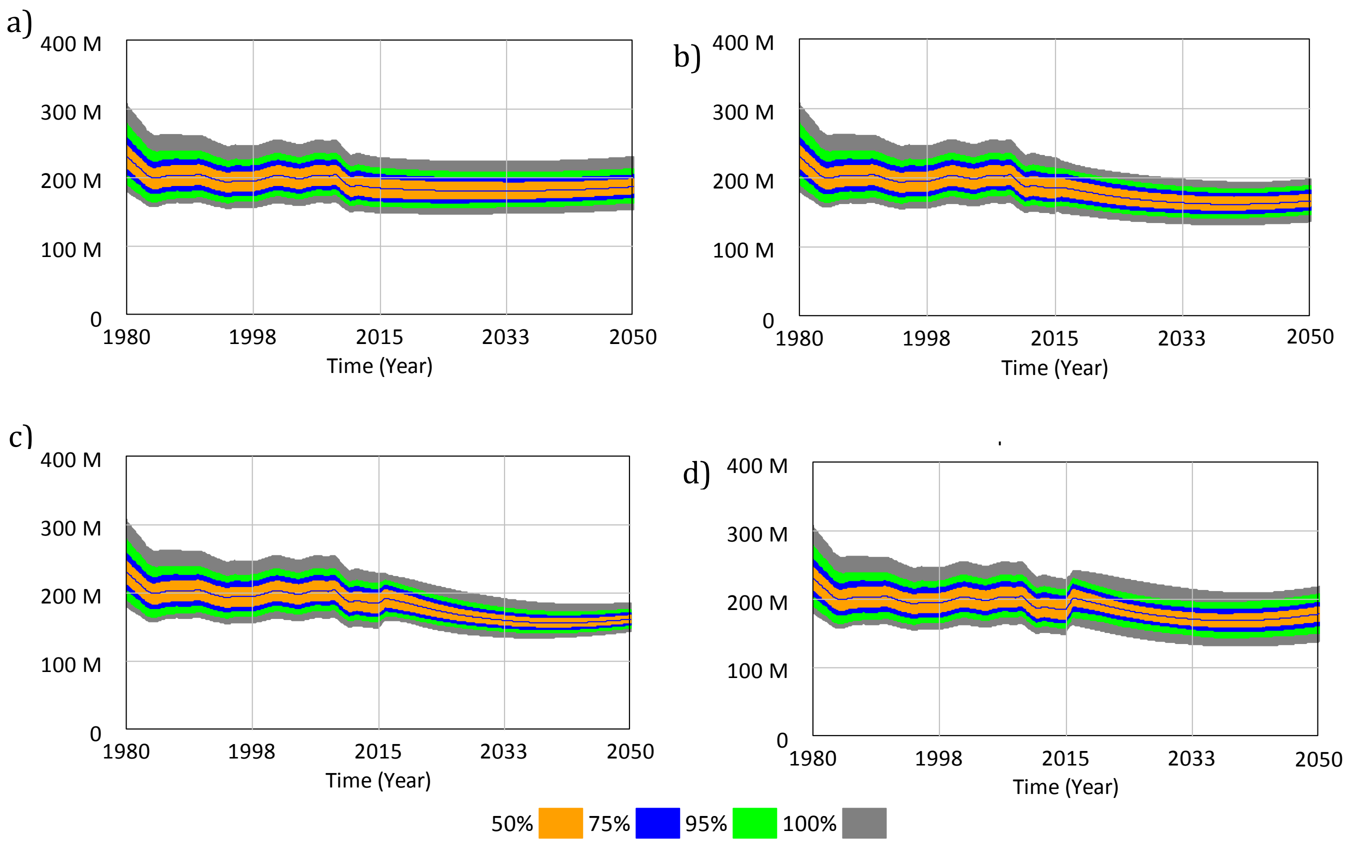


Figure 33. The multivariate dynamics of total annual PMF emissions (kgPM10-eq) a) BAU, b) S-HEV, c) S-PHEV, d) S-EV.

The normalized standard deviations (standard deviation divided by the mean values) for the year 2030 are 8% for the BAU and S-HEV scenarios, 6% for the S-PHEV scenario, and 7% for the S-EV scenario, whereas these values in 2050 are 7%, 5%, and 8%, respectively. The variation of PMF impacts decreases in the BAU, S-HEV, and S-PHEV scenarios, but increases in the S-EV scenario. The PMF impact ranges in 2050 are ±23%, ±18%, ±15%, and ±24% of the mean values of the BAU, S-HEV, S-PHEV, and S-EV scenarios, respectively. The S-EV has the highest uncertainty range in both 2030 and 2050, which is approximately 2 times greater than that of the S-PHEV in 2050. This range is also high for the BAU scenario in both 2030 and 2050. According to these results, based on a 90% confidence interval, the maximum PMF reduction potentials of HEVs and PHEVs are 1% and 5% in 2030 compared to 2015 emission levels, whereas EVs and ICVs (BAU scenario) may cause an increase of up to 3% and 9%, respectively, again compared to 2015 emission levels. In 2050, the PMF reduction potentials of the S-HEV and S-PHEV are 1% and 7%, respectively, while the BAU and S-EV scenarios demonstrate increases of 11% and 6%, respectively. Unlike the CO_2 emission impacts, the deterministic and stochastic values for PMF impacts indicated similar results, with PHEVs as the best alternative vehicle option compared to other vehicle types.

Table 30. PMF distribution parameters

Year	Scenario	Min	Max	Mean	Median	StDev	50%	75%	90%
2030	BAU	1.47E+08	2.23E+08	1.81E+08	1.81E+08	1.43E+07	1.81E+08	1.92E+08	2.00E+08
	S-HEV	1.35E+08	2.00E+08	1.66E+08	1.65E+08	1.25E+07	1.65E+08	1.75E+08	1.83E+08
	S-PHEV	1.36E+08	1.95E+08	1.62E+08	1.62E+08	9.88E+06	1.62E+08	1.70E+08	1.76E+08
	S-EV	1.36E+08	2.16E+08	1.73E+08	1.73E+08	1.27E+07	1.73E+08	1.81E+08	1.90E+08
2050	BAU	1.53E+08	2.30E+08	1.87E+08	1.87E+08	1.34E+07	1.87E+08	1.97E+08	2.04E+08
	S-HEV	1.37E+08	1.97E+08	1.67E+08	1.66E+08	1.15E+07	1.66E+08	1.75E+08	1.82E+08
	S-PHEV	1.42E+08	1.85E+08	1.61E+08	1.61E+08	7.27E+06	1.61E+08	1.66E+08	1.71E+08
	S-EV	1.38E+08	2.17E+08	1.77E+08	1.78E+08	1.44E+07	1.78E+08	1.87E+08	1.96E+08

Fig. 34 shows the histogram of the simulation results for PMF impacts in 2030 and 2050. AS can be seen from the figure, the uncertainty ranges of BAU, S-HEV, and S-PHEV decrease, while it is increasing for S-EV. The shape of the distributions are similar in 2030 and 2050, while distribution shape of BAU, S-HEV, and S-EV are more flat in 2050 compared to their shape in 2030.

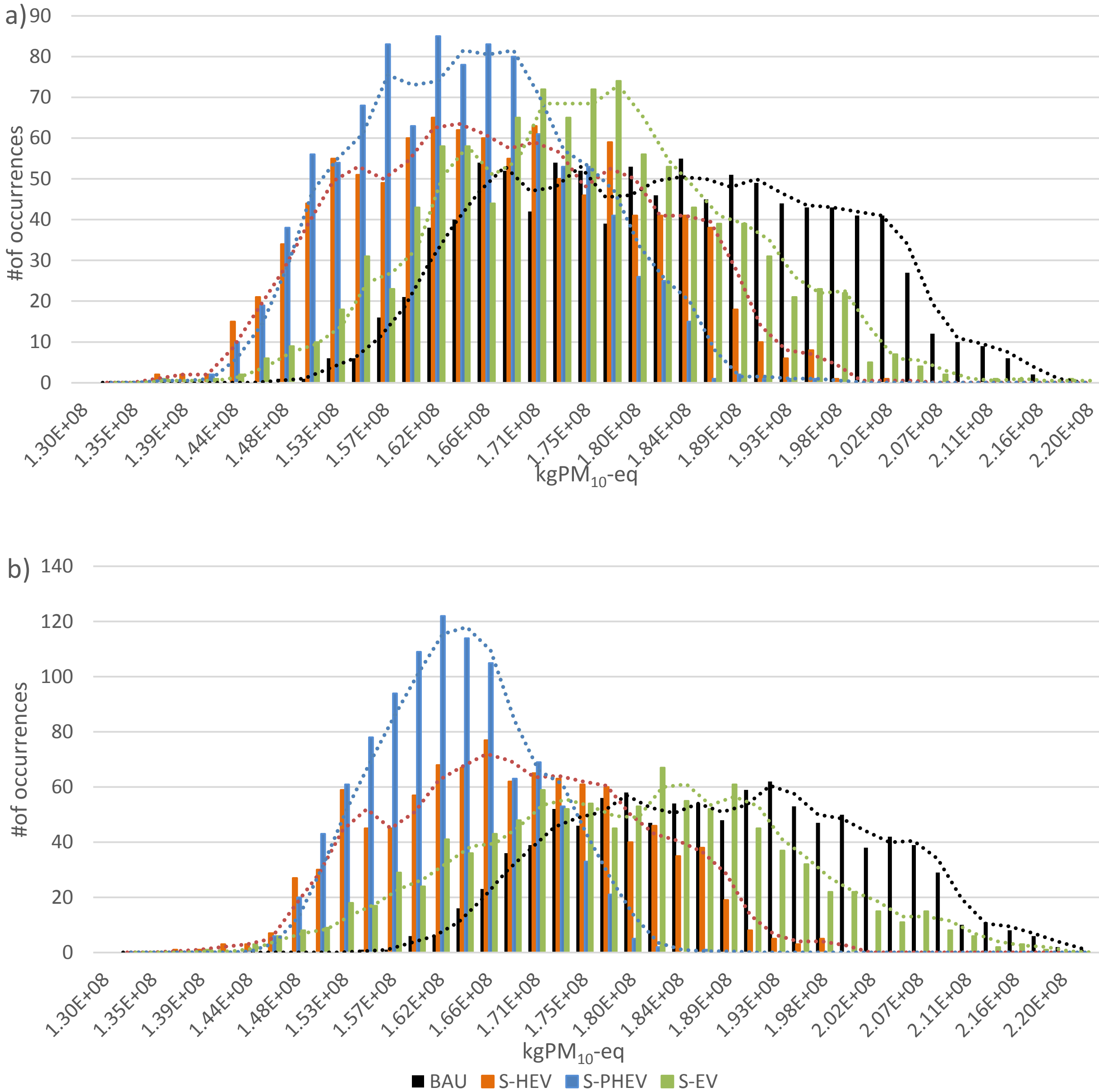


Figure 34. Histogram of the total PMF based on Monte Carlo simulations: **a)** in 2030, **b)** in 2050.

6.4.1.3. Photochemical oxidant formation

Fig. 35 shows the POF impacts for each scenario from 1980 to 2050. Same as the previous impact categories, the initial increase in 2016 is due to sudden increase in vehicle manufacturing impacts with respect to HEVs, PHEVs, and EVs, the manufacturing POF impacts of which are greater than those of ICVs. In this impact category, PHEVs and HEVs are better alternatives and have very similar impact trends. On the other hand, the S-EV scenario yielded worse results than the BAU case most of the time, except for a brief period between 2032 and 2043. As with the PMF impacts discussed previously, a reversed behavioral trend is observed after some point around the year 2038, owing mainly to the imbalances in manufacturing and operation phase impacts. Ordinarily, the operation-phase savings gradually reduce over time, whereas the manufacturing impacts increase as a result of new vehicle demand, leading the impacts of manufacturing phase to eventually outweigh the savings in the operation phase. This behavioral pattern was clearly observed with respect to the PMF and POF impacts, because the manufacturing and operation phase impacts are close to each other and changes in one such impact significantly affects the impact trend over time. According to the POF results based on deterministic values, HEVs and PHEVs are preferable for reducing the POF impacts of passenger vehicle transportation.

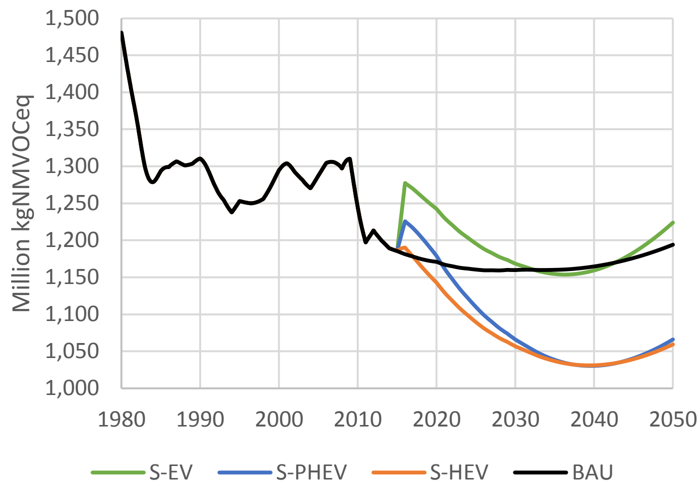


Figure 35. Total life cycle POF based on deterministic values.

Fig. 36 shows the stochastic results of the POF impacts for each scenario. Similar to the stochastic results of previous environmental impact categories, uncertainties associated with S-EV (Fig. 36-d) is higher than those of other scenarios. Although S-HEV and S-PHEV have a decreasing POF impact trend, the S-EV has a wide range of possible outcomes and 50% of the simulation results (the orange shaded area in Fig. 36-d) covers an area of decreasing trend. However, the impacts can be understood by evaluating the distribution parameters given in Table 31.

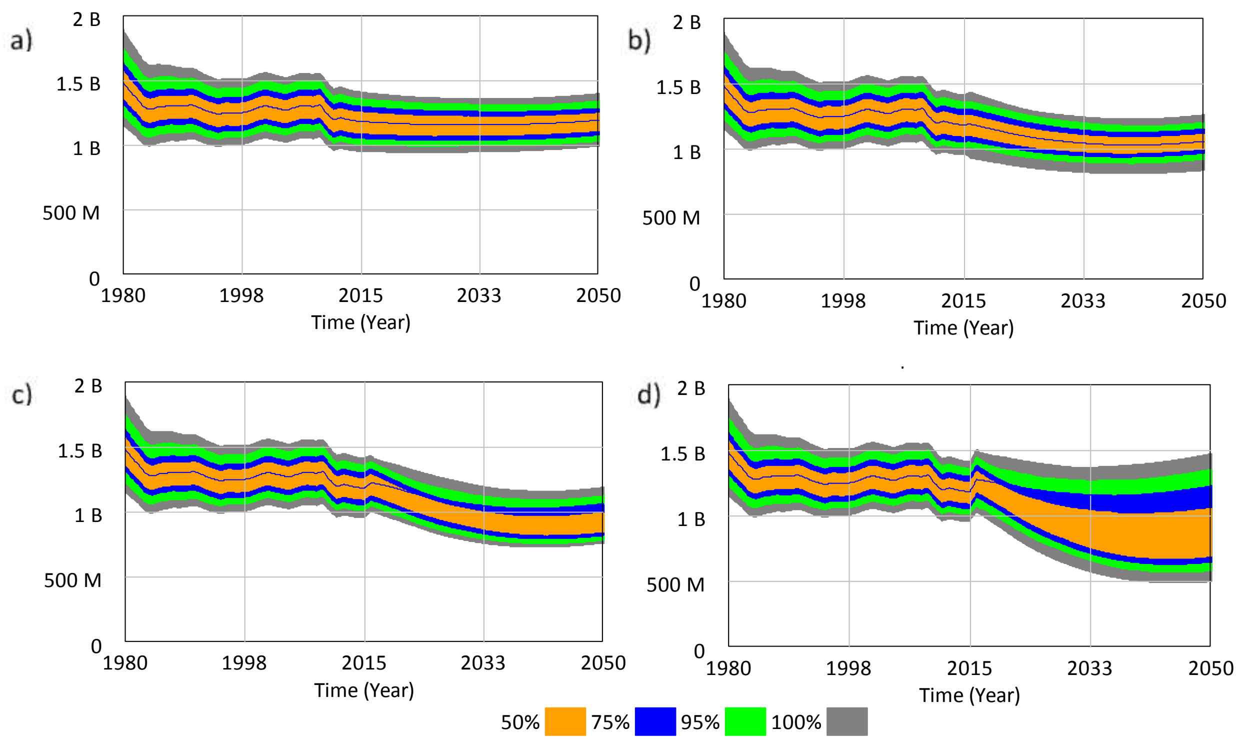


Figure 36. The multivariate dynamics of total annual POF (kgNMVOC-eq) **a)** BAU, **b)** S-HEV, **c)** S-PHEV, **d)** S-EV.

Table 31 shows the distribution parameters for POF emissions in 2030 and 2050. The normalized standard deviation of the S-EV scenario is found to be the highest at 18% and 26% of the its mean values in 2030 and 2050, respectively. The corresponding normalized standard deviations for BAU and S-EV are both 8% in 2030 and 7% in 2050., while that of the S-PHEV scenario is 9% in 2030 and 11% in 2050. The maximum POF impact value for the S-EV scenario is approximately 1.5 and 1.7 times greater than its mean value in 2030 and 2050, respectively, while the corresponding minimum values are 66% and 56% of the S-EV's mean value in 2030 and 2050, respectively. These ranges are smaller for other scenarios, which are approximately ±20%, ±21%, and ±25% in both 2030 and 2050 for the BAU, S-HEV, and S-PHEV scenarios, respectively. Based on a 90% confidence interval, the maximum POF impact reduction potentials of HEVs and PHEVs are 1% and 8% in 2030, respectively, while ICVs and EVs increase the POF impacts by 8% and 1% in 2030, all compared to 2015 emission levels. These corresponding reduction potentials in 2050 are 1%, 9%, 10%, and 6%, respectively, again compared to 2015 emission levels. Hence, it can be concluded that PHEVs are the better alternative based on stochastic results with a 90% confidence interval, which is similar to what was proposed based on the deterministic results (Fig. 35). It should be noted that, according to the results based on deterministic values, the S-PHEV and S-HEV scenarios had very similar trends with almost the same POF impact reduction potentials by the final year. However, the stochastic results showed that the POF reduction potential of PHEVs is almost 9 times greater than those of HEVs. Furthermore, while the results based on deterministic values indicated that S-EV is worse than BAU scenario, as opposed to results based on deterministic values, S-EV performed better than the BAU in the terms of POF impacts. Another interesting finding is that the S-EV scenario had the best performance on average, demonstrating much better results than the S-HEV and BAU scenarios and slightly better results than the S-PHEV scenario in both 2030 and 2050.

Table 31 POF distribution parameters

Year	Scenario	Min	Max	Mean	Median	StDev	50%	75%	90%
2030	BAU	9.47E+08	1.36E+09	1.15E+09	1.14E+09	8.99E+07	1.14E+09	1.22E+09	1.27E+09
	S-HEV	8.26E+08	1.25E+09	1.05E+09	1.05E+09	8.26E+07	1.05E+09	1.11E+09	1.17E+09
	S-PHEV	7.78E+08	1.22E+09	9.58E+08	9.53E+08	8.75E+07	9.53E+08	1.02E+09	1.08E+09
	S-EV	6.11E+08	1.37E+09	9.27E+08	8.86E+08	1.65E+08	8.86E+08	1.05E+09	1.18E+09
2050	BAU	9.94E+08	1.40E+09	1.18E+09	1.17E+09	8.36E+07	1.17E+09	1.25E+09	1.30E+09
	S-HEV	8.31E+08	1.25E+09	1.05E+09	1.05E+09	7.58E+07	1.05E+09	1.11E+09	1.16E+09
	S-PHEV	7.57E+08	1.18E+09	9.18E+08	8.97E+08	9.73E+07	8.97E+08	9.88E+08	1.07E+09
	S-EV	4.93E+08	1.46E+09	8.75E+08	8.04E+08	2.31E+08	8.04E+08	1.05E+09	1.25E+09

The histogram distributons of the simulations are presented in Fig. 37. According to these histograms and the parameters shown in Table 4, distribution of S-EV skewed to the left and its mean value has the lowest POF impacts fallowed by the S-PHEV. Therefore, stocastic results basedon 90% confidence interval did not favored S-EV which has long tail untill the right end of the distributions. S-EV had the greatest uncertainty ranges in all of the nevirnmental indicators, which mainly stem from the uncertainties associated with the source of the electricity generation to power EVs.

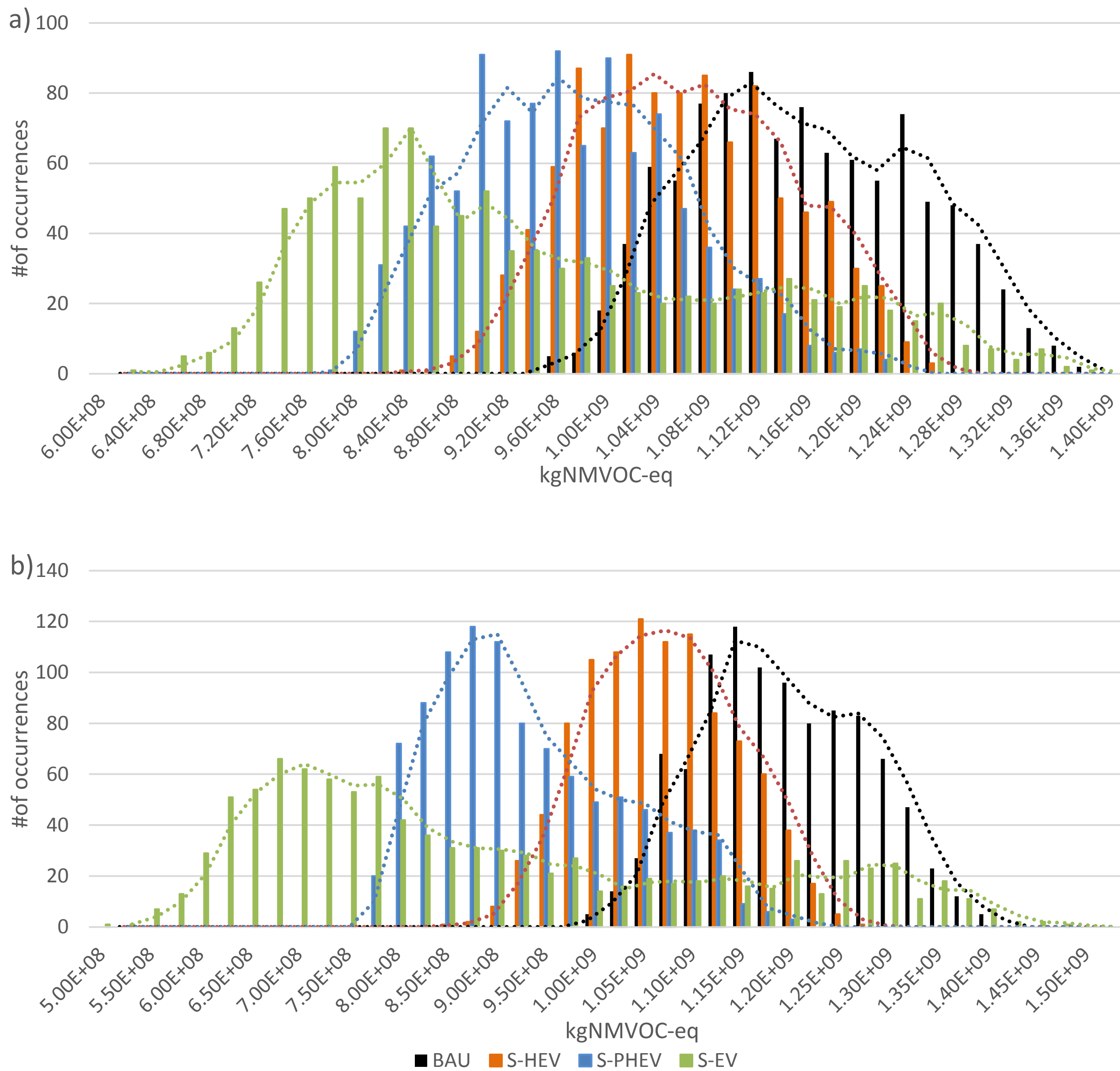


Figure 37. Histogram of the total POF based on Monte Carlo simulations: **a)** in 2030, **b)** in 2050.

6.4.2. Economic impacts

Economic impacts are evaluated based on annual vehicle ownership costs to the drivers and the contrubion to the U.S. GDP, which are explained in the following sub-sections.

6.4.2.1. Vehicle ownership cost

Fig. 38 shows the vehicle onwership costs based on the deterministic values presented in Table 1 for each vehicle type. The annualized total life-cycle cost of EVs are much higher than those of other alternative vehicles when they are introduced to the market in 2009-2010, whereas the ownership costs of HEVs and PHEVs are relatively lower in the same years. On the other hand, the ownership costs of each vehicle type converge over time to a very close grouping by 2050, showing a decreasing trend in ownership costs mainly due to fuel efficiency improvements and advances in battery technology. The sharpest decrease is observed in the ownership costs of EVs due to decreases in battery costs and in the initial puchase price of EVs, with the overall ownership costs of EVs reaching their lowest value by 2050.

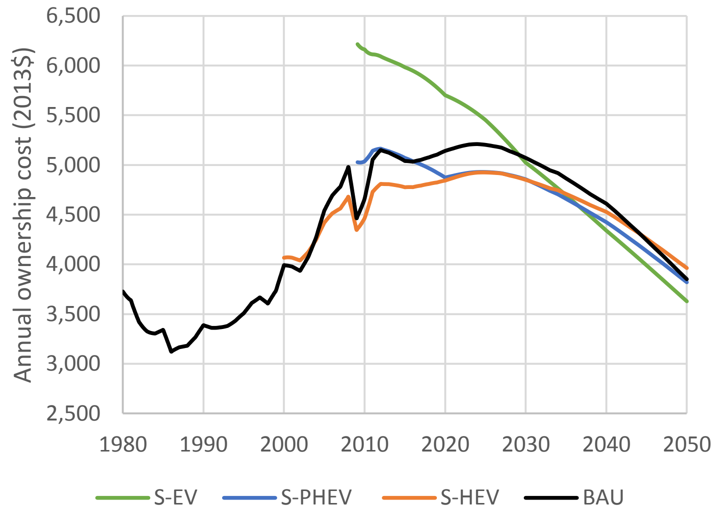


Figure 38. Annual vehicle ownership costs based on deterministic values

The stochastic results for ownership costs are presented in Fig. 39. Uncertainty rage associated with ownership cost of EVs (Fig. 39-d) has a decreasing trend and reaches its lowest range by 2050. Ownership costs of ICVs (Fig. 39-a) has also relatively higher uncertainty range and a relatively steady range with through time. Smallest uncertainty ranges was observed in the ownerships costs of HEVs (Fig. 39-b) and PHEVs (Fig-39-c). While ownership costs of EVs and PHEVs have decreasing trends, HEVs and ICVs have slight fluctuating behavior and uncertainty range.

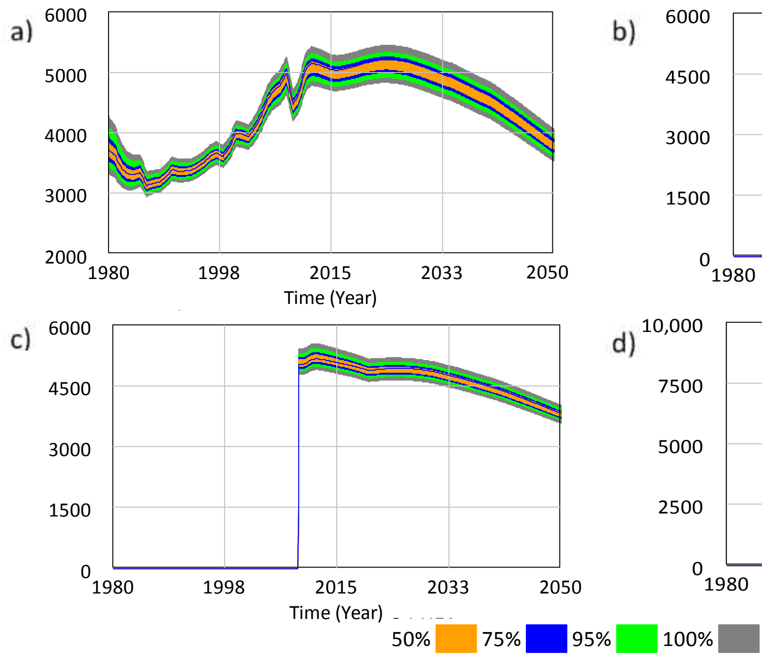


Figure 39. The multivariate dynamics of total annual vehicle ownership cost (2013$) **a)** BAU, **b)** S-HEV, **c)** S-PHEV, **d)** S-EV.

Table 32 shows the distribution parameters of the ownership cost simulations for each vehicle type in 2030 and in 2050. The standard deviation of the S-EV scenario is 5% and 4% of the mean in 2030 and 2050, respectively. Likewise, the maximum ownership cost for the S-EV scenario is approximately 1.16 and 1.14 times greater than its mean value in 2030 and 2050, respectively, while its corresponding minimum ownership cost is about 89% of its mean value in in 2050. In other words, the estimated ownership costs of EVs are approximately ±%15 and ±%11 of the mean value in 2030 and 2050, respectively. The ownership costs of ICVs, HEVs, and PHEVs are ±%6, ±%6, and ±%5 of their mean values in 2030, whereas these ranges in 2050 are ±%7, ±%6, and ±%6 of their corresponding mean values, respectively. According to these results, within a 90% confidence interval, PHEV is the only vehicle option that can reduce the ownership cost compared to other vehicle types, and its reduction potential is as low as 1% by 2030 compared to ICV ownership costs in 2015. On the other hand, the ownership costs of EVs and ICVs are higher in 2030 compared to ICV ownership costs in 2015. The ownership cost reduction potentials of all vehicle types become much greater in 2050, at which point cost reductions reach as low as approximately 20% for all vehicle types compared to ICV ownership costs in 2015. The stochastic results indicate a similar outcome, and the uncertainty associated with ownership costs is in fact found to be relatively smaller than those of environmental impacts.

Table 32 Vehicle ownership cost distribution parameters

Year	Scenario	Min	Max	Mean	Median	StDev	50%	75%	90%
2030	BAU	4808.37	5374.74	5082.26	5083.27	103.583	5083.51	5154.19	5220.96
	S-HEV	4612.73	5145.58	4854.27	4854.2	95.7818	4854.48	4922.38	4978.71
	S-PHEV	4676.26	5178.08	4909.06	4909.36	81.6018	4909.37	4962.48	5016.1
	S-EV	4594.75	6079.18	5221.13	5200.78	254.876	5200.82	5395.11	5560.12
2050	BAU	3628.23	4114.92	3860.22	3860.78	89.5717	3860.8	3923.38	3977.72
	S-HEV	3776.18	4204.01	3977.24	3976.71	78.4187	3976.89	4032.93	4078.09
	S-PHEV	3667.96	4094.1	3869.22	3868.5	67.749	3868.64	3915.39	3956.08
	S-EV	3394.33	4285.33	3765.88	3756.84	141.499	3757.12	3863.98	3957.5

Fig. 40 shows the histogram of the vehicle ownership cost results for each vehicle type in 2030 and 2050, whose parameters are given in Table 5. According to the figure, uncertainty range of EV becomes smaller and its location respect to distribution of other vehicles changes in the period of between 2030 and 2050. Also, the shape of the distribution for EV ownership cost changes, while other distributions have relatively similar shape compared to their distributions in 2030.

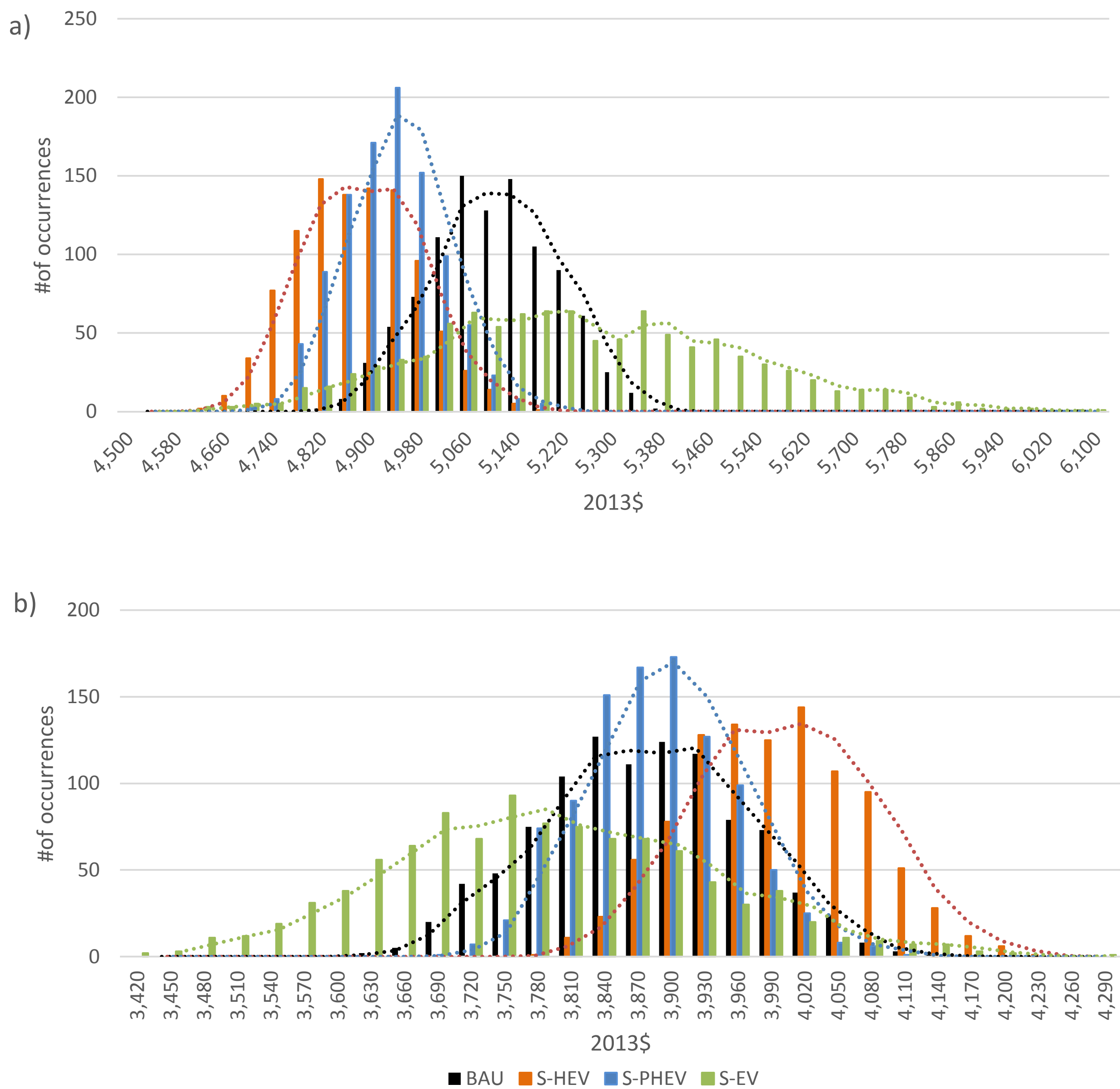


Figure 40 Histogram of the vehicle ownership costs based on Monte Carlo simulations: a) in 2030, b) in 2050.

6.4.2.2. Contribution to GDP

Fig. 41 shows the total life-cycle contribution to GDP for each scenario based on deterministic values. While the BAU and S-HEV scenarios both have increasing trends, the GDP contributions of the S-PHEV and S-EV scenarios tend to fluctuate more, mainly due to the constantly shifting balance between increases in VMT and advances in fuel economy. While the former stimulates the consumption of fuel (gasoline and/or electricity), the latter (including battery efficiency improvements) reduces the consumption of gasoline and electricity. PHEVs and EVs contribute more to the GDP due to their higher operating and purchase costs when they are introduced to the market, but as battery and electric vehicle prices decrease over time and fuel efficiencies increase, the amount of money spent on batteries and/or electricity decreases, in turn reducing the overall contribution to GDP to some extent. Overall, HEVs are shown to have the highest contribution to GDP by 2050, with ICVs (the BAU scenario) as a close second.

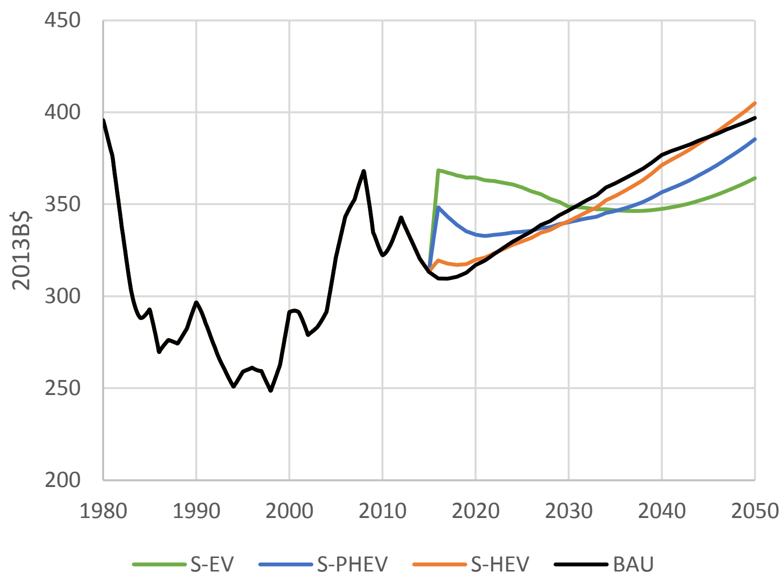


Figure 41 Annual contribution to GDP based on deterministic values

The stochastic results are presented in Fig. 42 for each scenario. . As with the stochastic trends of the S-EV scenario observed in previous impact categories, the uncertainty range is higher than those of other scenarios. The BAU, S-HEV, and S-PHEV scenarios all have increasing trends of contribution to GDP, while the S-EV scenario's contribution to GDP fluctuates significantly based on either stochastic or deterministic values. No significant change in uncertainty ranges is observed for the BAU, S-HEV, or S-PHEV scenarios, but the uncertainty range for the S-EV scenario increases suddenly after 2015 and fluctuates thereafter until 2050.

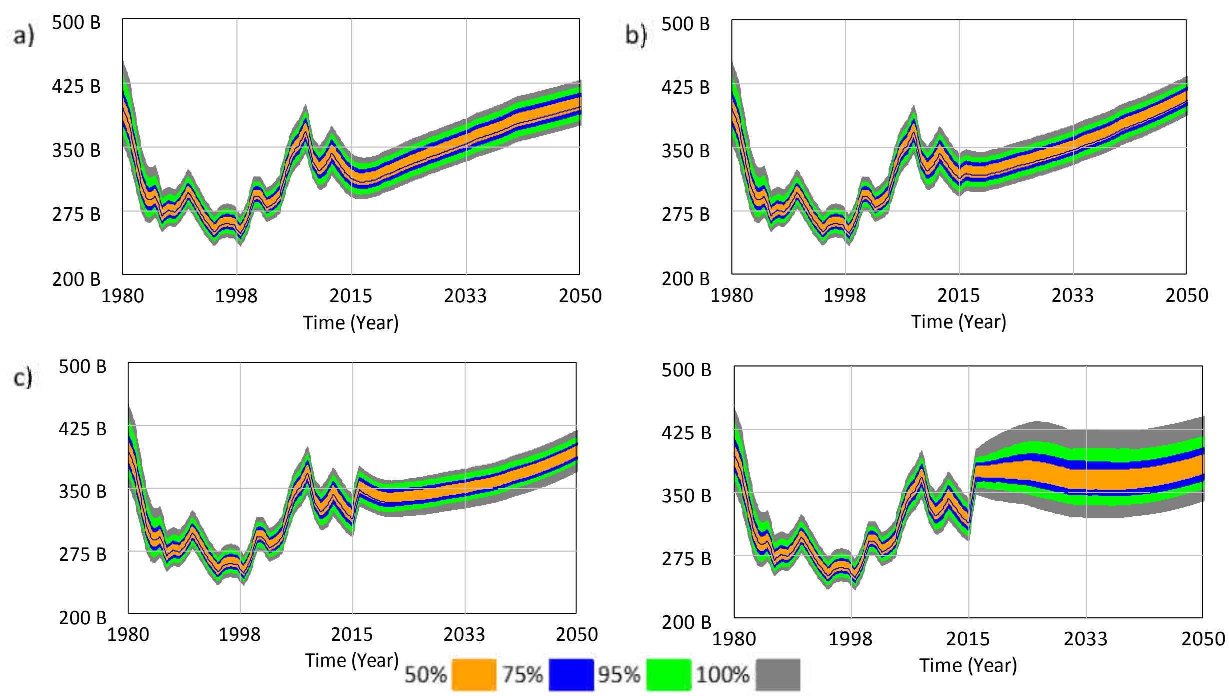


Figure 42 The multivariate dynamics of the contribution to GDP (2013$) **a)** BAU, **b)** S-HEV, **c)** S-PHEV, **d)** S-EV.

Table 33 shows the distribution parameters of contribution to GDP for each scenario in 2030 and 2050. The standard deviation values are all relatively small, with 2030 values of 3% for both the BAU and S-HEV scenarios, 2% for the S-PHEV scenario, and 5% for the S-EV scenario. The GDP contribution range for the S-EV scenario is around 30% and 26% of the mean value in 2030 and 2050, respectively, while the corresponding range is around 14% for all other scenarios in both 2030 and 2050. In other words, the uncertainty range of the S-EV is approximately two times greater than that of any other scenario. However, the uncertainty range of S-EV with respect to GDP contribution is smaller than its corresponding uncertainty ranges for the environmental impact categories (Section 3.1). According to the results, within a 90% confidence interval, all of the considered scenarios yield increases in

GDP contribution relative to 2015 contributions. The additional GDP contribution of the BAU scenario is 15% in 2030 and 31% in 2050, both relative to its 2015 contributions. Both the S-HEV and S-PHEV scenarios increase the contribution to GDP by 13% from 2015 to 2030; by 2050, these potential contribution increases reach up to 28% of 2015 contributions. The S-EV scenario, however, is found to be the highest potential contributor to GDP in 2030 with a 22% increase compared to 2015 contributions. Finally, within a 90% confidence interval, the S-HEV scenario shows the highest potential of GDP contribution by 2050, with a contribution increase of around 33% compared to 2015 contributions.

Table 33 Contribution to GDP distribution parameters

Year	Scen.	Min	Max	Mean	Median	StDev	50%	75%	90%
2030	BAU	3.23E+11	3.74E+11	3.48E+11	3.48E+11	9.41E+09	3.48E+11	3.54E+11	3.60E+11
	S-HEV	3.20E+11	3.67E+11	3.42E+11	3.42E+11	8.71E+09	3.42E+11	3.49E+11	3.54E+11
	S-PHEV	3.19E+11	3.66E+11	3.44E+11	3.44E+11	8.12E+09	3.44E+11	3.50E+11	3.55E+11
	S-EV	3.17E+11	4.20E+11	3.62E+11	3.62E+11	1.64E+10	3.62E+11	3.73E+11	3.85E+11
2050	BAU	3.72E+11	4.26E+11	3.98E+11	3.98E+11	9.99E+09	3.98E+11	4.05E+11	4.11E+11
	S-HEV	3.83E+11	4.31E+11	4.07E+11	4.07E+11	8.81E+09	4.07E+11	4.13E+11	4.19E+11
	S-PHEV	3.65E+11	4.15E+11	3.90E+11	3.90E+11	7.84E+09	3.90E+11	3.96E+11	4.00E+11
	S-EV	3.37E+11	4.36E+11	3.80E+11	3.79E+11	1.60E+10	3.79E+11	3.90E+11	4.01E+11

Fig. 43 shows the histogram of the GDP contribution values for each scenario in 2030 (Fig. 43a) and in 2050 (Fig. 43b). From the figure, the uncertainty range of the S-EV scenario is largest in both 2030 and 2050, and no significant change is observed in the shape of the distributions between 2030 and 2050. One of the main changes is that the distribution of the S-EV is shifted to the left in 2050 compared to its distribution in 2030. The distributions for the BAU, S-HEV, and S-PHEV scenarios are very similar in 2030, whereas they have moved slightly apart from one another by 2050.

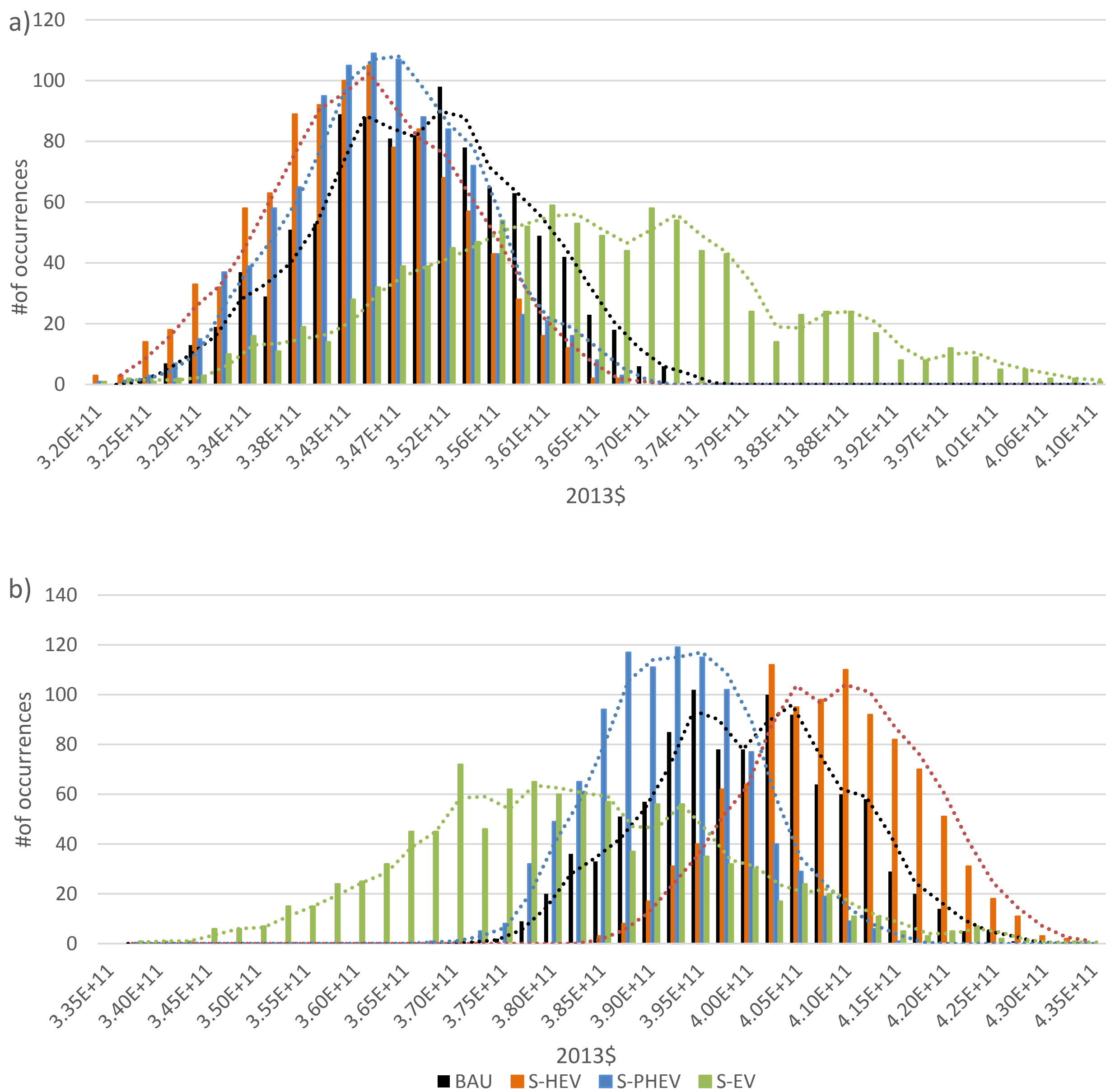


Figure 43 Histogram of the contribution to GDP based on Monte Carlo simulations: **a)** in 2030, **b)** in 2050.

6.4.3. Social Impacts

Social impacts, employment generation and human health impacts, are presented in the following sub-sections.

6.4.3.1. Employment generation

The total employment generation in the transportation sector and in all related sectors in its supply chain is presented in Fig. 44, based on the deterministic values presented in Table 28. The trend of employment generation is very similar to that of GDP contribution, since these two variables are linearly correlated. Similar to previous impact categories, the initial increase in the scenarios is due to an initial increase in demand for new vehicles, which thereby stimulates the vehicle-manufacturing sector and increases the employment generated in this sector. Although the demand for new vehicles increases over time and thus continues to generate employment, improvements in fuel efficiency and battery technology reduced fuel consumption, including batteries, electricity, and gasoline. For the S-EV scenario, the loss of employment due to these improvements ultimately outweighs the positive employment generation due to increased EV manufacturing demand, resulting in a decreasing trend until 2040, when the positive employment generation due to increased demand once again becomes dominant. For all other scenarios, the employment generation demonstrates an almost steady increasing trend, with the sole exception of the S-PHEV scenario from 2015 to 2020. The overall employment generation is highest for the S-HEV and BAU scenarios, both of which ultimately reach nearly identical employment generation rates by around 2050.

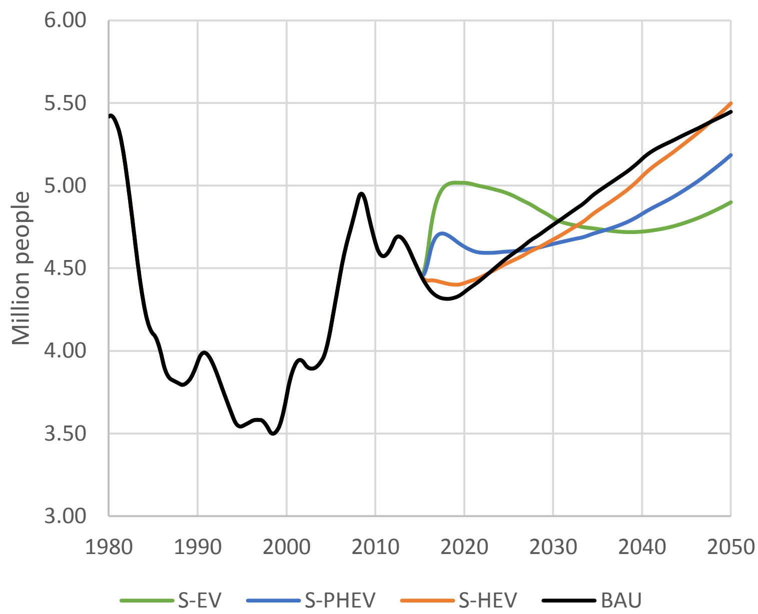


Figure 44. Total life cycle employment generation based on deterministic values

Stochastic results for employment generation are presented in Fig. 45 for each scenario. The uncertainty ranges for employment generation are found to be higher than those for previous impact categories, with the 50% uncertainty range (the orange area in the figure) covering an especially large area. The uncertainty ranges for the BAU and S-EV scenarios are slightly higher than those of other scenarios. As opposed to the fluctuating behavior observed in the results based on deterministic values, the stochastic results appear to have steadier behavior, most demonstrating increasing trends. The uncertainty range for the S-PHEV scenario (Fig. 18c) has a relatively decreasing trend, while that of the S-EV scenario increases briefly between 2015 and 2025. A more detailed analysis of the uncertainty analysis can be made by evaluating the values presented in Table 34, in which the distribution parameters for each scenario are shown for 2030 and 2050.

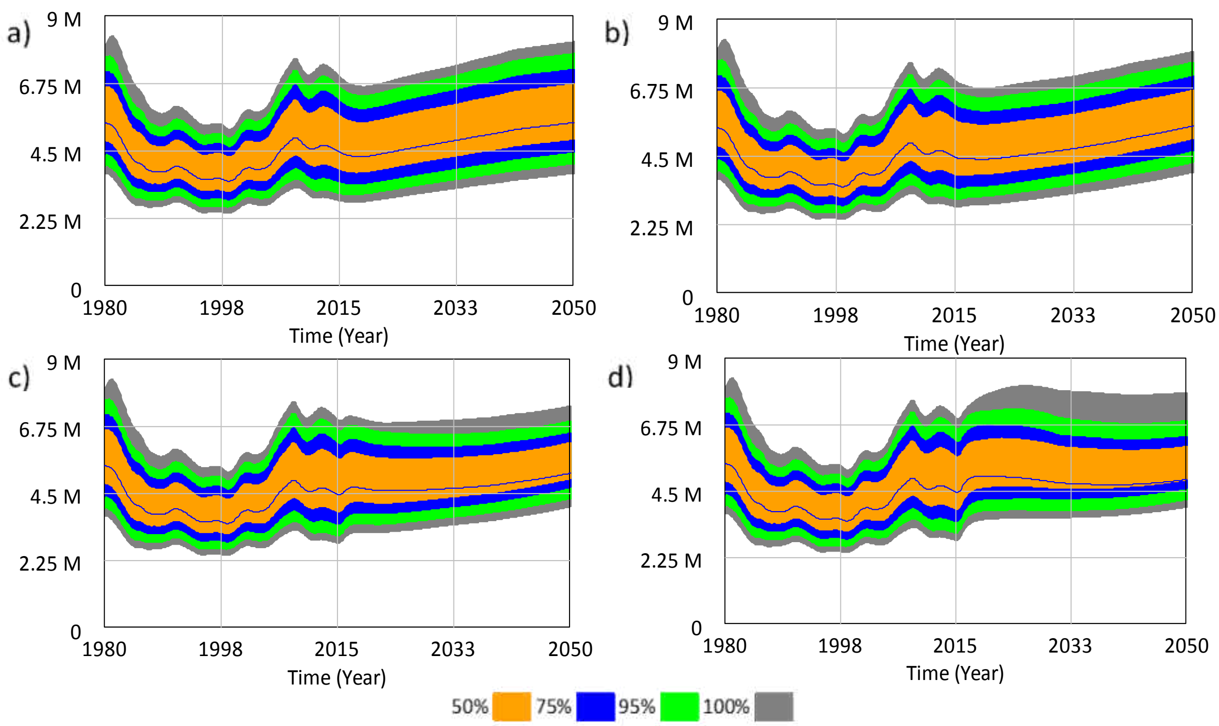


Figure 45. The multivariate dynamics of the employment generation (#of people) a) BAU, b) S-HEV, c) S-PHEV, d) S-EV.

The normalized standard deviation values are all relatively high at 20% for the BAU scenario, 19% for the S-HEV scenario, 16% for the S-PHEV scenario, and 17% for the S-EV scenario in 2030; these values in 2050 are 19% for the BAU scenario, 16% for the S-HEV scenario, and 13% for both the S-PHEV and S-EV scenarios. The variations between the minimum and maximum employment generation values in 2030 are approximately ±39%, ±38%, ±35%, and ±40% of the mean values of the BAU, S-HEV, S-PHEV, and S-EV scenarios in 2030, respectively, whereas these variations in 2050 are ±37%, ±33%, ±39%, and ±36% of the mean values, respectively. Within 90% confidence interval, all scenarios lead to an increase in employment in the U.S. transportation sector. Employment generation in 2030 (relative to employment levels in 2015) by the BAU, S-HEV, S-PHEV, and S-EV scenarios are 36%, 31%, 27%, and 36% in 2030, respectively, while the corresponding 2050 employment values are 53%, 50%, 36%, and 33% compared to transportation-related employment levels in 2015 for the BAU, S-HEV, S-PHEV, and S-EV scenarios, respectively. According to the stochastic results, within 90% confidence interval, the employment generation potential is greatest for the BAU scenario, whereas this generation potential is highest for the S-HEV scenario according to the results based on deterministic values. In 2030, the employment generation potentials are highest for the BAU and S-EV scenarios.

Table 34. Employment generation distribution parameters

Year	Scenario	Min	Max	Mean	Median	StDev	50%	75%	90%
2030	BAU	3.18E+06	7.19E+06	5.09E+06	5.09E+06	1.01E+06	5.09E+06	5.92E+06	6.49E+06
	S-HEV	3.20E+06	7.03E+06	4.99E+06	5.00E+06	934499	5.00E+06	5.76E+06	6.29E+06
	S-PHEV	3.38E+06	6.88E+06	4.98E+06	4.98E+06	810818	4.98E+06	5.63E+06	6.08E+06
	S-EV	3.56E+06	7.88E+06	5.30E+06	5.26E+06	896458	5.26E+06	6.01E+06	6.52E+06
2050	BAU	3.75E+06	8.09E+06	5.81E+06	5.82E+06	1.08E+06	5.82E+06	6.69E+06	7.30E+06
	S-HEV	3.97E+06	7.92E+06	5.85E+06	5.86E+06	955813	5.86E+06	6.62E+06	7.17E+06
	S-PHEV	4.05E+06	7.37E+06	5.55E+06	5.55E+06	730892	5.55E+06	6.14E+06	6.51E+06
	S-EV	3.91E+06	7.77E+06	5.40E+06	5.35E+06	726972	5.35E+06	5.96E+06	6.38E+06

Fig. 46 shows the histogram of the distributions for each scenario type in 2030 and 2050. In 2030, the distribution shapes of scenarios are very similar, whereas distributions of S-EV and S-PHEV become more close to a bell shape curve in 2050.

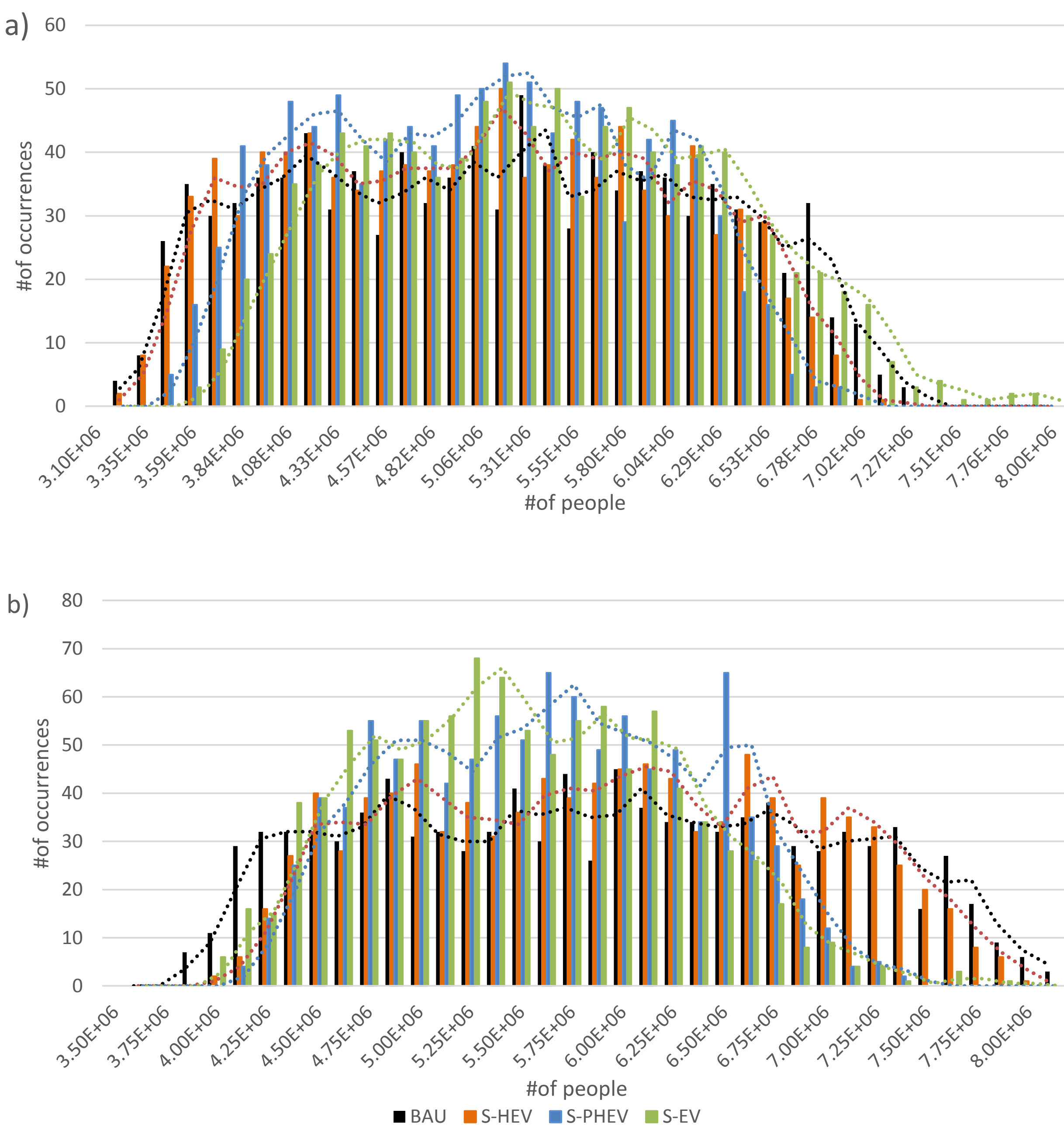


Figure 46. Histogram of the employment generation based on Monte Carlo simulations: **a)** in 2030, **b)** in 2050.

6.4.3.2. Human health impacts

Human health impacts are the total impacts due to air pollution and climate change. Fig. 47 shows the human health impacts from 1980 to 2050 for each scenario, based on the deterministic values presented in Table 28. According to the figure, the human health impacts have a decreasing trend, with the S-PHEV and S-EV scenarios demonstrating the highest reduction potential compared to other scenarios. The reduction rate decreases for all scenarios except for the BAU scenario and reaches saturation by 2050, mainly because of the limited reduction potentials of fuel efficiency improvements compared to rapidly increasing travel demand.

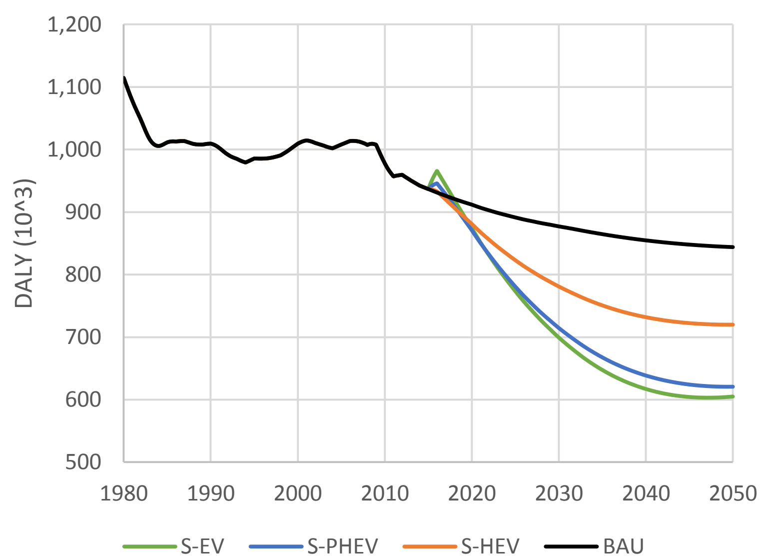


Figure 47. Total life cycle human health impacts based on deterministic values

Stochastic results for human health impacts are presented in Fig. 48 for each scenario. The uncertainty ranges for human health impacts are found to be greater than those of previous impact categories. The 50% range, the area shaded with orange color, appears to be greater and close to the minimum values. The uncertainty ranges gradually getting smaller for S-HEV (Fig. 48-b) and S-PHEV (Fig. 48-c), while they are realty constant for BAU scenario (Fig. 48-a) and S-EV (Fig. 48-d). The width shaded areas are not symmetric according to the line of mean value (blue line). The widths above the orange shaded area are greater than those of bellow the orange shaded area.

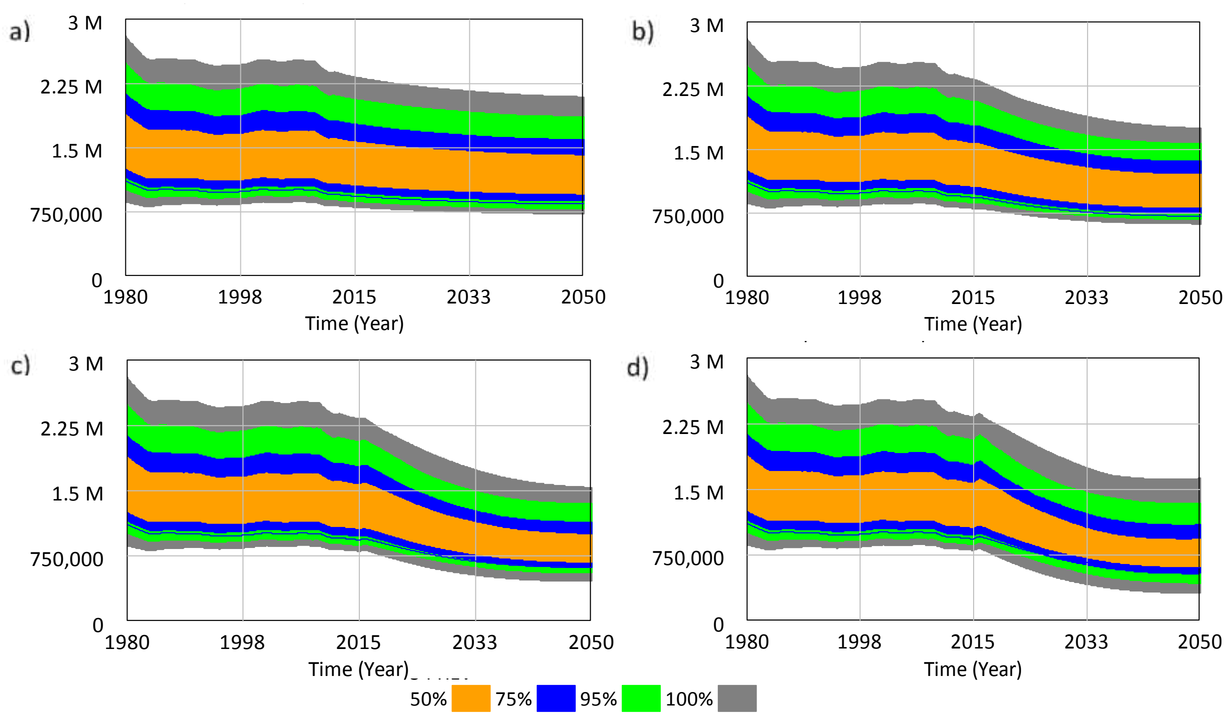


Figure 48. The multivariate dynamics of the human health impacts (DALY) a) BAU, b) S-HEV, c) S-PHEV, d) S-EV.

Table 35 shows the diistribution parameters for each scenario in 2030 and 2050. The normalized standard deviations in 2030 are 25%, 24%, 25%, and 27% in 2030 for the BAU, S-HEV, S-PHEV, and S-EV scenarios, respectively, whereas their corresponding 2050 values are 24%, 24%, 25%, and 30%, respectively. The maximum human health impacts of the BAU and S-HEV scenarios are approximatelly 1.7 times greater than their mean values in both 2030 and 2050, whereas their corresponding minimum values are approximately 60% of their mean values in both 2030 and 2050. On the other hand, the maximum human health impacts of the S-PHEV scenario are times 1.8 times greater than its mean value in both 2030 and 2050, while its minimum value is approximately 55% of its mean in 2030 and 53% of its mean in 2050. For the S-EV scenario, the maximum value of human health impacts is 1.9 times greater than its mean value in 2030 and 2.1 times greater than its mean value in 2050, while the corresponding minimum values are 48% of its mean in 2030 and 40% of its mean in 2050. The human health impacts have the highest uncertainty ranges compared to previous impact categories due to more significant inherent uncertainties embedded in spatial factors, such as the specific locations of air emissions and the higher unceraintes related to end-point characterization factors for the human health impacts of different air pollutants and of climate change in general. According to the stochastic results with a 90% confidence interval, as opposed to the results based on deterministic values, neither ICVs (BAU scenario), HEVs, nor PHEVs are expected to decrease human health impacts, but rather are expected to increase human health impacts from 2015 to 2030 by 27%, 13%, and 2%, respectively. Furthermore, the human health reduction potential of EVs is as low as 1% in 2030, which was found to be much greater in the results based on deterministic values. In

2050, the BAU and S-HEV scenarios still show increases in human health impacts by 23% and 4% relative to 2015 values, but now PHEVs and EVs indicate a decrease in human health impacts from 2015 to 2050 by 12% and 14%, respectively.

Table 35. Human health impact distribution parameters

Year	Scen.	Min	Max	Mean	Median	StDev	50%	75%	90%
2030	BAU	756131	2.18E+06	1.26E+06	1.20E+06	308517	1.20E+06	1.47E+06	1.71E+06
	S-HEV	674191	1.93E+06	1.12E+06	1.08E+06	274733	1.08E+06	1.31E+06	1.52E+06
	S-PHEV	556233	1.80E+06	1.00E+06	955868	249401	955880	1.18E+06	1.37E+06
	S-EV	454705	1.82E+06	952518	901588	254795	901700	1.12E+06	1.33E+06
2050	BAU	729494	2.09E+06	1.21E+06	1.16E+06	295645	1.16E+06	1.41E+06	1.65E+06
	S-HEV	625610	1.76E+06	1.03E+06	990672	251680	990888	1.21E+06	1.39E+06
	S-PHEV	457848	1.54E+06	858041	815297	215790	815386	998898	1.18E+06
	S-EV	315191	1.63E+06	791527	749094	239585	749144	928884	1.16E+06

Fig. 22 shows the histogram of the distributions of human health impacts in 2030 and in 2050. The shape of the distributions is similar to a triangular distribution, in which the mean values are closer to the lower values. There is no significant change in the shape of the distributions between 2030 and 2050.

a)

b)

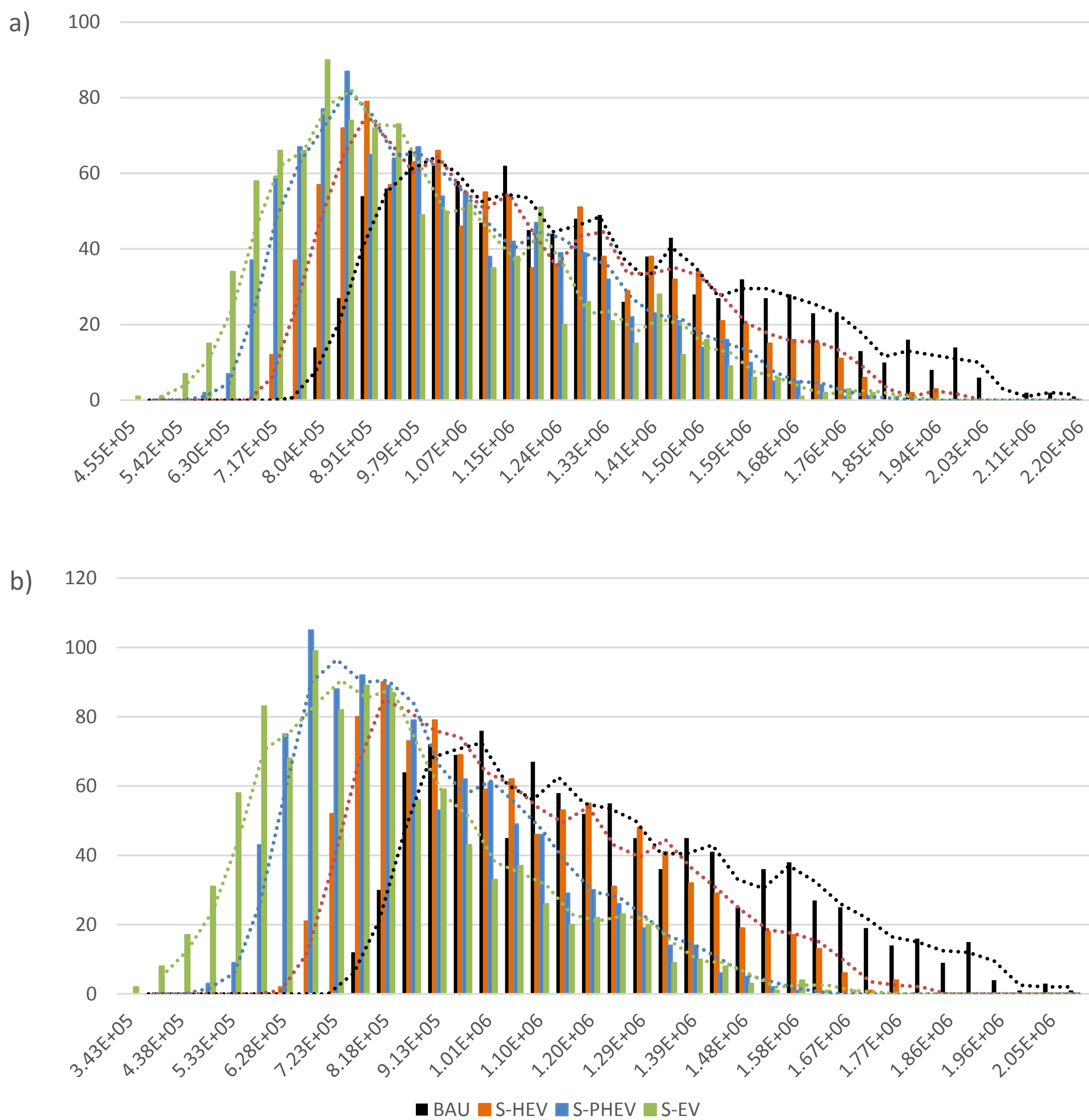


Figure 49. Histogram of the human health impacts based on Monte Carlo simulations: **a)** in 2030, **b)** in 2050.

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

In this dissertation, novel methodological frameworks are presented to advance state-of-the-art and state-of-the-practice in the transportation sustainability research as well as in the Life Cycle Sustainability Assessment Framework.

Chapter 3 demonstrates the effects of spatial and partially temporal variations (scenario 2) on the GHG emissions and energy consumption of some alternative vehicle technologies and highlights how these factors can influence the vehicle technology preference at state level. Also, analysis results revealed that the impacts of battery and vehicle manufacturing are much smaller than that of operation phase of the vehicles. Based on comparative evaluation of three different scenarios, it can be concluded that the use of renewable energy sources to power EVs/PHEVs should be encouraged to achieve reduction in GHG emission and energy consumption. Although solar energy has become popular as a source of electric power, number of solar charging stations is still very limited. Increased concerns regarding the high carbon intensive structure of the U.S. electricity grid have stimulated the development of more effective powering ways of EVs/PHEVs. Considering that there is significant energy losses during electricity generation, distribution, and transmission, use of on-site solar energy can save these losses and provide more efficient way of powering EVs/PHEVs. Additionally, the market share of PHEVs is expected to increase (Eudy & Zuboy, 2004), which might require some additional upgrades in the transmission and distribution systems and construction of new power plants in the future. The increased electricity demand are usually provided through either with conventional ways, with large power plants located far from the demand center, or 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(Li, Lopes, & Williamson, 2009). As the power generation unit cost has been declining for solar technologies, the use of PVs is expected to be greater(The U.S. Energy Information Administration, 2014). PVs can serve as charging stations for EVs/PHEVs and a power generation source to grid at the same time. Similarly, roof-top PV panels in residential and commercial buildings can serve as a distributed power generation source and as an environmental friendly recharging option for EVs/PHEVs.

In Chapter 3, although the economic feasibility of the scenarios are not investigated, use of renewable energy to power electric vehicles is inevitable to achieve carbon-free transportation system in the U.S. It should be also noted that inclusion of marginal electricity scenario is the most realistic scenario among the proposed policies and inclusion of it suggested by various researchers(Chen et al., 2008; Dotzauer, 2010; Elgowainy et al., 2010; Hawkes, 2010; McCarthy & Yang, 2010; Thomas, 2012). Hence, implementation of renewable energy based charging options for EVs/PHEVs are highly recommended. On the other hand, the market penetration of these vehicle types should be analyzed and estimated to develop more effective, environmental friendly and economically viable policies. Another important point is that the reduction potential of all alternative vehicle technologies in the scenarios 1 and 2 are the marginal reductions which may not be enough to reduce or even stabilize the GHGs stored in the atmosphere. Estimating these impacts from such dynamic system requires a holistic dynamic system approach in which all of the variables of the system and the interactions among them are captured (Onat, Egilmez, et al., 2014). Moreover, since the sustainability concept is an optimization process among the three pillars known as environment, economic, and social dimensions (Murat Kucukvar, Noori, et al., 2014), impacts from the adoption of alternative vehicle technologies should be analyzed with inclusion of these three dimensions. Integration of all sustainability dimensions and dynamic modeling approach are step to analyze the impacts of alternative vehicle technologies. Therefore, Chapter 5 and 6 focuses on these research gaps.

The U.S. population is expected to rise significantly, but accessible water supplies are not. According to the U.S. Department of Energy, until 2020, the expected population growth ranges between 20% and 50% in most water-stressed regions of the U.S. (Sandia National Laboratory 2015). This growth, in turn, will also substantially increase the demand for passenger cars and vehicle miles of travel, so it will be essential for the U.S. to gain a detailed understanding of the interdependencies of water-reliant vehicle systems, promote the adoption of water- and energy-efficient BEVs, and develop energy production technologies to reduce water consumption and withdrawal rates. These goals can be achieved through bridging research and practice gaps by integrating the following three initiatives:

(1) More thoroughly analyzing the water footprints of alternative passenger cars using life-cycle-based holistic methodologies,

(2) Providing state-based incentives for water-efficient transportation vehicles, especially in highly water-sensitive and water-stressed states, and

(3) Minimizing water-related impacts from energy production supply chain activities including resource mining, energy production, and energy distribution.

This dissertation is a first and critical step toward an integrated water footprint analysis of alternative passenger cars in the U.S., and the results will provide a vital guidance for decision makers when developing sustainable vehicle transportation policies in the most water-stressed areas in the U.S. The policy analysis scenarios used in this study can also be very helpful to test different electricity generation options for alternative electric vehicles based on average and marginal electricity mixes on a case-by-case basis, and may also prove useful to test newly proposed options such as, in this case, charging EVs solely with photovoltaic (PV) technology. Using an uncertainty-based water withdrawal and consumption analysis like that of this study, decision makers will also be able to use stochastic estimation to see the difference between water consumption and water withdrawal for each state, and the findings of this dissertation will help policy makers to propose state-specific electric vehicle use policies considering current water supply risks as well as the estimated availability of water resources in the future. Based on the analysis results of Chapter 4, the following points are highlighted:

❖ 100% solar-charging options have the lowest water withdrawal and consumption rates, and can therefore serve as an important power source in most water-stressed states, including California (CA), Arizona (AZ), Nevada (NV), Florida (FL), Texas (TX), and New Mexico (NM). All of these states are expected to have significant population increases in near future, and so the number of vehicle miles traveled is expected to increase immensely for each of these states. However, these regions can also benefit from their warm climate and long periods of sunshine, allowing them to effectively install and implement solar charging stations for charging electric vehicles.

❖ For the average electricity mix generation scenarios considered in this study, the water consumption and withdrawal of the states analyzed ranged between 0.01 and 0.05 gallons per VMT. However, exceptions were observed in some states, including Idaho (ID), Maine (ME), Alaska (AK), Montana (MT), New York (NY), Oregon (OR), South Dakota (SD), Vermont (VT), Washington (WA) and Tennessee (TN), where the net water consumption rate was shown to reach up to 4.6 gal/mil. These unusually high values are primarily due to higher shares of hydropower plants for the total electricity generation of each of these states. However, looking at the more realistic marginal electricity mix scenarios of each state, their respective net water withdrawals increased substantially, while their total water consumption values showed a decreasing trend due to higher reliance on fossil-fuel energy sources such as coal and/or natural gas.

❖ In addition, for PHEV20s and PHEV40s, the maximum water withdrawal amounts for the average electricity mix scenarios of each state are always higher than those of the corresponding marginal electricity mix and 100% solar charging scenarios.

- ❖ Under a 100% solar charging scenario, the total water withdrawal and consumption rates of PHEV40s were found to be less than those of PHEV20s for all states, because PHEV40s operate in electricity mode more often due to their higher AER. Since petroleum is a more water-intensive resource than solar energy according to the NREL database (NREL 2011), the larger petroleum consumption of PHEV20s increased their net water footprint.

- ❖ Although selecting appropriate alternative passenger cars can have a significant impact on the total water footprint of vehicle transportation, water use in electricity generation and distribution is also an important factor to consider for the water footprint. In particular, power plant cooling systems (coal, natural gas, nuclear, etc.) require large amounts of water, and current cooling technologies therefore have high water consumption/withdrawal impacts. In this regard, one potential avenue of research might be to develop new, more water-efficient cooling systems that would thereby reduce or even eliminate the need for fresh water resources, thus significantly reducing the overall water footprints of BEVs and PHEVs in the U.S.

- ❖ It should also be kept in mind that BEVs can be an effective solution for many states to minimize the net water footprint of passenger transportation. Hence, it is important to note that, even with the existing electric power generation mix, various policy incentives such as tax credits and carpool lane access might be implemented with respect to BEVs to make them more attractive to consumers and to promote the adoption of electric cars nationwide. However, there are still important barriers for a sustainable future for electric vehicles in the U.S. For example, affordability and accessibility are still among the most significant socio-economic constraints preventing the more widespread adoption of electric vehicles (Onat et al. 2015b). According to the U.S. Department of Energy, "The high-purchase price gets part of the blame for consumer hesitancy to buy electric vehicles. While the market has been growing quickly, additional cost reduction of electric vehicle technology is required to directly compete on a cost basis with conventional vehicles" (National Science Foundation 2015). Another major challenge for making electric vehicles a strong choice for consumers is the current relative lack of accessibility to fast charging stations, as the relatively small number of large-scale vehicle-charging stations makes recharging electric vehicles inconvenient for public usage For this reason, the authors conclude that minimizing the current and future water footprint of BEVs in most water-stressed areas will require a joint effort by research institutes, federal and local governments, and society as a whole. Incentives for EVs, such as tax credits, the development of energy-efficient electricity production technologies considering the entire supply chains, and the improvement of accessibility and affordability for BEVs, will continue to become important policy areas that need urgent attention for a more sustainable future for electric vehicles.

The framework presented in Chapter 5 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 of this study is that 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 to 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;

- BEVs are mostly found to be a better option in the environmental impact categories such as CO_2 emissions and PMF. While these environmental impacts are higher between 2015 and mid-2020s, CO_2 emissions and PMF impacts of BEVs significantly decreased towards 2050 due to battery and fuel efficiency improvements. POF impacts of BEVS are found to be highest, whereas HEVs and PHEVs have the lowest POF impact.
- 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.
- Analysis results revealed that even though the entire U.S. automobile stock is replaced with BEVs, it has a negligible impact on slowing down to rapidly increasing

atmospheric temperature. Hence, more ambiguous and international efforts are crucial to reverse or slow down the increasing atmospheric temperature.

❖ While the vehicle ownership cost of BEVs is much larger in early years when the EVs are introduced to the market, these costs significantly decrease towards 2050. The ownership costs of all vehicle options decrease towards 2050 as the fuel efficiency and batteries are improved. BEVs had the highest benefit (cost reduction) owning to these improvements. Operation phase costs of HEVs were found to be lowers until 2030 when operation phase costs of BEVs become lowest.

❖ GDP contribution of manufacturing phase becomes more important towards 2050, whereas GDP contribution of operation phase lowers for BEVs, PHEVs, and partially HEVs. Overall, GDP contribution of BEVs were found to be highest for BEVs until 2030s, than it starts to decrease toward 2050. The contribution of HEVs became the largest in 2050 with an increasing trend since they are introduced to the market.

❖ Newly commercialized technologies such as BEVs and PHEVs generate more employment at the beginning and reaches an equilibrium afterwards. However, employment generation of HEVs and ICVs has a steady increasing trend due to rising travel demand and developments in the associated sectors.

❖ Manufacturing phase human health impacts are much higher than the human health impacts in the operation phase. Overall, the BEVs have the greatest potential on reducing human health impacts due to air pollution and climate change.

❖ Analysis results revealed that vehicle choice does not affect the public welfare significantly. Exogenous determinants of public welfare, life expectancy, income, and education overwhelm the effects of vehicle choice. However, this effect is not necessary same for all products and therefore should be taken into consideration for LCSA of products and systems.

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 provide 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. Hence, Chapter 6 deal with uncertainties inherent to the U.S. transportation.

In Chapter 6, the uncertainties associated with sustainability impacts of alternative vehicle technologies in the U.S. The system dynamics model is used to quantify triple bottom line impacts and to deal with uncertainties. This analysis is acritical effort towards deepening and broadening the existing life cycle sustainability assessment framework. The presented approach provided a more comprehensive sustainability assessment framework by dealing with uncertainties with a novel approach as well as capturing the dynamic relations among the parameters of U.S. transportation system, environment, society, and the economy. Uncertainty analysis allowed us to identify the likelihood of the impact reduction potentials of different vehicle types as well as the behavioral limits of the scenarios. Some of the important findings of Chapter 6 are summarized as follows:

- ❖ PHEVs are found to be better options to minimize transportation related CO_2 emissions, PMF, and POF impacts compared to other vehicle types. According the results with 90% confidence interval, PHEVs have capability reducing the transportation related annual CO_2 emissions, PMF, and POF impacts up to 23%, 7%, and 9% by 2050 compared to 2014 levels.
- ❖ Analysis results reveal that the results with consideration of uncertainties can be significantly different than those of without consideration of uncertainties. Therefore, when developing policies the robustness of proposed scenarios should be valuated with consideration of uncertainties as well as the dynamic feedback mechanisms.
- ❖ Vehicle ownership costs of each vehicle type have decreasing trends and they are tend to reach a saturation in long term with no significant ownership cost difference in long term. According the results with 90% confidence interval, EVs and PHEVs are the most promising alternative for ownership cost reduction in the long term. However, they are not expected to be a better alternative in near term. HEVs can be better alternatives until 2030s in the terms of ownership cost reduction.
- ❖ Contribution to GDP is highest for EVs in near term, whereas, in long term, no significant difference is observed among the scenarios. Although all of the vehicle types contributes to GDP in both near and long term, the newer technologies

such as EVs and PHEVs can stimulate the research and development better and pave the way technological advancement. Therefore, these vehicle types can be more preferable considering their potential to contribute the economy.

- All of the scenarios generate significant employment. According to the results with 90% confidence interval, EVs have the greater potential of employment generation in near term, which also makes EVs more preferable due to their ability to create green jobs and contribute the advancement in the battery technology. In the long term, BAU scenario and S-HEV performed better as they still will be creating more jobs in the petroleum production and distribution sector.

- Results of the uncertainty analysis (based on 90% confidence interval) showed that EVs are the best alternative both in near and long term to reduce human health impacts stemming from air pollution and global warming.

- The highest uncertainty is observed in the impacts of S-EV in all of the impact categories. This is mainly due to uncertainties related to the electric power generation sector. The fuel source of the electric power generation can significantly change the impacts of electric vehicles.

- Selection of different vehicle types has an insignificant effect on some macro-level indicators such as public welfare, income index, and human health index. However, effects of these indicators should not be neglected when developing transportation related policies. Furthermore, such macro-level socio-economic indicators should be considered in the integrated system based life cycle sustainability assessments.

Overall, EVs and PHEVS are found to be better alternative in most of the impact categories. It should be noted that all of the environmental impacts presented here are the annual impacts. The cumulative CO_2 emissions, PMF, and POF impacts of the transportation system have increasing trends for all scenarios. Observing these behaviors is inevitable since there is no outflow specifically to reduce cumulative transportation impacts. For instance, the carbon sequestration through trees and oceans cannot identify and select to absorb the emissions from transportation among those of many other sources. Hence, assigning an outflow, a carbon sequestration mechanism, for specifically transportation emissions is not a realistic approach. On the other hand, within the entire model, the relationships are defended based on cumulative impacts such as increasing atmospheric temperature is calculated through the accumulated CO_2 emissions in the atmosphere, which is modeled using the DICE model (Nordhaus, 2006). The climate model induces the accumulated transportation emissions, as well as the emissions from rest of the U.S. and the world, since the global warming is a subject of a much wider system. It should be also noted that none of the scenarios has a significant impact on changing global temperature increase since their reduction emission reduction potential is very limited compared to the emissions from entire world. Therefore, strong collaborative efforts is crucial to fight climate change.

Although the dynamic model provides a comprehensive sustainability assessment framework, it can be improved significantly by integration of multi-criteria decision making and adaptive policy scenarios. Considering that there are many conflicting objectives among different indicators, one alternative can be the best for an impact category, while it can perform worst in another impact category (Onat, Kucukvar, Tatari, & Zheng, 2015). Sustainable solutions should propose a balanced solution in which all of the impacts are reduced as much as possible while maintaining or increasing the benefits, which requires a multi criteria decision making framework integrated with the integrated sustainability assessment framework proposed in this research.

Results of this dissertation can be beneficial for policy makers, industry stakeholders, and researchers towards proposing more sustainable solutions and developing better decision making frameworks. The outcomes of this dissertation can pave the way for advancement in the state-of-the-art and state-of-the-practice in the sustainability research by presenting novel approaches to deal with uncertainness and complex systems.

REFERENCES

Abbas, K. A., & Bell, M. G. H. (1994). System dynamics applicability to transportation modeling. *Transportation Research Part A: Policy and Practice*, *28*(5), 373–390. http://doi.org/10.1016/0965-8564(94)90022-1

Akhtar, M., Wibe, J., Simonovic, S., & MacGee, J. (2013). Integrated assessment model of society-biosphere-climate-economy-energy system. *Environmental Modelling & Software*, *49*, 1–21.

Argonne National Laboratory. (2014a). The VISION Model. Retrieved June 9, 2014, from http://www.transportation.anl.gov/modeling_simulation/VISION/

Argonne National Laboratory. (2014b). Transportation Technology R&D Center web page. Retrieved from http://www.transportation.anl.gov/

Baldoni, F., Falsini, D., & Taibi, E. (2010). A System Dynamics Energy Model for a Sustainable Transportation System. In *Proceedings of the 28th International Conference of the System Dynamics Society*.

Barber, N., Hutson, S., Linsey, K., Lovelace, J., & Maupin, M. (2009), Estimated use of water in the United States in 2005 (p. 52), US Geological Survey, Reston, VA.

Barlas, Y. (1996). Formal aspects of model validity and validation in system dynamics. *System Dynamics Review*, *12*(3), 183–210. Retrieved from http://www.ie.boun.edu.tr/labs/sesdyn/publications/articles/Barlas_1996.pdf

Barnes, G., & Langworthy, P. (2003). *The Per-mile Costs of Operating Automobiles and Trucks*. Retrieved from http://conservancy.umn.edu/handle/11299/909

Barnett, B., Ofer, D., Yand, Y., Oh, B., Remple, J., McCoy, C., … Sririramulu, S. (2009). PHEV Battery Cost Assessment. Retrieved February 3, 2015, from https://www1.eere.energy.gov/vehiclesandfuels/pdfs/merit_review_2009/energy_storage/es_02_barnett.pdf

Bastani, P., Heywood, J. B., & Hope, C. (2012). The effect of uncertainty on US transport-related GHG emissions and fuel consumption out to 2050. *Transportation Research Part A: Policy and Practice*, *46*(3), 517–548. http://doi.org/10.1016/j.tra.2011.11.011

Blackhurst, B., Hendrickson, C., & Vidal, J. (2010), "Direct and indirect water withdrawals for US industrial sectors", Environmental science & technology, 44(6), 2126-2130.

Bossel, H. (2007). *System Zoo 3 Simulation Models–Economy*.

Brinkman, N., Wang, M., Weber, T., & Darlington, T. (2005). Well-to-wheels analysis of advanced fuel/vehicle systems—a North American study of energy use, greenhouse gas emissions, and criteria pollutant. *Argonne Natl. Lab, Argonne, IL*. Retrieved from http://scholar.google.com/scholar?q=Brinkmann%2C+Wang+M%2C+Weber+T%2C+Darlington+T++&btnG=&hl=tr&as_sdt=0%2C10#0

Burke, A. F. (2007). Batteries and Ultracapacitors for Electric, Hybrid, and Fuel Cell Vehicles. *Proceedings of the IEEE*, *95*(4), 806–820. http://doi.org/10.1109/JPROC.2007.892490

Burnham, A., Wang, M., & Wu, Y. (2006). Development and Applications of GREET 2.7 — The Transportation Vehicle-Cycle Model. *Energy*, 124. http://doi.org/10.2172/898530

Bradley, T., & Frank, A. (2009), “Design, demonstrations and sustainability impact assessments for plug-in hybrid electric vehicles”, Renewable and Sustainable Energy Reviews, 13(1), 115-128.

CALCAS. (2009). D17 Final Report: Options for Deepening and Broadening LCA. Retrieved February 3, 2014, from http://www.estis.net/includes/file.asp?site=calcas&file=B501D8D5-ADC1-4DBA-8EFC-71A764FCFE5A

Carnegie Mellon University Green Design Institute. (2008). Economic Input-Output Life Cycle Assessment (EIO-LCA). Retrieved from http://www.eiolca.net/index.html

Center for Electric Car and Energy Conversion. (2014). Center for Electric Car and Energy Conversion web page. Retrieved from http://www.uml.edu/research/ecec/

Chateau, J., Rebolledo, C., & Dellink, R. (2011). An Economic Projection to 2050: The OECD“ ENV-Linkages” Model Baseline. Retrieved from http://www.oecd-ilibrary.org/content/workingpaper/5kg0ndkjvfhf-en

Chen, Y., Sijm, J., Hobbs, B. F., & Lise, W. (2008). Implications of CO2 emissions trading for short-run electricity market outcomes in northwest Europe. *Journal of Regulatory Economics*, *34*(3), 251–281. http://doi.org/10.1007/s11149-008-9069-9

Chevrolet. (2014). 2014 Chevrolet Volt Specifications. Retrieved from http://www.chevrolet.com/volt-electric-car/specs/dimensions.html

Ciroth, A., Fleischer, G., & Steinbach, J. (2004). Uncertainty calculation in life cycle assessments. *The International Journal of Life Cycle Assessment*, *9*(4), 216–226. http://doi.org/10.1007/BF02978597

Committee for a Study of Potential Energy Savings and, & Greenhouse Gas Reductions from Transportation. (2011). *Policy Options for Reducing Energy Use and Greenhouse Gas Emissions from U.S. Transportation: Special Report 307*. Washington DC,.

Cooney, G., Hawkins, T. R., & Marriott, J. (2013). Life Cycle Assessment of Diesel and Electric Public Transportation Buses. *Journal of Industrial Ecology*, n/a–n/a. http://doi.org/10.1111/jiec.12024

Curran, M. A. (1996). *Environmental Life-Cycle Assessment* (1st ed.). New York: McGraw-Hill Professional Publishing.

Davies, E., & Simonovic, S. (2011). Global water resources modeling with an integrated model of the social–economic–environmental system. *Advances in Water Resources*, *34*, 684–700.

De Schryver, A. M., Brakkee, K. W., Goedkoop, M. J., & Huijbregts, M. A. J. (2009). Characterization Factors for Global Warming in Life Cycle Assessment Based on Damages to Humans and Ecosystems. *Environmental Science & Technology*, *43*(6), 1689–1695. http://doi.org/10.1021/es800456m

Delucchi, M. (2003). *A lifecycle emissions model (LEM): lifecycle emissions from transportation fuels, motor vehicles, transportation modes, electricity use, heating and cooking fuels, and materials*.

Delucchi, M. A., & Lipman, T. E. (2001). An analysis of the retail and lifecycle cost of battery-powered electric vehicles. *Transportation Research Part D: Transport and Environment*, *6*(6), 371–404. http://doi.org/10.1016/S1361-9209(00)00031-6

Denholm, P., & Short, W. (2006). An Evaluation of Utility System Impacts and Benefits of Optimally Dispatched Plug-In Hybrid Electric Vehicles. *NREL Report noTP-620*, 41. Retrieved from http://www.nrel.gov/docs/fy07osti/40293.pdf

DOT. (2013). U.S. Department of Transportation Proposes New Minimum Sound Requirements for Hybrid and Electric Vehicles. Retrieved from http://www.dot.gov/briefing-room/us-department-transportation-proposes-new-minimum-sound-requirements-hybrid-and

Dotzauer, E. (2010). Greenhouse gas emissions from power generation and consumption in a nordic perspective. *Energy Policy*, *38*(2), 701–704. http://doi.org/10.1016/j.enpol.2009.10.066

Egilmez, G., Kucukvar, M., & Tatari, O. (2013a). Supply chain sustainability assessment of the U.S. food manufacturing sectors: a life cycle-based frontier approach. *Resources, Conservation and Recycling*.

Egilmez, G., Kucukvar, M., & Tatari, O. (2013b). Sustainability assessment of U.S. manufacturing sectors: an economic input output-based frontier approach. *Journal of Cleaner Production*, *53*(null), 91–102. http://doi.org/10.1016/j.jclepro.2013.03.037

Egilmez, G., & Tatari, O. (2012). A dynamic modeling approach to highway sustainability: Strategies to reduce overall impact. *Transportation Research Part A: Policy and Practice*, *46*(7), 1086–1096. Retrieved from *http://www.sciencedirect.com/science/article/pii/S0965856412000754*

Elena, G., & Esther, V. (2010), "From water to energy: The virtual water content and water footprint of biofuel consumption in Spain", *Energy Policy, 38(3), 1345-1352.*

Elgowainy, A., & Burnham, A. (2009). Well-to-wheels energy use and greenhouse gas emissions of plug-in hybrid electric vehicles. *… International Journal of …*. Retrieved from http://www.autonomie.net/docs/6 - Papers/WTW/welltowheels_energy_use.pdf

Elgowainy, A., Han, J., Poch, L., & Wang, M. (2010). Well-to-wheels analysis of energy use and greenhouse gas emissions of plug-in hybrid electric vehicles. Retrieved from http://www.osti.gov/bridge/product.biblio.jsp?osti_id=982352

Engholm, A., Johansson, G., & Persson, A. Å. (2013). Life Cycle Assessment: of Solelia Greentech's Photovoltaic BasedCharging Station for Electric Vehicles. Retrieved from http://www.diva-portal.org/smash/record.jsf?pid=diva2:626019

EPA. (2009). Clean Energy - eGRID. Retrieved from http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html

EPA. (2013). Gasoline Emission Factor-Calculations and References. Retrieved from http://www.epa.gov/cleanenergy/energy-resources/refs.html

EPA. (2014). *Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 - 2014*. Washington DC. Retrieved from http://www.epa.gov/otaq/fetrends-complete.htm

Eudy, L., & Zuboy, J. (2004). *Overview of Advanced Technology Transportation, 2004 Update*. Oak Ridge, Tennessee.

Ercin, A., Aldaya, M., & Hoekstra, A. (2011), "Corporate water footprint accounting and impact assessment: the case of the water footprint of a sugar-containing carbonated beverage", *Water Resources Management*, 25(2), 721-741.

Ercin, A., Aldaya, M., & Hoekstra, A. (2012), "The water footprint of soy milk and soy burger and equivalent animal products", *Ecological Indicators*, 18, 392-402.

Executive Office of the President. (2013). *President Obama's Climate Action Plan*. Washington DC.

Facanha, C., & Horvath, A. (2007). Evaluation of Life-Cycle Air Emission Factors of Freight Transportation. *Environmental Science & Technology*, *41*(20), 7138–7144. http://doi.org/10.1021/es070989q

Faria, R., Marques, P., Moura, P., Freire, F., Delgado, J., & de Almeida, A. T. (2013). Impact of the electricity mix and use profile in the life-cycle assessment of electric vehicles. *Renewable and Sustainable Energy Reviews*, *24*, 271–287. http://doi.org/10.1016/j.rser.2013.03.063

Faria, R., Moura, P., Delgado, J., & de Almeida, A. T. (2012). A sustainability assessment of electric vehicles as a personal mobility system. *Energy Conversion and Management*, *61*, 19–30. http://doi.org/10.1016/j.enconman.2012.02.023

Faron, G., Pagerit, S., & Rousseau, A. (2009). Evaluation of PHEVs fuel efficiency and cost using Monte Carlo analysis. In *EVS 24 Conference*. Stavanger, Norway: Argonne National Laboratory. Retrieved from http://www.researchgate.net/profile/Aymeric_Rousseau/publication/228817350_Evaluation_of_PHEVs_fuel_efficiency_and_cost_Using_Monte_Carlo_Analysis/links/0046351efe69ad7edd000000.pdf

Feng, Y. Y., Chen, S. Q., & Zhang, L. X. (2013). System dynamics modeling for urban energy consumption and CO_2 emissions: A case study of Beijing, China. *Ecological Modelling*, *252*, 44–52. http://doi.org/10.1016/j.ecolmodel.2012.09.008

Fiddaman, T. (2008). Tom Fiddaman's System Dynamics Model Library. Retrieved September 2, 2014, from http://www.metasd.com/models/

Fiksel, J. (2006). Sustainability and resilience: toward a systems approach. ProQuest. Retrieved from http://sspp.proquest.com/static_content/vol2iss2/0608-028.fiksel-print.html

Finkbeiner, M., Schau, E. M., Lehmann, A., & Traverso, M. (2010). Towards Life Cycle Sustainability Assessment. *Sustainability*, *2*(10), 3309–3322. http://doi.org/10.3390/su2103309

Finnveden, G. (2000). On the limitations of life cycle assessment and environmental systems analysis tools in general. *The International Journal of Life Cycle Assessment*, *5*(4), 229–238. http://doi.org/10.1007/BF02979365

Finnveden, G., Hauschild, M. Z., Ekvall, T., Guinée, J., Heijungs, R., Hellweg, S., … Suh, S. (2009). Recent developments in Life Cycle Assessment. *Journal of Environmental Management*, *91*(1), 1–21.

Fthenakis, V.; Kim, H. (YEAR?), "Life-Cycle Uses of Water in U.S. Electricity Generation", *Renewable Sustainable Energy Rev. 2010*, 14(7), 2039–2048.

Florida Solar Energy Center. (2014). Electric Vehicle Transportation Center web page. Retrieved from http://www.fsec.ucf.edu/en/research/transportation/index.htm

Ford, A. (1996). Testing the snake river explorer. *System Dynamics Review*, *12*(4), 305–329. Retrieved from http://doi.wiley.com/10.1002/(SICI)1099-1727(199624)12:4<305::AID-SDR110>3.0.CO;2-4

Ford, A. (1999). *Modeling the Environment, Second Edition*. Island Press. Retrieved from http://www.amazon.com/Modeling-Environment-Second-Andrew-Ford/dp/1597264733

Forrester, J. W. (1961a). *Industrial Dynamics*. New York: Wiley-Interscience. Retrieved from http://www.amazon.com/Industrial-Dynamics-Jay-Wright-Forrester/dp/0915299887

Forrester, J. W. (1961b). *Industrial Dynamics*. MIT Press, Cambridge, MA.

Forrester, J. W. (1971a). *World dynamics*. Cambridge, MA: Wright-Allen Press. Retrieved from http://en.scientificcommons.org/52458913

Forrester, J. W. (1971b). *World dynamics. Wright-Allen Press, Cambridge, MA*. Wright-Allen Press, Cambridge, MA.

Furuoka, F. (2009). Looking for a J-shaped development-fertility relationship: Do advances in development really reverse fertility declines. *Economics Bulletin*, *29*(4), 3067–3074. Retrieved from http://core.kmi.open.ac.uk/download/pdf/6502169.pdf

Furuoka, F. (2010). The fertility-development relationship in the United States: new evidence from threshold regression analysis. *Economics Bulletin*, *30*(3), 1808–1822. Retrieved from http://www.accessecon.com/Pubs/EB/2010/Volume30/EB-10-V30-I3-P165.pdf

Gaines, L., & Nelson, P. (2010). Lithium-ion batteries: examining material demand and recycling issues. *Minerals, Metals and Materials Society*. Retrieved from http://www.transportation.anl.gov/pdfs/B/626.PDF

Gerbens-Leenes, P., Hoekstra, A., & Van der Meer, T. (2009), "The water footprint of energy from biomass: A quantitative assessment and consequences of an increasing share of bio-energy in energy supply", *Ecological economics*, 68(4), 1052-1060

Geyer, R. (2008). Parametric Assessment of Climate Change Impacts of Automotive Material Substitution. *Environmental Science & Technology*, *42*(18), 6973–6979. http://doi.org/10.1021/es800314w

Gonder, J., Brooker, A., Carlson, R. B., & Smart, J. (2009). Deriving in-use PHEV fuel economy predictions from standardized test cycle results. In *2009 IEEE Vehicle Power and Propulsion Conference* (pp. 643–648). IEEE. http://doi.org/10.1109/VPPC.2009.5289788

Guinée, J. B., Heijungs, R., Huppes, G., Zamagni, A., Masoni, P., Buonamici, R., … Rydberg, T. (2011). Life cycle assessment: past, present, and future. *Environmental Science & Technology*, *45*(1), 90–6. http://doi.org/10.1021/es101316v

Hadley W., S., & Tsvetkova, A. (2008). *Potential Impacts of Plug-in Hybrid Electric Vehicles on Regional Power Generation*. Oak Ridge, Tennessee. Retrieved from www.ornl.gov/info/ornlreview/v41_1_08/regional_phev_analysis.pdf

Halog, A., & Manik, Y. (2011). Advancing Integrated Systems Modelling Framework for Life Cycle Sustainability Assessment. *Sustainability*, *3*(12), 469–499. http://doi.org/10.3390/su3020469

Han, J., & Hayashi, Y. (2008). A system dynamics model of CO_2 mitigation in China's inter-city passenger transport. *Transportation Research Part D: Transport and Environment*, *13*(5), 298–305. http://doi.org/10.1016/j.trd.2008.03.005

Hawkes, A. D. (2010). Estimating marginal CO_2 emissions rates for national electricity systems. *Energy Policy*, *38*(10), 5977–5987. http://doi.org/10.1016/j.enpol.2010.05.053

Hawkins, T. R., Gausen, O. M., & Strømman, A. H. (2012). Environmental impacts of hybrid and electric vehicles—a review. *The International Journal of Life Cycle Assessment*, *17*(8), 997–1014. http://doi.org/10.1007/s11367-012-0440-9

Hawkins, T. R., Singh, B., Majeau-Bettez, G., & Strømman, A. H. (2013). Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. *Journal of Industrial Ecology*, *17*(1), 53–64. http://doi.org/10.1111/j.1530-9290.2012.00532.x

Hoekstra, A. & Mekonnen, M. (2012), "The water footprint of humanity", *Proceedings of the National Academy of Sciences*, 109(9), 3232-3237.

Heijungs, R., Huppes, G., & Guinée, J. B. (2010). Life cycle assessment and sustainability analysis of products, materials and technologies. Toward a scientific framework for sustainability life cycle analysis. *Polymer Degradation and Stability*, *95*(3), 422–428. http://doi.org/10.1016/j.polymdegradstab.2009.11.010

Hendrickson, C., Lave, L. B., & Matthews, H. S. (2006). *Environmental life cycle assessment of goods and services: an input-output approach*. Resources for the Future.

Hendrickson, C. T., Lave, L. B., & Matthews, H. S. (2005). *Environmental life cycle assessment of goods and services: an input-output approach*. Resources for the Future.

Hendrickson, C. T., Lester, B. L., & Matthews, H. S. (2006). *Environmental Life Cycle Assessment of Goods And Services: An Input-Output Approach*. Washington DC. Retrieved from http://books.google.com/books?hl=tr&lr=&id=NZm6qWiHwYoC&pgis=1

Hu, M., Kleijn, R., Bozhilova-Kisheva, K. P., & Di Maio, F. (2013). An approach to LCSA: the case of concrete recycling. *The International Journal of Life Cycle Assessment*, *18*(9), 1793–1803. http://doi.org/10.1007/s11367-013-0599-8

Huang, Y. A., Weber, C. L., & Matthews, H. S. (2009). Categorization of Scope 3 emissions for streamlined enterprise carbon footprinting. *Environmental Science & Technology*, *43*(22), 8509–15. http://doi.org/10.1021/es901643a

Huijbregts, M. (2002). Uncertainty and variability in environmental life-cycle assessment. *The International Journal of Life Cycle Assessment*, *7*(3), 173–173. http://doi.org/10.1007/BF02994052

Huijbregts, M. A. J., Norris, G., Bretz, R., Ciroth, A., Maurice, B., von Bahr, B., … de Beaufort, A. S. H. (2001). Framework for modelling data uncertainty in life cycle inventories. *The International Journal of Life Cycle Assessment*, *6*(3), 127–132. http://doi.org/10.1007/BF02978728

Hung, M.-L., & Ma, H. (2008). Quantifying system uncertainty of life cycle assessment based on Monte Carlo simulation. *The International Journal of Life Cycle Assessment*, *14*(1), 19–27. http://doi.org/10.1007/s11367-008-0034-8

Huo, H., Zhang, Q., Wang, M. Q., Streets, D. G., & He, K. (2010). Environmental implication of electric vehicles in China. *Environmental Science & Technology*, *44*(13), 4856–61. http://doi.org/10.1021/es100520c

International Energy Agency (2012), "World Energy Outlook", Available at: http://www.worldenergyoutlook.org/resources/water-energynexus/. Accessed on May 5, 2015.

IPCC. (2007). *Mitigation of climate change: Contribution of working group III to the fourth assessment report of the Intergovernmental Panel on Climate Change*. *Intergovernmental Panel on Climate Change*.

IPCC Working Group I. (2001). *Climate Change 2001: The Scientific Basis. Summary for Policymakers. A Report of Working Group 1*. Cambridge, UK. Retrieved from http://www.grida.no/climate/ipcc_tar/wg1/pdf/WG1_TAR-FRONT.pdf

Jeong, K. S., & Oh, B. S. (2002). Fuel economy and life-cycle cost analysis of a fuel cell hybrid vehicle. *Journal of Power Sources*, *105*(1), 58–65. http://doi.org/10.1016/S0378-7753(01)00965-X

Jeswani, H. K., Azapagic, A., Schepelmann, P., & Ritthoff, M. (2010). Options for broadening and deepening the LCA approaches. *Journal of Cleaner Production*, *18*(2), 120–127. http://doi.org/10.1016/j.jclepro.2009.09.023

Jin, W., Xu, L., & Yang, Z. (2009). Modeling a policy making framework for urban sustainability: Incorporating system dynamics into the Ecological Footprint. *Ecological Economics*, *68*(12), 2938–2949. http://doi.org/10.1016/j.ecolecon.2009.06.010

Karabasoglu, O., & Michalek, J. (2013). Influence of driving patterns on life cycle cost and emissions of hybrid and plug-in electric vehicle powertrains. *Energy Policy*, *60*, 445–461. http://doi.org/10.1016/j.enpol.2013.03.047

Keith, D. W., & Farrell, A. E. (2003). Environmental science. Rethinking hydrogen cars. *Science (New York, N.Y.)*, *301*(5631), 315–6. http://doi.org/10.1126/science.1084294

Kelly, J. C., MacDonald, J. S., & Keoleian, G. A. (2012). Time-dependent plug-in hybrid electric vehicle charging based on national driving patterns and demographics. *Applied Energy*, *94*, 395–405. http://doi.org/10.1016/j.apenergy.2012.02.001

Kim, H.-J., McMillan, C., Keoleian, G. A., & Skerlos, S. J. (2010). Greenhouse Gas Emissions Payback for Lightweighted Vehicles Using Aluminum and High-Strength Steel. *Journal of Industrial Ecology*, *14*(6), 929–946. http://doi.org/10.1111/j.1530-9290.2010.00283.x

King, C. W., & Webber, M. E. (2008). The Water Intensity of the Plugged-In Automotive Economy. *Environmental Science & Technology*, *42*(12), 4305–4311. http://doi.org/10.1021/es0716195

Kloepffer, W. (2008). Life cycle sustainability assessment of products. *The International Journal of Life Cycle Assessment*, *13*(2), 89–95. Retrieved from http://www.springerlink.com/index/10.1065/lca2008.02.376

Klöpffer, W. (2007). Life-cycle based sustainability assessment as part of LCM. *Proceedings of the 3rd International Conference on Life Cycle Management*, 27–29. Retrieved from http://www.lcm2007.ethz.ch/presentation/Mo_3.06-Kloepffer.pdf

Kucukvar, M. (2013). *Life Cycle Sustainability Assessment Framework for the U.S. Built Environment*. Doctoral dissertation, University of Central Florida, Orlando.

Kucukvar, M., Egilmez, G., & Tatari, O. (2014). Sustainability assessment of U.S. final consumption and investments: triple-bottom-line input–output analysis. *Journal of Cleaner Production*, *81*, 234–243. http://doi.org/10.1016/j.jclepro.2014.06.033

Kucukvar, M., Noori, M., Egilmez, G., & Tatari, O. (2014). Stochastic decision modeling for sustainable pavement designs. *The International Journal of Life Cycle Assessment*. http://doi.org/10.1007/s11367-014-0723-4

Kucukvar, M., Noori, M., Egilmez, G., & Tatari, O. (2014). Stochastic decision modeling for sustainable pavement designs. *International Journal of Life Cycle Assessment*, 1–15.

Kucukvar, M., & Tatari, O. (2011). A comprehensive life cycle analysis of cofiring algae in a coal power plant as a solution for achieving sustainable energy. *Energy*, *36*(11), 6352–6357. http://doi.org/10.1016/j.energy.2011.09.039

Kucukvar, M., & Tatari, O. (2013). Towards a triple bottom-line sustainability assessment of the U.S. construction industry. *The International Journal of Life Cycle Assessment*, *18*(5), 958–972. http://doi.org/10.1007/s11367-013-0545-9

Kucukvar, M., & Tatari, O. (2013). Towards a triple bottom-line sustainability assessment of the US construction industry. *The International Journal of Life Cycle Assessment*.

Lang, J., Cheng, S., Zhou, Y., Zhao, B., Wang, H., & Zhang, S. (2013), "Energy and environmental implications of hybrid and electric vehicles in China", *Energies*, 6(5), 2663-2685.

Lee, S., Geum, Y., Lee, H., & Park, Y. (2012). Dynamic and multidimensional measurement of product-service system (PSS) sustainability: a triple bottom line (TBL)-based system dynamics approach. *Journal of Cleaner Production*, *32*, 173–182. http://doi.org/10.1016/j.jclepro.2012.03.032

Li, X., Lopes, L. A. C., & Williamson, S. S. (2009). On the suitability of plug-in hybrid electric vehicle (PHEV) charging infrastructures based on wind and solar energy. In *2009 IEEE Power & Energy Society General Meeting* (pp. 1–8). IEEE. http://doi.org/10.1109/PES.2009.5275171

Litman, T. A. (2009). Sustainable Transportation Indicators: A Recommended Research Program For Developing Sustainable Transportation Indicators and Data. In *Transportation Research Board 88th Annual Meeting*. Retrieved from http://trid.trb.org/view.aspx?id=882256

Litman, T., & Burwell, D. (2006). Issues in sustainable transportation. *International Journal of Global Environmental Issues*, *6*(4), 331–347. Retrieved from http://inderscience.metapress.com/index/A7M314BU3RTE2CB4.pdf

Lloyd, S. M., & Ries, R. (2008). Characterizing, Propagating, and Analyzing Uncertainty in Life-Cycle Assessment: A Survey of Quantitative Approaches. *Journal of Industrial Ecology*, *11*(1), 161–179. http://doi.org/10.1162/jiec.2007.1136

Lo, S.-C., Ma, H.-W., & Lo, S.-L. (2005). Quantifying and reducing uncertainty in life cycle assessment using the Bayesian Monte Carlo method. *The Science of the Total Environment*, *340*(1-3), 23–33. http://doi.org/10.1016/j.scitotenv.2004.08.020

Ma, H., Balthasar, F., Tait, N., Riera-Palou, X., & Harrison, A. (2012). A new comparison between the life cycle greenhouse gas emissions of battery electric vehicles and internal combustion vehicles. *Energy Policy*, *44*, 160–173. http://doi.org/10.1016/j.enpol.2012.01.034

MacPherson, N. D., Keoleian, G. A., & Kelly, J. C. (2012). Fuel Economy and Greenhouse Gas Emissions Labeling for Plug-In Hybrid Vehicles from a Life Cycle Perspective. *Journal of Industrial Ecology*, *16*(5), 761–773. http://doi.org/10.1111/j.1530-9290.2012.00526.x

Majeau-Bettez, G., Hawkins, T. R., & Strømman, A. H. (2011). Life cycle environmental assessment of lithium-ion and nickel metal hydride batteries for plug-in hybrid and battery electric vehicles. *Environmental Science & Technology*, *45*(10), 4548–54. http://doi.org/10.1021/es103607c

Markel, T. (2006). Plug-In HEV Vehicle Design Options and Expectations. In *ZEV Technology Symposium California Air Resources Board*. Sacramento, CA.

Marriott, J., & Matthews, H. S. (2005). Environmental Effects of Interstate Power Trading on Electricity Consumption Mixes. *Environmental Science & Technology*, *39*(22), 8584–8590. http://doi.org/10.1021/es0506859

Marshall, B. M., Kelly, J. C., Lee, T.-K., Keoleian, G. A., & Filipi, Z. (2013). Environmental assessment of plug-in hybrid electric vehicles using naturalistic drive cycles and vehicle travel patterns: A Michigan case study. *Energy Policy*, *58*, 358–370. http://doi.org/10.1016/j.enpol.2013.03.037

Mashayekhi, A. N. (1990). Rangelands destruction under population growth: The case of Iran. *System Dynamics Review*, *6*(2), 167–193. Retrieved from http://doi.wiley.com/10.1002/sdr.4260060204

Matthews, H. S., Hendrickson, C. T., & Weber, C. L. (2008). The Importance of Carbon Footprint Estimation Boundaries. *Environmental Science & Technology*, *42*(16), 5839–5842. http://doi.org/10.1021/es703112w

Matthews, H. S., Hendrickson, C. T., & Weber, C. L. (2008). The importance of carbon footprint estimation boundaries. *Environ. Sci . Technol .*, *42*, 5839–5842.

McCarthy, R., & Yang, C. (2010). Determining marginal electricity for near-term plug-in and fuel cell vehicle demands in California: Impacts on vehicle greenhouse gas emissions. *Journal of Power Sources*, *195*(7), 2099–2109. http://doi.org/10.1016/j.jpowsour.2009.10.024

Meadows, D. H., Randers, J., & Meadows, D. L. (1993a). *Beyond the Limits: Confronting Global Collapse, Envisioning a Sustainable Future*. Chelsea Green Publishing Company. Retrieved from http://www.amazon.com/Beyond-Limits-Confronting-Envisioning-Sustainable/dp/0930031628

Meadows, D. H., Randers, J., & Meadows, D. L. (1993b). *Beyond the Limits: Confronting Global Collapse, Envisioning a Sustainable Future*. Chelsea Green Publishing Company.

Meadows, D. H., Randers, J., & Meadows, D. L. (2004a). *Limits to Growth: The 30-Year Update*. Chelsea Green. Retrieved from http://www.amazon.com/Limits-Growth-Donella-H-Meadows/dp/193149858X

Meadows, D. H., Randers, J., & Meadows, D. L. (2004b). *Limits to Growth: The 30-Year Update*. White River Junction, VT: Chelsea Green. Retrieved from https://books.google.com/books?hl=en&lr=&id=QRyQiINGW6oC&oi=fnd&pg=PR9&dq=limits+to+growth+2004&ots=Gp6P8J53n-&sig=xOuZjVQmYw4w4osWBqs15f6Wz3g#v=onepage&q=limits to growth 2004&f=false

Meldrum, J., Nettles-Anderson, S., Heath, G., & Macknick, J. (2013). Life cycle water use for electricity generation: a review and harmonization of literature estimates. *Environmental Research Letters*, *8*(1), 015031. http://doi.org/10.1088/1748-9326/8/1/015031

Meyer, M. J. (2011). Understanding the challenges in HEV 5-cycle fuel economy calculations based on dynamometer test data. Retrieved from http://scholar.lib.vt.edu/theses/available/etd-11092011-115101/

Mekonnen, M., & Hoekstra, A. (2014), "Water footprint benchmarks for crop production: A first global assessment", *Ecological indicators*, 46, 214-223.

Mekonnen, M. and Hoekstra, A. (2011), *National water footprint accounts: the green, blue and grey water footprint of production and consumption*, Value of Water Research Report Series No.50.

Messagie, M., Boureima, F., Matheys, J., Sergeant, N., Turcksin, L., Macharis, C., & Van Mierlo, J. (2010), "Life Cycle Assessment of conventional and alternative small passenger vehicles in Belgium", In *Vehicle Power and Propulsion Conference (VPPC), 2010 IEEE* (pp. 1-5). IEEE.

Michalek, J. J., Chester, M., Jaramillo, P., Samaras, C., Shiau, C.-S. N., & Lave, L. B. (2011). Valuation of plug-in vehicle life-cycle air emissions and oil displacement benefits. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(40), 16554–8. http://doi.org/10.1073/pnas.1104473108

Minx, J., Wiedmann, T., Wood, R., Peters, G. P., Lenzen, M., Owen, A., … Ackerman, F. (2009). Input-Output Analysis and Carbon Footprinting: an Overview of Applications. *Economic Systems Research*, *21*(3), 187–216. http://doi.org/10.1080/09535310903541298

Mirchi, A., Madani, K., Watkins, D., & Ahmad, S. (2012). Synthesis of System Dynamics Tools for Holistic Conceptualization of Water Resources Problems. *Water Resources Management*, *26*(9), 2421–2442. http://doi.org/10.1007/s11269-012-0024-2

MIT Electric Vehicle Team. (2014). MIT Electric Vehicle Team web page. Retrieved from http://web.mit.edu/evt/links.html

Myrskylä, M., Kohler, H.-P., & Billari, F. C. (2009). Advances in development reverse fertility declines. *Nature*, *460*(7256), 741–3. http://doi.org/10.1038/nature08230

NASA. (2014). Global Annual Mean Surface Air Temperature Change. Retrieved February 10, 2015, from http://data.giss.nasa.gov/gistemp/graphs_v3/

National Household Travel Survey. (2009). Online Analysis Tools- Table Designer. Retrieved from http://nhts.ornl.gov/tools.shtml

National Transportation Statistics (2013), Available at: http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/national_transportation_statistics/index.html. Accessed on May 1, 2015.

National Science Foundation (2015), "Improving electric vehicle sales may require solving unique chicken and egg problem", Available at: https://www.nsf.gov/mobile/discoveries/disc_summ.jsp?cntn_id=133947&org=NSF. Accessed on April 5, 2015.

National Renewable Energy Laboratory. (2013). U.S. Life Cycle Inventory Database. Retrieved from http://www.nrel.gov/lci/

National Renewable Energy Laboratory. (2014). National Renewable Energy Laboratory Electric Vehicle Grid Integration Team web page. Retrieved from http://www.nrel.gov/vehiclesandfuels/project_ev_grid_integration.html

NREL (2011), "A Review of Operational Water Consumption and Withdrawal Factors for Electricity Generating Technologies", Available at: http://www.nrel.gov/docs/fy11osti/50900.pdf. Accessed on May 1, 2015.

Nissan. (2014). 2014 Nissan Leaf Specifications. Retrieved from http://www.nissanusa.com/electric-cars/leaf/versions-specs/

Nordhaus, D. W. (2006). RICE and DICE Models of Economics of Climate Change. Retrieved September 3, 2014, from http://www.econ.yale.edu/~nordhaus/homepage/dicemodels.htm

Notter, D. A., Gauch, M., Widmer, R., Wäger, P., Stamp, A., Zah, R., & Althaus, H.-J. (2010). Contribution of Li-ion batteries to the environmental impact of electric vehicles. *Environmental Science & Technology*, *44*(17), 6550–6. http://doi.org/10.1021/es903729a

Oak Ridge National Lab. (2013). Transportation Energy Data book. Retrieved from http://cta.ornl.gov/data/chapter8.shtml

Oak Ridge National Laboratory. (2013). *Transportation Energy Data Book Edition 32*. Oak Ridge, Tennessee.

Oak Ridge National Laboratory. (2014). the National Transportation Research Center web page. Retrieved from http://www.ntrc.gov/

Onat, N. C., Egilmez, G., & Tatari, O. (2014). Towards greening the U.S. residential building stock: A system dynamics approach. *Building and Environment*, *78*, 68–80. http://doi.org/10.1016/j.buildenv.2014.03.030

Onat, N. C., Kucukvar, M., & Tatari, O. (2014a). Integrating triple bottom line input–output analysis into life cycle sustainability assessment framework: the case for US buildings. *The International Journal of Life Cycle Assessment*, *19*(8), 1488–1505. http://doi.org/10.1007/s11367-014-0753-y

Onat, N. C., Kucukvar, M., & Tatari, O. (2014b). Scope-based carbon footprint analysis of U.S. residential and commercial buildings: An input–output hybrid life cycle assessment approach. *Building and Environment*, *72*, 53–62. Retrieved from http://www.sciencedirect.com/science/article/pii/S0360132313003004

Onat, N. C., Kucukvar, M., & Tatari, O. (2014c). Towards Life Cycle Sustainability Assessment of Alternative Passenger Vehicles. *Sustainability*, *6*(12), 9305–9342. http://doi.org/10.3390/su6129305

Onat, N. C., Kucukvar, M., & Tatari, O. (2015). Conventional, Hybrid, Plug-in Hybrid or Electric Vehicles? State-based Comparative Carbon and Energy Footprint Analysis in the United States. *Applied EnergyEnergy*.

Onat, N. C., Kucukvar, M., Tatari, O., & Zheng, Q. P. (2015). Combined Application of Multi-Criteria Optimization and Life-Cycle Sustainability Assessment for Optimal Allocation of Alternative Passenger Cars in U.S. *Journal of Cleaner Production*.

Ou, X., Zhang, X., & Chang, S. (2010), "Scenario analysis on alternative fuel/vehicle for China's future road transport: Life-cycle energy demand and GHG emissions" *Energy Policy*, 38(8), 3943-3956.

Pindyck, R. S. (2011). Modeling the Impact of Warming in Climate Change Economics. In *The Economics of Climate Change: Adaptations Past and Present* (p. 47–). the National Bureau of Economics Research-Libecap and Steckel. Retrieved from http://www.nber.org/papers/w15692

Pruyt, E. (2007). Dealing with uncertainties? combining system dynamics with multiple criteria decision analysis or with exploratory modelling. In *Proceedings of the 25th International Conference of the System Dynamics Society*. Retrieved from http://www.systemdynamics.org/conferences/2007/proceed/papers/PRUYT386.pdf

Råde, I. (2001). Requirement and Availability of Scarce Metals for Fuel-Cell and Battery Electric Vehicles. Chalmers University of Technology. Retrieved from http://publications.lib.chalmers.se/publication/668-requirement-and-availability-of-scarce-metals-for-fuel-cell-and-battery-electric-vehicles

Randers, J. (2000a). From limits to growth to sustainable development or SD (sustainable development) in a SD (system dynamics) perspective. *System Dynamics Review*, *16*(3), 213–224. http://doi.org/10.1002/1099-1727(200023)16:3<213::AID-SDR197>3.3.CO;2-5

Randers, J. (2000b). From limits to growth to sustainable developmentor SD (sustainable development) in a SD (system dynamics) perspective. *System Dynamics Review*, *16*(3), 213–224. Retrieved from http://doi.wiley.com/10.1002/1099-1727(200023)16:3<213::AID-SDR197>3.0.CO;2-E

Raykin, L., MacLean, H. L., & Roorda, M. J. (2012). Implications of driving patterns on well-to-wheel performance of plug-in hybrid electric vehicles. *Environmental Science & Technology*, *46*(11), 6363–70. http://doi.org/10.1021/es203981a

Reap, J., Roman, F., Duncan, S., & Bras, B. (2008). A survey of unresolved problems in life cycle assessment. *The International Journal of Life Cycle Assessment*, *13*(4), 290–300. http://doi.org/10.1007/s11367-008-0008-x

Rebitzer, G., Ekvall, T., Frischknecht, R., Hunkeler, D., Norris, G., Rydberg, T., … Pennington, D. W. (2004). Life cycle assessment part 1: framework, goal and scope definition, inventory analysis, and applications. *Environ. Int.*, *30*(5), 701–20. http://doi.org/10.1016/j.envint.2003.11.005

ReCiPE. (2009). ReCiPe LCIA Methodology. Retrieved from http://www.lcia-recipe.net/project-definition

Rydh, C. J., & Sandén, B. A. (2005). Energy analysis of batteries in photovoltaic systems. Part I: Performance and energy requirements. *Energy Conversion and Management*, *46*(11-12), 1957–1979. http://doi.org/10.1016/j.enconman.2004.10.003

RYDH, C., & SVARD, B. (2003). Impact on global metal flows arising from the use of portable rechargeable batteries. *The Science of The Total Environment*, *302*(1-3), 167–184. http://doi.org/10.1016/S0048-9697(02)00293-0

Saeed, K. (1994). *Development Planning and Policy Design: A System Dynamics Approach*. Bookfield: Avebury: Avebury. Retrieved from http://www.amazon.com/Development-Planning-Policy-Design-Dynamics/dp/185628672X

Sager, J., Apte, J. S., Lemoine, D. M., & Kammen, D. M. (2011). Reduce growth rate of light-duty vehicle travel to meet 2050 global climate goals. *Environmental Research Letters*, *6*(2), 024018. http://doi.org/10.1088/1748-9326/6/2/024018

Sala, S., Farioli, F., & Zamagni, A. (2012a). Life cycle sustainability assessment in the context of sustainability science progress (part 2). *The International Journal of Life Cycle Assessment*, *18*(9), 1686–1697. http://doi.org/10.1007/s11367-012-0509-5

Sala, S., Farioli, F., & Zamagni, A. (2012b). Progress in sustainability science: lessons learnt from current methodologies for sustainability assessment: Part 1. *The International Journal of Life Cycle Assessment*, *18*(9), 1653–1672. http://doi.org/10.1007/s11367-012-0508-6

Samaras, C., & Meisterling, K. (2008). Life Cycle Assessment of Greenhouse Gas Emissions from Plug-in Hybrid Vehicles: Implications for Policy. *Environmental Science & Technology*, *42*(9), 3170–3176. http://doi.org/10.1021/es702178s

Santoyo-Castelazo, E., & Azapagic, A. (2014). Sustainability assessment of energy systems: integrating environmental, economic and social aspects. *Journal of Cleaner Production*, *80*, 119–138. http://doi.org/10.1016/j.jclepro.2014.05.061

Schade, B., & Schade, W. (2005). Assessment of Environmentally Sustainable Transport Scenarios by a Backcasting Approach with ESCOT. In *Proceedings of the 23rd International Conference of the System Dynamics Society*.

Schmidt, W.-P., Dahlqvist, E., Finkbeiner, M., Krinke, S., Lazzari, S., Oschmann, D., … Thiel, C. (2004). Life cycle assessment of lightweight and end-of-life scenarios for generic compact class passenger vehicles. *The International Journal of Life Cycle Assessment*, *9*(6), 405–416. http://doi.org/10.1007/BF02979084

Schryver, A. De. (2011). Value choices in life cycle impact assessment of stressors causing human health damage. *Journal of Industrial …*. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1530-9290.2011.00371.x/full

Schryver, A. De, Van Zelm, R., Humbert, S., McKone, T. E., & Huijbregts, M. A. J. (2011). Value choices in human health endpoint modelling. Retrieved from http://www.lcacenter.org/LCA9/presentations/77.pdf

Scown, C., Horvath, A., & McKone, T. (2011), “Water footprint of US transportation fuels”, *Environmental science & technology*, 45(7), 2541-2553.

Shah, V. P., & Ries, R. J. (2009). A characterization model with spatial and temporal resolution for life cycle impact assessment of photochemical precursors in the United States. *The International Journal of Life Cycle Assessment*, *14*(4), 313–327. http://doi.org/10.1007/s11367-009-0084-6

Sharma, R., Manzie, C., Bessede, M., Crawford, R. H., & Brear, M. J. (2013). Conventional, hybrid and electric vehicles for Australian driving conditions. Part 2: Life cycle CO_2-e emissions. *Transportation Research Part C: Emerging Technologies*, *28*, 63–73. http://doi.org/10.1016/j.trc.2012.12.011

Shiau, C., Samaras, C., Hauffe, R., and Michalek, J. (2009), “Impact of battery weight and charging patterns on the economic and environmental benefits of plug-in hybrid vehicles”, *Energy Policy*, 37(7): 2653–2663.

Shepherd, S. P. (2014). A review of system dynamics models applied in transportation. *Transportmetrica B: Transport Dynamics*, *2*(2), 83–105. http://doi.org/10.1080/21680566.2014.916236

Stamford, L., & Azapagic, A. (2012). Life cycle sustainability assessment of electricity options for the UK. *International Journal of Energy Research*, *36*(14), 1263–1290. http://doi.org/10.1002/er.2962

Stamford, L., & Azapagic, A. (2014). Life cycle sustainability assessment of UK electricity scenarios to 2070. *Energy for Sustainable Development*, *23*, 194–211. http://doi.org/10.1016/j.esd.2014.09.008

Stefanova, M., Tripepi, C., Zamagni, A., & Masoni, P. (2014). Goal and Scope in Life Cycle Sustainability Analysis: The Case of Hydrogen Production from Biomass. *Sustainability*. Retrieved from http://www.mdpi.com/2071-1050/6/8/5463/htm

Stephan, C. H., & Sullivan, J. (2008). Environmental and Energy Implications of Plug-In Hybrid-Electric Vehicles. *Environmental Science & Technology*, *42*(4), 1185–1190. http://doi.org/10.1021/es062314d

Sterman, J. (2012). Sustaining sustainability: creating a systems science in a fragmented academy and polarized world. *Sustainability Science*. Retrieved from http://link.springer.com/chapter/10.1007/978-1-4614-3188-6_2

Sterman, J. D. (2000). *Business Dynamics: System Thinking and Modeling for a Complex World*. Boston.

Silva, C., Ross, M., & Farias, T. (2009), "Evaluation of energy consumption, emissions and cost of plug-in hybrid vehicles", *Energy Conversion and Management*, 50(7), 1635-1643.

Suh, S., & Huppes, G. (2005). Methods for Life Cycle Inventory of a product. *Journal of Cleaner Production*, *13*(7), 687–697. http://doi.org/10.1016/j.jclepro.2003.04.001

Suh, S., Lenzen, M., Treloar, G. J., Hondo, H., Horvath, A., Huppes, G., … Norris, G. (2004). System Boundary Selection in Life-Cycle Inventories Using Hybrid Approaches. *Environmental Science & Technology*, *38*(3), 657–664. http://doi.org/10.1021/es0263745

Suh, S., & Nakamura, S. (2007). Five years in the area of input-output and hybrid LCA. *The International Journal of Life Cycle Assessment*, *12*(6), 351–352.

Sullivan, J. L., Burnham, A., & Wang, M. (2010). *Energy-consumption and carbon-emission analysis of vehicle and component manufacturing.* Argonne, IL (United States). Retrieved from http://www.osti.gov/scitech/biblio/993394

Sullivan, J. L., Clark, C. E., Han, J., & Wang, M. (2010). *Life-cycle analysis results of geothermal systems in comparison to other power systems.* Argonne, IL (United States). Retrieved from http://www.osti.gov/scitech/biblio/993694

Tatari, O., Nazzal, M., & Kucukvar, M. (2012). Comparative sustainability assessment of warm-mix asphalts: A thermodynamic based hybrid life cycle analysis. *Resources, Conservation and Recycling*, *58*(null), 18–24. http://doi.org/10.1016/j.resconrec.2011.07.005

The National Research Council. (2013). Spreadsheets for Transitions to Alternative Vehicles and Fuels. Retrieved September 8, 2015, from http://www.nap.edu/tavf/

The U.S. Department of Transportation. (2009). *National Household Survey-Summary of Household Travel Trends*.

The U.S. Energy Information Administration. (2014). *Annual Energy Outlook with projections to 2040*. Washington DC. Retrieved from www.eia.gov/forecasts/aeo

The U.S. Energy Information Administration. (2015a). Electricity cost. Retrieved April 3, 2015, from http://www.eia.gov/electricity/data.cfm#sales

The U.S. Energy Information Administration. (2015b). Gasoline cost. Retrieved April 3, 2015, from http://www.eia.gov/petroleum/gasdiesel/

The World Energy Outlook. (2012). *Water for Energy Is energy becoming a thirstier resource?*

Thomas, S. (2012). US marginal electricity grid mixes and EV greenhouse gas emissions. *International Journal of Hydrogen Energy*, *37*(24), 19231–19240. http://doi.org/10.1016/j.ijhydene.2012.09.146

Toyota. (2014a). 2014 Toyota Corolla Specifications. Retrieved from http://www.toyota.com/corolla/#!/Welcome

Toyota. (2014b). 2014 Toyota Prius-HEV Specifications. Retrieved from http://www.toyota.com/prius/features.html#!/weights_capacities/1223/1225/1227/1229

Toyota. (2014c). 2014 Toyota Prius-PHEV Specifications. Retrieved from http://www.toyota.com/prius-plug-in/features.html#!/mechanical/1235/1237

Transportation Energy Data book. (2012). Transportation and the Economy-Car Operating Cost per Mile, 1985–2012. Retrieved from http://cta.ornl.gov/data/chapter10.shtml

Transportation Energy Data Book. (2012).

Trappey, A. J. C., Trappey, C. V., Hsiao, C.-T., Ou, J. J. R., & Chang, C.-T. (2012). System dynamics modelling of product carbon footprint life cycles for collaborative green supply chains. *International Journal of Computer Integrated Manufacturing*, *25*(10), 934–945. http://doi.org/10.1080/0951192X.2011.593304

Traverso, M., Asdrubali, F., Francia, A., & Finkbeiner, M. (2012). Towards life cycle sustainability assessment: an implementation to photovoltaic modules. *The International Journal of Life Cycle Assessment*, *17*(8), 1068–1079. http://doi.org/10.1007/s11367-012-0433-8

Traverso, M., Finkbeiner, M., Jørgensen, A., & Schneider, L. (2012). Life Cycle Sustainability Dashboard. *Journal of Industrial Ecology*, *16*(5), 680–688. http://doi.org/10.1111/j.1530-9290.2012.00497.x

the U.S. Bureau of Labor Statistics. (2015). Industry Output and Employment Projections. Retrieved March 1, 2014, from http://www.bls.gov/emp/ep_data_industry_out_and_emp.htm

Vanham, D., Mekonnen, M., & Hoekstra, A. (2013), “The water footprint of the EU for different diets”, *Ecological indicators*, 32, 1-8.

U.S. Environmental Protection Agency Office of Transportation and Air Quality. (2006). *Fuel Economy Labeling of Motor Vehicles: Revisions to Improve Calculation of Fuel Economy Estimates*. Retrieved from http://www.epa.gov/carlabel/documents/420r06017.pdf

U.S. Geological Survey (USGS). (2014). Commodity Statistics and Information. Retrieved from http://minerals.usgs.gov/minerals/pubs/commodity/

the U.S. Social Security. (2014). Life Tables for the United States Social Security. Retrieved May 5, 2014, from http://www.ssa.gov/oact/NOTES/as120/images/LD_fig2a.html

UC Davis Plug-In Hybrid & Electric Vehicle Research Center. (2014). UC Davis Plug-In Hybrid & Electric Vehicle Research Center web page. Retrieved from http://phev.ucdavis.edu/

United Nations. (2014). *Human Development Report 2014 Sustaining Human Progress: Reducing Vulnerabilities and Building Resilience*. Retrieved from Sustaining Human Progress: Reducing Vulnerabilities and Building Resilience

United Nations Envionment Program. (2004). *Why Take A Life Cycle Approach?*

USDOT. (2013). *National Transportation Statistics 2013*.

USGS. (2009). *Mineral commodity summaries*. Reston, Virginia.

Valdivia, S., Ugaya, C. M. L., Hildenbrand, J., Traverso, M., Mazijn, B., & Sonnemann, G. (2012). A UNEP/SETAC approach towards a life cycle sustainability assessment—our contribution to Rio+20. *The International Journal of Life Cycle Assessment*, *18*(9), 1673–1685. http://doi.org/10.1007/s11367-012-0529-1

Valdivia, S., Ugaya, C., Sonnemann, G., & Hildenbrand, J. (2011). Towards a Life Cycle Sustainability Assessment-Making informed choices on products. In *UNEP/SETAC Life Cycle Initiative*. Paris. Retrieved from http://scholar.google.com/scholar?q=Valdivia+Towards+a+Life+Cycle+Sustainability+Assessment-Making+informed+choices+on+products+valdivia&btnG=&hl=tr&as_sdt=0%2C10#1

Venkatesh, A., Jaramillo, P., Griffin, W. M., & Matthews, H. S. (2011). Uncertainty analysis of life cycle greenhouse gas emissions from petroleum-based fuels and impacts on low carbon fuel policies. *Environmental Science & Technology*, *45*(1), 125–31. http://doi.org/10.1021/es102498a

Wang, J., Lu, H., & Peng, H. (2008). System Dynamics Model of Urban Transportation System and Its Application. *Journal of Transportation Systems Engineering and Information Technology*, *8*(3), 83–89. http://doi.org/10.1016/S1570-6672(08)60027-6

Wang, M. Q., S. Plotkin, et al. (1997), "Total Energy-Cycle Energy and Emissions Impacts of Hybrid Electric Vehicles", Argonne National Laboratory.

WBCSD. (2004). *Mobility 2030: meeting the challenges to sustainability*. Geneva, Switzerland.

Weber, C. L., Jiaramillo, P., Marriott, J., & Samaras, C. (2010). Life cycle assessment and grid electricity: what do we know and what can we know? *Environmental Science & Technology*, *44*(6), 1895–901. http://doi.org/10.1021/es9017909

Weidema, B., Ekvall, T., & Heijungs, R. (2009). *Guidelines for application of deepened and broadened LCA*. *Deliverable D18 of work package*. Retrieved from http://www.leidenuniv.nl/cml/ssp/publications/calcas_report_d18.pdf

White, K. P., Dajani, D. S., & Wright, D. (1974). System Dynamics Approach to Urban Planning. *Journal of the Urban Planning and Development Division*, *100*(1), 43–56. Retrieved from http://cedb.asce.org/cgi/WWWdisplay.cgi?7400461

Wi, H., & Park, J. (2013). Analyzing uncertainty in evaluation of vehicle fuel economy using FTP-75. *International Journal of Automotive Technology*, *14*(3), 471–477. http://doi.org/10.1007/s12239-013-0051-x

Wiedmann, T. O., Lenzen, M., & Barrett, J. R. (2009). Companies on the Scale. *Journal of Industrial Ecology*, *13*(3), 361–383. Retrieved from http://doi.wiley.com/10.1111/j.1530-9290.2009.00125.x

Winz, I., Brierley, G., & Trowsdale, S. (2008). The Use of System Dynamics Simulation in Water Resources Management. *Water Resources Management*, *23*(7), 1301–1323. http://doi.org/10.1007/s11269-008-9328-7

Wood, R., & Hertwich, E. G. (2012). Economic modelling and indicators in life cycle sustainability assessment. *The International Journal of Life Cycle Assessment*, *18*(9), 1710–1721. http://doi.org/10.1007/s11367-012-0463-2

World Energy Outlook (2012), "Water for Energy Is energy becoming a thirstier resource?" Available at: http://www.worldenergyoutlook.org/media/weowebsite/2012/WEO_2012_Water_Excerpt.pdf. Accessed on May 1, 2015.

Wu, J., Vankat, J., & Barlas, Y. (1993). Effects of patch connectivity and arrangement on animal metapopulation dynamics: a simulation study. *Ecological Modelling*, *65*(3-4), 221–254. Retrieved from http://dx.doi.org/10.1016/0304-3800(93)90081-3

Yoshino, H., Fong, W.-K., Matsumoto, H., & Lun, Y.-F. (2009). Application of System Dynamics model as decision making tool in urban planning process toward stabilizing carbon dioxide emissions from cities. *Building and Environment*, *44*(7), 1528–1537. Retrieved from http://www.sciencedirect.com/science/article/pii/S036013230800187X

Zamagni, A. (2012). Life cycle sustainability assessment. *The International Journal of Life Cycle Assessment*, *17*(4), 373–376. http://doi.org/10.1007/s11367-012-0389-8

Zamagni, A., Buttol, P., Buonamici, R., Masoni, P., Guinée, J. B., Huppes, G., … Rydberg, T. (2009). Blue paper on life cycle sustainability analysis. Retrieved January 5, 2015, from http://www.calcasproject.net/

Zamagni, A., Pesonen, H.-L., & Swarr, T. (2013). From LCA to Life Cycle Sustainability Assessment: concept, practice and future directions. *The International Journal of Life Cycle Assessment*, *18*(9), 1637–1641. http://doi.org/10.1007/s11367-013-0648-3

Zhang, Y., Bishop, G. A., & Stedman, D. H. (1994). Automobile emissions are statistically gamma distributed. *Environmental Science & Technology*, *28*(7), 1370–4. http://doi.org/10.1021/es00056a029

Zoumides, C., Bruggeman, A., Hadjikakou, M., & Zachariadis, T. (2014), "Policy-relevant indicators for semi-arid nations: The water footprint of crop production and supply utilization of Cyprus", *Ecological Indicators*, 43, 205-214.