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A Macro-Level Sustainability Assessment Framework for Optimal Distribution of Alternative Passenger Vehicles

Nuri Onat

University of Central Florida

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A MACRO-LEVEL SUSTAINABILITY ASSESSMENT FRAMEWORK FOR OPTIMAL DISTRIBUTION OF ALTERNATIVE PASSENGER VEHICLES

by

NURI CIHAT ONAT
B.S. Gazi University, 2010
M.S. University of Florida, 2012

A thesis submitted in partial fulfillment of the requirements
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Major Professor: Qipeng P. Zheng

ABSTRACT

Although there are many studies focusing on the environmental impacts of alternative vehicle options, social and economic dimensions and trade-off relationships among all of these impacts were not investigated sufficiently. Moreover, most economic analyses are limited to life cycle cost analyses and do not consider macro-level economic impacts. Therefore, this thesis aims to advance the Life Cycle Sustainability Assessment literature and electric vehicle sustainability research by presenting a novel combined application of Multi Criteria Decision Making techniques with Life Cycle Sustainability Assessment for decision analysis. With this motivation in mind, this research will construct a compromise-programming model (multi-objective optimization method) in order to calculate the optimum vehicle distribution in the U.S. passenger car fleet while considering the trade-offs between environmental, economic, and social dimensions of the sustainability. The findings of this research provide important insights for policy makers when developing strategies to estimate optimum vehicle distribution strategies based on various environmental and socio-economic priorities. For instance, compromise programming results can present practical policy conclusions for different states which might have different priorities for environmental impact mitigation and socio-economic development. Therefore, the conceptual framework presented in this work can be applicable for different regions in U.S. and decision makers can generate balanced policy conclusions and recommendations based on their environmental, economic and social constraints. The compromise programming results provide vital guidance for policy makers when optimizing the use of alternative vehicle technologies based on different environmental and socio-economic priorities. This research also effort aims to increase awareness of the inherent benefits of Input-Output based a Life Cycle Sustainability Assessment and multi-criteria optimization.

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LIST OF ACRONYMS (or) ABBREVIATION

AER   All-electric range

BEV   Battery Electric Vehicle

DOE   Department of Energy

EIO-LCA Economic Input-Output Life cycle Assessment

ELECTRE Elimination and Choice Translating Reality

EPA   United States Environmental Protection Agency

gCO2-eqv Carbon dioxide equivalent

GDP   Gross domestic product

gha   Global hectare area

GHG   Greenhouse gas

GREET   The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation

GWP   Global warming potential

IPCC   Intergovernmental Panel on Climate Change

kWh   Kilowatt hour

LCA   Life Cycle Assessment

LCI	Life Cycle Inventory
LCSA	Life cycle Sustainability Assessment
LDV	light duty vehicle
Li-ion	Lithium-ion
lt	Liter
M&R	Maintenance and repair
MADM	Multi-Attribute Decision Making
MCDM	Multi-Objective Decision Making
MJ	Mega joule
MRIO	Multi-regional input-output
NAICS	North American Industry Classification System
PHEV	Plug-in Hybrid Electric Vehicle
P-LCA	Process based Life cycle Assessment
PV	Photovoltaic
S1	Scenario 1
S2	Scenario 2
SETAC	Society of Environmental Toxicology and Chemistry

S-LCA   social life cycle assessment

TBL   Triple Bottom Line

UF   Utility factor

UNEP   The United Nations Environment Programme

VKT   Vehicle kilometers traveled

WBCSD   World Business Council for Sustainable Development

CHAPTER ONE: INTRODUCTION AND LITERATURE REVIEW

1.1.   Background Information

1.1.1. Transportation in the United States

Sustainable transportation and mobility are key components and central of sustainable development. Transportation sector is also an integrated component of economy and of society as a whole, as it is connected to almost all of the sectors that constitute the entire economy. While there is need for improving access to goods and services to support economic and social development, at the same time, the adverse environmental, social and economic impacts of exponentially growing transportation sector must be minimized (United Nations, 2012). In particular, concerns associated with global climate change, energy security, rising oil prices, and depletion of fossil fuels are stimulating the search for alternative vehicle technologies. Hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), and battery electric vehicles (BEV) are some of these alternative vehicle technologies, which can help to address the aforementioned issues by shifting transportation energy use from fossil fuels to electricity, under low carbon electricity generation scenarios (Onat, Kucukvar, & Tatari, 2015; Samaras & Meisterling, 2008).

In the United States, there are various efforts to increase adoption of these alternative vehicle technologies owing to their great potential of reducing fossil fuel consumption and GHG emissions. The U.S. road system has the largest network size in the world, as well as one of the largest network usage densities at three million Vehicle Miles

Traveled (VMT) per year. These factors make the U.S. transportation sector an important source of GHG emissions and energy consumption with 28% of the nation's total (Kucukvar, Noori, Egilmez, & Tatari, 2014). Additionally, transportation sector consumes immense amounts of petroleum and it is responsible for 67% of the total U.S. petroleum consumption. this high petroleum demand is more than the U.S. petroleum production (%141 of total petroleum production in the U.S.), which compromises national energy security and results in high dependency on fossil fuels, which compromises national energy security and result in high dependency on fossil fuels (Oak Ridge National Lab., 2013). Although the alternative vehicle technologies have great potential to minimize the negative economic, social, and environmental impacts of the fast-growing transportation sector, there are certain challenges against widespread adoption of these technologies. Some of these barriers are lack of infrastructure, customer's unwillingness to purchase these vehicles, high initial costs of BEVs, and insufficient all-electric range (Melaina & Bremson, 2008). In this regard, national agencies, state level authorities as well as international organizations support the adoption of the alternative vehicle technologies to increase their market penetration (DOE, 2011; DOT, 2013; Executive Office of the President, 2013; IPCC, 2007; WBCSD, 2004). For instance, The Obama administration and the Department of Energy (DOE) aim to reach one million electric vehicles (including HEVs, PHEVs, and BEVs) by 2015 and are trying to accelerate the sales by state and federal level incentives (DOE, 2011). In addition, a program by the DOE, EV-Everywhere Challenge, aims to promote the development and research activities to reduce battery costs, increase the all-electric range of electric vehicles, and make these vehicles affordable for

American families (DOE, 2013). While all of these efforts are necessary and useful, it is more important to understand the macro-level social, economic, and environmental (termed as the triple bottom line) impacts of alternative vehicle technologies to be able to develop more effective policies and guide the offering of incentives to the right domain.

1.1.2. Life Cycle Assessment

Life Cycle Assessment (LCA) is a well-known and widely-used approach used to quantify environmental impacts related to the life cycle of products, including raw material extraction, manufacturing, transportation, use, and final disposal (Rebitzer et al., 2004). LCA was introduced in the early 1990s as a practical and robust tool to assess and reduce the potential environmental loads of industrial activities (Finnveden et al., 2009). One of the most prominent strengths of LCA is to consider the whole product life cycle so as to avoid problems associated with working with a limited scope. In the literature, three LCA approaches have been used in many studies: process-based LCA (P-LCA), input-output based LCA (IO-LCA), and hybrid LCA which is the combination of the P-LCA and IO-LCA (Deng, Babbitt, & Williams, 2011; Suh et al., 2004). P-LCA divides the product's manufacturing process into individual process flows to quantify the related direct environmental impacts, providing a methodological framework to estimate the environmental impacts of specific processes (De Benedetto & Klemeš, 2009; Norgate, Jahanshahi, & Rankin, 2007). Among the LCA methodologies, P-LCA has been often used to analyze the environmental impacts of certain phases such as manufacturing, transportation, use and end-of-life without looking at the supply chain components. Thus, due to the narrowly defined system boundaries, some important environmental impacts in

the extended supply chains might be overlooked by the P-LCA method since it is not possible to include all of the upstream suppliers for impact assessment (Onat, Kucukvar, & Tatari, 2014b). To overcome these limitations, IO-LCA models have been initiated as robust methods in early 2000s (C. T. Hendrickson, Lester, & Matthews, 2006). The IO-LCA, which is widely used in literature for quantifying the environmental impacts of products or processes, is capable of covering the entire supply chain when quantify the overall environmental impacts. When working with large-scale systems such as manufacturing or transportation, IO-LCA models can be the better approach, as they provide an economy-wide analysis (Egilmez, Kucukvar, & Tatari, 2013). On the other hand, process-based analysis involves a limited number of processes, and the inclusion or exclusion of processes is decided on the basis of subjective choices, thereby creating a system boundary problem (Suh et al., 2004). Earlier studies on the direct and indirect carbon and energy footprint analysis of different economic sectors also showed that P-LCA suffers from significant truncation errors which can be on the order of 50% or higher (Kucukvar & Tatari, 2013; Lenzen, 2000; Matthews, Hendrickson, & Weber, 2008). Therefore, the I-O based LCA models provide a top-down analysis that uses sectorial monetary transaction matrixes considering complex interactions between the sectors of nations' economy (Hertwich & Peters, 2009). I-O technique is a suitable approach for calculation of environmental footprints (Hendrickson et al., 2005; Larsen and Hertwich, 2010; Minx et al. 2009).

Using the Economic Input-Output LCA (EIO-LCA) model, an I-O based LCA model, Matthews et al., (2008) analyzed the carbon footprints of different industrial sectors

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and the results of this study revealed that, on average, direct emissions from an industry account 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 IO-LCA is vital for tracking total environmental pressures across the entire supply chain network. As employed in this research, Hybrid LCA combines both the P-LCA and IO-LCA models to analyze process-specific and supply chain-related sustainability impacts. Although the IO-LCA was one of the most comprehensive LCA methods developed, due to its limited focus on only the environmental impacts, a new IO-LCA model needs to be developed to cover triple bottom line (TBL) impacts and provide a more robust analytical framework, which can be used to conduct a broader LCA of products or systems (Kucukvar, Egilmez, & Tatari, 2014; Onat, Kucukvar, & Tatari, 2014a).

Over the last decade, there has been a transition from LCA to Life Cycle Sustainability Assessment (LCSA), in which environmental, economic, and social dimensions of sustainability are integrated into a traditional LCA methodology (Ciroth, Finkbeier, & Hildenbrand, 2011; Sala, Farioli, & Zamagni, 2012; Zamagni, 2012). According to a recent 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 (Guinée et al., 2011). The United Nations Environment Programme (UNEP) and the Society of Environmental Toxicology and Chemistry (SETAC) have been working on possible methodological approaches and metrics in order to fully integrate triple bottom line aspects of sustainability to a single-dimensioned LCSA (S Valdivia, Ugaya, Sonnemann, &

Hildenbrand, 2011). In this framework, environmental LCA, life cycle cost (LCC), and social life cycle assessment (S-LCA) represent three independent methodologies to individually address the three pillars of sustainability (UNEP & SETAC, 2011). In the literature, Kloepffer (2008) first formulized the current LCSA framework with editorial comments obtained from Finkbeiner and Reiner, where the "LCSA=LCA+LCC+S-LCA" (Finkbeiner, Schau, Lehmann, & Traverso, 2010). According to a report by UNEP & SETAC, although there has been little progress toward improving the methodological aspects and extending the application areas for LCSA, LCSA is certainly an important framework and should be pursued (Sonia Valdivia et al., 2012).

LCSA is still a new concept, and the applications of this method in sustainability assessment research are highly limited. After a comprehensive review of authors, there are a limited number of studies found in the literature that used LCSA in a real case study for product LCSA, and the majority of those papers focused mainly on the methodological or conceptual aspects of LCSA. Hu et al. (2013) presented an approach to put the LCSA framework into practice by analyzing the triple bottom line life cycle implications of concrete recycling processes. In another paper, Traverso et al. (2012) analyzed the production steps of photovoltaic (PV) modules where environmental, economic and social impacts of Italian and German polycrystalline silicon modules are compared using LCSA. Although several studies emphasized the importance of system-based tools for LCA, the applications of LCSA for large systems are also missing. Guinée et al. (2011) highlighted the importance of LCSA framework in future LCA and discussed the necessity of system-based sustainability accounting methods such as IO LCA and hybrid LCA. Wood and

Hertwich (2012) also discussed the comprehensiveness of I-O analysis in LCSA, particularly for socio-economic analysis. In response to the current research needs regarding comprehensive LCSA methods, Kucukvar et al. (2014b) developed an optimization model in which input-output based LCSA and compromise programming methods are used in conjunction for a multi-criteria decision analysis of hot-mix and warm-mix asphalt mixtures. In a recent work, Onat et al. (2014c) used the LCSA framework for the TBL sustainability analysis of U.S residential and commercial buildings and demonstrated the usefulness of input–output modeling to quantify sustainability impacts as an integration into the LCSA framework.

1.1.3. Multi Criteria Decision Making

Multi-criteria Decision Making (MCDM) is a type of operations research model widely used to solve decision making problems where multiple criteria and alternatives exist. In the literature, Multi-Attribute Decision Making (MADM) and Multi-Objective Decision Making (MODM) represent two main categories of MCDM methods. In these models, the primary goals are to select the best alternative or group of alternatives into predefined preference sets based on performance over multiple criteria. MADM approaches are generally employed to solve problems involving selection from different sets of decision alternatives. On the other hand, MODM models focus on design rather than selection, by considering tradeoffs in design constraints (Triantaphyllou, 2000).

There are numerous types of MCDM models used in environmental decision making problems. Examples of these models include the Analytical Hierarchy Process, the

Preference Ranking Organization Method for Enrichment Evaluation, Elimination and Choice Translating Reality, the Technique for Order Preference by Similarity to Ideal Solutions, Compromise Programming, the Weighted Sum Method, the Weighted Product Method and the VIKOR method (Figueira, Greco, & Ehrgott, 2005; Wang, Jing, Zhang, & Zhao, 2009; Zavadskas & Antuchevičiene, 2004). These MCDM approaches have been applied for various types of problems, including problems related to infrastructures (Kucukvar et al., 2014a), environmental decision making (Cheng, Chan, & Huang, 2003), sustainable energy planning (Streimikiene, Balezentis, Krisciukaitienė, & Balezentis, 2012; Wang et al., 2009), and supplier evaluation and selection (Boran, Genç, Kurt, & Akay, 2009; Ho, Xu, & Dey, 2010).

To strengthen LCA as a tool and to improve its usefulness for sustainability decision-making, an integration of MCDM approaches into LCA studies will be critical (Hermann, Kroeze, & Jawjit, 2007; Jeswani, Azapagic, Schepelmann, & Ritthoff, 2010). In the literature, MCDM methods have been extensively applied to LCA. To name a few, Boufateh and Perwuelz (2011) used a MCDM method to analyze the results of the LCA of textile products. In another paper, MCDM is integrated into LCA to select the best composite material alternative (Milani & Eskicioglu, 2011). Linkov and Seager (2011) presented a MCDM approach and integrated uncertain information collected from risk analysis and LCA for nanomanufacturing and the management of contaminated sediments. You et al. (2012) used a joint application of MCDA and LCA for a case study of biomass production chains. Liu et al. (2012) applied a combination of risk assessment, LCA, and MCDM to a case study in a waste recycling facility. Kucukvar et al. 2014b used a fuzzy

MCDM approach in order to rank the life cycle sustainability performance of warm-mix and hot-mix asphalt pavements constructed in the U.S. Although various LCA models have been developed for environmental analyses of alternative vehicle technologies, few studies found in the literature considered MCDM as an integrated decision making framework for alternative vehicle technologies. Also, none of these studies employed a joint application of MCDM and LCSA. For example, Tzeng et al. (2005) presented a MCDM model for alternative fuel buses for public transportation, selecting AHP, TOPSIS and VIKOR methods as MCDM methods. Mohamadabadi et al. (2009) developed a MCDM model to select the best fuel-based vehicles for road transportation, considering several factors (including economic, environmental and social factors) and utilizing PROMETHEE as a MCDM method. Donateo et al. (2008) used an optimization model to design a hybrid electric vehicle based on two steps: optimization and decision making. Traut et al. (2012) developed a hybrid LCA model and constructed an optimization model to determine optimal designs for internal combustion vehicles (ICVs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs), selecting the costs and greenhouse gas emissions of each vehicle alternative as conflicting objectives. However, none of the aforementioned studies used multi-objective optimization models considering the direct and indirect social, economic, and environmental impacts of alternative vehicles from a LCSA perspective.

It is critical to note that analyzing a possible transition from petroleum-based transportation vehicles to electric vehicles require a holistic LCSA, because all possible on-site and upstream supply chain TBL impacts and all tradeoffs related to shifting from

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petroleum to electricity (employment, tax, import, carbon emissions, etc.) should be taken into consideration. Consequently, such an integration of MODM with LCSA will provide critical guidance to policymakers, thereby contributing significantly to the development of sustainable alternative vehicle selection and development strategies. Although LCA methods have recently gained popularity in sustainable transportation research, particularly with respect to electric vehicles, the integration of LCSA of alternative vehicle technologies with MCDM can play a vital role in the evaluation and optimization of the life cycle sustainability performance of these vehicle technologies. Hence, this study proposes an integration of LCSA with MODM in order to assess the socio-economic and environmental impacts of vehicle alternatives and optimize the distribution of vehicle types given a set of conflicting objectives.

Although there is limited research available on combined applications of LCSA and input-output analysis, joint applications of MODM and LCSA are also rare. Finkbeiner et al. (2010) discussed the conceptual framework for LCSA, and the "Life Cycle Sustainability Dashboard" and "Life Cycle Sustainability Triangle" are presented as examples of MODM tools for both experts and non-expert LCA practitioners. Halog and Manik (2011) presented the importance of integrating decision-making models (such as agent-based modeling, system dynamics, and optimization) into the LCSA to yield a holistic sustainability assessment. Bachmann (2012) also discussed the importance of multi-criteria decision making in LCSA for power generation technologies. However, in an editorial article on LCSA and its future, it is emphasized that "more research is needed to make decision making frameworks operational in the LCSA framework" (Zamagni,

2012). On the other hand, there are numerous studies addressing issues related to the environmental impacts of alternative vehicle technologies (Elgowainy and Burnham, 2009; Faria et al., 2013, 2012; Kelly et al., 2012; Marshall et al., 2013; Nanaki and Koroneos, 2013; Raykin et al., 2012; Samaras and Meisterling, 2008; Sharma et al., 2013; Strecker et al., 2014). For more information about the studies focusing on the environmental impacts of alternative vehicle technologies, please see the referred review studies (Hawkins, Gausen, & Strømman, 2012; Nordelöf, Messagie, Tillman, Ljunggren Söderman, & Van Mierlo, 2014).

1.2. Thesis Objectives

Although, there is limited research available on combined applications of LCSA and input-output analysis, the joint applications of MODM and LCSA are also rare. Finkbeiner et al. (2010) discussed the conceptual framework for LCSA, and the "Life Cycle Sustainability Dashboard" and "Life Cycle Sustainability Triangle" are presented as examples of MODM tools for both experts and non-expert LCA practitioners. Halog and Manik (2011) presented the importance of integrating decision making models such as agent-based modeling, system dynamics, and optimization into the LCSA for a holistic sustainability assessment. Bachmann (2012) also discussed the importance of multi-criteria decision making in LCSA of power generation technologies. However, in an editorial article on LCSA and its future, it is emphasized that "more research is needed to make decision making frameworks operational in the LCSA framework" (Zamagni, 2012). On the other hand, although the literature is abundant with studies focusing on environmental impacts of alternative vehicle technologies (Faria et al., 2012; Hawkins et al., 2012; Nanaki

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& Koroneos, 2013; Nordelöf et al., 2014; Onat et al., 2015; Samaras & Meisterling, 2008; Strecker et al., 2014), social and economic dimensions of adoption of these vehicle technologies were not investigated sufficiently. Furthermore, studies covering economic dimensions are mostly limited to life cycle cost analyses and do not investigate the economy wide impacts of alternative vehicle technologies. Considering that the fundamental concept of sustainability encompasses issues related to economy, environment, and society as a whole, studies analyzing issues related to the adoption of alternative passenger vehicles shouldn't focus on only environmental or economic aspects, but should instead evaluate the alternatives considering their triple bottom line (TBL) impacts all together, as well as the trade-off relationships among these bottom lines. In this regard, this research aims to advance the LCSA literature and electric vehicles' sustainability research by filling two major knowledge gaps: "lack of integration of I-O analysis for LCSA of electric vehicles" and "lack of combined applications of MCDM techniques with LCSA for decision analysis". Furthermore, the LCA literature on sustainability analysis of alternative vehicle technologies needs a holistic LCSA analysis in which both direct and supply-chain-related indirect triple bottom line sustainability implications of vehicles are analyzed. With this motivation in mind, this research will utilize a holistic I-O technique for supply chain-linked LCSA of alternative electric vehicle technologies in U.S., and will construct a compromised programming model (multi-objective optimization method) in order to calculate the optimum vehicle allocation in U.S passenger vehicle fleet considering the trade-offs between environmental, economic, and

social dimensions of the sustainability. In this study, the following objectives were set forth:

1) to quantify economic, social, and environmental impacts of alternative passenger vehicles,

2) to compare these alternatives and evaluate their macro-level sustainability impacts,

3) to highlight how the inclusion of economic and social perspectives can assist the policy goals towards encouraging use of alternative vehicles on national level,

4) to compare TBL impacts of manufacturing, operation, and end-of-life phases of the alternative vehicle technologies, and

5) to estimate optimal allocation of the alternative passenger vehicles based on their negative and positive TBL impacts.

CHAPTER TWO: METHODOLOGY

In this thesis, life cycle assessment and multi-objective optimization methods are utilized, which are explained in detail in the following sections. First, the scope of the analysis is represented, and the system boundary is defined. Second, the sustainability metrics, known as TBL, indicators are introduced, and their calculation steps are briefly explained. Third, data sources and specific calculations associated with each life cycle phase are presented. Fourth, a multi-objective optimization model (Compromise Programming or CP) is developed to calculate the optimal allocation of passenger vehicles in the U.S. The multi-objective optimization model consists of the conflicting environmental and socio-economic objectives and the associated weights for each objective. The weights of these objectives varied between 0 and 1 to account for decision makers' preferences in the terms of environmental and social-economic goals and the importance given for each. Additionally, there are two scenarios considered in this analysis: Scenario 1 is based on existing electric power infrastructure in the U.S. with no additional infrastructure requirement, while Scenario 2 is an extreme scenario in which electricity to power BEVs and PHEVs are generated through solar charging stations only.

2.1.   Scope of the Analysis

This analysis covers all life cycle phases from material extraction, processing, manufacturing, and operation phases to the end-of-life phases of vehicles and batteries. The system boundary of the analysis is represented in Fig. 1. The vehicle technologies are internal combustion vehicles (ICVs), HEVs and PHEVs with all-electric ranges (AER) of 10, 20, 30, and 40 miles of electric powered drive, and BEVs. AER is defined as the total miles can be driven in electric mode (engine-off) with an initially fully charged battery until the engine turns on for the first time (Markel, 2006). All of the battery types utilized in the alternative passenger vehicles are lithium ion (li-ion) batteries. The useful life time for these vehicles is assumed to be 150,000 miles and the functional unit is defined as 1 mile of vehicle travel. Each color in Fig. 1 represent one vehicle type and the arrows indicate that there is a relationship between the associated vehicle and the corresponding process. For instance, electricity generation and construction of solar charging stations are the processes that are related to BEVs and PHEVs only. Similarly, the battery manufacturing and end-of-life of batteries are not calculated for the ICVs as they do not utilize li-ion batteries.
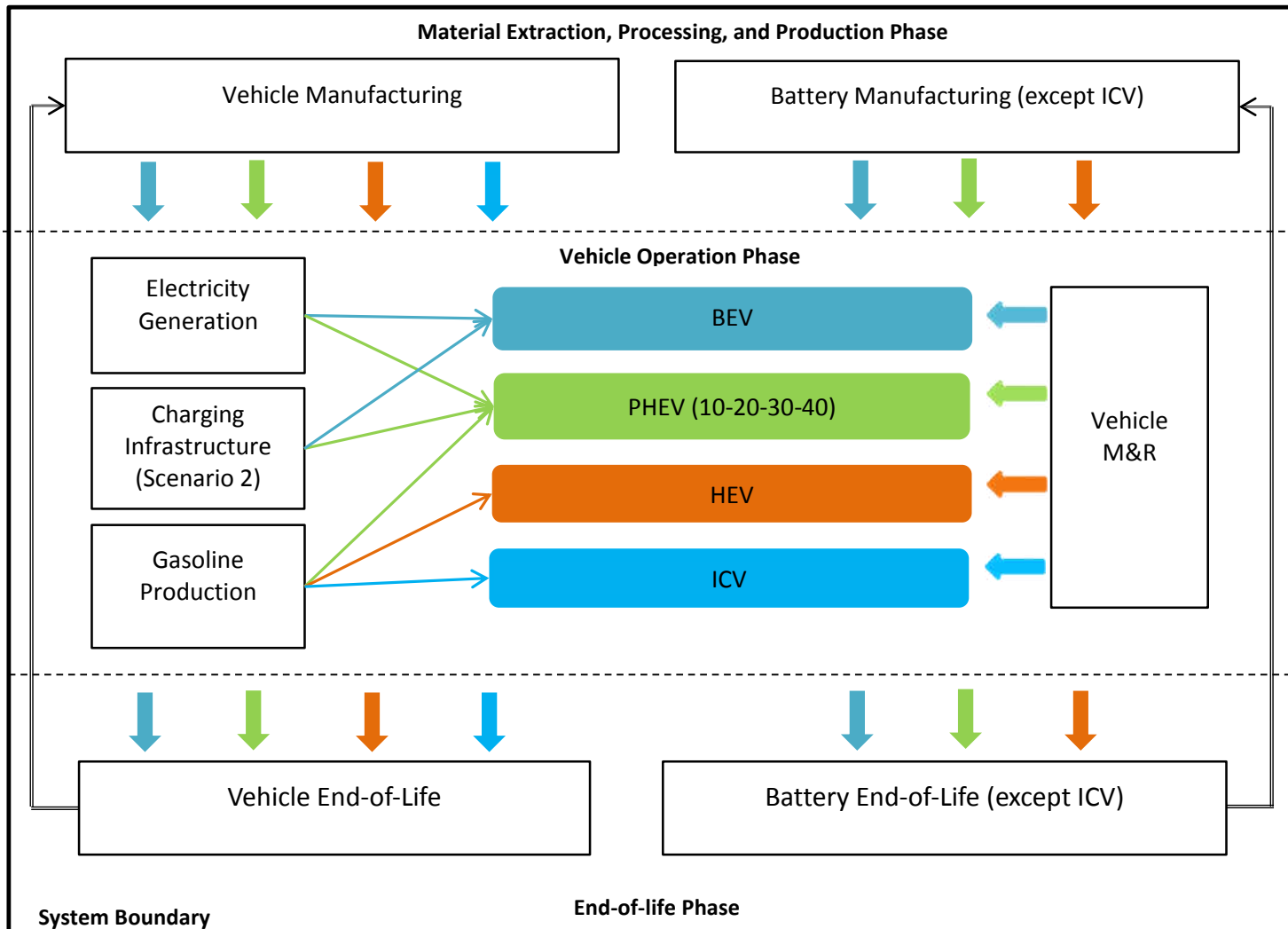
Figure 1 System boundary of the Analysis

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2.2.   The TBL-LCA model and Sustainability Indicators

The TBL-LCA model is an I-O-based sustainability accounting tool, which is utilized to quantify environmental, economic, and social impacts associated with alternative passenger vehicles. The I-O analysis was introduced by Wassiliy Leantief in the 1970s (Leontief, 1970), since than various extensions of this methodology were developed. I-O models are composed of identical sectors and the money flow among these sectors which constitute the whole economy of a country, a region, or the entire world depending on the scope and structure of the data (C. T. Hendrickson et al., 2006; Murray & Wood, 2010; Tukker et al., 2009). Most of the developed countries publish their I-O tables consisting of financial flow data among the defined sectors. The financial flow data is represented by supply and use tables. The U.S. Bureau of Economic Analysis (BEA), publishes these tables periodically, once in a 5 year period, in which all sectors are classified according to North American Industry Classification System (NAICS) (BEA, 2002, 2008). Environmentally extended I-O (EEIO) models such as the Economic Input output LCA (the EIO-LCA) (Carnegie Mellon University Green Design Institute, 2008) and the Ecologically-based LCA (Eco-LCA) (OSU- The Ohio State University, 2013) incorporate the financial flow data from the supply and use tables with environmental impact factors reflecting the environmental impacts of the sectors per commodity output in the terms of monetary units. In addition to environmental indicators, the TBL-LCA model incorporates social and economic indicators and presents an I-O based holistic sustainability accounting framework. In the TBL-LCA model, industry-by-industry I-O mythology was utilized, which was also used in previous I-O based TBL models developed

for the UK and Australian economies (Foran, Lenzen, Dey, & Bilek, 2005; Wiedmann & Lenzen, 2009). Also, the conversion of supply and use tables into an industry-by-industry I-O table is conducted based on the fixed industry sales assumptions. For more detailed information about the transformation of supply and use tables please see the reference reports published by the Eurostat (Eurostat, 2008) and the United Nations (United Nations, 1999).

In the TBL-LCA model, the I-O multipliers represent the total impacts, which are accumulations of direct and indirect (supply chain) impacts per unit of final demand of commodities produced by the NAICS sectors. The monetary transactions between the sectors are represented as set of matrices. The Use matrix, mostly denoted as **U**, expresses the financial flow due to the consumption of commodities by sectors. While the columns represent the commodities, the sectors using those commodities are placed in the rows. For example, the monetary value of steel consumption of the automobile manufacturing sector is in the intersection of the steel manufacturing sector in the row and automobile manufacturing sector in the column. The Make (supply) matrix, usually denoted as **V**, shows the production of commodities by each sector. In the Make matrix, the columns and rows represent the commodities and sectors, respectively. However, the intersections of the rows and columns represent the production of the commodity by the sector in the row (Miller & Blair, 2009).

$$B = [b_{ij}] = \left[\frac{U_{ij}}{X_j} \right] \qquad\qquad\qquad (1)$$

$$D = [d_{ij}] = \left[\frac{V_{ij}}{q_i} \right] \qquad\qquad\qquad (2)$$

In Eq. 1 and 2, the Use and Make matrices are expressed with the technical coefficient matrices **B** and **D**, respectively. As a part of the U matrix, u_{ij} stands for the monetary value of the purchase of commodity i by sector j. X_j is the total output of sector j. Hence, b_{ij} is the amount of commodity i needed for generating one dollar output of sector j. On the other hand, v_{ij} represents the monetary value of the output of commodity i by sector j and q_i is the output of commodity i. Therefore, d_{ij} is the fraction of total output of commodity i that is produced by the sectors. Eq. 3 is the total impact vector which indicates the total sustainability impacts per unit of final demand (Miller & Blair, 2009).

$$r = E_{dir}[(I-DB)^{-1}]f \qquad\qquad\qquad (3)$$

In Eq. 3, **I** represents the identity matrix and **f** stands for the final demand vector of industries. Also, the formulation **[(I-DB)$^{-1}$]** represents the total requirement matrix, which is also known as the Leontief inverse (Leontief, 1970). **E$_{dir}$** is a diagonal matrix consisting of the triple bottom line impact values per dollar output of each sector.

In this study, 16 macro-level indicators were selected to represent environmental, economic, and social impacts. Table 1 shows the selected indicators and their brief definitions. These indicators are utilized as multipliers (impact per $M of output) to quantify impacts associated with each activity. Data required to calculate these multipliers

are obtained via publicly available resources such as the Bureau of Economic Analysis (BEA, 2002) , the Bureau of Labor Statistics (BLS, 2002), the Global Footprint Network (GFN , 2010), and Carnegie Mellon's EIO-LCA software (CMU, 2008). For more detailed information about the TBL-LCA model and the sustainability indicators, please see the reference study published by Kucukvar and Tatari (2013). Although majority of the LCA analysis is conducted with the industrial TBL multipliers, there are some processes which are not represented by the sectors in the model. In these cases, process impacts are calculated manually. For instance, the driving activity within the operation phase of vehicles cannot be represented by any of the 428 sectors. In this case, the amount of fuel consumed is calculated and multiplied by the relevant factor, such as CO_2 emissions from burning one gallon of gasoline. This approach is termed as tiered hybrid I-O analysis in the literature (Suh et al., 2004). Similar approaches can be found in (C. Hendrickson, Lave, & Matthews, 2006). A detailed explanation of these calculations will be presented in the following section.

Table 1 Brief description of sustainability indicators

Bottom lines	TBL Indicator	Unit	Description
Economic	Import (foreign purchase)	$	The monetary value of products and services purchased from foreign countries to produce domestic commodities.
	Gross Operating Surplus (business profit)	$	The available capital of corporations, which allows them to pay taxes, to repay their creditors, and to finance their investments.
	Gross Domestic Product (GDP)	$	Economic value added by the U.S. sectors
Social	Employment	emp-hr	The full-time equivalent employment hours for each U.S. sector
	Government Tax	$	Taxes collected from production and imports, government revenues
	Injuries	#worker	The number of non-fatal injuries associated with the U.S. sectors
	Income	$	The compensation of employees, wages, and salaries
Environmental	Carbon Footprint	gCO_2-eqv	The total GHG emissions of each sector
	Water Withdrawal	lt	The total amount of water withdrawals of each sector.
	Energy Consumption	MJ	The total energy consumption of industries.
	Hazardous Waste Generation	st	The amount of hazardous waste (EPA's RCRA) generated by U.S. sectors

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Bottom lines	TBL Indicator	Unit	Description
Environmental	Fishery	gha	The estimated primary production required to support the fish caught.
	Grazing	gha	The amount of livestock feed available in a country with the amount of feed required for the livestock produced.
	Forestry	gha	The amount of lumber, pulp, timber products, and fuel wood consumed by each U.S. sector.
	Cropland	gha	The most bio-productive of all the land use types and includes areas used to produce food and fiber for human consumption.
	CO_2 uptake land	gha	The amount of forestland required to sequester GHG emitted by sectors.

## 2.3.	Life Cycle Inventory

Vehicle features such as weight, battery power requirements, and material compositions are obtained from the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) vehicle cycle model (Burnham, Wang, & Wu, 2006). Direct and indirect impacts of activities such as automobile and battery manufacturing, electric power generation, gasoline supply, and savings due to recycled batteries and vehicles are calculated via the TBL-LCA model. First, the monetary values (producer prices) of each process, material, or activity are calculated based on the defined functional unit, which represent the estimated demand from associated sectors as a result of a certain process, such as the fuel required for an ICV to travel 1 mile. These monetary values are inputs for the TBL-LCA model, and are multiplied by the corresponding sector's TBL multipliers. On the other hand, direct impacts such as tailpipe emissions and direct energy consumption while driving are calculated by using process level data. Table 2 lists each activity or process along with a brief description and the corresponding NAICS sector. TBL impact multipliers per $M output of each sector are provided in Table 3. Detailed calculation steps and data sources associated with the vehicle and battery manufacturing, operation, and end-of-life phases are provided in the following subsections.

Table 2 Process descriptions and corresponding NAICS sectors through life cycle of vehicles

LCA phases	NAICS sector ID	NAICS sector name	Process Description
Manufacturing Phase	335912	Primary Battery Manufacturing	Li-ion battery manufacturing for vehicles
	336111	Automobile manufacturing	Manufacturing of passenger vehicles
Operation phase — Driving related process	221100	Electric power generation, transmission, and distribution	Impacts associated with electricity generation, T&D to power vehicles
	324110	Petroleum refineries	Gasoline production and supply for vehicles
	811100	Automotive repair and maintenance, except car washes	Vehicle repair and maintenance
Operation phase — Solar Charging station const.	334413	Semiconductor and related device manufacturing	Manufacturing of solar modules and installed system
	327320	Ready-mix concrete manufacturing	Concrete manufacturing
	331110	Iron and steel mills	Steel Manufacturing
	321212	Veneer and plywood manufacturing	Medium density fibreboard manufacturing
	32551	Paint and coating manufacturing	Paint and coating manufacturing
	230101	Other Nonresidential (layer 1)	Construction of the charging station (layer 1 only)
End-of-Life phase	331110	Iron and steel mills	Savings from recycled steel extracted from vehicles and batteries
	33131A	Alumina refining and primary aluminum production	Savings from recycled aluminum extracted from vehicles and batteries

LCA phases	NAICS sector ID	NAICS sector name	Process Description
	331420	Copper Rolling, Drawing, Extruding, and Alloying	Savings from recycled copper extracted from vehicles and batteries
	327211	Flat glass manufacturing	Savings from recycled glass extracted from vehicles
End-of-Life phase	325211	Plastics material and resin manufacturing	Savings from recycled plastic extracted from vehicles
	325212	Rubber and plastics hose and belting manufacturing	Savings from recycled rubber extracted from vehicles
	339910	Jewelry and Silverware Manufacturing	Savings from recycled platinum extracted from vehicles

Table 3 TBL impact multiplier per $M output of each sector

		Econ.		Social				Environmental									
	NAICS sector Ids	Foreign Purchase (M$)	Business Profit (M$)	Employment-hr	Income (M$)	Government Tax (M$)	Injuries (# worker)	Fishery (gha)	Grazing (gha)	Forestry (gha)	Cropland (gha)	Carbon Fossil Fuel (gha)	Carbon Electricity (gha)	GHG Total (t)	Total Energy (TJ)	Water (kgal)	Haz. Waste (st)
Man. Ph.	**335912**	0.296	0.533	23357	0.429	0.031	0.552	0.098	0.102	3.17	3.98	97.67	41.73	540.40	8.44	6682	364000
	336111	0.969	0.370	28422	0.564	0.043	0.847	0.173	2.762	3.73	9.86	100.51	42.15	547.56	8.48	8313	416000
Operation phase	**221100**	0.099	0.488	16125	0.364	0.143	0.290	0.273	0.174	1.34	3.88	1853.92	13.08	8243.87	98.22	219474	125000
	324110	0.853	0.545	16099	0.345	0.100	0.329	0.153	0.126	1.73	4.67	492.07	57.46	2776.52	31.57	8546	4120000
	811100	0.101	0.314	37423	0.594	0.076	0.865	0.187	0.411	1.59	3.52	61.90	34.16	312.32	4.74	5184	172000
	334413	0.445	0.433	23202	0.519	0.039	0.486	0.135	0.126	2.05	3.47	93.33	54.59	579.07	7.36	7751	1080000
	327320	0.106	0.373	32622	0.576	0.044	1.036	0.189	0.152	1.91	7.71	638.17	68.34	2715.16	23.39	16526	373000
	331110	0.445	0.306	32844	0.627	0.058	1.014	0.215	0.245	2.87	6.14	546.56	123.69	3669.30	51.02	20233	1450000
	321212	0.363	0.319	39062	0.596	0.082	1.357	0.185	1.074	498.95	29.74	145.85	68.18	747.68	16.69	17770	183000
	32551	0.234	0.383	27653	0.563	0.044	0.639	0.204	0.228	3.61	33.42	195.35	56.83	1041.96	16.18	138965	2080000

		TBL indicators															
		Econ.		Social				Environmental									
	NAICS sector Ids	Foreign Purchase (M$)	Business Profit (M$)	Employment-hr	Income (M$)	Government Tax (M$)	Injuries (# worker)	Fishery (gha)	Grazing (gha)	Forestry (gha)	Cropland (gha)	Carbon Fossil Fuel (gha)	Carbon Electricity (gha)	GHG Total (t)	Total Energy (TJ)	Water (kgal)	Haz. Waste (st)
	230101	0.000	0.082	20919	0.443	0.005	0.603	0.000	0.000	0.00	8.29	48.00	7.69	200.00	3.16	216	0
End-of-Life phase	**331110**	0.445	0.306	32844	0.627	0.058	1.014	0.215	0.245	2.87	6.14	546.56	123.69	3669.30	51.02	20233	1450000
	33131A	0.676	0.349	31203	0.574	0.063	0.916	0.233	0.301	3.06	4.76	510.62	298.61	3303.36	48.06	37142	233000
	331420	0.583	0.331	32034	0.606	0.056	0.997	0.241	0.274	3.30	6.68	217.08	84.17	964.65	15.97	12935	334000
	327211	0.236	0.423	30176	0.528	0.041	0.992	0.164	0.140	5.44	5.71	443.78	105.47	2044.36	37.30	16690	320000
	325211	0.431	0.384	25825	0.537	0.066	0.510	0.247	0.277	3.02	55.21	435.45	94.45	2398.31	40.33	24632	5610000
	325212	0.445	0.321	34988	0.619	0.039	1.055	0.197	0.251	9.56	28.24	167.28	63.45	864.33	14.29	15336	1090000
	339910	2.368	0.308	36677	0.620	0.047	0.984	0.198	0.150	2.29	3.38	115.59	46.68	738.35	8.78	8045	240000

*GDP ($M) multiplier for each sector is equal to 1.00.

2.3.1. Vehicle and Battery Manufacturing

Vehicles and battery components are calculated separately to distinguish between battery and vehicle manufacturing impacts by using two NAICS sectors as presented in Table 2. The body of the vehicles was assumed to be identical since the price premium for alternative vehicles such as HEVs, PHEVs, and BEVs over a conventional vehicle primarily stem from the additional battery and electronics. Vehicle bodies considered in this analysis are assumed to be similar to an existing Toyota Corolla. Although there are other factors affecting this price premium such as design and manufacturing cost, the price and impacts of manufacturing a Toyota Corolla are used as a baseline for analyzing the manufacturing impacts of all vehicles. This assumption is consistent with Samaras's study (Samaras & Meisterling, 2008). After calculating the producer price (assumed to be 80% of the retail price) of a Corolla, this monetary input was multiplied by the associated impact multipliers provided in Table 3. It should be noted that all producer price values used in this analysis was converted to $2002, since the TBL-LCA model uses 2002 as a benchmark year.

In this analysis, the lifetime of the batteries and vehicles are assumed to be same, and the batteries are not replaced operation phase of the vehicles. In the case of the battery being replaced in the future, the impacts from battery production may not necessarily be doubled, since the battery industry is improving rapidly and the environmental impacts such as GHG emissions and energy consumption might be lower than they are today. Battery weights, specific power, and capacity are derived from the GREET 2.7 vehicle cycle model (Argonne Transportation Technology R&D Center, 2010; Burnham et al.,

2006), in which the vehicle configurations are calculated using Autonomie software (Autonomie, 2007; Elgowainy & Burnham, 2009) that is developed under U.S. DOE Energy Vehicle Technologies Program. After the battery weights and specific power requirements are calculated through GREET 2.7 model, the costs associated with production of these li-ion batteries are derived from Argonne National Laboratory's cost estimation study for li-ion batteries (Argonne Transportation Technology R&D Center, 2000). Once the manufacturing costs of each battery are obtained, these values are multiplied by the multipliers of associated NAICS sector provided in Table 3. Battery properties and associated cost values are presented in Table 4.

Table 4 Properties of Li-ion batteries for each vehicle type

Vehicle type	Battery weights (lb)	Battery energy outputs (kwh)	Cost per energy output ($2002/kwh)
ICV	0.0	0	0
HEV	41.2	28*	36.96*
PHEV10	119.2	4.0	201.94
PHEV20	208.5	7.0	201.94
PHEV30	387.3	13.0	201.94
PHEV40	536.3	18.0	201.94
BEV	821.3	38.0	201.94

2.3.2. Operation Phase

In the literature, the operation phase impacts associated with vehicles are calculated in two main stages: "well-to-tank (WTT)" and "tank-to-well (TTW)". While the former covers upstream impacts such as raw material extraction, fuel production and fuel delivery, the latter refers to direct impacts including tail pipe emissions and direct energy consumption during operation of vehicles (Elgowainy & Burnham, 2009). WTT impacts are calculated by utilizing sector multipliers of the TBL-LCA model presented in Table 3. The producer price ($) for one gallon of petroleum and/or for one kWh of electricity is used to calculate per mile fuel costs for each vehicle. Then, the impacts of supplying electricity or gasoline are calculated by multiplying the monetary value of per mile consumption by the associated sector multiplier. The fuel economy (FE) of ICV and HEV are assumed to be 30 and 50 miles per gallon (mpg), respectively, whereas the FE for PHEVs is assumed to be 50 mpg in gasoline mode and 0.29 kWh/mile in electric mode. FE values of these vehicles are similar to those of the Corolla and Prius models available in the market. Also, FE for EV is assumed to be 0.32 kWh/mile. The electricity required to travel a mile includes regenerative braking benefits as well as efficiency losses in the battery, charger, and electric motor. Although these vehicles are generic, the FE values are similar to their counterparts available in the market except for the PHEV20, PHEV30 and PHEV40 (Chevrolet, 2014; Nissan, 2014; Toyota, 2014a, 2014b, 2014c). TTW impacts are calculated using data from the U.S. Environmental Protection Agency (EPA) for direct energy consumption and GHG emissions (U.S. EPA, 2013; U.S. EPA Office of Transportation and Air Quality, 2006). TTW impacts are calculated only for the indicators

of GHG emissions and energy consumption since there is no other direct impact according to the selected indicators.

A calculation method is used for the PHEVs, since they use both electricity and gasoline. The portion driven with electricity is determined by utility factors (UF) for each PHEV. To calculate UFs, the national daily cumulative VMT distribution is constructed, which indicates the percentage of cumulative daily VMT less than a given distance per day. As the main objective is to estimate what percentage of daily travel can be powered by PHEV, their AER features determines this percentage. For instance, vehicles traveling less than 30 miles per day compromise approximately 63% of the daily VMT in the U.S. (U.S. DOT, 2009), which means the UF of PHEV30 is 0.63. The UFs for each PHEV are calculated based on the data obtained from 2009 National Household Travel Survey (NHTS) (NHTS, 2009). Through these calculations, the UFs for PHEV10, PHEV20, PHEV30, and PHEV40 are found to be 0.29, 0.5, 0.63, and 0.71, respectively. Hence, the total impacts for PHEVs can be calculated as follows;

$$(\text{Impacts per mile})_i = UF\big(FE_{\text{Elct.}}(\text{WTT impacts}_{\text{Power generation}})_i + (\text{TTW impacts})_i\big)$$

$$+ (1 - UF)\big(\frac{1}{FE_{\text{gasoline}}}(\text{WTT impacts}_{\text{gasoline production}})_i + (\text{TTW impacts})_i\big) \quad (4)$$

Where i= Different TBL indicators

In Eq. 4, the first part of the equation represents the impacts associated with electricity consumption, while second part represents impacts associated with the gasoline driven mode. For the EV calculation, the UF is equal to 1. When calculating the impacts of ICV and HEV, only the second portion of the equation is used since they use only gasoline. In other words, the UF for HEV and ICV are both equal to 0.

For Scenario 2, the electricity to power the EVs, and the electric mode portion of the PHEVs is generated through solar charging stations. Therefore, the impacts associated with the construction of a solar charging station are also quantified. Data for solar charging station including materials and installed capacity of power system are obtained from literature (Engholm, Johansson, & Persson, 2013). First, the amounts and corresponding monetary values for the materials are determined, and then multiplied by the associated sector multipliers provided in Table 3 to calculate TBL impacts such as the energy required to produce those materials. The first layer of the NAICS sector, "Other Nonresidential Construction", is used to calculate the impacts from the construction of the solar charging station. The total TBL impacts are then divided by the estimated total power generation to calculate impact per kWh of generation. The solar charging station is also assumed to be connected to the grid, and therefore transfers the electricity to the grid when it is not charging any vehicles (Engholm et al., 2013).

Another component of the operation phase to consider is the maintenance and repair (M&R) of the vehicles. The M&R costs are obtained from the U.S. Transportation Energy Data book (Transportation Energy Data book, 2012). The M&R costs for an EV and a

PHEV are approximately 65-80% of the M&R cost of an ICV, owing to fewer moving parts and components as well as lower maintenance requirements for electric motors in EVs (Delucchi & Lipman, 2001; Faria et al., 2013). In this analysis, the M&R costs of PHEVs are assumed to be 80% of that of the ICV, whereas M&R cost of the EV are assumed to be 70% of the ICV, and the cost for the HEV is assumed to be same as that of the ICV (Faria et al., 2013). After the M&R costs are determined for each vehicle, these monetary values are multiplied by the TBL multipliers of the associated sectors as provided in Table 3.

2.3.2. End-of-life Phase

The impacts of the end-of-life phases for the vehicles and battery are calculated by determining the savings from the recycled materials from each vehicle. The material composition of each vehicle and battery are derived from the GREET vehicle cycle model using the vehicle and battery weights and the percentage of each material (Argonne Transportation Technology R&D Center, 2010). Once the weights of each material are found for each vehicle, these materials are assumed to be credits. (Joshi, 1999). Basically, the net savings from the recycling of vehicle materials is the total TBL impacts of producing each recycled material minus the TBL impacts during the recycling process of the material. While the process impacts of the recycling process of each material are available in the literature for environmental impacts, no social or economic indicators were found, and there is no sector representing the recycling process of different materials in the TBL-LCA model. Therefore, the TBL impacts from the process of recycling are neglected. In other words, the end-of-life phase includes the credits from the recycled materials

provided in Table 2. Hence, in this study, the savings are less than the quantified end-of-life impacts. For more information about the quantification of end-of-life phase impacts using I-O methodology, please see the reference study (Joshi, 1999). Recycled materials for the batteries are copper, aluminum, and steel, and all of these materials are assumed to be 100% recycled (L Gaines & Nelson, 2010; Linda Gaines, Sullivan, Burnham, & Belharouak, 2010). Recycling rate for the vehicles are assumed to be 95% and the recycled materials are steel, aluminum, copper, plastic, rubber, and small amount of platinum (Argonne Transportation Technology R&D Center, 2010; Jody, Duranceau, Daniels, & Pomykala, 2011). Recycling rate of the aluminum is assumed to 90%, whereas other materials were each assumed to be recycled at a rate of 95% (EPA, 2013b).

2.4. Multi-objective Optimization Model

After each TBL indicator is quantified, the conflicting objectives are determined. GDP, employment, business profit, government tax, and income are the positive socio-economic impacts to be maximized, whereas all other economic, social, and environmental impacts are negative and must be minimized. MODM is critical to find the optimum allocation of alternative vehicle technologies to yield the best possible set of values for the objective. In order to achieve this goal, a Compromise Programming (CP) model, which is mostly used for solving multi-objective linear, nonlinear, or integer programming problems, is established to optimize the above-mentioned conflicting objectives. The CP approach, which was first introduced by Zeleny (1973), aims is to find a solution set closest to the ideal solution point in terms of some measures of distance. The solution procedure involves evaluation of subset of non-dominated solutions with a distance-based function

that measures how close these points come to the ideal solution. The distance-based function is presented in Eq. 5, where the La metric, representing the degree of closeness to the ideal point, is used to find the distance between the two points, Z_k^* and Z_k (x) (Chang, 2011).

$$L_a = \left\{ \sum_{k=1}^{p} \text{л}_k^a (Z_k^*(x) - Z_k(x))^a \right\}^{1/a} \tag{5}$$

Where $1 \leq a \leq \infty$, $Z_k^*(x)$ is the ideal solution for the objective k and Z_k (x) is a function of the objective k. The weight of each objective is represented by л and p is the number of objective functions. Considering that each objective has different units, normalization is needed to make the units commensurable. After the normalization process, a range from 0 to 1 will be given to the values. The normalization function is presented as follows (Chang, 2011):

$$Z = \frac{Z_K^* - Z_K(X)}{Z_K^*} \tag{6}$$

After the normalization step, the distance-based compromise programing equation can be written as follows:

$$\text{Min } L_a = \text{Min} \left\{ \sum_{k=1}^{p} л_k^a \left(\frac{Z_k^*(x) - Z_k(x)}{Z_k^*(x)} \right)^a \right\}^{1/a} \tag{7}$$

Subject to:

$$\sum_{k=1}^{p} л_k = 1, \qquad л_k \geq 0, \ and \quad 1 \leq a \leq \infty$$

In Eq. 7, Z_k^* values are obtained by optimizing objective functions individually. Also, the parameter $л_k$, which represents the weight of each objective function, reflects the relative importance of each objective from the decision maker's point of view. The optimization model is constructed based-on the mathematical structure of CP presented in Eq. 7. The model is presented as follows:

Index;

i : Sustainability indicator

m : Vehicle type

p : Number of vehicle types

k : Number of sustainability indicators

Parameters;

A_{im}: The impact of vehicle m for sustainability indicator i

W_i: The weight of sustainability indicator i

Decision variables;

X_{im}: The percentage of vehicle type m for sustainability indicator i

Objective functions;

$$Min\ Z_i(x) = \sum_{i=1}^{k} \sum_{m=1}^{p} W_i A_{im} X_{im} \qquad \textbf{(8)}$$

Subject to

$$\sum_{m=1}^{p} X_{im} = 1 \quad for \quad i = 1, 2, 3, \ \dots \ , r$$

$$X_{im} \geq 0 \qquad for \quad i = 1, 2, 3, \ \dots \ , r \quad and \quad for \quad m = 1, 2, 3, \dots \ , p$$

In total, there are 17 objective functions, in which positive impacts (Employment, income, GDP, business profit, and government tax) are manipulated by multiplying -1, after which all of the objective functions are minimized. The solutions of the multi-objective optimization problem are based on the shortest distance from the ideal point in geometrical sense, which is also known as the Euclidean distance. The relative weights of each environmental objective are obtained from Version 4.0 of the BEES (Building for

Economic and Environmental Sustainability) software which was developed by the National Institute of Standards and Technology (NIST) (Lippiatt, 2007). NIST collected data from a volunteer stakeholder panel to develop these set of weights. However, there were no separate weights for each of the land footprint categories analyzed and, therefore these are assumed to be identical. The weights of the environmental impacts and the mythology of their calculations can be found in the reference publication (Gloria, Lippiatt, & Cooper, 2007). On the other hand, there is no widely accepted consensus about the relative importance among the three dimensions of the sustainability and among the individual indicators within the social and economic bottom lines (Finkbeiner et al., 2010). Therefore, weights of socio-economic and environmental indicators ranges from 0 to 1 for socio-economic and environmental bottom lines and these weights are allocated to the indicators within these bottom lines based on the abovementioned assumptions and weights from NIST. Individual impact categories within the socio-economic dimension are assumed to be equally important. Finally, the optimization problem is solved for each weighting case.

CHAPTER THREE: SUSTAINABILITY IMPACTS OF ALTERNATIVE PASSENGER VEHICLES

Analysis results are presented in the following subsections based on quantified economic, social, and environmental impacts attributed to each life cycle phase for each of the two analyzed scenarios. Also, the alternative vehicle technologies are compared, and their optimum allocations within the U.S. passenger vehicle stock are presented based on the proposed scenarios and quantified TBL impacts.

3.1.   Economic Impacts

Economic impacts of the alternative vehicle technologies are presented in Fig. 2. The proposed scenarios don't affect the impacts of ICVs and HEVs and therefore, they are presented with single columns in the figure. Majority of the imports occur at the vehicle manufacturing phase, is responsible for 57-87% and 57-82% of the total imports in Scenario 1 and Scenario 2, respectively. The second highest importer phase is the operation phase, the imports share of which ranges between 13-31% in Scenario 1 and 3-20% in Scenario 2. On the other hand, the savings due to vehicle and battery end-of-life phases range from 1% to 3%. The contribution of battery manufacturing to imports is highest for the BEV with 15% of its total life cycle imports. While the ICV yields the highest import value in Scenario 1, BEV dominates in Scenario 2 due to high imports resulting from the purchase of solar modules to be used in solar charging stations. It is important to highlight that constructing solar charging station increased the imports of PHEVs and EVs significantly because of the imported solar modules to be used in constructing the solar

charging stations proposed by Scenario 2. Solar modules account for 98% of the imports needed to construct a solar charging station. The rest of the materials such as steel, concrete, fibreboard accounts for only 2%. Hence, if the negative impacts associated with Scenario 2 are aimed to minimized, the solar charging station should be manufactured domestically. It should be noted that import impacts associated with existing conditions, which refers to Scenario 1, shows that imports made in operation phase of ICV is much higher than that of alternative vehicle technologies and switching to renewable energy sources does not fix the issue but instead makes the situation worse.
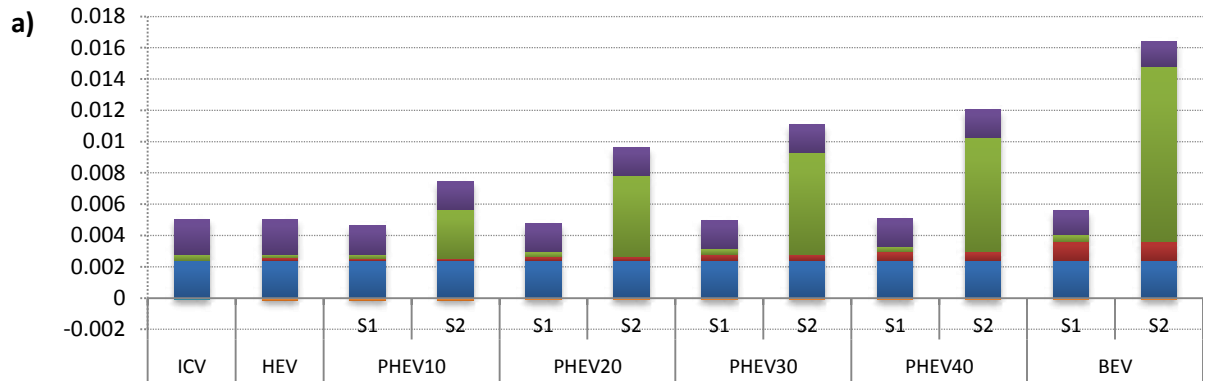
Figure 2 Economic impacts of alternative vehicle technologies: **a)** Foreign Puchase ($ per mile), **b)** Business Profit ($ per mile), **c)** GDP ($ per mile)

In the business profit and GDP impact categories, alternative vehicle technologies appeared to be more profitable and contribute more to the GDP than the ICV. Furthermore, Scenario 2 increases the contribution of PHEVs and BEVs significantly due to the construction of solar charging stations. In the business profit category, the total contributions of vehicle and battery manufacturing are more than the 50% of the total profit in Scenario 1. On the other hand, the operation phase dominates in Scenario 2 with more than 40% of the total. M&R is also important contributor for both business profit and GDP. End-of-life phases do not have a significant impact in either of these impact categories. The BEV has the highest contribution to GDP and business profit in both scenarios. Powering BEVs with solar charging station increased the contribution of BEVs to GDP and business profit approximately by factors of 1.5 and 1.7, respectively. Hence, the positive impacts of electric vehicles on GDP and business profit can be increased significantly by constructing solar charging stations to power PHEVs and EVs.

3.2. Social Impacts

Social impacts of the vehicles are presented in Fig. 3. In the terms of the contribution to employment and income, the contributions are relatively close to each other in Scenario 1, whereas the contributions increase significantly if solar charging stations are built to power EVs and PHEVs. The main reason for this is the employment generated as a result of construction activities, with almost 80% of the employment increase coming from the construction of new solar charging stations. On the other hand, vehicle manufacturing and M&R are the highest contributing phases for employment and income compared to other phases in Scenario 1. In both scenarios, the BEV has the highest

contribution to the employment and income impact categories. The contribution of battery manufacturing ranges phase between 3% (HEV) to 22% (BEV) in the employment and income impact categories. On the other hand, government tax draws a completely different picture due to the government incentives (federal tax credits) allocated for the purchase of PHEVs and EVs. These credits are given at the time of purchase and therefore, it is associated with the automobile manufacturing phase. The taxes collected throughout the life cycle of the vehicles are highest for the ICV, and vehicle manufacturing played the most crucial role in this category for every vehicle, while the M&R phase is the second highest contributor to taxes after vehicle manufacturing. On the other hand, when the operation phases of the vehicles are compared, the alternative vehicles PHEVs and BEVs generate more taxes than the ICV in both scenarios. Based on the employment, income, and tax impact categories, the construction of solar charging stations is a favorable strategy to maximize these positive impacts. However, injuries during the operation phase of the BEV make up 70% of its life cycle in Scenario 2 due to the construction of solar charging stations. The injuries resulting from the life cycles of BEVs are highest in both scenarios. In Scenario 1, injuries associated with automobile manufacturing contribute the most to injuries with up to 61% of the total, the second highest contributor being the M&R phase.
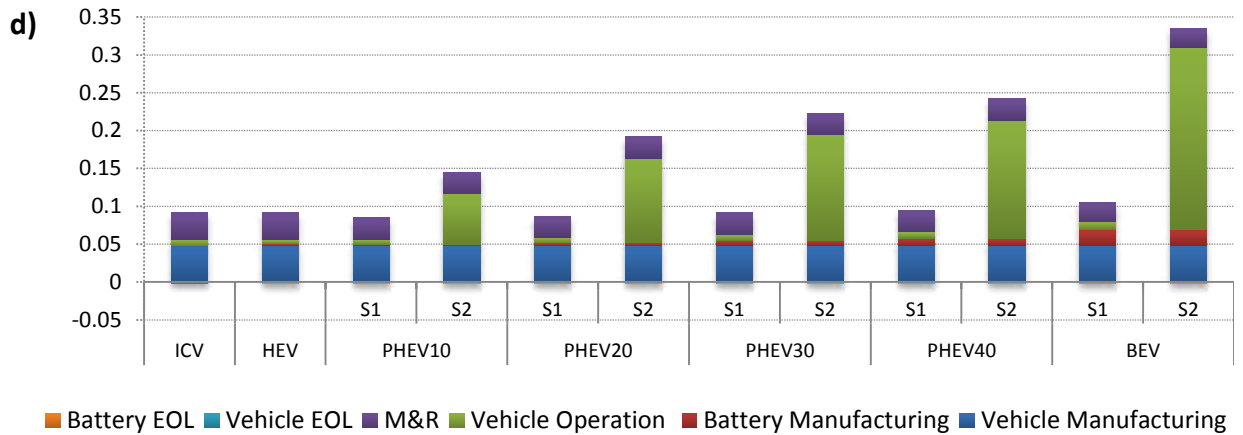
d)
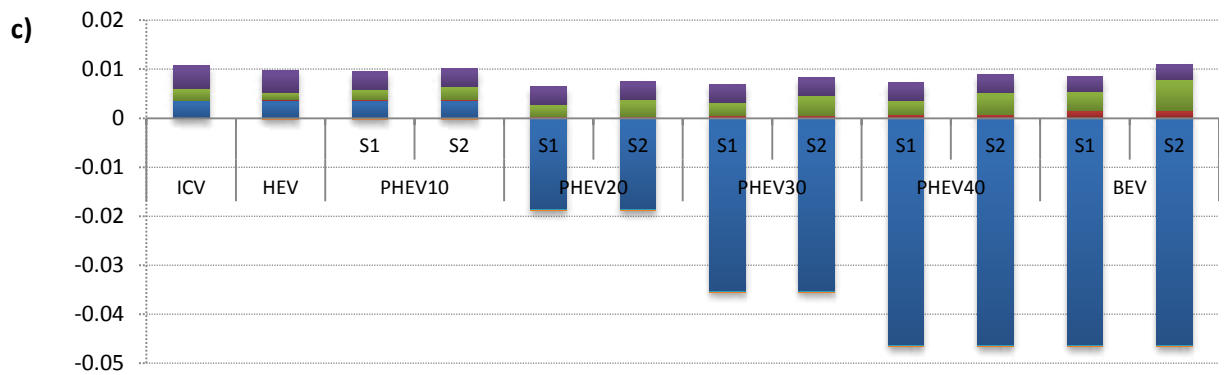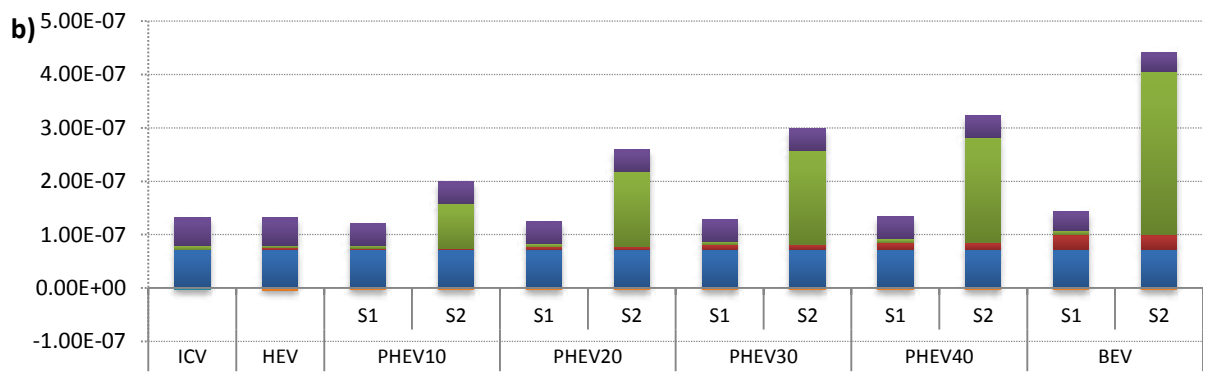
Figure 3 Social impacts of alternative vehicle technologies: **a)** Employment (hr per mile), **b)** Injuries (#worker per mile), **c)** Government Tax ($ per mile), **d)** Income ($ per mile)

3.3. Environmental Impacts

Fig. 4 shows the environmental impacts of the vehicles. The vehicle operation phase is the most dominant phase in all of the environmental impact categories. The ecological land footprint impacts are presented as accumulations of the five land footprint categories. The ICV has the highest impact in almost all of the environmental categories except for water withdrawals. The HEV has the second highest ecological land footprint impact, after the ICV. The ecological land footprint of BEVs is slightly higher than that of PHEVs in both scenarios. Powering EVs and PHEVs through solar charging stations slightly reduced their ecological land footprint. In Scenario 2, GHG emissions of the BEV is second highest after the ICV due to the GHG emission intensity of electric power generation sector in the U.S. Powering EVs via solar charging stations could reduce its GHG emissions up to 34%. This reduction potential is relatively less in PHEVs, for which

it ranges between 9% to 23% depending on AERs and UFs of each PHEV. Per mile energy consumption of vehicles is relatively similar to GHG impacts. It is because of the high correlation between energy consumption and GHG impacts due to the fossil fuel dependency in power generation sector. The second highest energy consumption impacts come from the BEV, and these impacts are relatively closer to each other compared to their GHG impacts. The least energy intensive vehicle option is the HEV in Scenario 1, whereas the energy performance of the PHEV10 is better than rest of the vehicles in Scenario 2. The energy consumption of BEVs and PHEVs can be reduced up to 14% by powering them with solar charging stations. The only environmental impact category that favors ICVs against alternative vehicle technologies is the water footprint. The BEV is the most water intensive vehicle type in both scenarios. However, the water footprint of the BEV can be reduced by up to 85% of their operation phase water footprint by powering them with solar charging stations. While a majority of the water footprint of BEV and PHEVs is attributed to operation phase, water footprint of manufacturing and end-of-life phases are relatively much smaller. Also, hazardous waste generated through the life cycle phases of alternative vehicles are highest for ICVs in Scenario 1, with 71% generated in the operation phase of the ICV. Although the BEV generates the least hazardous waste in Scenario 1, it became the worst alternative in Scenario 2 in terms of hazardous waste the construction and manufacturing the materials of solar charging station, which respectively account for 62% and 34% of the total hazardous waste generated to build a solar charging station.
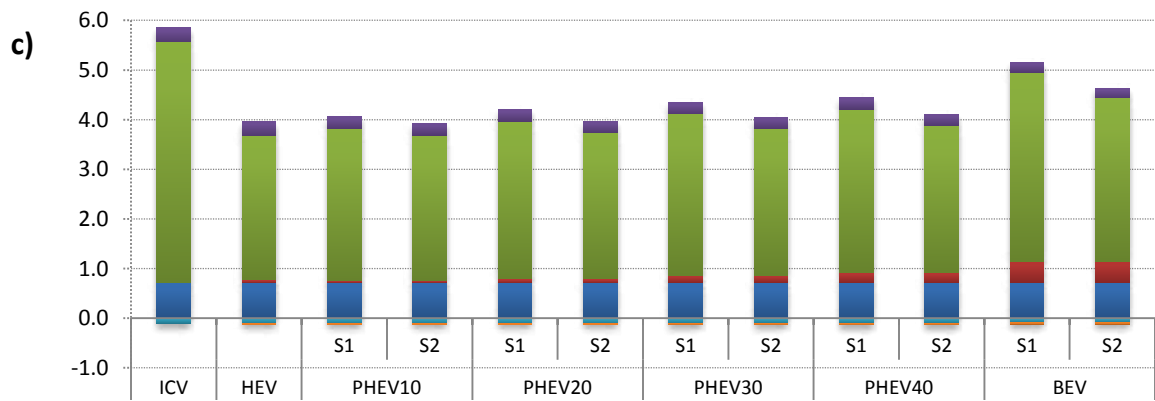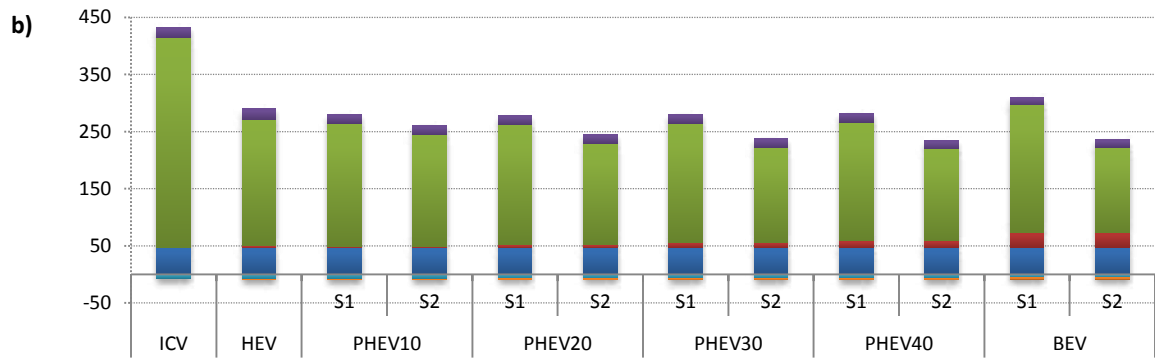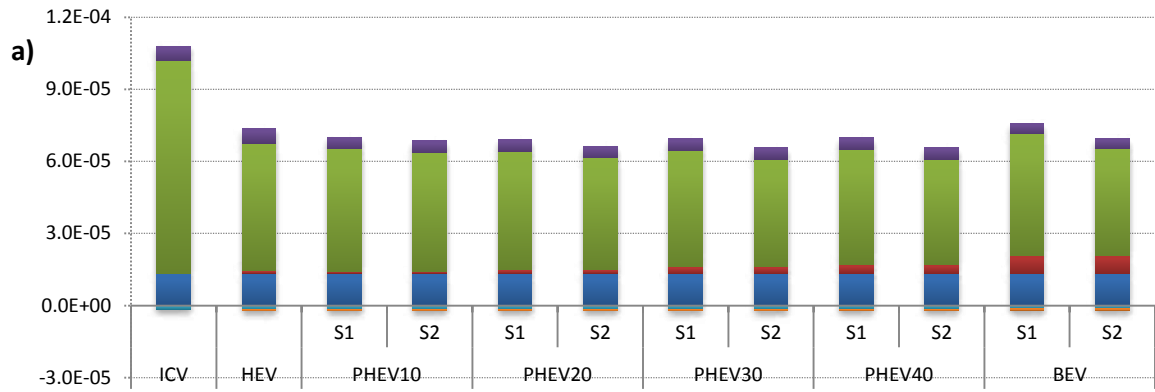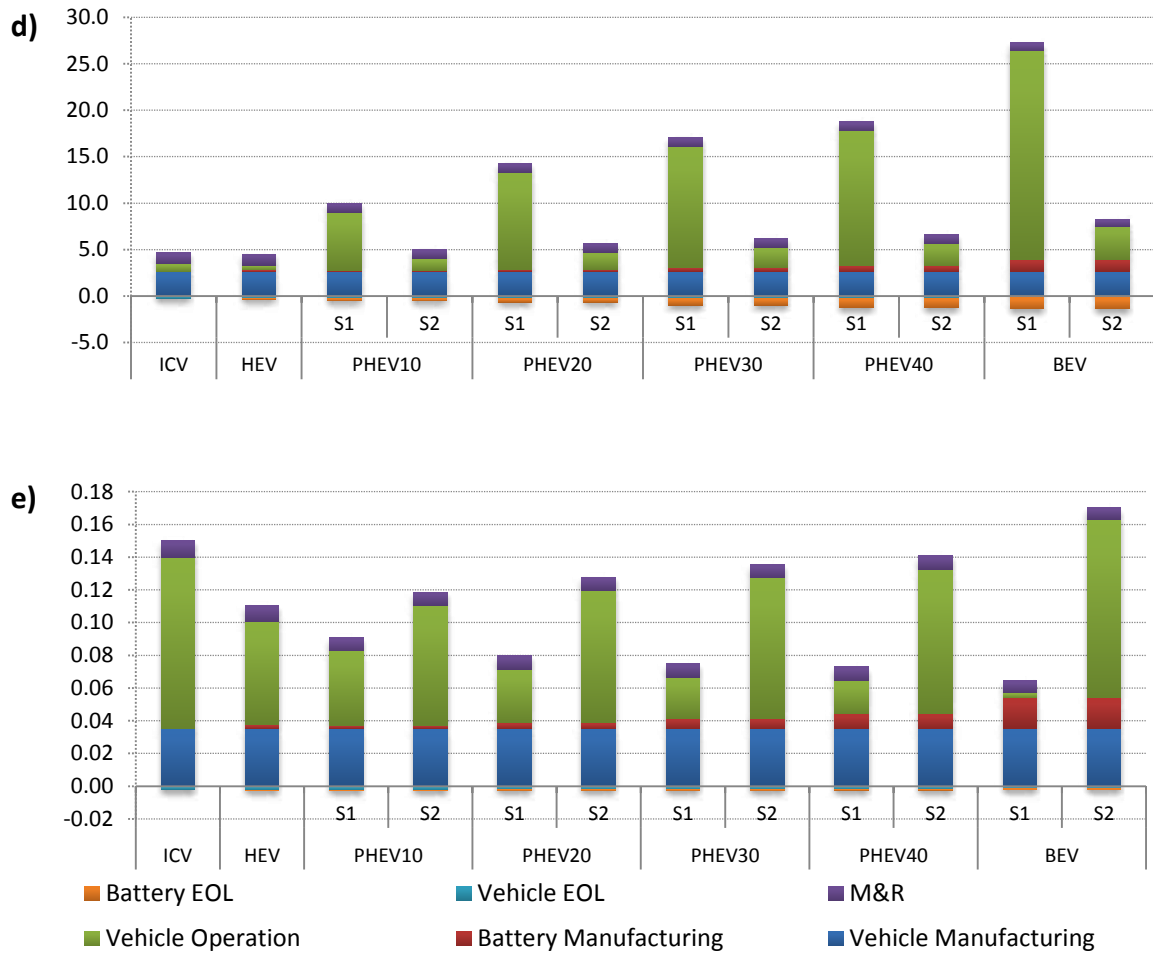
Figure 4 Environmental impacts of alternative vehicle technologies: **a)** Total ecological land footprint (gha per mile), **b)** GHG emission (gCO$_2$-eqv per mile), **c)** Energy consumption (MJ per mile), **d)** Water withdrawal (lt per mile), **e)** Hazardous waste (st per mile)

3.4.   Comparison of Alternative Vehicle Technologies

In addition to the above-mentioned analyses and, the total life cycle TBL impacts of the vehicle alternatives are compared for Scenario 1 and Scenario 2, and the results are shown in Figure 5. Each vehicle's pattern in the spider diagram indicates its relative contribution to or impact on each TBL category. Figure 5 highlights the anomalies where the indicators are significantly higher or lower compared to one another on the spider diagrams, depicting the relative performance of all alternative vehicle technologies in one integrated diagram. As can be seen from the figure, for most of the impact categories, the two extreme lines were represented by either the BEV or the ICV, while all other vehicle types were relatively close to each other in terms of their benchmarked impacts. However, the relative sizes of the impact differences are shown to increase considerably in Scenario 2. Although this representation allows policy makers to make a better comparison, when it comes to selection of alternative vehicles, the selection process requires a multi objective decision making framework. Hence, the following section focuses on the optimum allocation of these vehicle technologies.
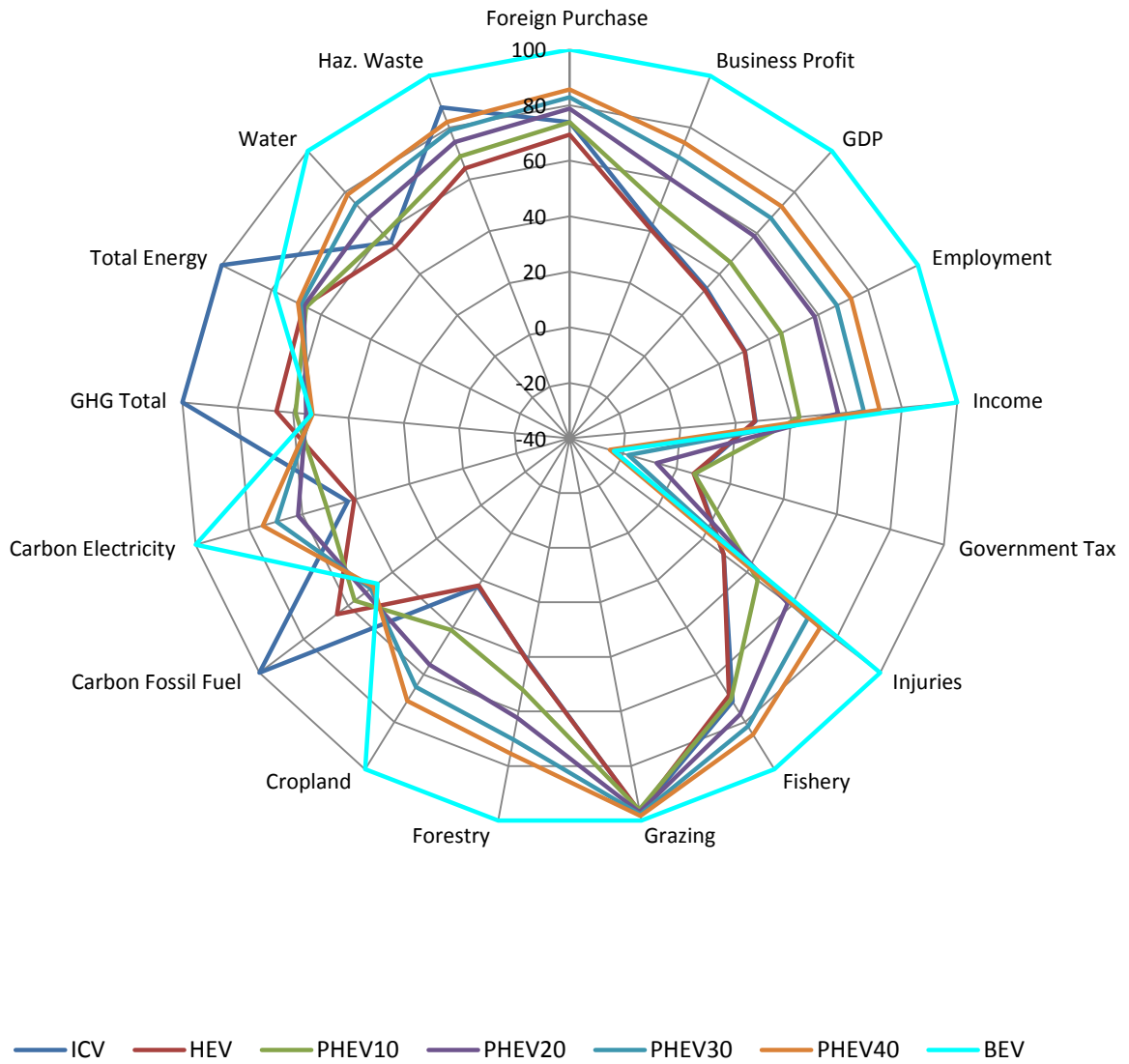
a)
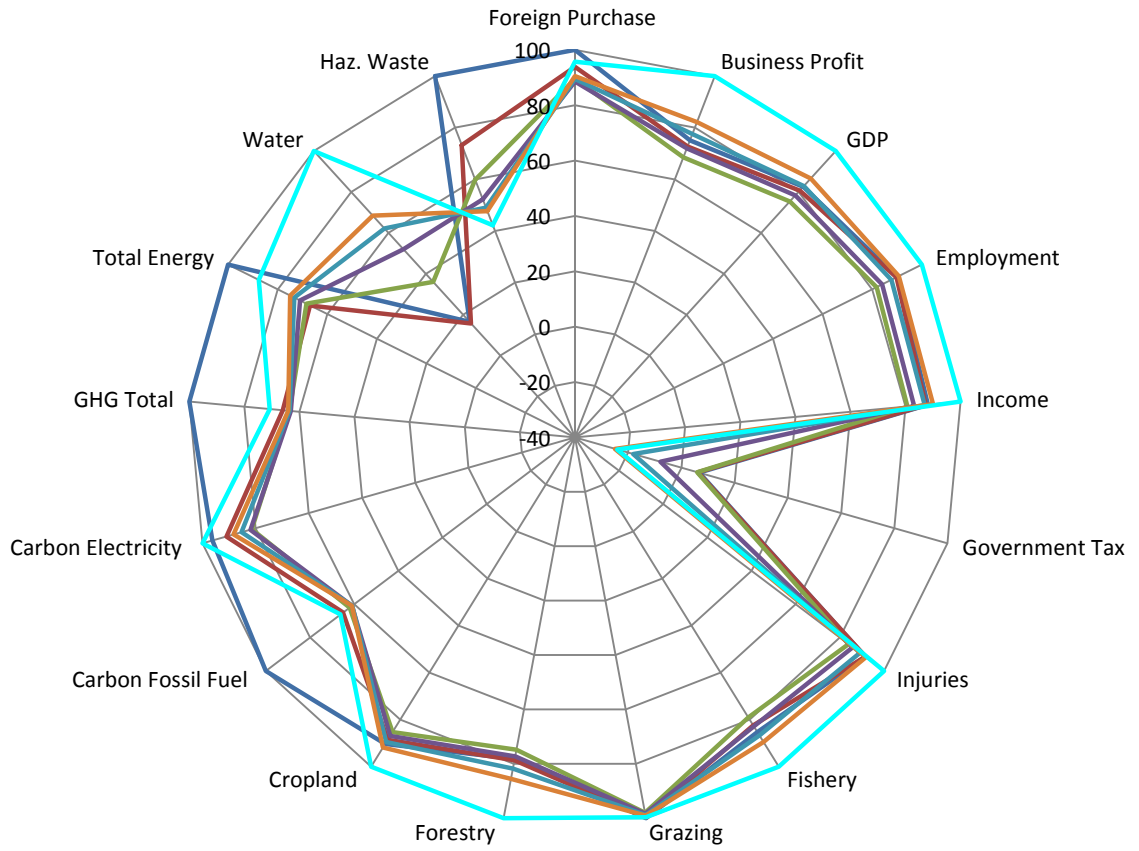
b)

Figure 5 Comparison of alternative vehicles; **a)** Scenario 1, **b)** Scenario 2

CHAPTER FOUR: OPTIMAL DISTRIBUTION OF ALTERNATIVE VEHICLE OPTIONS

4.1. Optimal Distribution of Alternative Vehicle Options

The optimal distributions of the evaluated alternative passenger vehicles are presented in Fig. 3 for Scenarios 1 and 2. In order to account for variability in decision maker's priorities, the weights of the environmental and socio-economic impacts are ranged between 0 and 1. This weighting scenario give flexibility to decision-makers by assigning varied weights for sustainability indicators based on their priorities. For instance, when decision maker gives 100% weight to environmental impact category, the overall weight of environment impacts (represented by ENV) will be 1 and the weight of socio-economic impacts (represented by SE) will be zero. When decision makers give the same weight for environmental and socio-economic impacts, the weights will be equally distributed to both impact categories as 50%. As presented in Fig. 3, the HEV is found to have the highest distribution rate in Scenario 1. In addition, when compared to HEV, the PHEV10 is selected in small percentages until the weight of environmental indicators is reduced to 0.2 percent. When the weight of environmental indicators is 1 in Scenario 1, the optimum distribution of vehicles is composed of the HEV with 88% and the PHEV16 with 12%. On the other hand, in Scenario 1, most of the PHEVs are not selected. In a balanced weighting case in Scenario 1, where the environmental and socio-economic indicators have equal importance, the HEV accounts for 91% of the vehicle distribution, whereas the

PHEV16 comprises only 9% of the vehicle fleet. When SE weights are higher than 0.6, PHEV is not given any share of the vehicle fleet distribution; this highlights how the existing characteristics of the power generation sector do not favor electric vehicles in most cases, and the real vehicle distribution is similar to the result where the weight of socio-economic indicators is set to 1. Hence, the model favors the vehicle alternative using gasoline in the most efficient way; among the proposed alternatives, this corresponds to the HEV. In 2013, almost 100,000 PHEV and BEV were sold in the U.S. however the net market share of electric vehicles is less than 1% (Hybrid Cars, 2014). In order to meet the President Obama's sustainable transportation goal of one million electric vehicles in the U.S. fleet by 2015, the market share should be increased from 1% in 2013 to roughly 6 % of the automobile market (Rascoe and Seetharaman, 2013). Based on our findings, the BEV is selected for distribution only when the weight of socio-economic indicators is 1, in which case its share is as low as 0.5% while the rest of the vehicle distribution is composed of ICVs. On the other hand, as an alternative vehicle option, the optimal distribution of HEV is found to be over 90% for most of the weighting scenarios. Hence, it is important to note that with the existing electric power generation mix, various forms of policy incentives such as tax credits and carpool lane access might be given to HEV to making it more attractive to consumers and promote the adoption of HEV nationwide (ICCT, 2014).
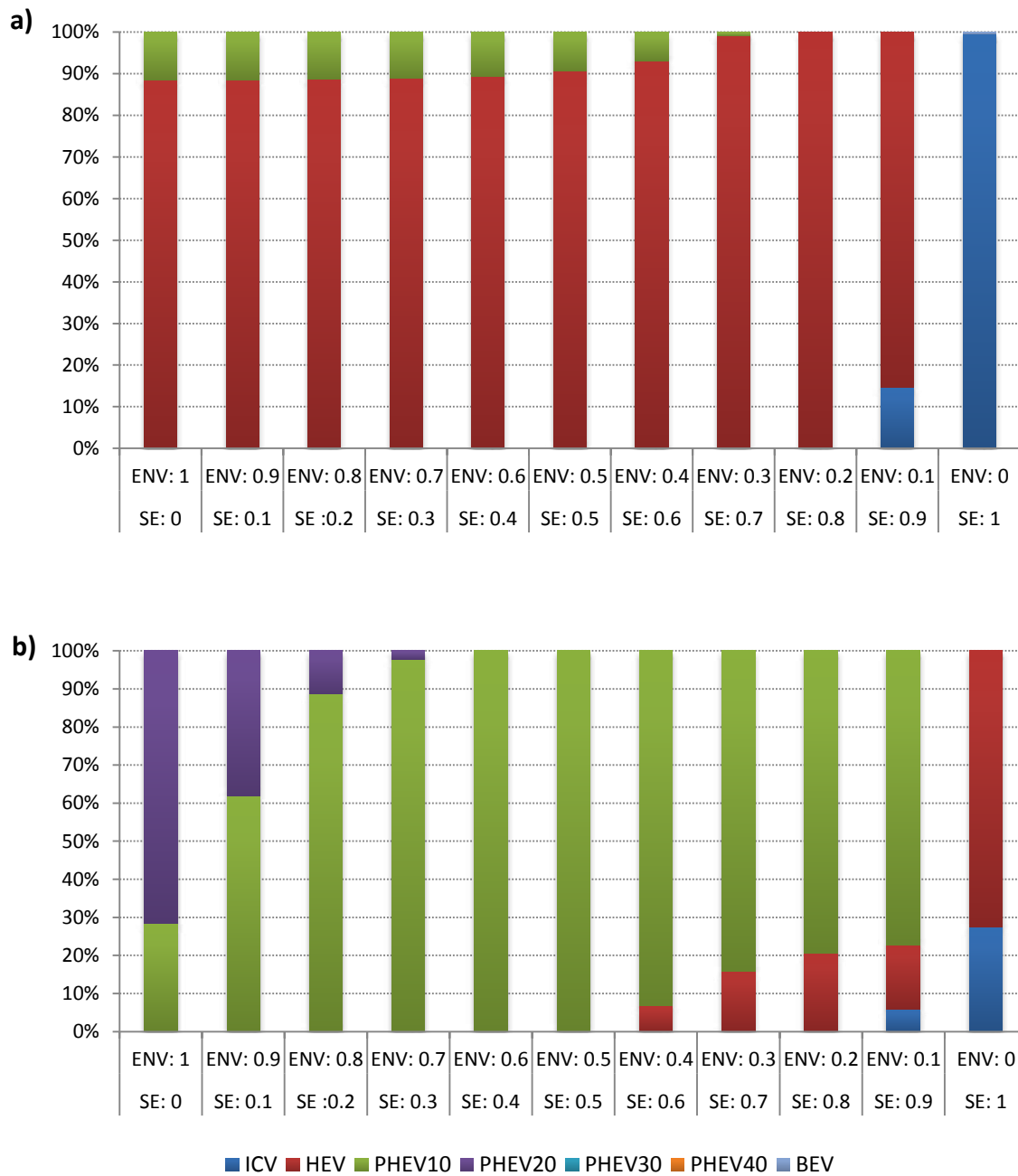
Figure 6 Optimum distribution of alternative vehicles: **a)** Scenario 1, **b)** Scenario 2

In Scenario 2, the model selects more vehicle types for fleet distribution, but the PHEV30 and PHEV40 are not selected in any of the weight combinations. The PHEV10 is the most often selected vehicle option in this scenario. In fact, in a balanced weighting situation (where environmental and socio-economic indicators are deemed equally important), 100% of the optimum vehicle distribution is given to the PHEV16. In another case, where the environmental indicators are assigned a weight fraction of 1, 72% and 28% of U.S. passenger cars are allocated to the PHEV20 and the PHEV10, respectively. When socio-economic weights increased from 0.6 to 1, the HEV's vehicle distribution share started to increase. In the other extreme case, in which socio-economic indicators are assigned a weight fraction of 1, only the HEV and the ICV are selected, with distribution percentages of 73% and 27%, respectively.

It should be kept in mind that Scenario 2 is an extreme case where 100% electricity demand of PHEV and BEV is supplied by solar charging stations. However, this scenario still gives a vital guidance for regional policy making where solar charging stations become the first option among the charging alternatives. Obviously, the most realistic case is represented by Scenario 1 where the existing power generation infrastructure is used when determining the optimal distribution of vehicle technologies in the U.S. fleet. Hence, government incentives for HEVs seem to be more realistic and effective strategy to have more balanced sustainable transportations policies in terms of environmental performance and socio-economic development. For the administration to meet its 2015 goal for electric vehicles, electrified vehicles would have double their market share; however demand for hybrids and electric vehicles has been weaker than expected. As of today, HEVs, PHEVs

and BEVs account for only 3.3 percent of the total automobile market in the U.S. (Hybrid Cars, 2014). The optimization model results clearly indicate that there is a strong need for significant changes in government incentives for electric vehicle sales and consumer behavior to reach the optimum vehicle distribution scenarios suggested by MCDM model.

4.2. Trade-off Relationships Between Objectives and Bottom Lines

The trade-off relationships between some of the conflicting objectives are presented to give more insight about the results. Fig. 4 shows the trade-off relationships between contribution to GDP and a set of environmental impacts such as GHG emissions, energy consumption, water consumption, and ecological land footprint. All of the impact categories are based on the functional unit (per mile impacts of the vehicle mix). The relationship between other socio-economic benefits (business profit, employment) and the abovementioned environmental impacts have very similar trend with the relationships presented in Fig. 4. Hence, these trade-offs are not separately presented. Environmental impacts of maximizing contribution to GDP are relatively lower for Scenario 1, in which slope of Pareto curves are higher compared to those of Scenario 2. In other words, Scenario 1 provided more efficient results. The results showed that as we allowed more environmental impacts, contribution to GDP increases, and the vehicle mix changes considerably. The change in vehicle mix is more rapid for the conflicting objectives of employment and the environmental impacts compared to those of GDP and environmental impacts. The trade-off curves can be used in several ways to inform policy makers. One of the ways can be setting upper limit for the environmental impacts considering their positive socio-economic impacts. For instance, in Scenario 1, when the CO_2 emissions are allowed

to increase from 270 to 275 gCO$_2$ per mile, the contribution to GDP is extra \$0.018 per mile. However, when the C0$_2$ emissions are allowed to increase from 275 to 280 gCO$_2$ per mile, the extra contribution to GDP is about 5 times less, \$0.004/mile. Similar pattern is observed for conflicting objectives of GDP and ecological land footprint. On the other hand, a majority of the tradeoff curves are straight linear lines and they do not allow such interpretation.
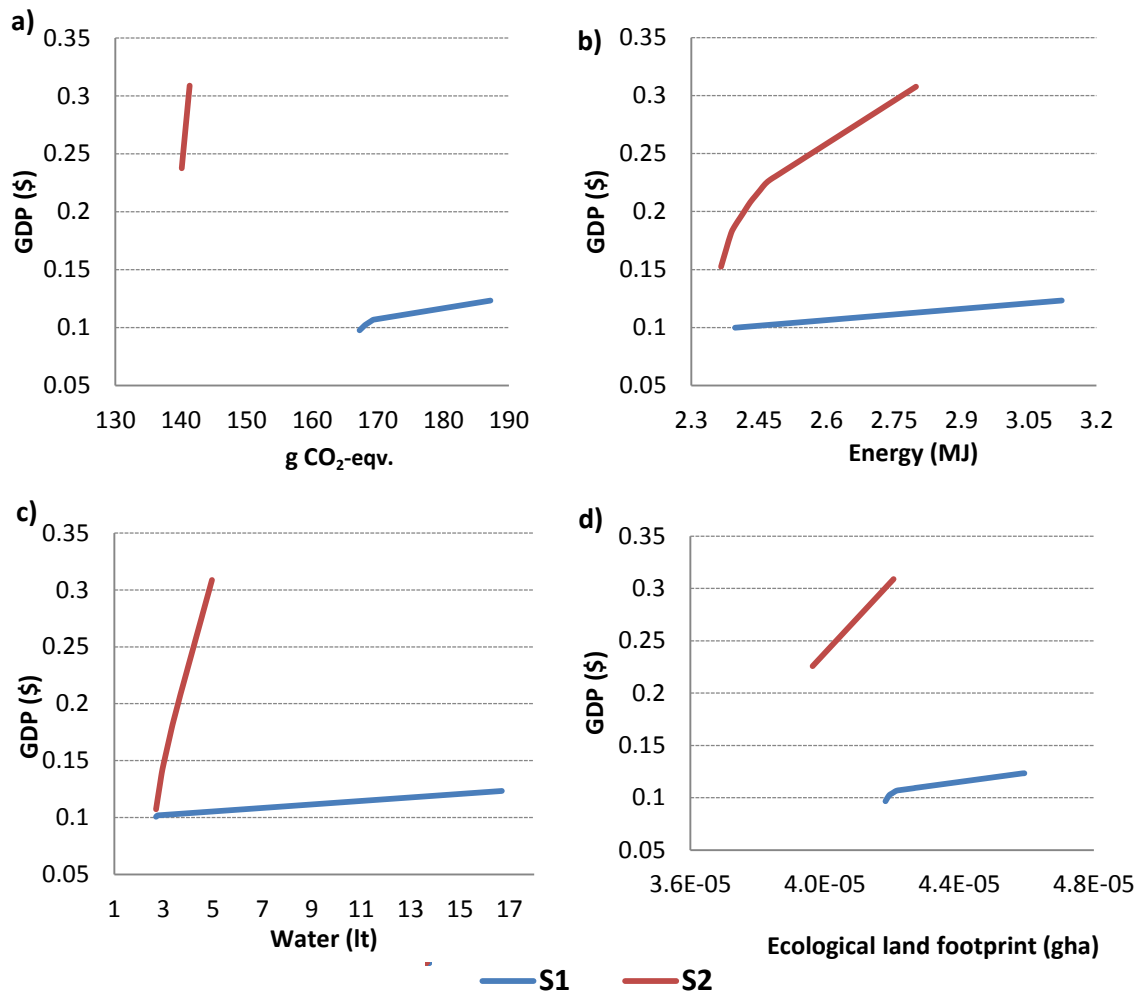
Figure 7 Trade-off relationship between GDP and environmental impacts

Additionally, the trade-off relationships between the bottom lines are also shown in Fig. 5. Environmental, economic, and social indicators are normalized to obtain the impact ranging from 0 to 1. Economic and social impact index indicates the benefits, whereas the environmental impact index represents negative environmental impacts. In other words, while economic and social impact indexes indicate better sustainability

performance when their values are higher, environmental impact index indicates better sustainability performance when its value is lower.
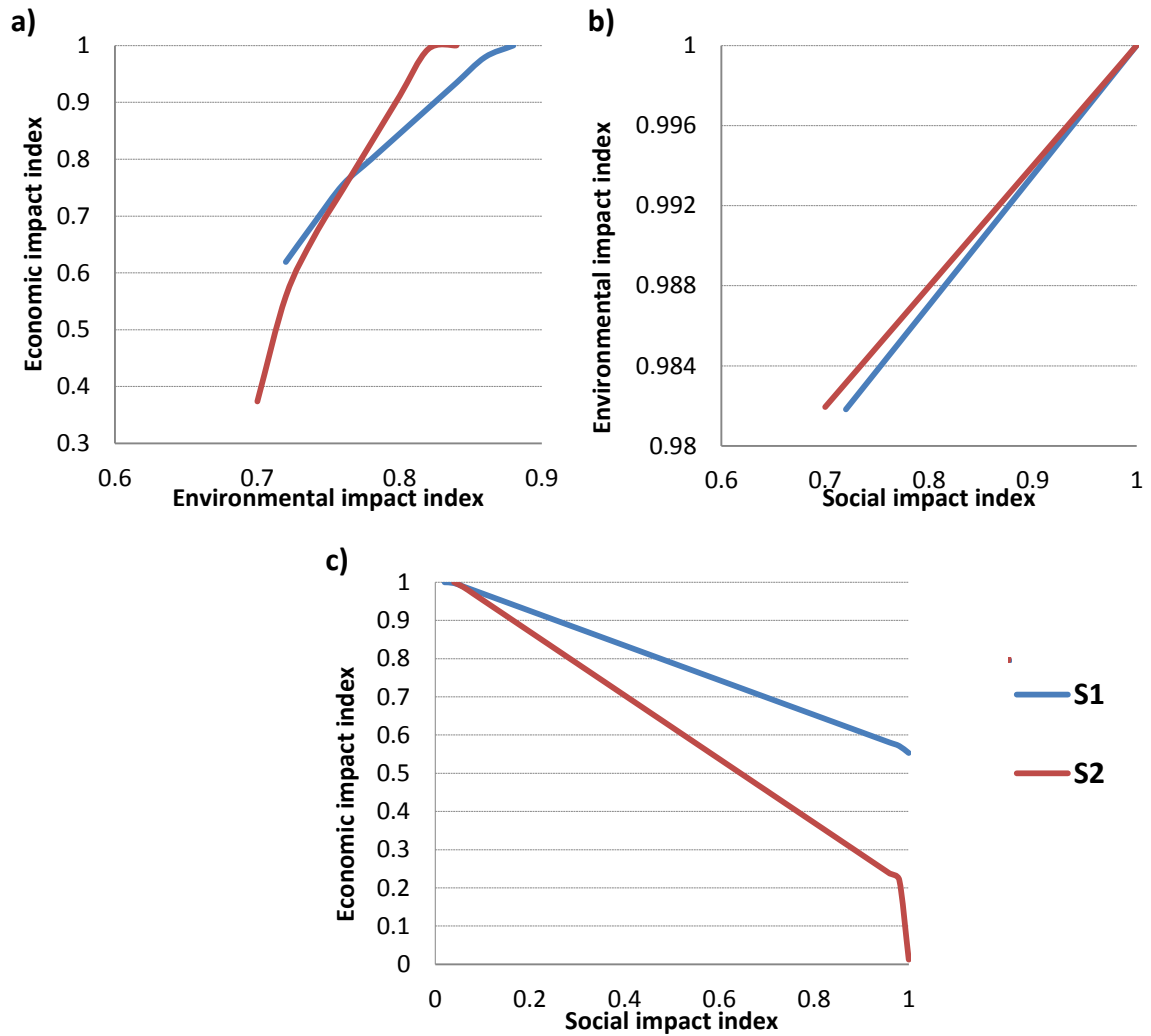

Figure 8 Trade-off relationship between TBL impacts

CHAPTER FIVE: CONCLUSION

5.1.   Summary of Findings

This paper presented a novel decision making framework by combining both LCSA and compromise programming methods in order to advance the-state-of-the-art in LCSA of alternative passenger cars and the state-of-the practice in U.S. passenger transportation sustainability. Most of the reviewed studies concentrated more on the limited environmental implications of vehicle life cycles by ignoring the macro-scale socio-economic impacts. 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 LCSA framework to make economically viable, socially acceptable, and environmentally benign policies towards achieving sustainability for future transportation systems. However, until now practical use of LCSA in sustainability research and environmental policy making is very limited (Van Der Giesen et al. 2013; Zamagni et al. 2013). Hence, the fundamental methodological contributions of this paper are (a) to extend a system boundary of LCSA framework to the national economy (called a macro-level or economy-wide sustainability assessment in Guinee et al. 2011), (b) analyze the trade-offs between the life cycle sustainability indicators, and (c) provide a practical decision making platform for policy makers considering the conflicting environmental, social and economic objectives, simultaneously.

The findings of this research provide important insights for policy makers when developing strategies to estimate optimum vehicle allocation strategies based on various environmental

and socio-economic priorities. For instance, compromise programming results can present practical policy conclusions for different states which might have different priorities for environmental impact mitigation and socio-economic development. Therefore, the conceptual framework presented in this work can be applicable for different regions in U.S. and decision makers can generate balanced policy conclusions and recommendations based on their environmental, economic and social constraints. This research also highlights the usefulness of a joint use of MCDM models and a LCSA framework. The compromise programming results provide vital guidance for policy makers when optimizing the use of alternative vehicle technologies based on different environmental and socio-economic priorities. Hence, this research aimed to increase awareness of the inherent benefits of I-O based LCSA and constrained optimization. Based on the research findings, the following conclusions are highlighted:

❖ The most critical recommendation of this research is that concentrating on the environmental aspects of the sustainable transportation problem might be misleading for policy makers and compromise social and economic benefits while trying to diminish environmental impacts. The results of the distribution model also showed that, as environmental and socio-economic priorities are changed, there is a significant change between optimum vehicle use strategies.

❖ The results for Scenario 1 also indicate that, when environmental indicators have more importance, HEVs are favored. On the other hand, if only socio-economic aspects are considered, ICVs are preferred over other vehicle alternatives. In

Scenario 2, when environmental indicators have higher weights than socio-economic indicators, PHEV10s and PHEV20s are preferred, and when the opposite is true, HEVs and ICVs are also selected by the optimization model.

❖ Trade-off analysis results indicate that, when policy makers have higher tolerance to more environmental impacts, contribution to GDP increases, which in turn changes the optimal vehicle mix considerably.

❖ When looking more closely at the results of this research, especially the findings of the optimization model, it is likely to conclude that there is a strong need to restructure the current power generation and supply infrastructure in the U.S in order to achieve more balanced sustainability performance goals in the future. This is because the current state of the U.S.'s power generation infrastructure does not support the widespread adoption of PHEVs and BEVs under the assumptions made for the indicators selected by this study.

❖ Sustainable transportation policies aiming to promote the widespread adoption of PHEVs and BEVs fail to address important social and economic impacts associated with the vehicles' life cycles. For instance, affordability and accessibility are still among the most critical socio-economic constraints hindering the adoption of electric vehicles in U.S. 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". Also, accessibility to fast charging facilities still remains other challenge to make electric vehicles a strong choice for consumers and the relatively small number of large-scale vehicle-charging stations makes recharging electric vehicles inconvenient (NSF, 2015). In addition, the optimum vehicle distribution results in Scenario 1, regardless of the weight allocation of environmental and socio-economic metrics, never suggest the use of these vehicle technologies due to current environmental limitations observed in the power generation sector, such as carbon-intensive power generation, high water dependence, lower energy efficiency to power the vehicles, etc.

❖ Overall, determining the optimum mixture of vehicle options in the U.S. is a dynamic problem in and of itself, and so finding the best possible solution requires multi-stage solutions and futuristic scenario evaluations. It is also important to note that the calculated UFs are all national averages, and that driving patterns vary from region to region; thus, the quantified impacts of PHEVs might be different in different regions. Driving conditions can also significantly affect the outcome of future analyses, since the fuel efficiency of each vehicle is related to driving behavior and cycles (Karabasoglu & Michalek, 2013; Raykin et al., 2012).

5.2. Thesis Limitations and Future Work

Although this paper presented a novel approach combining I-O based LCSA with MCDM for alternative vehicle sustainability research, the authors suggest the following solutions to the current limitations of their methodology:

❖ First, this paper used a high-sector resolution single-region I-O model that is not capable of capturing global trade-links between trading partners. Therefore, there is a strong need for certain improvements to develop more effective and accurate framework. First, although we used the most detailed I-O tables worldwide (discerning 426 economic sectors of U.S economy), the level of aggregation in I-O tables is still a critical point that needs to be addressed for a hybrid LCA approach. The findings of recent studies also showed that the disaggregation of I–O data is superior to aggregating environmental data for determining I–O multipliers and minimizing uncertainties found in LCA results (Lenzen, 2011; Steen-Olsen et al. 2014; Weinzettel et al. 2014). Therefore, the authors propose to extend the current analysis with high country and sector resolution MRIO. This level of disaggregation is critical for the analysis of alternative electric vehicles, which require large amounts of vehicle and battery parts and imported solar infrastructure materials. Among the MRIO initiatives, the EXIOPOL covers the 27 EU member states as well as 16 non-EU countries (Tukker et al. 2009). This global MRIO database seeks to obtain detailed information on economic sectors and differentiates 129 sectors. The EXIOPOL uses detailed sector and product accounts

compared to other MRIO databases, but the current version used 2000 I-O data, and there is no socio-economic integration with the current database.

❖ Second, a novel integrated application of TBL-LCA and MCDM is presented as a sustainability assessment framework to evaluate alternative passenger cars in the U.S. With future developments in I-O research, better models that encompass temporal and spatial variations can be introduced, and better frameworks can be presented in the future. For this purpose, the inclusion of a system dynamics perspective can lead to a better understanding of system behavior and improve the effectiveness of future policies (Onat et al. 2014d). Understanding system behavior is essential to reveal the dynamic relationships between the various social, economic, and environmental impacts associated with the adoption of alternative vehicle options, since the transportation sector and the adoption of alternative vehicles each involve a series of interconnected causal relationships that will need to be analyzed from a systems thinking perspective.

❖ Third, although uncertainties related to be power generation is partially covered by proposing two extreme scenarios, there are other sources of uncertainties which are not addressed in this study. Especially, uncertainties stemming from temporal and spatial variations such as effects of driving patterns and behaviors on fuel economy, charging time and location, battery performances, and regional TBL impact variations in associated sectors can affect the results of this study significantly. As the data availability and methodological approaches are improved, these

uncertainties should be addressed along with the integrated TBL dimensions and system dynamics modeling.

❖ Fourth, the current paper selected important social indicators that can be integrated with I-O analysis for a holistic LCSA. It is important to note that the social impacts of alternative passenger transportation are not limited to injuries, employment, income, and taxes, and so the authors also suggest an integration of several key social indicators into the LCSA of electric vehicles in the U.S., such as quality of life, employment by income and gender group, security and safety, health effects, affordability, equity, etc. Also, inclusion of mid-point environmental indicators such ozone depletion potential, acidification, etc. can enrich the results and interpretation of LCSA studies along with a greater number of social and economic indicators. The social LCA method (S-LCA) is still in its infancy and faces challenges due to methodological inconsistencies, lack of consensus for the selection of social parameters, and difficulties in data collection for specific processes. Therefore, substantial analytical research should be performed in order to make S-LCA more applicable within the LCSA of sustainable transportation (Jeswani et al. 2010; Onat et al. 2014b).

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