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Development of Regional Optimization and Market Penetration Models For Electric Vehicles in the United States

Mehdi Noori
University of Central Florida, mehdi.noori7@gmail.com

DEVELOPMENT OF REGIONAL OPTIMIZATION AND MARKET PENETRATION MODELS FOR THE ELECTRIC VEHICLES IN THE UNITED STATES

by

MEHDI NOORI
B.S. University of Tehran, 2007
M.Sc. Amirkabir University of Technology, 2010
M.Sc. University of Central Florida, 2013

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ABSTRACT

Since the transportation sector still relies mostly on fossil fuels, the emissions and overall environmental impacts of the transportation sector are particularly relevant to the mitigation of the adverse effects of climate change. Sustainable transportation therefore plays a vital role in the ongoing discussion on how to promote energy insecurity and address future energy requirements. One of the most promising ways to increase energy security and reduce emissions from the transportation sector is to support alternative fuel technologies, including electric vehicles (EVs). As vehicles become electrified, the transportation fleet will rely on the electric grid as well as traditional transportation fuels for energy. The life cycle cost and environmental impacts of EVs are still very uncertain, but are nonetheless extremely important for making policy decisions. Moreover, the use of EVs will help to diversify the fuel mix and thereby reduce dependence on petroleum. In this respect, the United States has set a goal of a 20% share of EVs on U.S. roadways by 2030. However, there is also a considerable amount of uncertainty in the market share of EVs that must be taken into account. This dissertation aims to address these inherent uncertainties by presenting two new models: the Electric Vehicles Regional Optimizer (EVRO), and Electric Vehicle Regional Market Penetration (EVReMP). Using these two models, decision makers can predict the optimal combination of drivetrains and the market penetration of the EVs in different regions of the United States for the year 2030.

First, the life cycle cost and life cycle environmental emissions of internal combustion engine vehicles, gasoline hybrid electric vehicles, and three different EV types (gasoline plug-in hybrid EVs, gasoline extended-range EVs, and all-electric EVs) are evaluated with their inherent

uncertainties duly considered. Then, the environmental damage costs and water footprints of the studied drivetrains are estimated. Additionally, using an Exploratory Modeling and Analysis method, the uncertainties related to the life cycle costs, environmental damage costs, and water footprints of the studied vehicle types are modeled for different U.S. electricity grid regions. Next, an optimization model is used in conjunction with this Exploratory Modeling and Analysis method to find the ideal combination of different vehicle types in each U.S. region for the year 2030. Finally, an agent-based model is developed to identify the optimal market shares of the studied vehicles in each of 22 electric regions in the United States. The findings of this research will help policy makers and transportation planners to prepare our nation's transportation system for the future influx of EVs.

The findings of this research indicate that the decision maker's point of view plays a vital role in selecting the optimal fleet array. While internal combustion engine vehicles have the lowest life cycle cost, the highest environmental damage cost, and a relatively low water footprint, they will not be a good choice in the future. On the other hand, although all-electric vehicles have a relatively low life cycle cost and the lowest environmental damage cost of the evaluated vehicle options, they also have the highest water footprint, so relying solely on all-electric vehicles is not an ideal choice either. Rather, the best fleet mix in 2030 will be an electrified fleet that relies on both electricity and gasoline. From the agent-based model results, a deviation is evident between the ideal fleet mix and that resulting from consumer behavior, in which EV shares increase dramatically by the year 2030 but only dominate 30 percent of the market. Therefore, government subsidies and the word-of-mouth effect will play a vital role in the future adoption of EVs.

Keywords: Electric Vehicles, Life Cycle Cost, Environmental Damage Cost, Water Footprint, Market Penetration, Inherent Uncertainty, Stochastic Optimization, Agent Based Modeling, Exploratory Modeling and Analysis.

This work is dedicated to my parents "Mansour" and "Mahin", my brother "Majid", and my sisters "Maryam" and "Mahya".

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CHAPTER ONE: INTRODUCTION

1.1. Research Problem Statement*

Climate change is real and as we increasingly altering the planet, we make ourselves in danger of outcomes of this change. Our society more likely will be overwhelmed by this change and cannot be adapted. It is already late to stop the climate change. Human-induced climate change continues to result in extreme weather conditions, [1]. Other effects of climate change include major shortage in water supply, dramatic loss of Arctic sea ice, more extreme winter and spring weather, and a higher amount of vaporized water in the air causing more heavy rainfalls and an increase in short-term precipitation. [2–10]. Almost 97 percent of scientists believe in human-induced climate change [11], contributing to an increasing amount of attention given to the mitigation and adaptation of its effects. Policymakers around the globe are tackling how to curb the causes of climate change at both national and international scales. One of the ways to mitigate the effects of climate change is to reduce greenhouse gas (GHG) emissions. The reduction of GHGs has become a policy-driver for many societies due to the growing threat of global temperature and storm intensity increase.

United States Environmental Protection Agency (EPA) points out the rise in temperature, changes in the pattern and amount of rainfalls, decrease in the amount of ice, sea level rise, and rise in the oceans acidity as the future effects of climate change [10]. The

* Parts of this dissertation will appear in peer-reviewed journal papers co-author by dissertation author.

US average temperature will increase between 4 and 11 Fahrenheit by 2100, with the number of days warmer than 90 degrees rising throughout the United States (See Figure 1). This increase will lead to more intense extreme climate events.

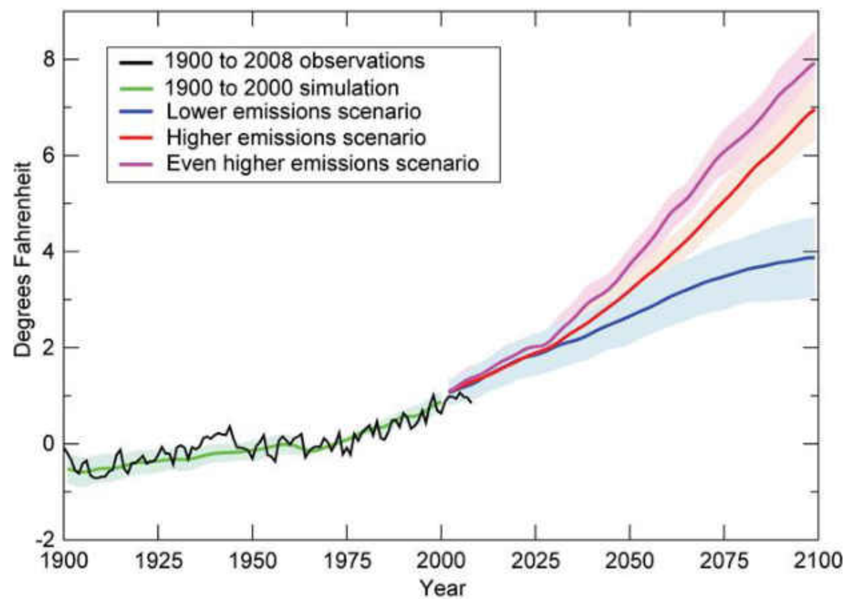


Figure 1. Observed and Projected U.S. Temperature [10]

With researchers and policy makers pay more attention to this issue, the extreme weather conditions, the rising temperature, and probable outcomes are better studied, predicted and understood. One of the ways to mitigate the effects of climate change and alleviate global warming, is to reduce greenhouse gas (GHG) emissions. The reduction of GHGs has become a main goal for the society due to significance of global warming and climate change threat.

The environmental and emissions impacts of the transportation sector are directly relevant to ameliorating the effects of climate change. The transportation sector still relies mostly on fossil fuels. Transportation is responsible for almost 75 percent of oil imports and consumes 70 percent of the all oil used in the US [12], with obvious energy security and environmental implications. Globally, the transportation sector emits around 25 percent of GHGs and a considerable amount of other air pollutants,[13]. According to the Inventory of U.S. Greenhouse Gas Emissions and Sinks, 28 percent of total U.S. GHG emissions was emitted by the transportation sector in 2011 [14]. In the International Energy Agency's (IEA) 2°C scenario in reduction of global temperature by 2050 (2DS), the transportation share of CO2 reduction would be 21 % [15]. Managing transportation-related emissions will therefore play a significant role in reducing total emitted GHGs. Sustainable transportation plays a vital role in the ongoing discussion on energy insecurity and addressing future energy requirements. With demand for passenger vehicles continuing to grow, one way to mitigate transportation sector emissions is to increase the proportion of alternative fuel vehicles in the fleet. Among these new technologies, electric vehicles (EVs), including hybrid and all-electric vehicle types, have stimulated tremendous interest both in the United States and globally. Electric Vehicles help to diversify the fuel mix and reduce dependence on petroleum. The share of EVs in the transportation fleet has increased dramatically in recent years, mainly due to battery improvements and because electricity will be the most efficient and cheapest transport fuel in the future [16,17]. Also, compared to other alternative fuel technologies, battery electric vehicles establish the most promising transport integration technology [18]. These technology improvements, coupled with the potential to store electricity in vehicles as an integral part of the modernization of the electric grid, continue to increase the importance of EVs for our transportation future.

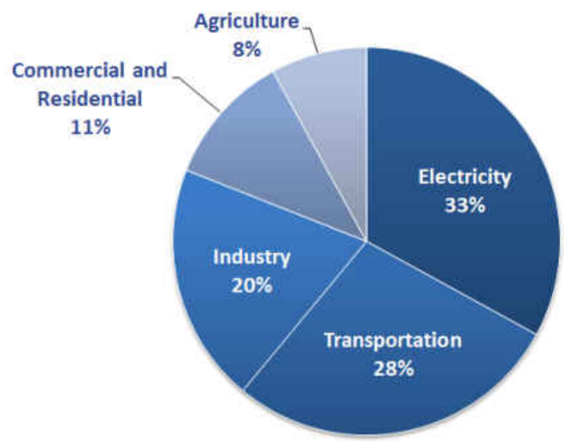


Figure 2. Inventory of U.S. Greenhouse Gas Emissions and Sinks [14]

By diversifying the fuel mix of the U.S. transportation sector, the electric vehicle industry helps to increase energy security and reduce dependence on petroleum. Moreover, the transportation industry has an enormous effect on greenhouse gas (GHG) emissions, and is responsible for 27% of all GHG emissions in the U.S. as of 2013 [19]. In the International Energy Agency's (IEA) 2°C scenario regarding global temperature reduction by 2050 (2DS), the transportation share of CO_2 reduction would be 21% [15]. Although Internal Combustion Engine Vehicles (ICEV) replaced electrified transportation by 1930, electric vehicles have been around for more than 100 years. The EV market shares have greatly increased in recent years due to energy insecurity concerns, the increasing trends in oil prices, improvements in electrical power storage, and electricity's current status as the cheapest and most efficient energy source for the transportation sector in the foreseeable future [16,17]. Governments are now embracing the development of EVs on the road by setting goals to improve the EV industry. Although the Obama administration has backed off of its goal of one million electric vehicles on the road by 2015 [20], others have set a goal of an EV share of 20% in the U.S. transportation new sales fleet by 2030 [21]. In another example, California has implemented a Zero Emission Vehicle (ZEV) mandate that requires automobile companies to produce for sale a certain percentage of zero emission vehicles, including EVs and hydrogen fuel cell vehicles; by 2025, approximately 15% of all new light-duty vehicles sold in the state of California must be either electric or fuel-cell powered [22]. The U.S. Government now also offers financial incentives to consumers to lower first-time costs, offering up to $7,500 in tax credits for EVs purchased in or after 2010; this incentive will be phased out after 200,000 vehicles from the qualified manufacturers [23]. Furthermore, the U.S. Government also supports research and development for new technologies to accommodate the movement towards a more electrified vehicle fleet. Moreover, manufacturers and consumers are supporting this technological shift by designing EVs that are more reliable and by helping to mitigate GHG emissions. Additionally, significant cost reductions for EV components such as batteries have further stimulated this market share growth. However, despite all of these efforts and the current collective movement to facilitate the electrification of the U.S. transportation fleet, there are still barriers hindering the widespread adoption of EVs as a viable transportation option, including various technological, financial market, and policy challenges to the full deployment of EVs. The United States currently has the largest number of electric vehicles on the road, with almost 43 percent of all EVs sold in the U.S. However, EVs only comprised less than 1% of new car sales in the U.S. as of 2014 [24]. Therefore, greater adoption rates must be met in order to achieve the mid-term and long-term market share goals for EVs as described previously [25]. In light of these challenges, it is increasingly necessary to study EV market shares in more detail. Market forecasting is currently a well-developed and well-studied field with implications in various other fields (economics, business, finance, systems engineering, etc.), but often fails to consider uncertainties in the different factors affecting market shares. For this reason, market evaluations of new EV technologies is facing increasing degrees of complexity due to difficulty in modeling the relevant system factors [26].

This trend makes it vital to study EVs in further detail. Policy-makers, scientists, and manufacturers typically understand the importance of life cycle cost (LCC) and life cycle environmental emissions (LCEE) of EVs in their ongoing discussions. However, often missing from the dialogue is the environmental damage cost (EDC) and water footprint (WFP) of EVs. EDC is estimated using LCEE and the unit cost of environmental degradation for each air pollutant. In fact, access to more comprehensive information might result in a completely different policy direction. On the other hand, there are many uncertain variables in evaluating the LCC, EDC, and WFP of EVs. This study first aims to improve upon the life cycle analysis of different EV technologies by addressing primarily the uncertainties in these metrics simultaneously. Then, using the most probable range of values, this study aims to predict the most appropriate combination of EVs and ICEVs that should be on the road in 2030, considering economic costs, environmental damage costs, and water footprint. Second, this study aims to evaluate the market penetration of the EVs considering its inherent uncertainty. In order to achieve this goal, first the purchase price, maintenance and refueling cost (M&R), environmental damage cost (EDC), and water footprint (WFP) of the studied vehicle are estimated, considering their uncertainty ranges. Then, an agent-based model (ABM) is developed to simulate the market penetration of the EVs in the U.S. market. Finally, different scenarios are applied and the plausible outcome is analyzed using the exploratory modeling and analysis (EMA) concept.

Here, five different vehicle types are compared and analyzed: Internal Combustion Engine Vehicle (ICEV), Gasoline Hybrid Electric Vehicle (HEV), Gasoline Plug-in Hybrid Electric Vehicle (PHEV), Gasoline Extended Range Electric Vehicle (EREV), and All-Electric Vehicle (BEV). For PHEVs, when the battery is preliminarily used and especially in hard acceleration conditions, the gasoline engine facilitates driving the vehicle. An EREV is a type of PHEV with a larger battery that powers the vehicle until depleted, at which point the vehicle switches to gasoline power. Therefore, PHEVs consume gasoline during charge depleting mode, while EREVs do not. For the purposes of this study, it is assumed that PHEVs have an all-electric range of 10 miles and EREVs have an all-electric range of 40 miles.

1.2. Aims and Objectives

The outreaching goal of this study is to fill the above mentioned gap by answering the following research questions using different methodologies such as Agent-based modeling and Exploratory Modeling and Analysis:

What are the uncertain variables in studying the life cycle cost, life cycle environmental emissions, and water footprint of electric vehicles and what are their varying ranges?

How can we quantify the above mentioned vehicle attributes?

What are the environmental damage costs of different electric vehicle technologies?

How can we optimize the share of the electric vehicles in the market for the future, considering their life cycle cost, environmental damage cost, and water footprints?

How consumers respond to the current market situations?

What will be the actual market penetration of the electric vehicles in the United States?

How can we integrate the uncertainties of the system in the decision making and market penetration evaluation of electric vehicles?

This study distinguishes itself from previous efforts in several ways. First, the Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET) tool, developed by the Argonne National Laboratory (ANL), is used to find the LCC of different EVs. This tool was recently released and has yet to be used extensively by the research community. This study builds on AFLEET to create a new model called the Electric Vehicles Regional Optimizer (EVRO), which considers all possible uncertainties of LCC to account for the whole picture of EV costs. Second, although there have been some efforts to analyze the environmental damage costs of EVs, this effort integrates uncertainties into the EDC using the variability in the LCEE as well as the unit environmental damage cost of each air pollutant. Third, previous studies frequently use an average U.S. electricity mix in their analysis. Here, the LCC, EDC, and WFP of EVs is estimated for different electricity generation mixes, based on 22 U.S. electric grid regions. In addition, a stochastic optimization tool is coupled with Exploratory Modeling and Analysis (EMA) to find the best EV drivetrain mix for each U.S. electric grid region for the year 2030. Finally, an agent-based model (ABM) is developed with the Exploratory Modeling and Analysis (EMA) method to integrate the relevant uncertainties into the market share of EVs in the year 2030.

The rest of the dissertation is structured as follows: First, the existing literature on the LCC, LCEE, WFP, EMA, and ABM of EVs is described. Second, the methodology and general assumptions are described, the concept of EDC is discussed and added to the analysis through consideration of the LCEE of different EV drivetrains, and the mathematical content of the Electric Vehicles Regional Optimizer (EVRO) and Electric Vehicle Regional Market Penetration (EVReMP) models is discussed. Then, the uncertainties are presented and explained. Finally, the results and implications of the EVRO and EVReMP models are illustrated and ideas for future study are presented.

1.3. Organization of Dissertation

To answer the defined research questions, the dissertation is organized as follows:

1st Chapter: Introduction and Literature Review

This chapter will present the general information about the U.S. Electric Vehicle industry and market, and importance of studying the life cycle cost, life cycle environmental emissions, and water footprint of EVs. In addition, it will include the research problem statement, aims and objectives, and organization of the dissertation.

2st Chapter: Introduction and Literature Review

This chapters described the existing literature on life cycle cost, life cycle environmental emissions, water footprint, exploratory modeling and analysis, and agent based models used in the electric vehicles area.

3nd chapter: Methodology

This chapter explains the mathematical content of the developed electric vehicle regional optimizer and electric vehicle market penetration models.

4nd chapter: Analysis Results

This chapter involves the analysis results of the two developed models for the electric vehicles in the United States.

5nd chapter: Conclusion, discussion, and future studies

In this chapter the results of the proposed methodologies and their significance for the U.S. Electric Vehicle Industry 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 TWO: LITERATURE REVIEW

2.1. Introduction

In this chapter, the previous literature on life cycle cost, life cycle environmental emissions, water footprint, exploratory modeling and analysis, and agent based models used in the electric vehicles area is described.

2.2. Life Cycle Cost, Life Cycle Environmental Emissions, and Water Footprint of EVs

The Life Cycle Cost (LCC) and Life Cycle Environmental Emissions (LCEE) of EVs have been extensively studied, and there are several studies on the Water Footprint (WFP) of EVs in the literature. A summary of the existing literature is described in the following subsections.

2.2.1. Life Cycle Cost (LCC) of EVs

Often cited in the literature is the detailed LCC analysis of EVs by the Argonne National Laboratory (ANL). ANL compares several vehicle cost, fuel price, and government subsidy scenarios to understand the future role of EVs in the vehicle market [27]. However, they admit that predicting the future role of EVs in the market has some complexities, due to the inherent uncertainty of oil prices, lack of knowledge about future customers' behavior toward new technologies, the performance and cost of future technologies, and future governmental action. ANL's costs are based on a "technology success" scenario. Argonne has used a model called

Automotive System Cost Model (ASCM), developed by the Oak Ridge National Lab [28]. It gives the costs of 5 different vehicle types using 35 different components. For the vehicle size, weight, power, and energy, they have used the ANL's vehicle simulation tool, Powertrain System Analysis Toolkit (PSAT). These two models are used as the base models for Argonne's GREET tool [29]. ORNL mentions there are three different main uncertainties in the cost analysis of EVs: uncertain design evolution including new technologies, effects of learning and scale in mass production, and unpredictable changes in material costs. Another main assumption that the GREET model makes is that overhead and auto dealer fees make up as much as 50% of the manufacturing costs. This is another uncertainty in their life cycle cost analysis.

ANL also uses the National Energy Modeling System (NEMS) for their projections. NEMS is a large scale computational-based model of the U.S. energy economy through the year 2030 [30]. It forecasts various factors such as energy and fuel pricing using a variety of different factors, including consumption, production, imports and exports of energy, cost and performance of different energy technologies, and demographic data [31]. Due to its specialized structure and difficulty of use, NEMS has only been used by EIA and a few other organizations. In another study, the design of EVs was optimized using both the ANL study and an integer programming method to consider annualized life cycle cost and annualized GHG emissions [32]. The result was that the high price of gas caused PHEVs to dominate the future market and in turn, petroleum consumption.

Aguirre et al. conducted a LCC analysis of conventional gasoline, hybrid, and all-electric vehicles. They presented their results in two different categories: initial and usage costs. Their results indicate that overall, the studied BEV has more net present cost value than the ICEV and HEV. However, the usage costs of the studied electric vehicle are lower than the studied ICEV and HEV. They concluded the HEV is the cheapest option over its lifetime [33]. Ghosh compared the total lifetime cost associated with PHEVs and BEVs based on their initial, lifetime fuel, and lifetime maintenance costs. He assumed a 10 year lifetime for the vehicles. They found the BEV to have a lower total lifetime cost than the PHEVs, and that the PHEV with 10 mile electric range cost less than the EREV [34].

2.2.2. Life Cycle Environmental Emissions (LCEE) of EVs

The LCEE of EVs has received substantial attention in the literature. However, various authors have made differing assumptions about vehicle weights, battery sizes, propulsion and fuel efficiency, how broadly to draw a boundary around the life cycle analysis (LCA), and electricity mix. For instance, in one of the most recent publications from the University of Central Florida, a state-based carbon and energy footprint analysis was performed for conventional, hybrid, plug-in hybrid, and electric vehicles [35]. Moreover, The Union of Concerned Scientists published an informative report that investigated emissions from charging electric vehicles on a regional scale, including upstream emissions from building power plants, extracting and transporting fuel, converting fuel into electricity, and delivering electricity to the point of use [36]. In addition, Viñoles-Cebolla et al. developed an integrated model to estimate the life cycle emissions of different vehicles using primary vehicle data such as weight, engine technology, and fuel type [37]. Zhang et al. proposed a simulation model to analyze the economic and environmental performance of EVs, testing different conditions such as the electricity generation mix, smart charging control strategies, and real-time pricing mechanisms [38].

Additionally, different studies report their assumptions and results using a range of metrics, including per fuel volume, per kW of battery, or per-distance-traveled. Some authors don't specify the emissions intensity of the electricity used to charge. Treatment of the production, operation and disposal life cycle stages also varies, with some studies reporting on each stage individually and some rolling all stages into one life cycle value. One commonality is the emphasis on the battery as the primarily distinguishing attribute of EVs relative to ICEVs. Battery manufacture, usable state of charge, degradation rate, replacement requirements, and environmental impacts, are all relevant to life cycle analysis of EVs [33,34,39–41]. In order to address the existing literature on the emissions of electric vehicles with the most clarity, we have divided the remaining discussion into production, operation, and disposal life cycle phases.

Production Emissions: Trucking, shipping and rail transportation methods are required for the movement of batteries and vehicle parts before manufacturing, as well as the movement of whole vehicles after manufacturing, and these transportation emissions contribute to the LCEE. The production phase often also includes the sourcing of raw materials and assembly of the vehicle. Production stage emissions for ICEVs range from 4 t CO2e to 10 t CO2e [41–44]. HEVs, PHEVs, and BEVs contain batteries which vary in size and material depending upon the vehicle's characteristics such as fuel economy and all-electric range. The manufacture of batteries typically increases vehicle production stage emissions for these electric vehicles relative to an ICEV [33]. For example, Notter et al. conclude that the battery causes between 7% and

15% of the energy or environmental impact of the overall lifecycle of an EV and Aguirre et al. concluded that the battery production alone is responsible for 3-24% of life cycle emissions, based on the battery capacity [33,40]. Helms et al. provided the low estimate in the literature of 6.5 t-CO_2Eq for production emissions of EVs (Helms et al., 2010).

Operation Emissions: For mid-sized ICEVs more than three quarters of lifecycle emissions result from the use phase of vehicle life, causing emissions of 18-27 t-CO_2e [44]. Emissions during the use phase currently account for the majority of lifecycle vehicle emissions, although as fuel efficiencies improve across the vehicle fleet, emissions created in the production of vehicles will make up a greater share of total lifecycle vehicle emissions for new vehicles. Operational emissions are a function of the emissions intensity of the fuel (or combination of fuels used) and the fuel efficiency of the vehicle. Fuel-based emissions for gasoline include emissions from direct burning of gasoline and upstream emissions from crude oil extraction, transportation, refining and distribution. Fuel-based emissions for electricity include the pre-combustion, upstream GHG emissions of the power plant fuel mix. Emissions from gasoline were estimated at a range of 2.90 – 2.99 kg CO_2e/L [42,45,46], which is essentially the operational emissions of ICEVs. Similar to ICEVs, HEVs also rely completely on gasoline, but have higher fuel efficiency [45].

PHEVs present challenges for estimating operational emissions because they rely on a combination of electricity and gasoline. Driver behavior assumptions are therefore important factors, as once the battery is drained of grid-sourced electricity, a PHEV drives as if it had a normal hybrid engine. Some PHEVs will even drive in blended (using some gasoline) mode before the battery is drained of grid-sourced electricity. The assumptions surrounding the availability of charging stations and the number of times PHEVs are charged are also important for calculating the share of emissions from electricity or gasoline (Davies & Kurani, 2013; Samaras & Meisterling, 2008). The U.S. Department of Transportation National Household Travel Survey (NHTS) has been used by many to estimate the relative electricity and gas usage of PHEVs, typically on a national average basis with one charge assumed per day [45,48]. Individual behaviors like commute distance and charging at the workplace could have marked effects on any individual's emissions.

BEVs, meanwhile, are assumed to be solely powered by grid-sourced electricity. Electric vehicle emissions are highly dependent on generation source. Pre-combustion and upstream GHG emissions of the power plant fuel mix for the U.S. can contribute an extra 9% above direct power plant emissions on average (calculated using an assumption of 8-14% upstream emissions for coal and 13-20% upstream emissions for natural gas), resulting in an additional 54 g CO2e/kWh for the average U.S. mix [45]. Most authors have assumed a U.S. national electricity mix, with some authors performing sensitivity analyses to investigate low carbon or high carbon generation sources. For instance, the Union of Concerned Scientists published a report that investigated emissions from charging electric vehicles by region, and shows how integral electric generation mix is to the operational emissions of EVs [36]. In Europe, Based on the average electricity production mix, which had more than 50% generation from fossil fuels at the time of the study, Notter et al. calculated that an internal combustion engine breaks even with an EV if its fuel economy is more than 60 mpg [40]. One study developed a model to estimate the life cycle emissions using the primary vehicle data such as weight, year of manufacture, engine technology, and fuel type used [37].

Disposal Emissions: Disposal and end of life scenarios have been extensively evaluated in other field of studies such as in pavement sustainable materials [49–51], green power [52], and automotive industry [53]. Largely, the disposal stage of the lifecycle has been ignored in the literature. Most authors exclude these emissions because they represent such a small fraction of the overall total lifecycle emissions. In the European Union, legislation has mandated recycling and recovery rates of batteries at 85% by 2006 and 95% by 2015 [40]. It is estimated that natural resource savings from recycling Li-ion batteries are 51%. Batteries are not currently recycled in the U.S. because it is not technologically or economically feasible, as recycling currently uses more energy and costs than using raw materials to make new batteries. Aguirre et al. conclude that if a battery were recycled emissions of 0.68 t-CO2e would result. Ultimately, disposal of the vehicle parts and battery causes less than 1% of the lifecycle vehicle emissions in their analysis [33].

EV emissions are highly dependent on generation source. Most authors have assumed a U.S. national electricity mix, with some authors performing sensitivity analyses to investigate low carbon or high carbon generation sources. For instance, the Union of Concerned Scientists published a report that investigated emissions from charging electric vehicles by region, and showed how integral electric generation mix is to the operational emissions of EVs [36]. Pre-combustion and upstream GHG emissions of the power plant fuel mix for the U.S. can contribute an extra 9% above direct power plant emissions on average, resulting in an additional 54 g

CO2e/kWh for the average U.S. mix [45]. Additionally, transforming the transport fuel system to 100 percent renewable energy sources would require multiple measures and close integration of transport within the larger energy system [54]. Therefore, understating the future trend of transport and electricity fuel sources plays a vital role in the decision-making surrounding alternative fuel vehicles. Please see Table 1 for a summary of literature on LCEE of the studied vehicle types.

2.2.3. Water Footprint of EVs

The concept of “water footprint” analysis is to understand and address freshwater consumptive use by considering production and supply chains as a whole. Water Footprint focuses on blue water because water withdrawal from surface and groundwater sources constitutes a majority of the water use in electricity generation. The water use of power plant operations is an important aspect of the LCCA because use of water in electricity production prevents others from using the water for other purposes, and this resource is highly constrained in some parts of the U.S. The freshwater footprint of water withdrawal becomes a key factor in the siting of new plants and in water resource planning [55]. The concept of water and energy is fundamentally connected. 49% of the total fresh water withdrawals in the U.S. is caused by the thermoelectric power generation. The transportation industry is not heavily reliant on water so far, since 95% of the transportation fuels is supplied through petroleum fuels. However, as mentioned earlier, the share of the EVs are increasing in the fleet and reliance on water for generating electricity will increase in the near future [56]. Therefore, considering the WFP as a decision variable is one of the goals of this research.

Table 1. Summary of the literature on life cycle cost and life cycle environmental emissions

	Life Cycle Cost of EVs
Oak Ridge National Lab [28]	Automotive System Cost Model (ASCM). It gives the costs of 5 different vehicle types using 35 different components. It uses ANL's Powertrain System Analysis (PSAT).
Energy Information Agency [31]	National Energy Modeling System (NEMS). A large-scale computational-based model of the U.S. energy economy. It forecasts various factors (i.e. energy and fuel pricing) using a variety of different factors. It has a specialized structure and is very sophisticated to use.
Traut [32]	Design of EVs was optimized using both the ANL study and an integer programming method considering annualized LCC and annualized GHG emissions. High price of gas caused PHEVs to dominate the future market and, in turn, petroleum consumption.
Aguirre et al. [33]	Conducted a LCC analysis of conventional gasoline, hybrid, and all-electric vehicles. Determined that the BEV has more net present cost value than the ICEV and HEV studied. The usage costs of the BEV are lower than the ICEV and HEV. HEV is the cheapest option.
Zhang et al. [38]	They developed a model to analyze economic and environmental performance of EVs It is applied to case studies in Tokyo, Japan in 2030. Considered different electricity mix options, smart charging control strategies, real-time pricing mechanisms.
Kiviluoma and Meibom [57]	They estimate PHEV cost in the future power system, as well as benefits from smart EVs. Stochastic model was used to achieve more accurate operational cost results. The system cost to charge an EV was around 36 €/vehicle/year, In the case of smart EVs.
Ghosh [34].	Compared the total lifetime cost associated with PHEVs and BEVs. BEV to have a lower total lifetime cost, PHEV-10 cost less than the EREV.

Life Cycle Environmental Emissions

Production Emissions	
Carbon Trust [44]	A mid-size ICEV sold today has emissions of 6 t-CO_2Eq from manufacture and another 3 t-CO2e from making the raw materials such as steel and aluminum.
Shiau et al. [42]	Estimated 8.5t-CO_2Eq for the life cycle GHG emissions associated with any vehicle production (excluding battery production).
MacLean & Lave [41]	Provided the highest estimate, at 10 t-CO_2Eq, for production stage emissions of an ICEV.
Helms et al. [43]	Provided estimates on the low end, with ICEVs contributing approximately 4 t-CO_2Eq and EVs 6.5 t-CO_2Eq including battery emissions.
Operation Emissions	
Carbon Trust [44]	For mid-sized ICEVs more than three quarters of LCEE result from the use phase (18-27 t-CO_2Eq)
Shiau et al. [42]	Emissions from gasoline estimated at a level of 2.99 kg CO_2Eq/L
Samaras & Meisterling [45]	Emissions from gasoline estimated at a level of 2.97 kg CO_2Eq/L
Jaramillo et al. [46]	Emissions from gasoline estimated at a level of 2.90 kg CO_2Eq/L
Disposal Emissions	
Aguirre et al. [33]	Concluded that if a battery were recycled. Emissions of 0.68 t-CO_2e would result. Disposal of the vehicle parts and battery causes less than 1% of the LCEE.

2.3. Exploratory Modeling and Analysis

There are plenty of uncertain variables in the life cycle cost assessment of EVs. Uncertainty and variability are two different concepts. Variability in the input data means the ranges and the behavior of the system is known. But in uncertainty, the ranges are known; however the behavior of system to the uncertain variables is unknown. Uncertain situations do not necessarily imply the lack of knowledge, as increasing knowledge about the areas of high uncertainty, may lead to a more knowledge about the uncertainty and therefore increases the total uncertainty [58].

There are a few efforts done in the research community in order to address the uncertainties in the life cycle of electric vehicles. Aguirre et al. applied Monte Carlo simulation to account for the variability in the sensitivity analysis of their conventional gasoline vehicle and EVs comparison [59]. In their study, they assumed the most uncertain phase for the CV cars is the use phase. On the other hand, for the EVs the battery manufacturing along with use phase is considered to be uncertain. They pointed out that the effect of carbon incentives on EVs is also uncertain and needs further study. Based on their analysis, they concluded that hybrid cars are more cost effective than CVs. The EVs have the highest net present costs compared to two other comparison alternatives. Also, the breakpoint of CVs and EVs is reported where the gasoline price is increasing by rate of 13 percent. Considering the gasoline price is not changing, the cost breakpoint happens when the electricity price decreases by 5%.

One of the goals of this study is to apply the concept of Exploratory Modeling and Analysis (EMA) to the developed ABM model to account for the inherent uncertainty levels of the system. In one study by Kwakkel and Yücel, EMA as applied to a developed ABM model in the case of Dutch electricity transition [60], exploring plausible transition trajectories and their conditions for occurring. The mathematical content of the developed Electric Vehicle Regional Market Penetration (EVReMP) Model is described in the next section.

2.4. Agent Based Modeling

If we divide simulation methods in discrete-event and continuous approaches, Agent-Based Modeling (ABM) is a discrete-event simulation method that creates a virtual environment to model the interactions between different agents. Discrete event simulation is suitable in a situation where the variables change in discrete times and events are in discrete steps [61]. In the literature, other approaches are utilized in discrete-event simulation such as in automated storage and retrieval systems [62,63], in assignment problems [64], and queuing systems [61]. The ABM method has been applied to several fields of study, including population dynamics, epidemiology, biomedical applications, consumer behavior, vehicle traffic, and logistic simulations [65–69]. ABM is also used to model vehicle technology adoption, with different agents (consumers, automakers, policy makers, fuel suppliers, etc.) interacting in a virtual environment [68,70–72]. Consumers are the primary agents in some aspect of the vehicle technology adoption portrayed with the ABM method, whereas more current models have expanded this environment by considering automakers, policy makers, and fuel suppliers as agents as well. One of the advantages of the ABM method is its ability to use both hypothetical and data-driven consumer behavior during the modeling process [26].

EV market penetration has been extensively studied due to its importance in policy analysis. One of the more advanced agent-based models for evaluating the market share of EVs is the Virtual Automotive Market Place Model (acronym VAMPM) developed by the University of Michigan Transportation Research Institute (UMTRI) [70]. This model characterizes the market share of new technologies under different consumer, economic, and policy conditions, and considers four different agent types: consumers, governments, fuel producers, and vehicle producers/dealers. The unit cycle of the analysis is one month, and the agents communicate in each cycle based on their needs and benefits. The results indicate that, by 2015, sales of PHEVs could reach up to 3%. By 2020, sales could potentially reach up to 5 % and up to 20% in 30 years, with a final market penetration of 16% by 2040. As stated in [70], the ABM model should consider the income, addresses, transportation budget, vehicle preferences, driving needs, preferred travel times, and other relevant parameters. The VAAMP model considers some of these factors in a hypothetical "neighborhood" in which some assumptions are still made, such as the assumptions that and wage levels stay the same, that the effect of foreign currency changes on the price of exported vehicles does not affect the market, and there are no distinctions between cars and trucks.

Most of the ABM models in current literature were developed based on utility theory, in which the agent purchases a vehicle that maximizes his/her utility. For instance, Ting Zhang et al. proposed a novel ABM methodology to investigate factors that can facilitate the penetration of the alternative fuel technologies into the market [73], considering four different agents in their analysis: manufacturers, vehicles, consumers, and governments. The manufacturing agent tries to maximize its profit in each run by changing the vehicle design or its mark up. The Corporate Average Fuel Economy (CAFE) regulations are applied by the government agents, and affects manufacturer profit. Consumers choose vehicles with higher utility levels based on different vehicle attributes and consumer preferences. The mathematical content of this study is now used as a basis for the formulation of the developed ABM in this research. Moreover, a consumer choice probability model is developed for evaluating the market share of EVs in Iceland by

Shafiei et al. [74], with consumers weighing different vehicle attributes based on their own specific preferences. Sets of vehicle alternatives compete in each run based on the social influences as well as the attractiveness of consumers. The behavior of other agents also affects the decision of the agent. The mathematical content of the consumer choice model is also used to form the developed ABM in this analysis.

CHAPTER THREE: METHODOLOGY

3.1. Electric Vehicle Regional Optimizer (EVRO) Model

In this chapter, the methodology framework of the developed Electric Vehicle Regional Optimizer is explained. This Model is currently published and available in Journal of Energy [75]. The following subsections describe the conceptual basis and mathematical contents of the methodology. First, the developed Electric Vehicle Regional Optimizer (EVRO) and its relationship to the other parts of the methodology are illustrated. Second, in section 3.2, the concept of LCC is explained and the AFLEET model and its relationship to the EVRO model are described. Third, in section 3.3, the concept of Exploratory Modeling and Analysis (EMA) and the compromise programming optimization model are explained and their application within the EVRO model is described. Fourth, in section 3.4, the uncertainties in the LCC, LCEE, and WFP of EVs are presented and discussed, and the concept of Environmental Damage Cost (EDC) is presented using the LCEE of EVs and the unit damage cost of air pollutants. Finally, in section 3.5, the mathematical content of the Electric Vehicle Regional Optimizer (EVRO) is presented. Figure 1 illustrates the methodology used to develop the EVRO model. The core of EVRO is an optimization model, which is coupled with the concept of Exploratory Modeling and Analysis to account for the uncertainties in the input variables. Basically, the EVRO model is a combination of several different methodologies (those described in section 3), which enables the decision maker to see what would be the appropriate combination of drivetrain for different LCC, EDC, and WFP weights.

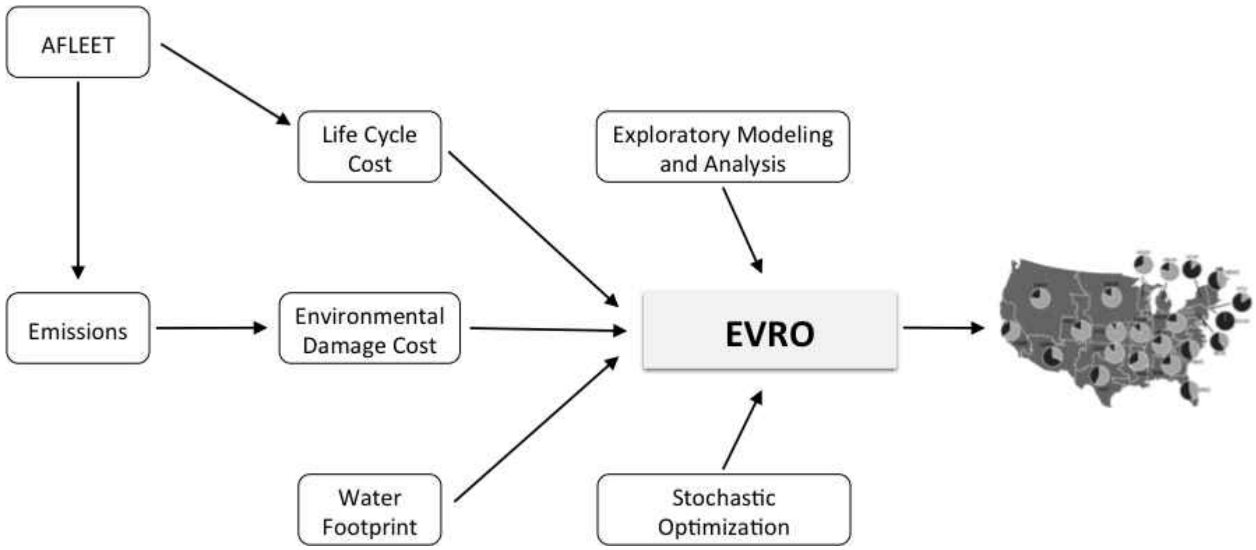


Figure 3.Illustration of EVRO model.

3.1.1. Life Cycle Cost Analysis (LCCA)

LCCA is a process to analyze the economic value of a project through evaluation of its fixed and variable costs over the life cycle of the project [76]. All of the costs associated with a project are considered, including the initial costs and the likely future costs associated with an activity over time. This tool is effective in conveying alternative investment scenarios to decision makers. LCCA incorporates discounted long-term agency costs, user costs, and performance periods. LCCA is used in different disciplines such as sustainable materials in pavement engineering [77]. The discount rate used for an LCCA can have significant influence on the results. In this research, the discount rate is considered to range between 0.65-1.15 percent, based on a one-year certificate of deposit rate [78]. The inflation rate, which affects future costs, is taken from the Congressional Budget Office's (CBO) yearly report, The Budget and Economic Outlook [79].

There are a few tools available to find the LCC of alternative fuel drivetrains. For instance, NREL has developed a tool called "Future Automotive Systems Technology Simulator" whose primary aim is to estimate the fuel economy, cost, and performance of a vehicle with specified powertrain components over standard drive cycles [80]. This tool takes a highly detailed approach, which does not match the scope of this study. AFLEET, a tool developed by Systems Assessment Group, Energy Systems Division, at the Argonne National Laboratory (ANL), is a more general tool better suited to the aim of this study [81]. AFLEET is developed for The Department of Energy's Clean City program and is able to estimate the petroleum use, GHG emissions, and cost of ownership of different alternative fuel technologies. The tool utilizes the background and methodology of the GREET (The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation) model [29]. For the cost analysis, AFLEET uses a variety of sources, such as Clean Cities Alternative Fuel Price Report and American Recovery and Reinvestment Act awards [81]. The EVRO model developed here uses AFLEET as a tool to estimate the LCC and the LCEE of the studied drivetrains. The outputs of AFLEET become the inputs of EVRO.

In the AFLEET model, two types of maintenance costs are considered for each vehicle type: scheduled and unscheduled. The developer team mentions that maintenance costs of different vehicle types are usually assumed the same. AFLEET does not take the battery replacement costs into account, due to the lack of data availability. In practice, battery replacement is possible, if not probable, at some point during the operational phase of the lifecycle and would cause a bump in costs and emissions for EV drivetrains. The battery replacement cycle is highly affected by technology improvements, and over time it is likely that battery replacement cycles will decrease, approaching the model's assumption of no replacement. Another key factor in the LCC of vehicles is the mileage per year assumption. AFLEET uses the same average mileage per year for all of the different vehicles. In reality, a vehicle is driven more miles per year earlier in its lifecycle. This correction is made in the EVRO model. AFLEET provides the total cost of ownership (TCO), which is the net present value of the fixed and variable costs associated with vehicle ownership. TCO is reported on a yearly basis, and includes the cost of financing, depreciation, insurance, licensing, and registration, as well as the cost of lifetime petroleum use, operation and maintenance. The inflation and discount rate values affect the TCO. Thus, in this study the costs are converted into 2012 dollars using the Consumer Price Index to calculate the net present cost of different EV technologies [82].

3.1.2. Optimization Model

3.1.2.1. Compromise Programming

A multi-objective optimization model is critical for finding a feasible alternative that yields the most preferred set of values for the objectives. Multi criteria decision making is used in different disciplines to find optimal policies and solutions such as in water resources [83], green power [84], and layout configuration [85]. Here, the objectives were to minimize Life Cycle Cost, Environmental Damage Cost, and Water Footprint within a regional analysis. The overarching goal was to find the most appropriate combination of drivetrains for each U.S. region based on these three metrics. In order to realize this goal, an optimization model, which is widely used for solving multi-objective linear, nonlinear or integer programming problems, was developed. This approach is based on applying the compromise programming process to select the ideal combination of drivetrains in each region given the three objectives (LCC, EDC, and WFP) and uses Exploratory Modeling and Analysis (EMA) to account for uncertainties in the input parameters. However, since the policy-makers might have different points of view regarding the importance of each objective, a weighting factor is applied to each objective. Eq.1. shows the general formulation of the optimization model:

$$L_a = \text{Min}\left\{\sum \pi_k \left(Z_k^* - Z_k(x)\right)\right\} \quad (1)$$

L_a represents the general objective function used, where Z_k^* is the ideal solution for objective function k, $Z_k(x)$ is the value of the objective function for parameter x, and π_k is the weight of each objective function [86]. Each of the objective functions is in monetary amounts. Therefore, normalization may not seem necessary. However, since the unit of LCC and EDC is different from WFP, normalization is performed. Therefore, the new optimization model can be written as:

$$\text{Min } L_a = \text{Min}\left\{\sum \pi_k \left(\frac{Z_k^* - Z_k(x)}{Z_k^*}\right)\right\} \quad (2)$$

Subject to:

$$\sum_{k=1}^{p} \pi_k = 1 \quad (3)$$

The decision maker can assign the weight of each objective function accordingly, to show the importance of each type of cost over the others. The weights range between zero and one, with a sum equal to one. Similar methodologies are used for optimization under uncertainty and variability [84,87–90] . Therefore, the optimization model is represented as follows:

Index:

$i: Car\ type\ indicator$

$j: region\ indicator$

Parameters:

$LCC_{ij}: The\ life\ cycle\ cost\ of\ car\ type\ i\ in\ region\ j$

$EDC_{ij}: The\ environmental\ damage\ cost\ of\ car\ type\ i\ in\ region\ j$

$WFP_{ij}: The\ water\ footprint\ of\ car\ type\ i\ in\ region\ j$

Decision Variable:

$X_i: The\ selection\ percentage\ of\ car\ type\ i$

Objective Functions:

$$Z_1(x) = \sum_i LCC_{ij} \times X_i \qquad \forall\, j \tag{4}$$

$$Z_2(x) = \sum_i EDC_{ij} \times X_i \qquad \forall\, j \tag{5}$$

$$Z_3(x) = \sum_i WFP_{ij} \times X_i \qquad \forall\, j \tag{6}$$

Subject to:

$$\sum_i X_i = 1 \tag{7}$$

$$X_i \geq 0 \qquad \forall\, i \tag{8}$$

The life cycle cost objective function is represented by $Z_1(x)$, the environmental damage cost objective function is represented by $Z_2(x)$, and $Z_3(x)$ represents the water footprint objective function. Hence, using the stochastic multi-objective decision-making approach, the ideal percentage of each drivetrain in each U.S. region is calculated. MATLAB® programming software along with Visual BASIC for Applications in Microsoft Excel is used for coding the stochastic optimization model [91,92]. The model is then run for 100,000 replications for each region.

3.1.2.2. Exploratory Modeling and Analysis

Actions today will contribute to the outcomes of the future. High interactions among economic, social, environmental and technological factors add to the uncertainty of the future. Most of the decisions today have to be made in a *deep uncertain* situation [93] where decision makers cannot agree on or do not know the relationships among the main factors of the system, the probability distribution of these varying factors, and the plausible alternative outcomes [94]. In these situations, uncertainty can be found in the initial inputs of the system, the relationships between the parameters inside the model, the logic of these relationships, the system boundaries, the model structure, and the variance between real and estimated behavior of the system.

EMA is a research methodology to deal with deep uncertainty and is based on the prominent work of Bankes [95]. It uses computational experiments to form an ensemble of plausible future outcomes, and assists in reasoning about situations where there is deep uncertainty. It builds a model based on available knowledge and data and uses it as a surrogate for the actual system to predict the system's behavior. The series of computational experiments are utilized to evaluate the implications of different changing assumptions and hypotheses. By exploring these implications, one can discover which of the system's behaviors is more reasonable and generally true [96].

EMA is used here to form all the plausible outcomes of LCC, EDC, and WFP of EVs. Integration of EMA and optimization enables us to generate, explore, and deeply analyze a large number of plausible future outcomes. Decision makers can then foresee the future outcomes of today's actions and can effectively take action in the inherently complex present. The general steps of applying EMA to a deeply uncertain problem are: understanding the uncertainties of the system of interest, developing an easily controllable computational model of the system's behavior, generating numerous plausible future outcomes, data analysis through the generated outcome, and defining and testing different policies [97,98]. All of these steps have been undertaken in this study. The use of EMA allows the estimation of the impact of the variability of input variables on the optimization model outputs. Applying this approach allows exploration of more than just the expected case and results in a set of combinations selected with different probabilities.

3.1.3. Assumptions and preliminary data

Dealing with uncertainties is crucial for an analysis of EV market penetration. The range of each uncertainty for this study was taken from the databases associated with each tool mentioned in sections 2.1 and 2.2. In the following subsections, the assumptions made when defining the uncertainties are presented and explained. The general assumptions and the range of uncertainty used as the input parameters in EVRO are provided in Table 2. Except for electricity and gasoline price, which are selected through a rectangular random function, it was assumed that each input parameter is uniformly distributed between the upper and lower limits.

Table 2. Model Parameters

Parameter	Source	Range
Analysis Period	[99]	2014-2030
Discount Rate	[78]	0.65-1.15
Inflation Rate	[79]	-10% , +10% of CBO's projections
Fuel Economy	[100]	Represented in section 2.3.1
Vehicle Miles Traveled (VMT)	[100]	-10% , +10% of EIA's projections
Electricity Price	[101]	Represented in section 2.3.1
Gasoline Price	[100,102]	Represented in section 2.3.1
Battery Production & Recycling Emissions	[103]	Represented in section 2.3.2
EDC	Existing literature	Table 5
WFP of Fuels	Existing literature	Tables 6, 7, and 8

3.1.3.1. Uncertainties in the Life Cycle Cost

GREET 1-2013 reports the passenger car engine efficiency for each vehicle type, with adjustments of EPA estimated miles per gallon (mpg) for on-road performance. It considers the Vehicle Miles Traveled (VMT) proportion as 43% city and 57% highway [29]. The engine efficiency of gasoline-powered vehicles are taken from the EIA's projected mpg for light duty vehicles [100]. Using this data, the effect of future changes in engine efficiency is taken into account. The fuel economy for the other drivetrains is based on the DOE and EPA's available data on vehicle drivetrains. The fuel economy of the non-ICEV drivetrains is a multiplication factor applied to the ICEV fuel economy. The mpg of HEV cars is assumed to be 1.3-1.4 times greater than regular gasoline-powered vehicles. For the PHEVs, AFLEET uses the GREET efficiencies of the PHEV-10. The mile per gallon equivalent (MPGe) for this type of vehicle is assumed to be 1.5-1.6 times greater than regular gasoline-powered cars. The MPGe of EREV cars is based on the PHEV-40 and is assumed to be 1.2-1.3 times greater than ICEVs, as increasing the battery size may decrease the charge sustaining fuel economy due to its higher weight [29]. The MPGe of different light duty EVs is assumed to be 3-3.4 times greater than regular gasoline-powered vehicles, as charging efficiency equals 85%.

According to the Transportation Energy Data Book, the average annual VMT for a gasoline-powered passenger vehicle is 12,400 miles [99]. For this study, the EIA's Vehicle Miles Traveld (VMT) projections are used for future VMT of light duty vehicles [100]. The average yearly mileage is assumed to vary within a 10% range of the EIA's reported VMT.

Of note is that the U.S. national electricity mix has changed a lot during the years covered by the literature, and the generation mix at any given time and location is highly dependent on a variety of factors, including the vehicle and charger design; time of day and time of year; geographic climate region; and load growth patterns and associated generation expansion [48]. Due to the importance of electricity mix, this study compares the LCC and LCEE of EVs in different electricity mix scenarios. The electricity market module regions from the National Energy Modeling System (NEMS) regional analysis were used. The energy mix as a source for the PHEVs, EREVs, and EVs is considered to follow the energy mix in each region. This regional configuration is a more appropriate approach than some other regional delineations (such as the North American Reliability Corporation regions) because the NEMS regions reflect a narrower range of electric generation types within each region. This results in a more accurate and more granular analysis of the effect electricity mix has on the LCEE of electric drivetrains. These regions also better reflect the cost to the consumer of charging an EV, an important aspect of the LCC.

U.S. Energy Information Administration publishes the Annual Energy Outlook (AEO) every year. This report contains information on the energy sector in the United States, with projections for the future. Figure 1 represents the variation in the electric generation mix for each of the NEMS regions, based on the EIA database [104] (Please see Figure 4 for the color codes). The y-axes in Figure 1 represent the percentage of each energy source in the electric generation mix in each U.S. electric region, from 2014 through 2030. These projected values are from AEO 2014 [105]. As indicated, the source type percentage varies dramatically by time for some of the regions. This variation is modeled by EVRO.

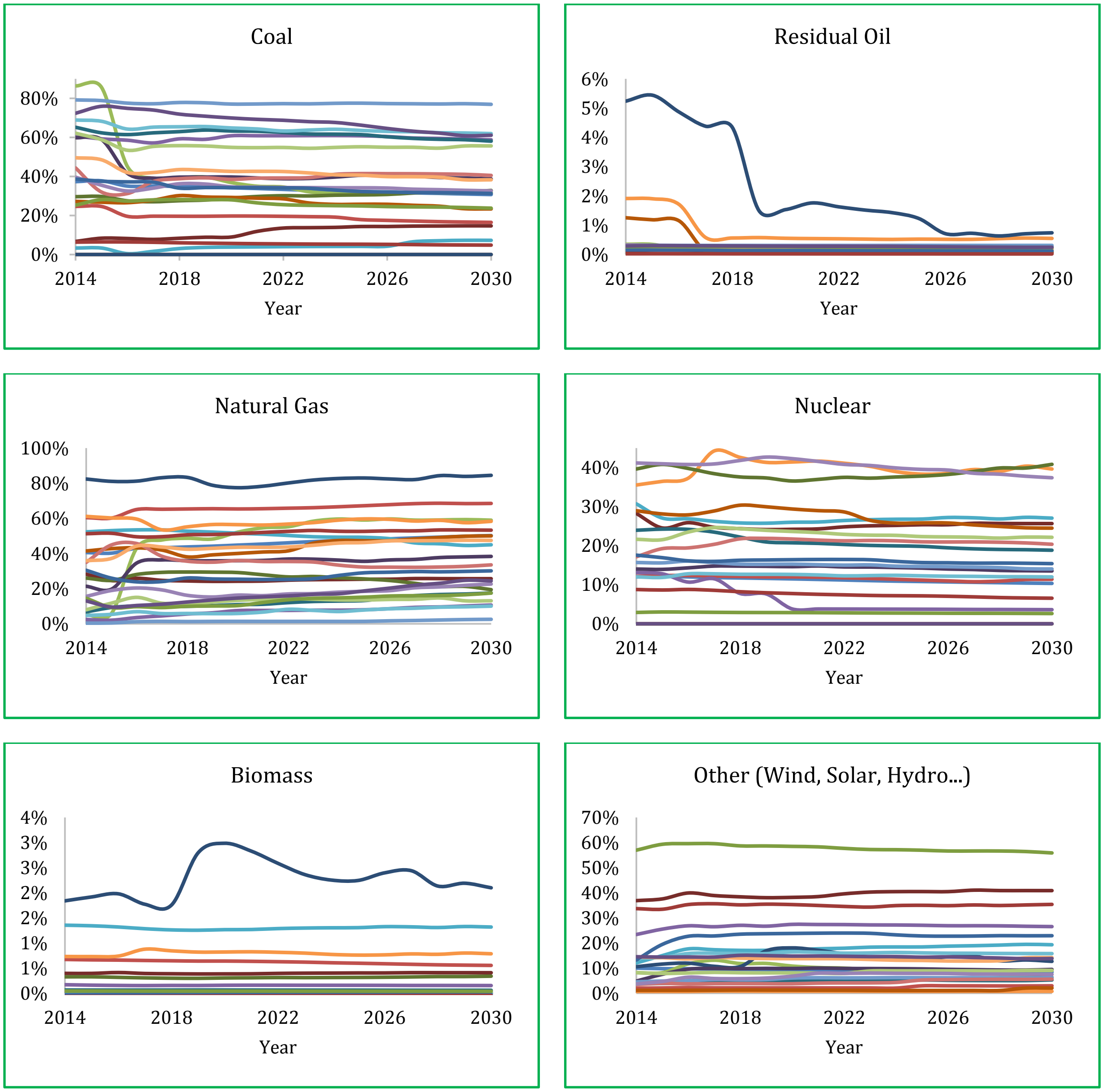


Figure 4. Electric generation mix variation by time, in different regions [105]

(Please see Figure 4 for the color code)

The levelized cost of new generation resources is considered to estimate electricity generation costs in the different electricity regions [101]. Here, the levelized cost of energy (LCOE) is used to compare the different energy sources. LCOE is the cost of generating electricity per kWh, including all of the capital, maintenance and operation costs of a power plant during its entire life cycle. In other words, LCOE is an annuity per kWh electricity, which has the same present value as the total cost of a power plant [106]. EIA publishes the regional variation in the LCOE for different electricity generation sources by NEMS electric regions, with future projections. This data is available for the power plants entering service in 2016, 2017, 2018, 2019, and 2040. The variation in LCOE for different electricity sources for the analysis period is estimated through an interpolation between the available data. Table 3 shows an example of regional variation for power plants entering service in 2019 [101].

Table 3. Regional variation in levelized cost of new generation resources [101]

Plant Type	**Range for total system levelized costs (2012 \$/MWh) for plants entering service in 2019**[1]		
	Minimum	**Average**	**Maximum**
Residual oil[2]	73.2	83.2	95.7
Natural gas	81.44	90.84	104.72
Coal	87	95.6	114.4
Nuclear power	92.6	96.1	102.0
Biomass	92.3	102.6	122.9
Others (Wind, Solar, Hydro, etc.)	115.96	148.4	217.58

[1] Government subsidies are not considered in these ranges

[2] EIA does not report the electricity price for residual oil power plants. Data from the 2009 New York State Energy Plan is used for this plant type.

EIA reports the LCOE of Wind, Solar, Hydro, etc. separately. However, the projections data for the electric generation mix is not available, and the LCOE of these plants types is combined. Since the regional variations in LCOE of the “Others” section is considerable, the renewable energy supply in each region is used to find a weighted average LCOE range for this plant type. The yearly renewable energy mix in each region is taken from Short-Term Energy Outlook and Winter Fuels Outlook, and the Emissions & Generation Resource Integrated Database (eGrid), which is a source of emissions data for U.S. electric power generation [107,108]. Therefore, by multiplication of the matrix of electricity generation mix and the matrix of LCOE, the electricity price ranges for different U.S. regions during the analysis period can be calculated. In order to take transmission losses into account, eGrid’s transmission loss factor for each region is used to estimate the cost of electricity after transmission losses [107]. Figure 2 shows the estimated cost of electricity for each year by region. Either each line represents the minimum, average, or maximum calculated electricity price for all U.S. electric regions. As indicated, the variation in electricity price decreases through the analysis period. Region 13 (Gateway) is responsible for the highest LCOE for most of the analysis period. The lower bound of electricity price switches between a few regions during the analysis period including region 7 (Long Island), region 8 (Upstate New York), and region 20 (California). These ranges are used to calculate the Total Cost of Ownership (TCO) of EVs.

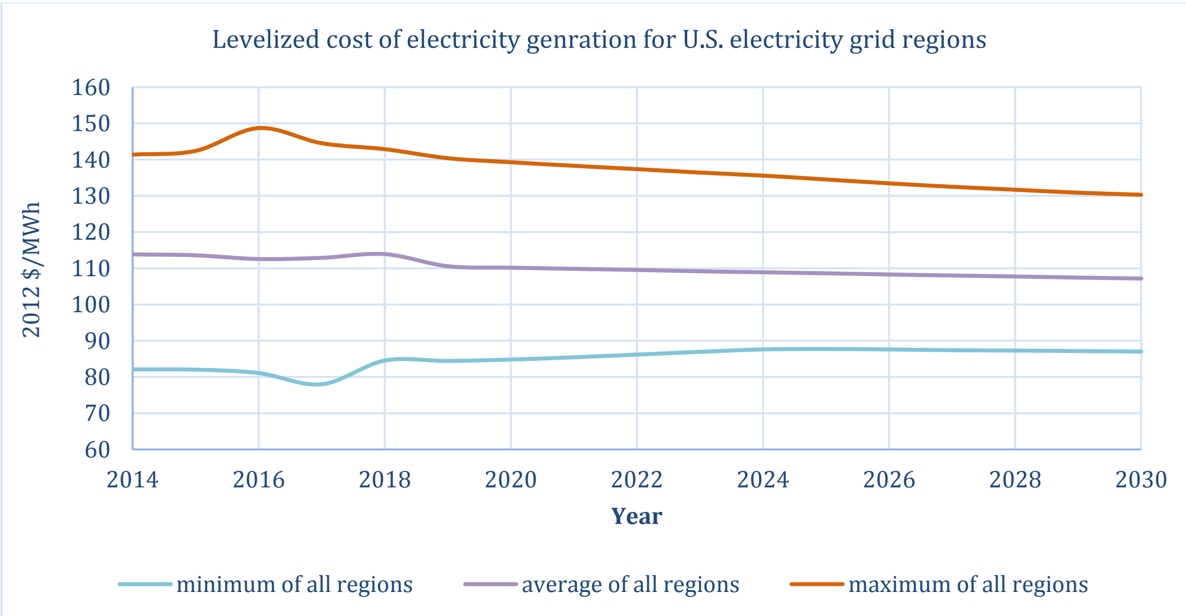
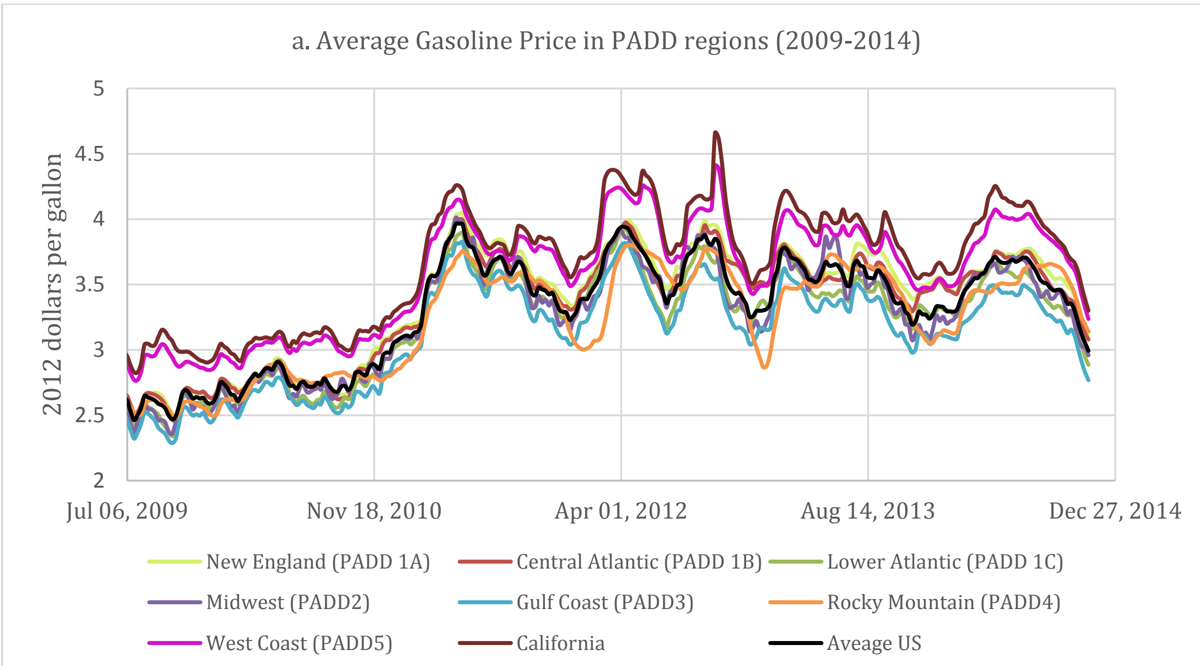


Figure 5. Electricity price ranges for different U.S. electric grid regions ($/MWh)

Gasoline prices vary from region to region. Regional gasoline prices are reflected in the Petroleum Administration for Defense Districts (PADDs), as reported in the EIA's Gasoline and Diesel Fuel Update [102]. We divide the average price of gasoline in each region by the US average to estimate the correction factor for gasoline price for each electricity region (see Table 2).

Then the projected price of each PADD region is estimated by multiplication of the correction factor and the EIA's projections for gasoline prices. We use the EIA's reference case as the average, and the high and low prices as the maximum and minimum (Please see Figure 3b). We use a rectangular random selection to generate the future gasoline prices based on these ranges. Figure 3a shows the historic price of regular gasoline for the PADD regions as well as the US average. Figure 3b represents the gasoline price projections for the reference, high price, and low price cases.



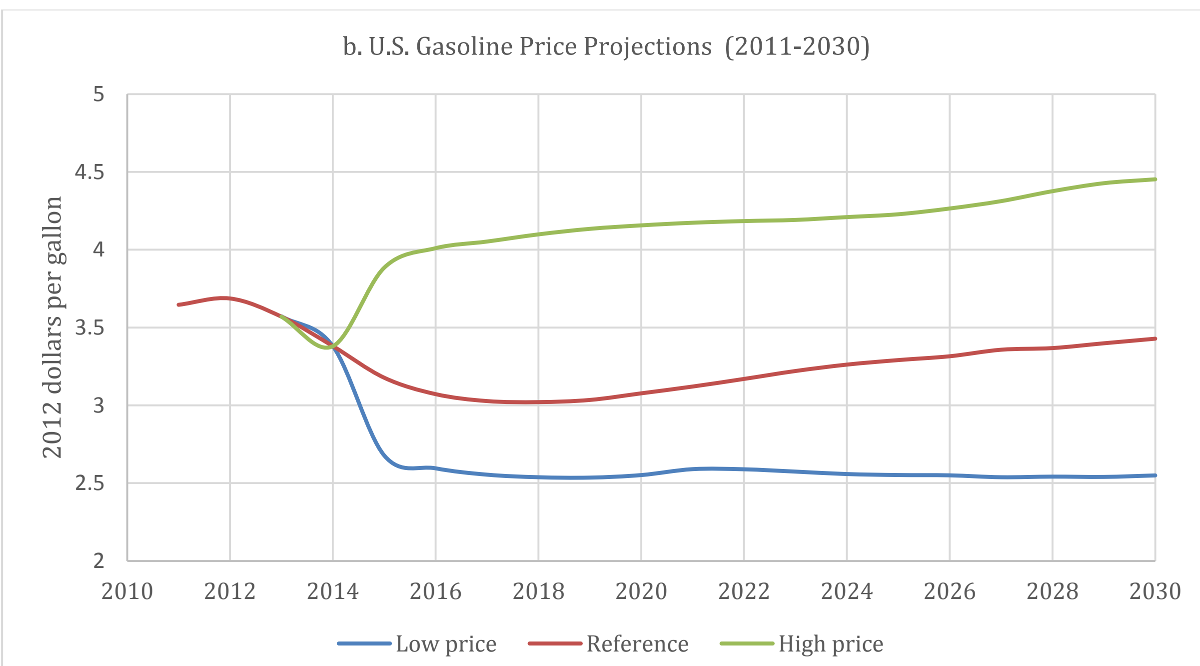


Figure 6. a. Average gasoline price in PADD regions [102] b. U.S. gasoline price projections [100]

Table 4. Correction factors for regular gasoline price in PADD regions based on [102]

PADD Region	Correction Factor
New England (PADD 1A)	1.02
Central Atlantic (PADD 1B)	1.01
Lower Atlantic (PADD 1C)	0.98
Midwest (PADD2)	0.99
Gulf Coast (PADD3)	0.95
Rocky Mountain (PADD4)	0.99
West Coast (PADD5)	1.09
California	1.11

Insurance, license and registration costs, taken from the AFLEET model, changed according to the variation in the inflation and discount rate. These costs are selected randomly in each replication for each vehicle type.

Finally, a programming code capturing all of the above assumptions is written using Visual Basic for Applications and is linked to the AFLEET model. This code chooses a randomly selected fuel economy, VMT, gasoline price, electricity price, discount rate, and inflation rate for each replication, in each year of the analysis period. However, during each replication, the gasoline escalation rate, electricity escalation rate, and VMT are constant and only the fuel economy varies from one vehicle type to another. All of the variables are assumed to be mutually exclusive of each other, meaning a change in one factor does not cause any change in another.

3.1.3.2. Uncertainties in Environmental Damage Costs

In the LCCA of alternative fuel vehicles, the externality and societal costs are often singled out [13]. These types of costs, which are commonly called "Environmental Damage Costs (EDC)," include costs that are associated with GHGs and local air pollutants. In this research, two steps are undertaken in order to find the EDC of different EV types: estimating the LCEE of different EV types, and assigning a cost value per unit mass of emissions [109]. The AFLEET model reports the LCEE of different EV types.

In the EDC analysis, there are considerable inherent uncertainties, including the uncertainties in the air pollutant damage costs and GHG costs, the variability in the oil costs, oil supply insecurity costs, and projected costs of mass-producing future vehicles [13]. These uncertainties make the LCC comparisons difficult. Table 5 shows ranges of environmental damage costs based on some previous studies [109–115]. These values have been adjusted for inflation and converted to 2012 values using the consumer price index, since the available data on LCOE for electric generation was available in 2012 dollars [82].

Table 5. Environmental Damage Costs per ton of emissions

Pollutant	**Cost, $ (2012)/ton pollutant**
Volatile Organic Compounds (VOC)	2,655 - 4,722
Carbon Monoxide (CO)	61 - 3,586
Oxides of Nitrogen (NOx)	132 - 11,425
Particulate Matter ≤ 10 μm (PM10)	1,784 - 12,500
Oxides of Sulfur (SOx)	825 – 5,632
Carbon Dioxide (CO_2) equivalent	2-104

The EDC can be calculated based on the following formula [109]:

$$EDC = \sum_{k} (C \times Emissions)_i \times VMT \times Life \tag{9}$$

Where;

EDC = Environmental Damage Cost, in $/vehicle

C = Cost per unit mass emissions, in $/g (See Table 5)

Emissions = Vehicle Emissions, in g/mile

VMT = Vehicle Miles Traveled, in miles/vehicle-year

Life = Average vehicle life time, in years

k= pollutant index

The direct emissions of a vehicle are estimated using the AFLEET tool. eGRID provides gross grid loss factors that can be used to estimate the indirect emissions associated with transmission and distribution losses [107]. Equation 2 below can then be used to calculate an emissions factor which covers both the indirect emissions and the line losses from the purchase of electricity [116]. The electricity purchases can then be multiplied by the emission factor to estimate the emissions associated with using electricity as the energy source for the EVs. eGrid only reports the amount of GHG and NO_x emissions in different US grid regions. To account for upstream CO, PM10, and VOC air pollutants, the well to pump emissions for different power plants are extracted from GREET. These emissions are multiplied by EIA's regional energy mix projections to calculate the upstream air pollutant emissions (Equation 3). GREET's well to pump emissions of gasoline are used for the upstream emissions of gasoline. The annual upstream emission rate of different power plants and gasoline is assumed to stay the same during the analysis period, due to lack of data availability.

$$Upstream_{kj} = \frac{(eGrid)_{kj}}{(1 - GGL_j)} \tag{10}$$

Parameters:

$Upstream_{kj}$: $Upstream\ amount\ of\ air\ pollut\ k\ in\ region\ j\ (lb/kWh)$

$eGrid_{kj}$: $eGRID\ annual\ emission\ rate\ in\ region\ j\ for\ air\ pollutant\ k\ (lb/kWh)$

GGL_j: $eGrid\ grid\ loss\ factor\ for\ region\ j$

Indexes:

$k: air\ pollutant\ index, for\ GHG\ and\ NOx$

$j: region\ index$

$$Upstream_{kjy} = \sum_{p} (WTP)_{kp} \times (EnergyMix)_{pjy} \tag{11}$$

Parameters:

$Upstream_{kjy}: Upstream\ amount\ of\ air\ pollutant\ k, in\ region\ j, for\ year\ y\ (lb/kWh)$

$WTP_{kp}: Well\ to\ Pump\ air\ pollutants\ of\ power\ plant\ p\ (lb/kWh)$

$EnergyMix_{pjy}: Generation\ percentange\ of\ electricity\ by\ powerplant\ p, in\ region\ j, for\ year\ y$

Indexes:

$k: air\ pollutant\ index, for\ CO, PM10, and\ VOC$

$j: region\ index$

$y: year\ index$

$p: power\ plant\ index$

The average age of vehicles in the U.S. is reported differently in the literature, ranging from 11.4 years [117] to over 20 years [118]. In this study, the average lifetime of a vehicle is considered to be 16 years, based on the Transportation Energy Data Book [99]. Neither of the emissions equations includes the discount rate. Thus, the effect of the time value of money was taken into account separately using the one year certificate of deposit rate [78].

It is assumed that recycling for all of the drivetrains is handled in the same way with the exception of the battery recycling. The recycling emissions of vehicle parts are not reported in the overall environmental impacts. Even though some believe that battery recycling is not cost effective in the current US economy [33], here it is assumed that all of the electric-powered vehicles use lithium-ion batteries and the production and recycling emissions of batteries are accounted for using the values in EPA's report on LCCA of lithium-ion batteries for EVs [103]. These values take the material extraction and processing, component and product manufacturing; product use, and end of life emissions of EV batteries into account.

3.1.3.3. Uncertainties in Water Footprint of Energy

The WFP of electricity reported in Wu & Peng, 2010 is used for this analysis (Please see Table 6). The data in the ANL's report on the water consumption of transportation fuels and the results of water consumption and water withdrawal of U.S. transportation fuels in Scown's University of California, Berkeley dissertation are used for the water footprint of gasoline [119,120]. The petroleum burned in the U.S. is mainly derived from crude oil production from conventional, shale, and oil sand resources. Although the water footprint of shale resources is higher than that of the other sources, it is assumed that the gasoline is extracted from conventional and oil sands resources, due to data availability.

Due to differences in the source of crude oil and the age of the wells, different technologies are used, which adds to the uncertainty of estimating water consumption and withdrawal. Moreover, the water consumption and withdrawal associated with the conversion of crude oil to gasoline varies from region to region. Lampert et al. suggested 0.5-2.5 gallons of water consumed per gallon of crude oil processed at refineries [119]. Table 5 shows the summary of ANL's reported water consumption (extraction, production, and refining). Scown has added the feedstock transportation, fuel transportation, storage, and distribution water footprint into her estimates. She has also performed a sensitivity analysis considering three different low, average, and high cases for water consumption and withdrawal. Her results indicate that water consumption ranges from 0.57 to 1.42 L/Km travelled and water withdrawal ranges between 0.96 and 1.85 L/Km travelled (See Table 6). These ranges as well as the ANL's reported data for water footprint are used for estimating the associated life cycle water footprint of each vehicle type, in each PADD region.

Table 6. Water Footprint (Withdrawal + Consumption) in Electricity Generation [55]

Plant Type	Water Footprint (gal/kWh)
Residual oil	22.63-22.83
Natural gas	1.32-22.52
Coal	17.83-18.26
Nuclear power	20.24-24.74[1]
Biomass	0.99-1.21[1]
Others (Wind, Solar, Hydro, etc.)	1.68-6.4

[1] Due to lack of data availability, these ranges are based on (-10%, +10%) of reported values.

Table 7. Water consumption (extraction, production, and refining) of gasoline production [119]

PADD Region	Water Consumption (gal/gal gasoline)
East Coast (PADD 1)	3.9-5.9
Midwest (PADD2)	2.6-4.6
Gulf Coast (PADD3)	2.8-4.8
Rocky Mountain (PADD4)	3.9-5.9
West Coast (PADD5)	5.9-7.9

Table 8. Water footprint of Oil to Gasoline [120]

Pathway	Water withdrawal (L/Km travelled)		
	Minimum	**Average**	**Maximum**
Crude Oil to Gasoline	1.53	2.55	3.27
Oil sands to Gasoline	2.27	2.82	3.43

3.2. Electric Vehicle Regional Market Penetration Model

This section will serve to explain the methodology framework in greater detail, and the following subsections will describe the conceptual basis and mathematical content of the methodology. First, the developed Electric Vehicle Regional Market Penetration (EVReMP) model and its relationships to other parts of the methodology are illustrated. Second (Section 2.1), a summary of the previously developed Electric Vehicle Regional Optimizer (ERVO) is explained. Third, (Section 2.2), the concept of Exploratory Modeling and Analysis (EMA) and the mathematical content of the agent-based model (ABM) developed in this study are explained. Fourth, Section 2.3 presents the inherent uncertainties in the purchase prices, maintenance and refueling cost, and water footprints of the studied vehicles as applicable. Figure 1 below illustrates the methodology used to develop the EVReMP model. The core of the EVReMP model is an agent-based model used in conjunction with the concept of Exploratory Modeling and Analysis to account for the relevant uncertainties in the input variables. Additionally, the EVReMP model used the outcome of the previously developed EVRO model. In short, the EVReMP model is a combination of several different methodologies (see Section 2) that will enable decision-makers to see what the market penetration of the studied drivetrain would be in the year 2030. The related research report at University of Central Florida is under review in the journal of Energy [121].

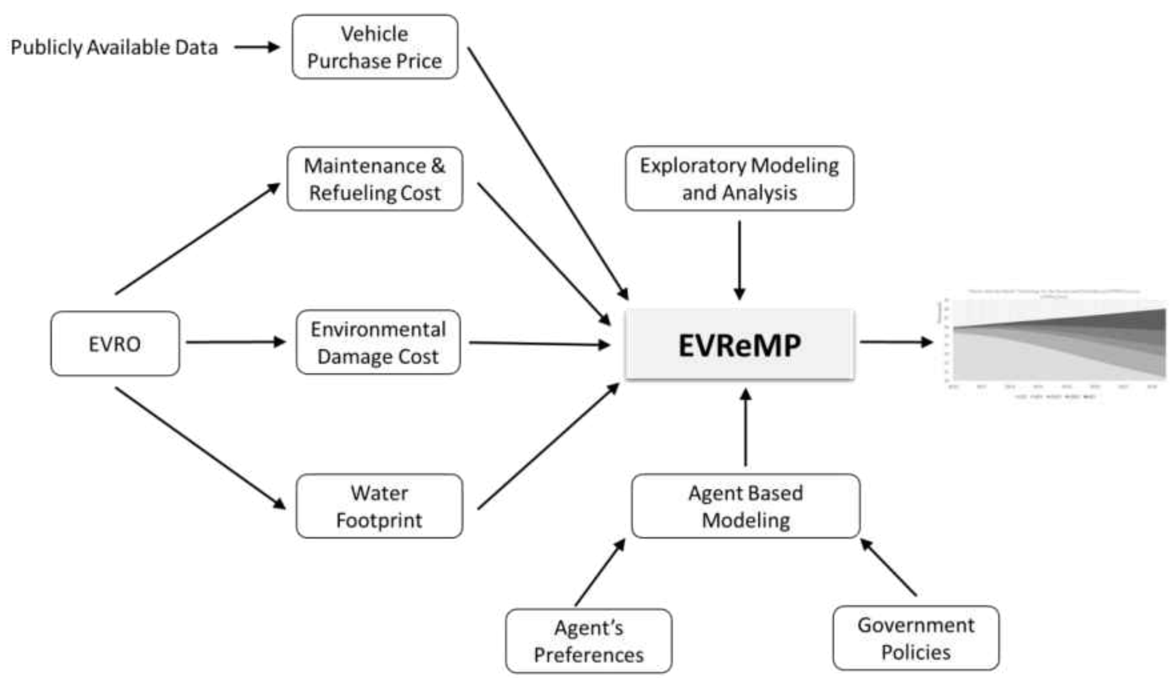


Figure 7. Illustration of EVReMP model

3.2.1. Electric Vehicle Regional Optimizer (EVRO)

EVRO is an optimization model previously developed by the authors; the related research report at University of Central Florida has recently been accepted for publication and will soon be available online [75]. This tool uses several previously established methodologies in Life Cycle Assessment, Decision Making Under Uncertainty, and Stochastic Optimization [52,84,87–89,122–124], and builds on the Argonne National Lab's Alternative Fuel Life-Cycle Environmental and Economic Transportation (AFLEET) model to estimate the life cycle cost (LCC) and life cycle environmental emissions (LCEE) of the studied vehicle types, after which the output of the AFLEET model will be used as the input of the EVRO model. The environmental damage cost (EDC) is taken into the account, including the costs associated with the mitigation of GHG and local air pollutant emissions. The water footprint (WFP) of the studied drivetrain is also estimated in the EVRO model, considering the first-tier and higher-tier withdrawals of petroleum extraction and/or electricity generation. Finally, an optimization model is coupled with the concept of Exploratory Modeling and Analysis, and is subsequently applied to the estimated LCCs, EDCs, and WFPs of the studied drivetrain to find the optimal drivetrain combination for the year 2030. Here, the EVReMP model builds on the EVRO model to estimate the maintenance and refueling costs, EDCs, and WFPs of each of the studied vehicles.

It is worth noting that there is a considerable amount of uncertainty in estimating vehicle attributes; for a thorough market penetration evaluation of EVs, dealing with these uncertainties is crucial. The EVRO model considers different uncertainty factors in order to evaluate the attributes of each vehicle type. The overall range of each uncertainty factor in the EVRO model was taken from publicly available data, and these ranges are summarized in Section 2.4.

3.2.2. Exploratory Modeling and Analysis

Most predictive models are designed so that known facts are consolidated to create a "best estimate" model. Such models are claimed to be an accurate case of that portion of the real world, but in reality they can only be considered valid when there is adequate useful data of sufficient quality that model designers can use empirical data to validate the model. This validation process is only possible when the situation is observable or measurable, the structure of the problem is constant over time, and sufficient data can be collected [60,125]; for many systems, however, these conditions are not met. Scientists use different terms to express such situations, and subsequent predictions under such conditions are largely rejected as wrong, bad, or useless [60,125–128]. On the other hand, our actions today affect the future behavior of the system. The degree of uncertainty with respect to the behavior of the system is directly proportional to the level of interaction among economic, social, environmental, and technological factors, and decision making with high levels of interaction involved in the system is said to be under deep (or severe) uncertainty [93,129–131]. This situation occurs when the overall relationships among the main components are the system cannot be agreed on by decision makers, when the probability distribution of these factors is uncertain, and/or when the most plausible outcome is not precisely predictable [94]. Uncertain aspects of these systems include the initial inputs of the system, the relationships among the parameters in the model, the logic associated with these interactions, the system boundaries, the model structure, and the difference between the real behavior of the system and the estimation presented in the model.

With all of this in mind, the Exploratory Modeling and Analysis (EMA) method is used to model the behavior of the system in this situation. The EMA methodology evaluates the behavior of the system under deep uncertainty, and is based on the prominent work of Bankes [95,96]. More specifically, the EMA method works by forming an ensemble of plausible outcomes using computational experiments based on available knowledge and data, and then using this set of plausible outcomes as a surrogate to predict the behavior of the system. In fact, instead of building one model and verifying it as a representation of the system, the EMA method creates an ensemble of models and explores the implications of these models [60]. By conducting such experiments, one can explore which of the determined plausible outcomes are more likely to occur given the system's behavior. Although the EMA methodology is relatively new and still under development, it has already been applied to a wide variety of disciplines and research topics, including climate change, production planning, economic analysis, healthcare, sustainable development, and transportation [89,94,96,132–135].

In this research, the EMA method is used to evaluate all of the plausible outcomes of the developed agent-based model (ABM). This integration of the EMA and ABM methodologies thereby enables decision-makers to generate, explore, and deeply analyze a large number of plausible future outcomes, allowing them to better understand the effect(s) of current uncertainties on the future market shares of electric vehicles. The required steps to apply the concept of EMA to a deeply uncertain problem are as follows [97,98]:

Conceptualize the policy problem,

Specify the relevant uncertainties,

Develop an easily controllable computational model of the system's behavior,

Generate numerous plausible future outcomes as needed,

Perform a data analysis with respect to the generated outcome(s), and Use the finalized model to define and test different policies as desired.

These steps are taken into account while using EMA in this effort. The conceptualization of the policy problem in this study is explained in Section 1, the mathematical content of the ABM model is described in further detail in Section 2.3, and the results after the model is run for 100,000 replications are discussed in Section 3.

3.2.3. Agent Based Modeling

An Agent-Based Model (ABM) is used to evaluate consumer behavior and to estimate the market penetration of the studied drivetrain; the mathematical content of the developed ABM for this study is described in this section. Four different agents (consumers, regions, governments, and vehicles) are considered in this model. Consumers seek to purchase a vehicle, maximizing the utility of the vehicle(s) in question. Governmental policies can affect consumer behavior in various ways, depending on the implications of each specific policy and/or set of policies. Vehicle attributes are derived from the EVRO model, with the EVRO analysis performed for each U.S. electric grid region. An ABM enables us to model the behavior of heterogeneous agents on a micro-level basis, although the effect(s) of macro-level policy implications can also be taken into account [73].

3.2.3.1. Consumer Agent

A group of vehicles compete for market penetration through a consumer choice algorithm. Figure 2 shows a general form of this part of the model, illustrating the transition between an agent who is potential buyer and an agent who buys a certain vehicle type. The purchase rate of a particular vehicle type depends on a variety of factors. Here, a combination of different existing methodologies is used to formulate the purchase price, and the word-of-mouth (WOM) effect, through which buyers can contact potential buyers and convince them to buy a particular vehicle type, is also taken into account.

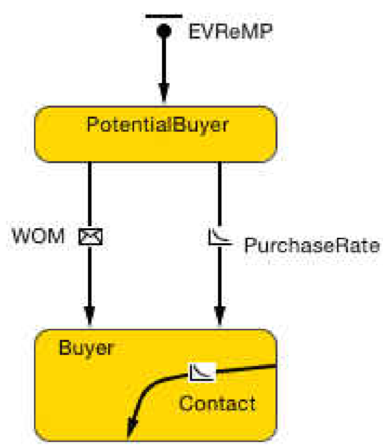


Figure 8. General illustration of the EVReMP model

Following [74], the purchase probability of vehicle j by agent i, at time t is calculated as:

$$P_{i,j,t} = \frac{W_{k,j,t}.\exp\left(\sum_{a=1}^{A}\beta_{i,a,t}.X_{a,j,t}\right)}{\sum_{j=1}^{V}W_{k,j,t}.\exp\left(\sum_{a=1}^{A}\beta_{i,a,t}.X_{a,j,t}\right)} \qquad (12)$$

Parameters:

$P_{i,j,t}$ = the probability of agent **i** purchasing vehicle **j** at time **t**

$\beta_{i,a,t}$ = the preference of customer **i** with respect to attribute **a** at time **t**

$X_{a,j,t}$ = Value of attribute **a** for agent **i** at time **t**

$W_{k,j,t}$ = the willingness of drivers of vehicle type **k** to consider vehicle **j** at time **t**

Indexes:

i = index for agents

j = index for vehicles

k = index for drivers of vehicle type **k**

A = number of attributes

V = number of vehicles

The vehicle attributes are taken from the EVRO model, which generates the EDC, the WFP, and the total Maintenance and Refueling Cost, and provides the applicable ranges for each of these parameters. The results of this analysis are being published in the journal of *Energy* [75]. The values of the vehicle attributes are available for each region, based on the relevant parameters (electricity mix, electricity price, gasoline price, etc.) and their respective projections until 2030, while the purchase prices of the studied drivetrain are likewise derived from publicly available data. The vehicle purchasing preference of each agent depends on the social and income categories of the agent in question, which are randomly selected from three different income categories and eight different social categories. The consumer preference is defined as how likely or unlikely a consumer is to buy a particular vehicle; for example, a customer with a higher income will tend to buy more expensive cars than a consumer with a lower income. The preferences of each agent with respect to each of the considered vehicle attributes are all taken from previous studies [74,136].

For purposes of this study, it has been assumed that the consumer must be familiar with a given vehicle before he/she is willing to purchase said vehicle. The consumer willingness to purchase a vehicle is considered based on two separate reference studies [74,137], where the willingness varies from 0 to 1. The willingness to purchase ICEVs and/or HEVs is considered to be equal to 1, while the corresponding willingness to purchase EVs varies randomly from 0 to 1, unless the agent is being contacted by another EV buyer and is convinced to consider purchasing an EV, in which case the willingness to purchase an EV becomes equal to one. In short, the willingness to purchase an EV is a function of the WOM effect. As can be seen in Figure 2, EV buyers contact other agents randomly, after which another random variable function (in terms of the WOM effect) is used to determine whether or not the contacted agents" willingness to consider EV becomes equal to their pre-set willingness to consider ICEVs or HEVs.

The availability of charging stations and the relatively low range of EVs will also affect the agents' decision on whether or not to consider a certain vehicle type. Therefore, based on previous studies [74,138], the following equation is used to take into account the refueling effects on EV shares:

$$RFE_{j,j,t} = \begin{cases} 1 & j = ICE \\ 1 - DP_{i,t} \, . \, e^{-\alpha . s_t} & j = EV \end{cases} \quad (13)$$

where;

$RFE_{j,j,t}$: Refueling effect for consumer i using vehicle j at time t

$DP_{i,t}$: Driving Pattern of cunsumer i

s_t: Availability and Social Acceptability of Charging Facility at time t

$\alpha > 0$: Scaling factor to calibrate the model

The parameter s_t, assumed to be equal to the proportion of consumers who have adopted EVs, is updated in each run based on the most current number of EV buyers. For model calibration purposes, α is considered to be equal to 3. In [74], $DP_{i,t}$ is considered to be 0.49, based on the total distance that a vehicle is driven per year. The average daily distance driven by U.S. drivers is estimated using data from the 2009 National Household Travel Survey (NHTS) [139], in which data was collected on daily trips taken in a 24-h period by over 150,000 interviewed households and 300,000 people, providing information about trip characteristics such as trip length, trip duration, and vehicle type used. The data for which was obtained from the post-processed NHTS 2009 dataset of 294,407 automobiles, which only included cars, vans, SUVs, and pickup trucks. Since the VMT per capita in the U.S. is almost double that of [140], the changing needs of consumers are likewise considered to be doubled. However, looking at the distribution of daily distance traveled in the U.S. as published by the NHTS, the weighted average of the VMT is 9.4 miles, meaning that approximately 70% of all trips are taken under this amount. Therefore, we assume that $\mathrm{DP_{i,t}}$ is randomly selected in each replication, varying between 0.49 and 0.7.

The probabilities estimated in the previous equation are therefore scaled by refueling effect factors, and the modified values are as follows:

$$\overline{\mathrm{P}}_{\mathrm{i,j,t}} = \frac{\mathrm{P_{i,j,t}} \times \mathrm{RFE_{j,j,t}}}{\sum_{\mathrm{j}} \mathrm{P_{i,j,t}} \times \mathrm{RFE_{j,j,t}}} \qquad (14)$$

After calculating the probability of each agent purchasing each vehicle, a cumulative distribution function is formed to calculate the sum of all of these purchase probabilities for buying all of the vehicles up to and including a particular vehicle [74]:

$$\mathrm{Q_{i,j,t}} = \sum_{h=1}^{j} \overline{\mathrm{P}}_{\mathrm{i,h,t}} \qquad (15)$$

A random variable Z is then generated from a uniform distribution function and compared to the cumulative distributed function in Formula 4. The vehicle type purchased by a particular agent is the type that ultimately has the closest outcome to the generated random variable Z such that the outcome is higher than Z. In other words:

$$If\ \mathrm{Q_{i,j-1,t}} \leq Z \leq \mathrm{Q_{i,j,t}}\ Then\ agent\ purchases\ Vehicle\ j \qquad (16)$$

In summary, Figure 3 shows the algorithm of the vehicle purchasing process, and the overall decision-making process starts by looping over the analysis period, the regions, and the agents in each region. The ABM model then assigns social and income category values to the agent, and based on these values, the purchase probability for the agent is estimated. Next, the vehicle's life of the agent and the vehicle lifetime are randomly generated and compared; if the vehicle's life of the agent is greater than the vehicle lifetime, the agent decides to buy a vehicle. However, if the vehicle's life of the agent is not greater than the vehicle lifetime, the agent may still decide to buy a vehicle; whether or not this is actually the case is determined by comparing the agent's purchase probability with the random variable A. If neither of these two simulation steps results in a vehicle purchase, then the agent in that particular iteration does not purchase any vehicle in that replication, and the analysis is repeated for the next agent. On the other hand, if the agent does decide to purchase a vehicle, the vehicle attributes are loaded from the Vehicle Agent, the agent's preferences are loaded based on existing literature, and the refueling effect and the agent's willingness to purchase a vehicle are estimated for the entire studied drivetrain. Next, the purchase probability of a given vehicle is estimated based on the aforementioned simulation process, and the cumulative distribution function (CDF) is calculated accordingly. Which vehicle type the agent ultimately buys is determined by comparing the generated random variable with the CDF as expressed in Equation 5. In this study, the AnyLogic software is used to formulate the ABM [141], and the generated data is then exported to Excel and Visual Basic for Application (VBA) is used for data analysis.

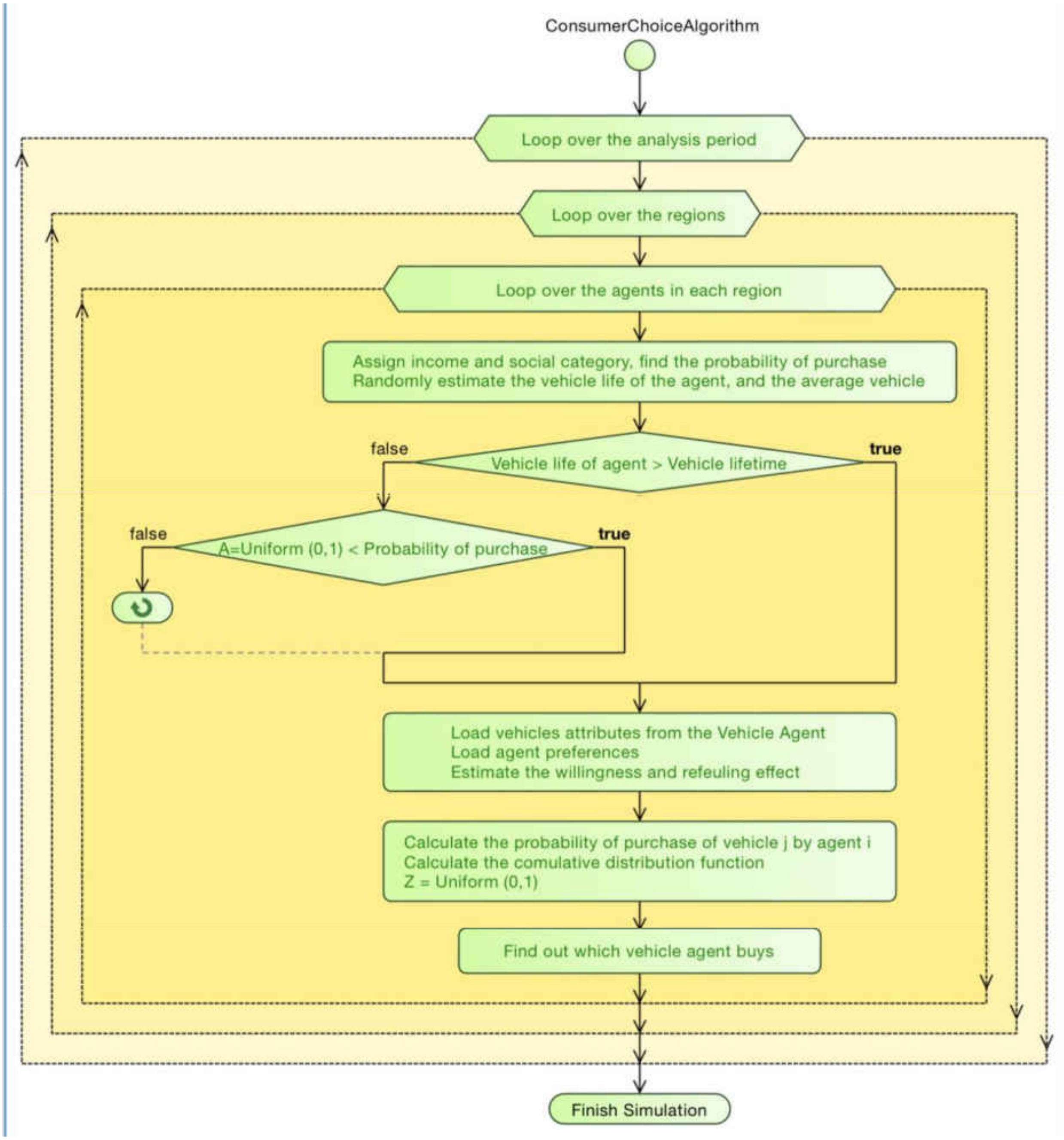


Figure 9. Algorithm of vehicle purchasing process

3.2.3.2. Region Agents

The analysis in this study is being performed entirely on a regional basis, and it must be noted that the U.S. national electricity mix has changed a lot during the years covered by the available literature. Moreover, the generation mix at any given time and location is highly dependent on a variety of factors, including the design of the vehicle and charger, time of day and/or the time of year, the relevant geographic climate region, and the applicable load growth patterns and associated generation expansion [48]. Due to the importance of electricity mix on M&R costs, EDC, and WFP, this study will compare these vehicle attributes under different electricity mix scenarios, using the electricity market module regions from the regional analysis provided by the U.S. National Energy Modeling System (NEMS). The energy mix used for recharging PHEVs and EVs is considered to follow the NEMS energy mix in each region. This regional configuration has been deemed more appropriate approach for this study than other regional delineations, such as those of the North American Reliability Corporation regions. The NEMS regions reflect a narrower range of electricity generation types within each region, resulting in a more accurate and more granular analysis of the effect(s) of the electricity mix on the market penetration of electric drivetrains. These regions also better reflect the refueling effect for an EV, which is an important aspect of the market share. Figure 5 in Section 3 shows the studied regions.

The current market share of EVs in the United States differs from region to region, with Washington having the largest market of EVs in the U.S. as of today, followed by the states of Hawaii and California [142]. In fact, the number of active agents in each region depends on the population and on the number of vehicles for said agent. Therefore, in this research, the number of agents in each region will be formulated as follows:

$$n_{i,t} = N \times (1 + r_p) \frac{p_{i,t}.\, v_{i,t}}{\sum_{i=1}^{22} P_i, t.\, V_{i,t}} \qquad (17)$$

Where;

$n_{i,t}$: Population of region **i** at time **t**

N: Total number of agents in the first year of the analysis

r_p: U. S. population growth rate

$p_{i,t}$: Population of region **i** at time **t**

$v_{i,t}$: Number of registered vehicles in region **i** at time **t**

U.S. census data and the Population Explorer tool are used to estimate the population of each NEMS region [143,144]; in this study, the number of agents changes based on the U.S. population growth, which for this study is assumed to have a value of 0.7 percent as indicated in [145]. To assume that the number of agents is equal to the population of United States is beyond the scope of this study, so instead we assume that there are 50,000 agents available as potential buyers, with these agents placed randomly in each region based on the indicator represented in Equation 6.

3.2.3.3. Vehicle Agents

Considering all currently available vehicle types in the market is beyond the scope of this study and would overly complicate this analysis. Moreover, each vehicle type has its own set of characteristics. Previous studies have considered a wide variety of vehicle characteristics (including vehicle weight, length, capacity, and acceleration), but we assume for purposes of this study that each agent has made his/her own decision regarding the class of vehicle to be purchased and is considering purchasing a passenger-sized vehicle from the same class. Within this class, there are 5 different vehicle types that the agent is trying to maximize his utilities to purchase, and so we will model the market penetration of the drivetrain once the customer has shortened his/her list to these 5 different vehicle types within the same class.

For the vehicle life of the agent, we use the same distribution as used in [74]: a normal distribution with a mean (average) of 15.9 years and a standard deviation of 4.2 years. The considered average lifetime of the vehicles considered in this study matches the reported U.S. average lifetimes of vehicles as summarized in the Transportation Energy Data Book [99], while the vehicle lifetime is likewise randomly selected from the uniformly distribution function U (0,15.9).

3.2.3.4. Government Agent

Government can affect the simulated system in several different ways. For instance, the applicable governing bodies can choose whether or not to support EV research and/or the development of new technologies to accommodate the movement towards an electrified fleet. However, the influence of the government on this system has not been modeled in this study;

instead, it is assumes that the government is offering financial incentives to consumers to lower the initial costs of EVs. The U.S. Government offers up to $7,500 in tax credits for EVs purchased in or after the year 2010, although the exact amount offered in incentives varies depending on factors such as battery capacity and vehicle body weight. This incentive is due to be phased out after 200,000 vehicles from the qualified manufacturers [23]. In addition, according to the EIA, several states offer additional incentives to further decrease the upfront purchasing costs of EVs for consumers; the state of California, for instance, offers rebates of $2,500 for BEVs and $1,500 for PHEVs. Therefore, the regional analysis performed in this study will also account for these regional incentives in the ABM model; a detailed summary of the considered incentives is provided in Section 2.4. Since the amount of paid incentives provided for EVs have not been consistent in recent years, and since the availability of these incentives is highly dependent on the overall political views of the current government during the analysis period, the developed ABM model uses a random variable to determine whether or not an agent receives these incentives, as well as whether or not the government decides to offer support for the adoption and/or development of EVs.

3.2.4. Assumptions and preliminary data

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

Table 9. Model Parameters in EVRO Model

Parameter	Source	Range
Analysis Period	[99]	2015-2030
Discount Rate	[78]	0.65-1.15
Inflation Rate	[79]	-10% , +10% of CBO's projections
Fuel Economy	[100]	EIA's projected mpg for light duty vehicles & AFLEET
Vehicle Miles Traveled (VMT)	[100]	-10% , +10% of EIA's projections
Electricity Price	[101]	EIA & proposed methodology in EVRO
Gasoline Price	[100,102]	EIA & proposed methodology in EVRO
Battery Production & Recycling Emissions	[103]	Represented in section 2.3.2
EDC	Existing literature	Proposed methodology in EVRO
WFP of Fuels	Existing literature	Proposed methodology in EVRO

How often an agent purchases a vehicle depends on his/her social group. Therefore, different social groups are defined in this research, and each agent is randomly assigned to a social group. The level of income the agent is then randomly selected among the pre-set income levels, and the purchase probability for each social category is estimated as summarized in Table 2 for different social and income categories. In 2014, 7.9 million passenger cars were sold in U.S., meaning that approximately 2.5 percent of Americans purchase a passenger car each year [146]. The vehicle purchase probabilities of each social group are taken from [74,136]. Since the data in both of these reports are based on different total populations (Iceland and Denmark, respectively), this study uses a scaled social group probability based on a purchasing rate of 2.5% in the U.S. (Table 2).

Table 10. Scaled Probability of Purchase

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

For vehicle purchase prices, AFLEET uses the average purchase price of different vehicle types in each category, but does not consider the regional average costs of vehicles. Instead, truecar.com is used to find the average MSRP of the studied vehicles [147]. The city with the highest population in each region is considered to estimate the purchase price for each region. Table 3 shows the minimum and maximum MSRPs of all studied regions for each vehicle type.

Table 11. Vehicle Purchase Price

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

Preferences in terms of the purchase price and maintenance and refueling costs are derived from the values found in available literature [74,136]. Since the EDC and the WFP are not amongst the attributes that every single agent cares about, whether the agent cares about these attributes or is indifferent will be randomly determined for each agent. If the agent considers environmental factors when making his/her decision, the associated preference is assumed to follow the values in Tables 4-6. These preferences are estimated in a way that the overall purchase probability associated with each attributes falls in a same order of magnitude. Tables 4-6 summarize the preferences of agents of different social and income categories with respect to each vehicle attribute.

Table 12. Log of Preferences of Low Income Category

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

Table 13. Log of Preferences of Medium Income Category

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

Table 14. Log of Preferences of High Income Category

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

The government also offers monetary incentives for purchasing EVs, so two types of government incentives (federal and regional) are considered in this analysis; these incentives are summarized in Table 7. Federal incentives are applied first, after which any applicable regional incentives are added to the federal incentive amounts to obtain the total incentive amount provided for any given region. The incentive rates listed in Table 7 are assumed to be constant for the entire analysis period, but whether or not the government actually offers these incentives is decided by the assumed scenario in the section 3 and also applying a random function to each analysis cycle. For instance, in the first scenario analysis in the results section, it is assumed that the government incentives are offered for the first 10 years and then randomly for the rest of analysis period (Please see section 3.4.).

Table 15. Government Incentives [22,148]

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

To model the willingness of an agent to purchase an EV, this study assumes that said willingness is influenced primarily by the word-of-mouth effect. Likewise, it is assumed that each agent contacts another agent once per month, and that the adoption fraction of the contacted agent is randomly selected as a value of up to 1%. Moreover, since there is no data available to definitively determine whether or not a specific individual within a particular household will decide upon a particular purchase [74], each agent is therefore defined as a household. Furthermore, each agent's tendency to buy a car will differ from one income level to another.

With this in mind, different scenarios can be applied in this analysis. In the developed model, for instance, gasoline and electricity prices are changed regularly using a random distribution given the estimated ranges from the EVRO model (Table 1), which are based on EIA projections. Moreover, government subsidies can be offered randomly any year. Finally, it is assumed that the economic situation simulated in the model stays the same, with no recessions or major economic improvements occurring during the analysis period. Based on the preliminary data and uncertainty ranges previously described, the ABM model is then run for 10,000 replications to cover most of the possible interactions between the varying factors, and the results of this analysis are described in Section 3.

3.2.5. Verification and Validation of ABM

One of the biggest challenges faced during the AB modeling process for this study is the verification and validation of the model and its results. Due to the heterogeneity of the agents in the model, there is a possibility of a new macro-level pattern emerging from the micro-level interactions between agents [149]. Thus, the main challenge in this effort is to determine how to properly validate the model and overcome the methodological obstacles associated with empirical validations. In general, validity for computational models is defined in terms of conceptual, internal, external, cross-model, data-related, and/or security-related validity [150]. Each of these types of validity are compared to an acceptable degree of confidence as defined by the modeler or decision maker. These specific validity types are described in further detail below.

The model is **conceptually valid** if it represents the conceptual and theoretical characteristics of the real world problem.

The model is **internally valid** if its programming code runs without any errors.

External validity means that the model output matches the real world data.

Cross-model validation compares the developed model with a similar model to check whether or not their respective outcomes match.

Data-related validity means that the data used in the model is adequate and accurate.

Finally, **security-related validity** means that adequate safeguards have been provided in the model to minimize the impacts of any issues that may adversely affect the model and/or its results.

This study uses the validation/verification process described in [73,151], in which four steps (grounding, calibrating, verifying, and harmonizing) are outlined to validate and verify computational models. After running the model for different numbers of agents, it was found that the number of agents does not significantly affect the market penetration results.

First, the model is **grounded** based on the research currently being performed by the Electric Vehicle Transportation Center (EVTC) [152]. This project is aimed at preparing transportation systems for the future influx of electric vehicles. The grounding of a model involves discussing why the model is reasonable, what its limitations and scope conditions are, and how it compares with current models. All of these steps have already been undertaken and summarized in previous sections. The grounding process can be enhanced by verbally explaining that the model demonstrates the key elements of a specific group and/or social process; in this case, different social and income categories are taken into account, and the model represents the involvement of each of these categories in the purchase of five different types of vehicles.

Calibration is used to tune up the model to fit the real world data. This is usually an iterative process in which one or more model characteristics are altered as necessary to ensure that the model output come as close to reality as possible. In this study, the model is first calibrated using parameters from several studies; parameters related to the purchase probability of a vehicle are derived from [74], while those related to the refueling effect of EVs are derived from [74,138], and all parameters from both of these references have been calibrated for the U.S. by comparing the U.S. population with the respective populations of Iceland and Denmark, for which the parameters had originally been calculated. During the calibration process, it was observed that the model has a consistent tendency to accept HEVs as an appropriate option as well as ICEVs, so consumer willingness with respect to HEVs was adjusted accordingly to reflect the real data. The preferences of each agent with respect to the EDC and WFP are likewise calibrated to more accurately reflect customer behavior.

The **verification** process is performed using a cross-model comparison with output data from the Light-duty Alternative Vehicle Energy Transitions (LAVE-Trans) model and with the Argonne National Lab's VISION model [153,154]. Both models are used to represent a business-as-usual (BAU) case in the National Research Council of the National Academies' (NRCNA) report, "Transition to Alternative Vehicles and Fuels" [155]. Here, first, a base-case model is formed based on average values for the purchase price, M&R cost, EDC, and WFP, while also assuming that no government subsidies are given during the analysis period and that agents do not interact with each other. The comparison reveals that the generated data from the EVReMP's base case model (Figure 4) does not differ significantly from the proposed BAU case as presented in [155]. A statistical verification method is used to compare the results of BAU case in NRCNA's report with those from the developed EVReMP base case model. Both One-Way ANOVA and two-tailed small-sampled matched pairs hypothesis tests reveal the significance level of less than 5 %. Statistical approaches are used in numerous studies to validate models and analyze data such as in pavement engineering [156–158], sustainable infrastructure [159–161], sustainable transportation [162], and process control [163].

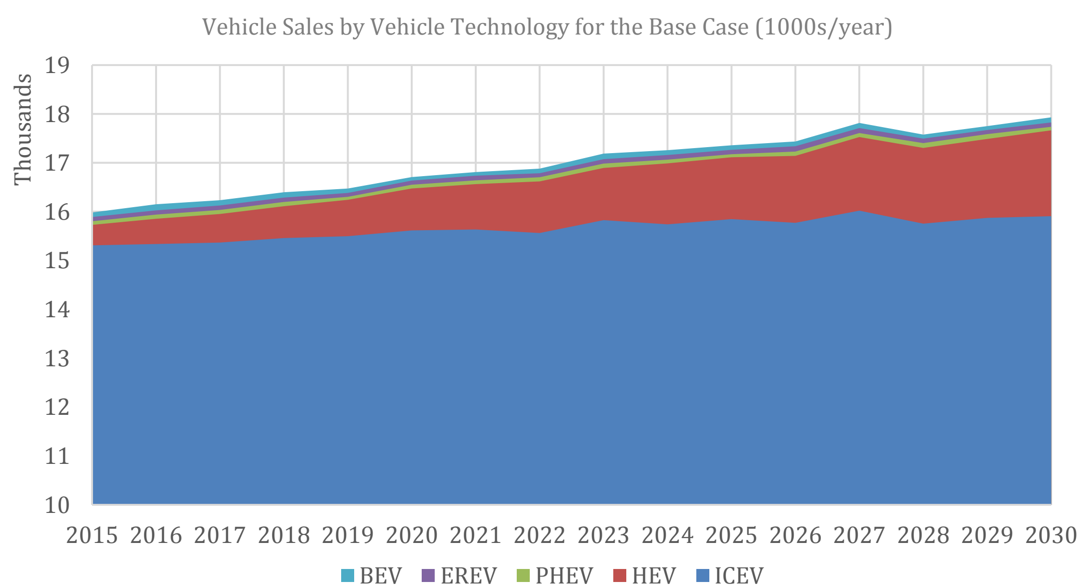


Figure 10. Vehicle Sales by Vehicle Technology for the Base Case (1000s/year)

The goal of **harmonization** is to demonstrate that the assumptions made in the model are "in harmony with" (i.e. adequately correspond to) the real world. To this end, the model is first validated by comparing it with the model presented in [155], and is then tested by applying the relevant government subsidies and comparing the resultant model with the model presented in one of the LAVE-Trans' reports [153].

After applying these steps, we are confident that the developed ABM accurately fits the real world and can therefore be used to evaluate the future market share of electric vehicles. Thus, with the model duly verified and validated, the results of this analysis are presented in the next section.

Moreover, we applied statistical verification and validation process as well. First, One Way Anova or Single Factor Anova test is applied to a set of sixteen data points from the NRC, BAU case and sixteen equivalent data points from the EVReMP model. Excel's Anova test toolbox is used to perform the analysis. The hypothesis here is that these two data series have the same mean with the confidence interval of 95%, i.e. α equals to 5%. The Table 16, summarized the results:

Table 16. Anova test results

Groups	Count	Sum	Average	Variance		
EVReMP	16	271967	16997.94	397900.9		
NRC's BAU Case	16	265414	16588.38	654096.7		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1341932	1	1341932	2.551207	**0.120691**	4.170877
Within Groups	15779963	30	525998.8			

As can been seen, P value is greater than 0.05 and therefore the hypothesis can be accepted.

In addition, since these data points are matched pairs, the following two tailed small-sample test of hypothesis about (μ_1 - μ_2) statistical test is applied. The test is two-tailed since an extreme value on either side of the sampling data would cause a rejections in the null hypotheses.

$$H_0 = (\mu_1 - \mu_2) = D_0 \quad (18)$$

$$H_a = (\mu_1 - \mu_2) \neq D_0 \quad (19)$$

$$t = \frac{\bar{d} - D_0}{\frac{s_d}{\sqrt{n}}} \quad (20)$$

Where $\bar{d}$ and s_d represent the mean and standard deviation of the sample of differences.

$$Rejection\ Region: |t| > t_{\frac{\alpha}{2}} \tag{21}$$

The significance level is chosen to be 0.05 and the t distribution is based on a (n-1) degree of freedom.

$$t = \frac{\bar{d} - D_0}{\frac{s_d}{\sqrt{n}}} = \frac{-409.56}{\frac{131146}{\sqrt{16}}} = -0.0125 \xRightarrow{therefore} |-0.0125| < 2.13 \tag{22}$$

Therefore, the hypothesis is accepted.

CHAPTER FOUR: ANALYSIS AND RESULTS

In this chapter, first the results of the developed Electric Vehicle Regional Optimizer (EVRO) are discussed. In this regard, the Life Cycle Cost (LCC), Environmental Damage Cost (EDC), and Water Footprint (WFP) of different Electric Vehicle (EV) drivetrains are presented, illustrating the ranges of uncertainty in the analysis. The most appropriate combination of EV drivetrains is shown for each U.S. National Energy Modeling System (NEMS) region. The NEMS regions and their abbreviations are indicated in Figure 3. Second, the results of the developed Electric Vehicle Regional Market Penetration (EVReMP) model are presented.

4.1. EVRO Results

4.1.1. Life Cycle Cost Results

The net present value of the total cost of ownership of the five different vehicle types for the 16-year lifetime is presented in this section. Since a variety of results can be shown for the 22 regions and five vehicle types, the LCC of vehicle types throughout the U.S. is explained and then the regional results of only the Internal Combustion Engine Vehicle (ICEV) and All-Electric Vehicle (BEV) are represented. Figure 4 shows the average net present value of total cost of ownership (TCO) for all of the studied regions. This value is the average of all captured LCCs for all of the replications in all U.S. regions. The error bars represent the ranges of data for each vehicle type. As discussed in section 2.1, the TCO includes the initial and depreciation costs, fuel costs (gasoline and electricity), maintenance and repair costs, and the insurance and registration costs.

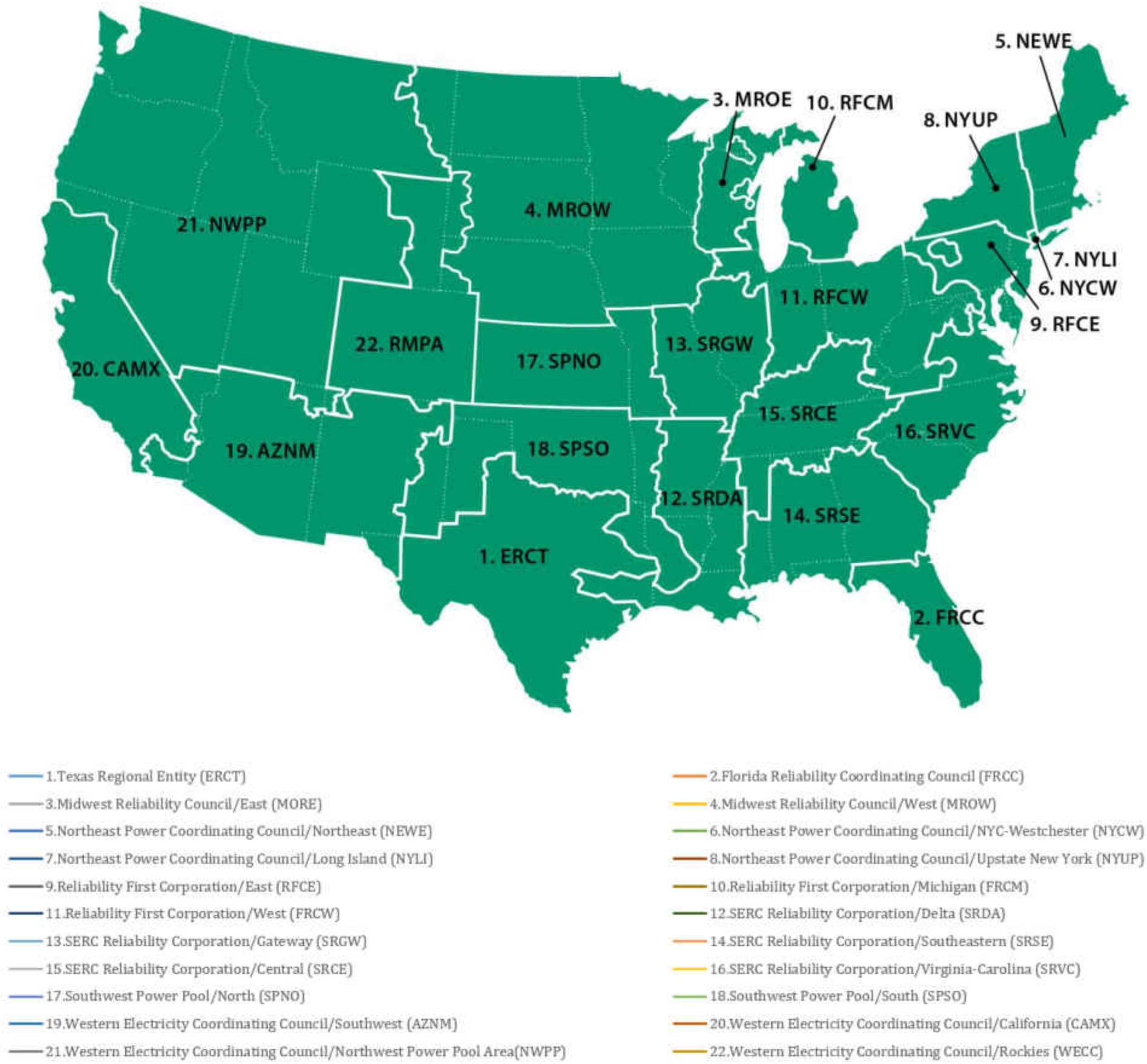


Figure 11. NEMS Electricity Market Module Regions [164]

The ICEV is the most cost effective vehicle type compared to the others, with an average TCO of $87,028. The lowest and highest LCC for the ICEV occurs in the Western Electricity Coordinating Council/Rockies (WECC) and Western Electricity Coordinating Council/ Southwest (AZNM) regions, with LCCs of $83,360 and $91,530 respectively. The BEV is the next most cost effective, with an average LCC of $89,244. The lowest and highest LCC for the BEV occurs in the Northeast Power Coordinating Council/Long Island (NYLI) and SERC Reliability Corporation/Central (SRCE) regions, with LCCs of $87,460 and $91,248 respectively. Hybrid Electric Vehicles (HEVs) and Extended Range Electric Vehicles (EREVs) are the next most expensive options, with similar average LCCs. The lowest LCC for these two occurs in region WECC with $86,422 for the HEV and $87,830 for the EREV. The highest LCC for the HEV and EREV happens in regions AZNM and SRCE, with LCCs of $93,596 and $92,229 respectively. Plug-in Hybrid Electric Vehicles (PHEVs) have the highest LCC among the vehicles studied, with an average LCC of $91,487. The lowest LCC of PHEVs, $88,362, can be found in region WECC, and the highest LCC, $94,546,is in region AZNM. Table 9 shows the summary of the LCC results. The uncertainty of the LCC decreases when moving from gasoline to electricity, due to higher data availability on electricity for the U.S. regions.

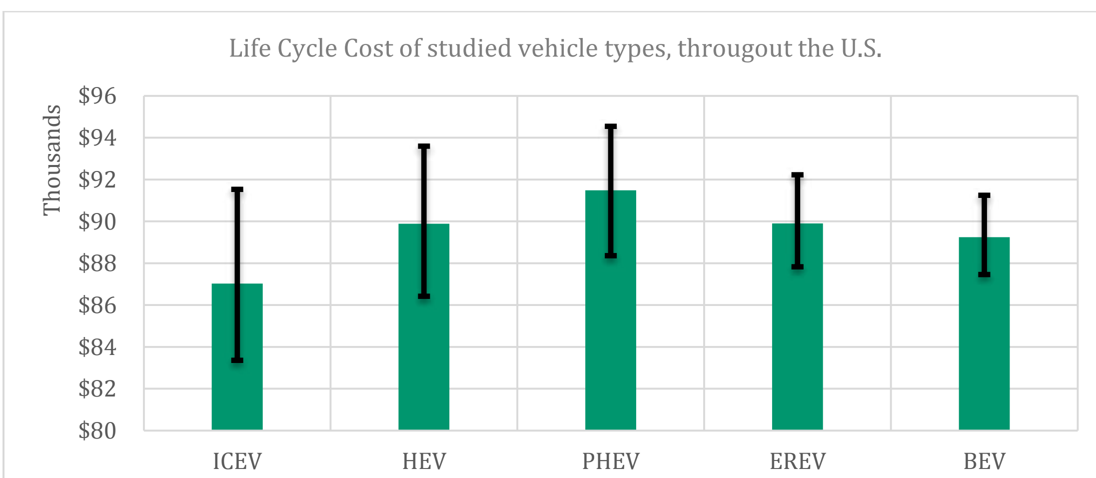
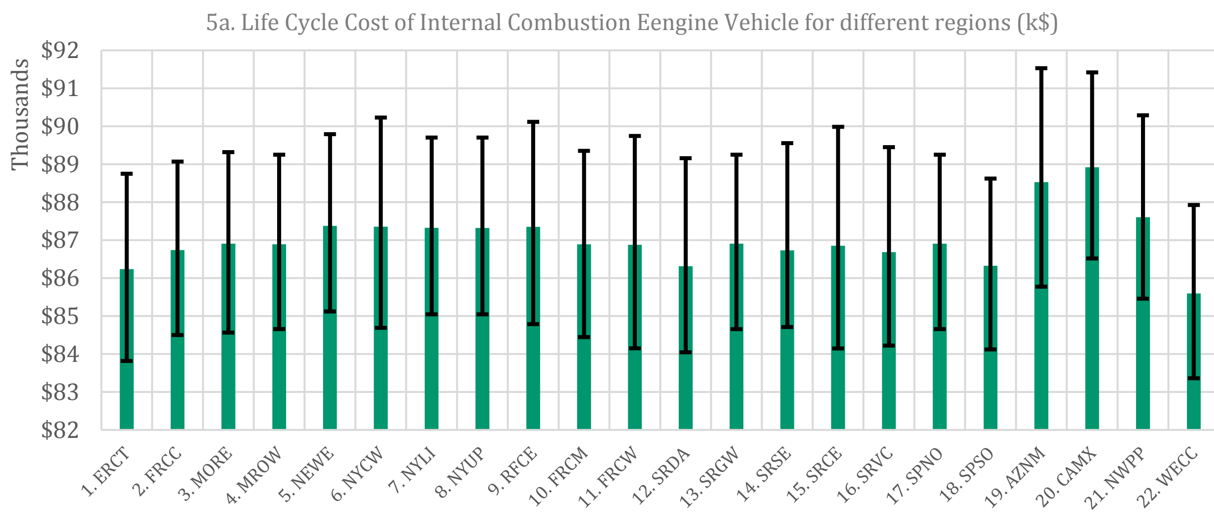


Figure 12. Life Cycle Cost of studied vehicles throughout U.S. (in Thousand Dollars)

Another way to look at the results is to compare the LCC of the five vehicle types in different U.S. regions. Here, the ICEV and BEV LCC results are presented. It is useful to compare the ICEV, which relies completely on gasoline, to the BEV, which relies completely on electricity. Figure 5a shows the LCC of driving an ICEV during its lifetime (16 years) in different U.S regions. On average, WECC is the cheapest ($85,597) and Western Electricity Coordinating Council/California (CAMX) is the most expensive ($88,922) region in which to drive an ICEV. The highest and lowest uncertainties happen in the SRCE and Southwest Power Pool/South (SPSO) regions respectively.

Looking at the LCC of BEVs in different U.S. regions, the variation seems to be lower, with Reliability First Corporation/East (RFCE) being the cheapest ($88,731) and SERC Reliability Corporation/ Gateway (SRGW) being the most expensive ($89,751) region in which to drive a BEV, on average (Please see Figure 5b). The highest and lowest variation in the LCC occurs in the Reliability First Corporation/West (FRCW) and AZNM regions respectively. The changes in life cycle cost of the studied vehicle types might be due to a variety of reasons, such as changes in the future price of electricity, the future electricity mix in the region, or the future gasoline price in the region. Looking at the CAMX region, the average costs of the ICEV ($88,922) and BEV ($88,948) are almost the same. However, the life cycle cost of ICEV varies in a larger range compared to BEV, because uncertainty in the future gasoline price is much higher than uncertainty in electricity price and electricity mix.



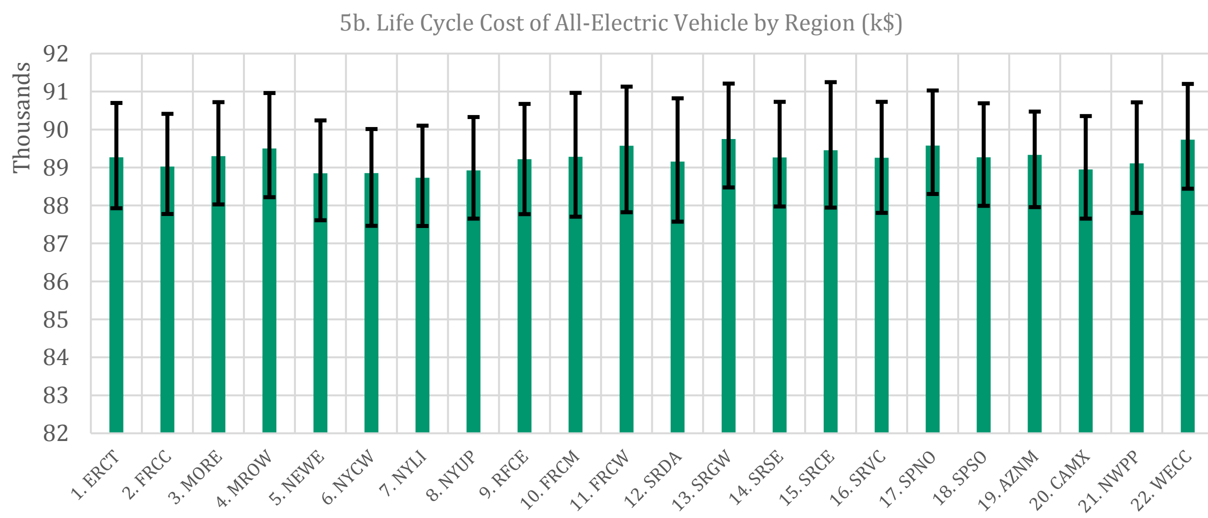


Figure 13a. Life Cycle Cost of Internal Combustion Engine Vehicle for different regions and 9b. Life Cycle Cost of All-Electric Vehicle for different regions, both in Thousand Dollars

4.1.2. Environmental Damage Cost Results

Figure 6a shows the Environmental Damage Cost (EDC) of the five vehicle types throughout the U.S. Compared to the LCC, the variation in EDC is much higher, due to the wider uncertainty ranges. Although the ICEV has the lowest LCC, it has the highest EDC relative to the alternatives, with an EDC of $5.19 million on average, over the vehicle lifetime. The lowest and highest EDC for the ICEV occur in the CAMX and Midwest Reliability Council/East (MORE) regions, with EDCs of $0.74 million and $10.75 million respectively. This is because the reported pollution emission from gasoline is the lowest in CAMX and highest in MORE.

As can be seen from the results, moving towards electric technology reduces the EDC dramatically. The BEV has the lowest average lifetime EDC, of a little less than $1 million. The lowest and highest estimated EDC for the BEV occurs in the Northeast Power Coordinating Council/ NYC-Westchester (NYCW) and Western Electricity Coordinating Council/ Northwest Power Pool Area (NWPP) regions, with EDCs of $0.12 million and $3.27 million, respectively. The main driver for WFP is its use in electricity generation. This is why the BEV, EREV, and PHEV have higher water use. The gasoline life cycle is the next main driver of water consumption. The HEV consumes the least water because it uses less gasoline than the ICEV.

The range of the results is much wider for the ICEV than the BEV and EREV. This difference in uncertainty range is mainly due to the higher variability in the gasoline-related EDC. At the same time, the lack of data availability in the unit EDC is another reason for this high difference. More data on environmental costs could potentially reduce uncertainty in future studies.

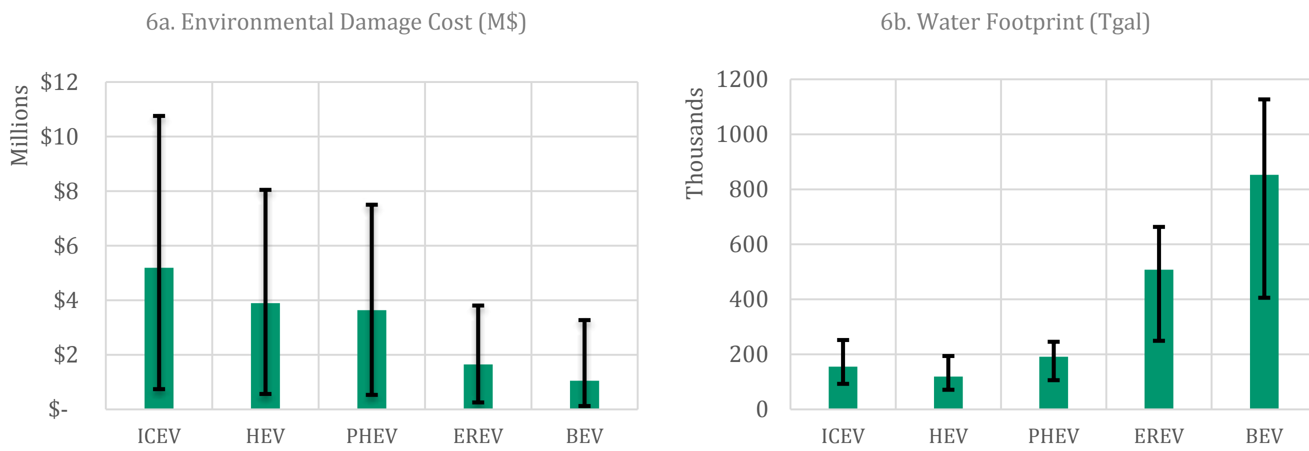


Figure 14a. Life Cycle Environmental Damage Costs for the studied vehicles (in Millions of Dollars), and 10b. Water Footprint of studied vehicles (in Thousand Gallons)

4.1.3. Water Footprint Results

The WFP of each vehicle type over its lifetime is presented in Figure 6b. The main driver for water consumption is its use in electricity generation and the gasoline life cycle is the next main driver of water consumption. The BEV is responsible for the highest water footprint compared to the alternatives. It consumes approximately 852 thousand gallons (Tgal) of water during its lifetime on average, mainly due to upstream electricity generation water consumption and battery production. The highest and lowest water consumption and withdrawal for the BEV happens in the SERC Reliability Corporation/ Virginia-Carolina (SRVC) and NYLI regions, with 1,127 Tgal and 406 Tgal of water, respectively. HEVs consume and withdraw the least amount of water during their lifetime, using 119 Tgal of water, on average. The smaller WFP results because HEVs do not rely on grid-sourced electricity, have smaller batteries than BEVs, and use less gasoline than ICEVs. The region with the lowest water footprint for the HEV is

SERC Reliability Corporation/Delta (SRDA) with 71 Tgal of water used, while the highest water use occurs in CAMX, with 194 Tgal of water.

In summary, Table 9 shows the LCC, EDC, and WFP calculated for the vehicle types studied here, and the region associated with each value. This table shows the variation in results throughout the U.S. There are several trends that emerge from the results. For instance, the southwestern region (AZNM) has the highest average LCC for the ICEV, HEV, and PHEV. This is because AZNM region is a part of PADD west coast region, which has the highest reported gasoline prices, and it has a relative high electricity price as well. Conversely, the Rockies region (WECC) has the lowest LCC for ICEVs, HEVs, PHEVs, and EREVs, because the price of gasoline and electricity is relatively low in this region.

Table 17. Key Findings of LCC, EDC, and WFP for the studied vehicle types

Decision Criteria	Vehicle Type	Average throughout U.S.	Minimum throughout U.S.	Maximum throughout U.S.
LCC	ICEV	$87.03 K	$83.36 K	$91.53 K
			WECC	AZNM
	HEV	$89.89 K	$86.42 K	$93.60 K
			WECC	AZNM
	PHEV	$91.49 K	$88.36 K	$94.55 K
			WECC	AZNM
	EREV	$89.90 K	$87.83 K	$92.23 K
			WECC	SPNO
	BEV	$89.24 K	$87.46 K	$91.25 K

Decision Criteria	Vehicle Type	Average throughout U.S.	Minimum throughout U.S.	Maximum throughout U.S.
			NYLI	SRCE
EDC	ICEV	$5.19 M	$741.07 K	$10.75 M
			CAMX	MORE
	HEV	$3.89 M	$563.84 K	$8.05 M
			CAMX	MORE
	PHEV	$3.64 M	$529.77 K	$7.50 M
			CAMX	MORE
	EREV	$1.65 M	$253.06 K	$3.81 M
			CAMX	NWPP
	BEV	$1.05 M	$121.26 K	$3.27 M
			NYUP	NWPP
WFP	ICEV	155.3 Tgal	92.55 Tgal	252.25 Tgal
			SRDA	CAMX
	HEV	119.5 Tgal	71.19 Tgal	194.04 Tgal
			SRDA	CAMX
	PHEV	191.5 Tgal	106.09 Tgal	245.84 Tgal
			NYLI	SRVC
	EREV	507.9 Tgal	249.18 Tgal	663.10 Tgal
			NYLI	SRVC
	BEV	852.6 Tgal	405.64 Tgal	1126.84 Tgal
			NYLI	SRVC

Turning to EDC, the California region (CAMX) has the minimum average EDC for the ICEV, HEV, PHEV, and EREV. The CAMX region has one of the lowest reliance on coal power plants and one of the highest hydro and renewable electricity sources, leading to a low environmental impact. The MORE region, in the Midwest, has the highest EDC for the ICEV, HEV, and PHEV; The EDC is high for the primarily electric drivetrains (EREV and BEV) in the NWPP region because the electricity mix is heavily reliant on fossil fuels in the mountain states. However, the values are lower than in the MORE region because of the hydro and renewable electricity sources of the Pacific Northwest. The New York (NYUP) region has the cleanest electricity mix from an environmental damage cost perspective, causing the BEV to have the lowest impact in that region. NYUP has the second highest hydro and renewable energy sources in the U.S. and a relative high nuclear power plant sources.

The lowest WFP for the three electrified vehicles occurs in the NYLI (New York Long Island) region, whereas the highest WFP for those vehicles is in the SRVC (in the southeast) region. This is because NYLI is located in the east coast PADD region with a relative low gas production WFP. At the same time, it has the highest biomass and natural gas electricity sources with a relative low electricity generated WFP. Conversely, the electricity mix in SRVC is heavily reliant on nuclear power plants, which has almost the highest amount of WFP among other power plant types (Please see Table 6).

4.1.4. Regional Optimization Results

One of the goals of this study was to incorporate all of the decision variables into one larger picture. Implementing a stochastic multi-objective decision-making approach finds the most appropriate combination of drivetrains in each region. In this section, this combination is illustrated by region. To accomplish this goal, the Exploratory Modeling and Analysis (EMA) approach is applied to the optimization model, where the variables are the percentage of selection of each vehicle type in each region, and the objective function is to minimize their LCC, EDC, and WFP at the same time. Individual weights were assigned to these objective functions. The weight of each objective function changes in 0.1 intervals from 0 to 1. Therefore, there are 66 different weight combinations between the three objective indicators. Using the EMA approach, the optimization is performed for all of the weight combinations, in all of the regions, for all of the replications. Since representing all of the results is out of the scope of this study, the optimized combination of the drivetrain with weights of LCC = 0.4, EDC = 0.5 and WFP = 0.1 is shown. Figure 7 shows the U.S. electric regions, with each pie chart representing the ideal combination of drivetrain for the year 2030. As can be seen in Figure 7, the ideal combination consists of just EREVs and BEVs throughout the entire U.S. On the east coast, BEVs are more favorable, while in the Midwest and Southern parts of the country, EREVs are more likely to be the optimal choice. This is because the electricity mix on the east coast has fewer environmental damage costs than that of the Midwest and South. The east coast has more hydro and renewable generation and natural gas, whereas the Midwest and South has a high proportion of coal generation. This trend changes in the ERCT and AZNM regions, where BEVs are more likely the optimal option. AZNM has a larger proportion of hydro and renewable electricity compared to the other southern regions, making it more optimal from both a LCC and EDC perspective. Likewise, ERCT has a relative high proportion of renewable sources, which reduces LCC and EDC for all-electric transportation.

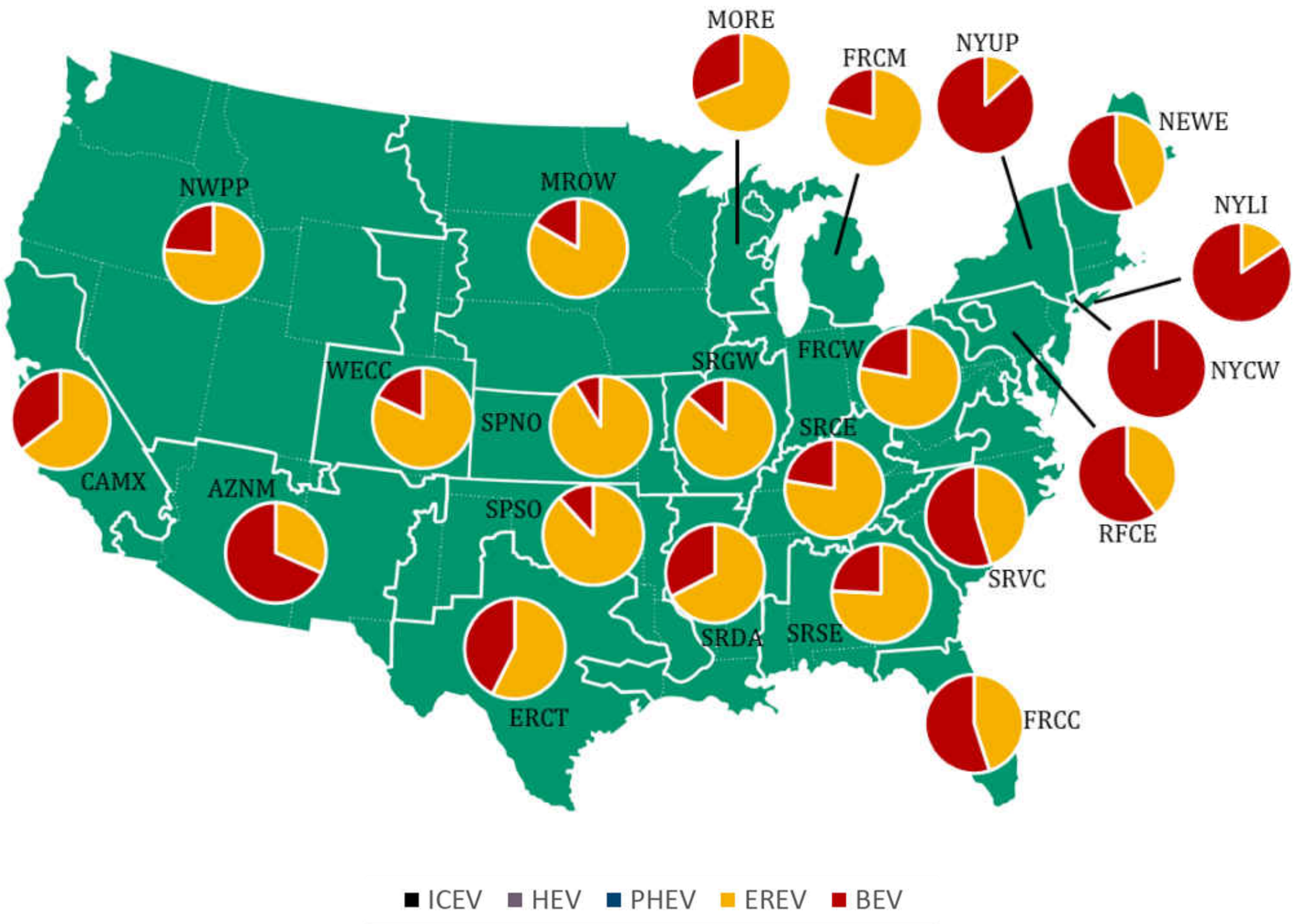


Figure 15. Ideal combination of drivetrain in year 2030, for weights of LCC=0.4, EDC=0.5, and WFP=0.1

A sensitivity analysis can be performed for the assigned weights. Figure 8a shows the sensitivity of EREV selection for all possible weights for each of the regions (see Figure 3 for the color codes). It has been assumed that the weight of WFP is static at 0.1 and the weights of the LCC and EDC change in a range of 0 to 0.9. The result indicates that the chance of selection of EREV as the optimal option increases when the weight of LCC increases, and the weight of EDC decreases. However, for the highest LCC weights, the EREV decreases in optimality.

Looking at the selection probability for the BEV, it is not an optimal drivetrain option for LCC weights higher than 0.6 (EDC weight of 0.3). However, for the lower LCC weights (higher EDC weights) it competes with EREV for best choice (see Figure 8b). Of note is that for weight selections where only the LCC matters, neither the EREV nor the BEV are the best option, and EVRO indicates the HEV is the best option. Moreover, the variation in optimal choice is very sensitive to the changes in the weight selection, as can be seen in Figure 8.

Another way to look at the results is to look at the entire optimization model outcome by combining all of the weight combinations, and getting an average of the percentage of selection for each vehicle type. In other words, the number of selection times in which a particular vehicle drivetrain is the optimal choice is summed, in all replications, for all weight combinations, and then the result is represented (Please see Figure 9). As indicated, some ICEVs still might be an optimal choice, in at least some of the weighting combinations (especially when the weight of LCC is very high). However, the share of ICEV is very low, with at most 7% of the optimal drivetrain selection within region SRDA. HEVs dominate most of the regions as an optimal choice, since they have better fuel efficiencies and have less environmental impact. More specifically, HEVs are a better option while the weight of the WFP is high (especially for WFP weight of more than 0.4). This trend changes dramatically in the west side of the country, where HEVs are replaced by PHEVs as the optimal choice. These vehicles are a better option when the weight of the LCC is very low (especially for LCC weight of less than 0.3). The percentage of EREVs and BEVs do not seem to change dramatically throughout the entire nation. These two vehicle types combined range between 40 and 51 percent of the fleet in all regions, for all of the weighting combinations. Specifically, these vehicles are a good option when the weight of the WFP is less than 0.3.

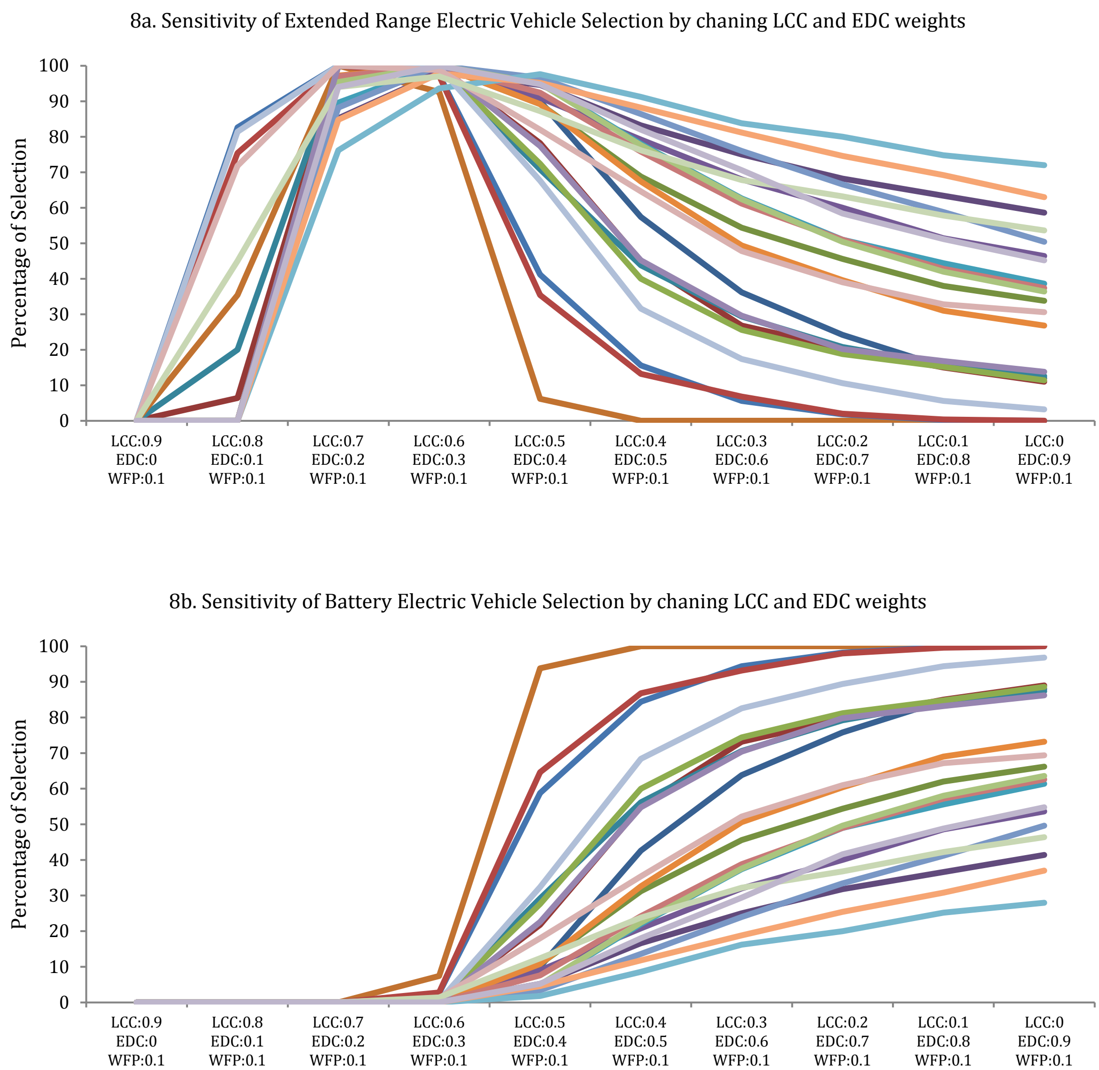


Figure 16a. Sensitivity of Extended Range Electric Vehicle Selection by changing LCC and EDC weights, and 8b. Sensitivity of All-Electric Vehicle Selection by changing LCC and EDC weights

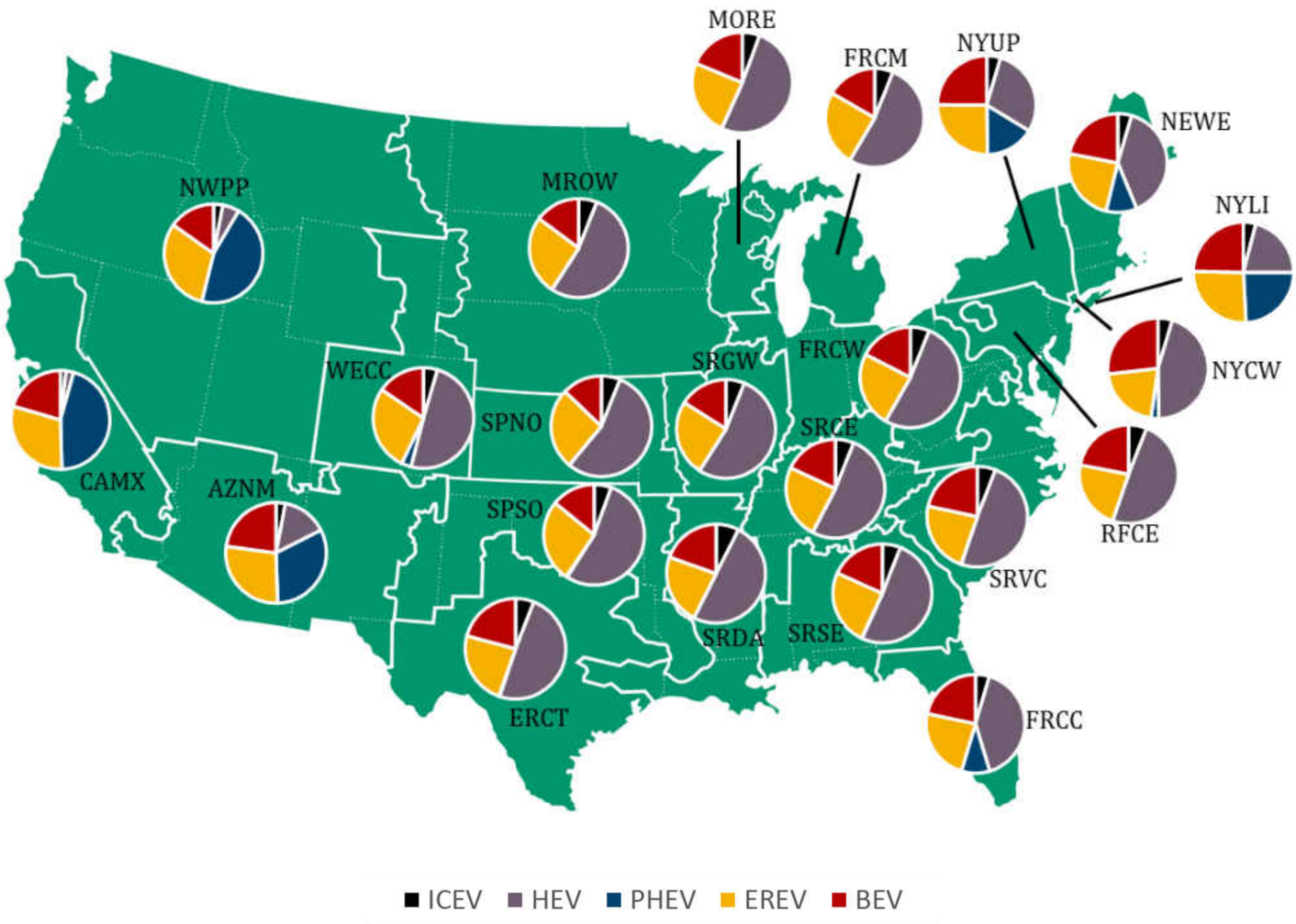


Figure 17. Ideal combination of drivetrain in year 2030, for the average of all of the weight combinations

4.2. EVReMP Results

4.2.1. Maintenance and Refueling Cost

The net present value of the Maintenance and Refueling (M&R) costs of the five different vehicle types are presented in this section for a 16-year lifetime. Due to the wide variety of possible results for all 22 regions and for all 5 vehicle types, these M&R costs are shown throughout the U.S. with only the regional variations with respect to ICEVs and All-Electric Vehicles (BEVs) shown in this paper, since these two vehicle types represent opposite extremes in terms of gasoline versus electricity as fuel options. Figure 6 shows the average net present values of the M&R costs for all of the studied regions, calculated in this analysis as the average of all captured M&R costs for all of the replications in all of the considered U.S. regions, with the error bars in the figure representing the M&R cost ranges for each vehicle type.

On average, the ICEV has the highest M&R cost with an average of $48,128. The lowest and highest M&R costs for the ICEV occur in the New York Up State (NYUP) region at $44,560 and in the Western Electricity coordination council/Southwest (AZNM) region at $52,329, respectively. Obviously, the M&R cost decreases as the vehicles' fuel economy rates (mpg) increase. The HEV has the second highest average M&R cost at $43,357, followed by the PHEV at $40,192, the EREV at $36,641, and finally the BEV at $33,582. The lowest and highest M&R costs of BEVs are found in the NYC-Westchester (NYCW) region at $31,743 and in the SERC Reliability Corporation/Central (SRCE) region at $35,471, respectively. The data uncertainty ranges decreases when moving from gasoline-powered vehicles to EVs due to better data availability on electricity for the U.S. regions.

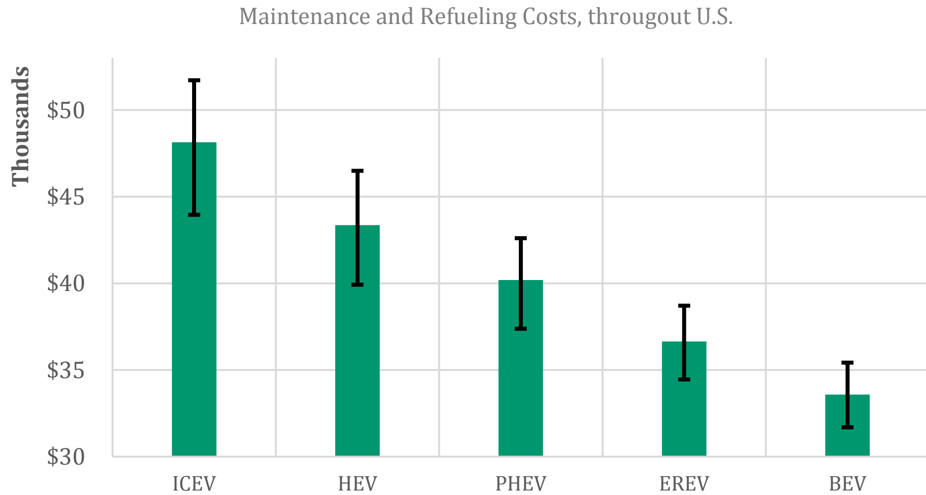
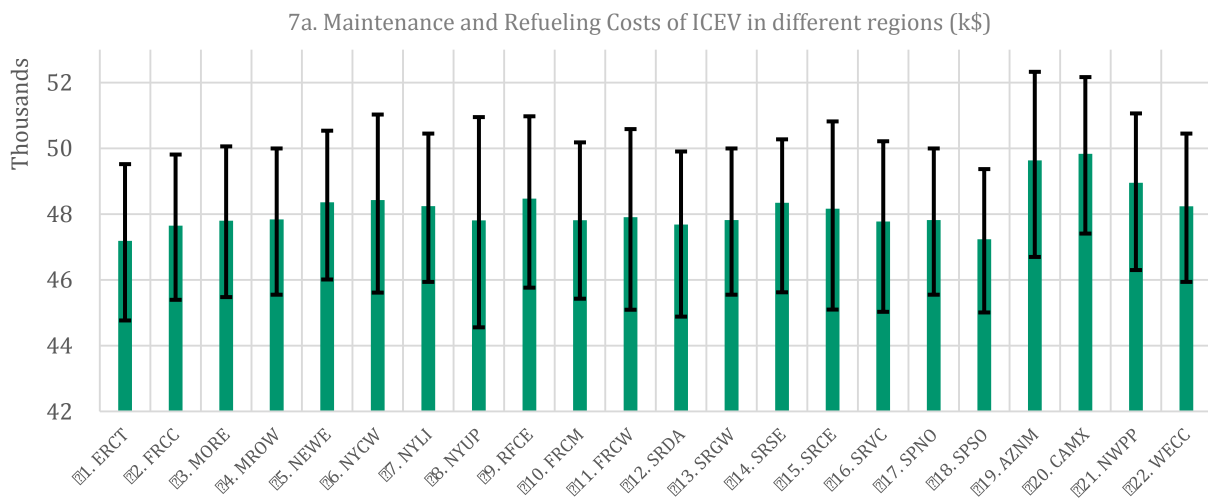


Figure 18. Maintenance and Refueling Cost of studied vehicles throughout U.S. (in Thousand Dollars)

A regional representation of the data is also possible; here, the regional variations in the M&R costs of ICEVs and BEVs are presented in Figures 7a and 7b, respectively, for a 16-year vehicle lifetime. This comparison is especially useful because ICEVs rely completely on gasoline as a fuel source while BEVs likewise rely completely on electricity. On average, driving an ICEV in the Texas Reliability Region (ERCT) has the cheapest M&R cost at $47,190, while California is the most expensive region to drive an ICEV with an M&R cost of $49,836 (Figure 7a).

The M&R costs of BEVs seem to have less variation, with NYWC being the cheapest ($32,862) and SERC Reliability corporation/Gateway the most expensive ($34,195) regions in which to drive a BEV, on average (Figure 7b). There are a number of possible reasons for the changes in M&R costs for the studied vehicle types, including future price changes for electricity, future changes in the electricity generation mixes in each region, and/or uncertainties with respect to future gasoline prices in each region.



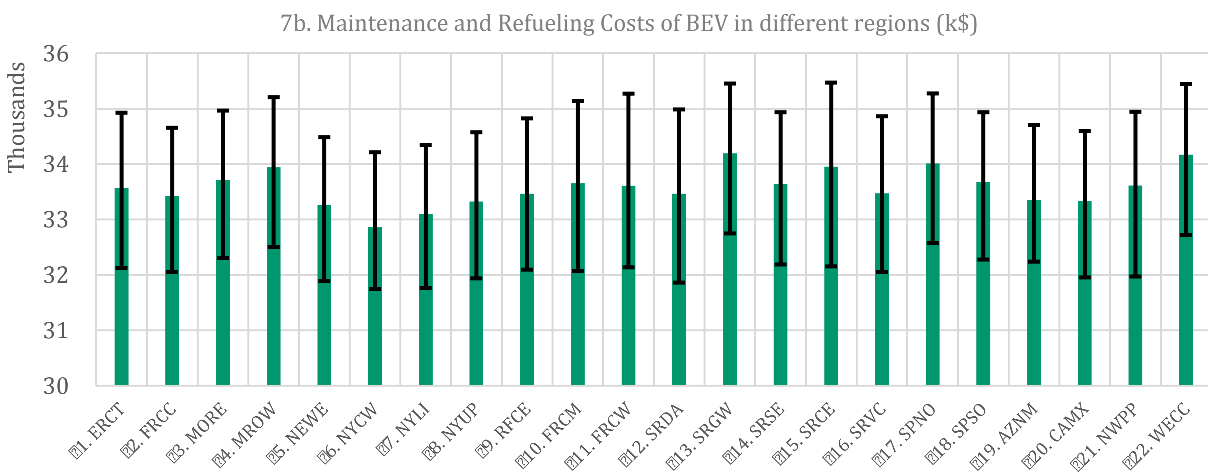


Figure 19a. Maintenance and Refueling Cost of Internal Combustion Engine Vehicle for different regions and 7b. Maintenance and Refueling Cost of All-Electric Vehicle for different regions, both in Thousand Dollars

4.2.2. Agent Based Modeling Results

As mentioned in section 2.3.2, there are 50,000 agents in each replication. Figure 9 shows how these agents are placed in each of the NEMS regions based on the population and number of registered vehicles in each region. The Reliability First Corporation/West (FRCW) region has the most agents with the California (CAMX) region as a close second, both containing almost 43 percent of the total number of agents in the model. Conversely, the NYC-Westchester (NYCW) has the lowest number of agents, followed by the Southwest Power Pool/North (SPNO) region.

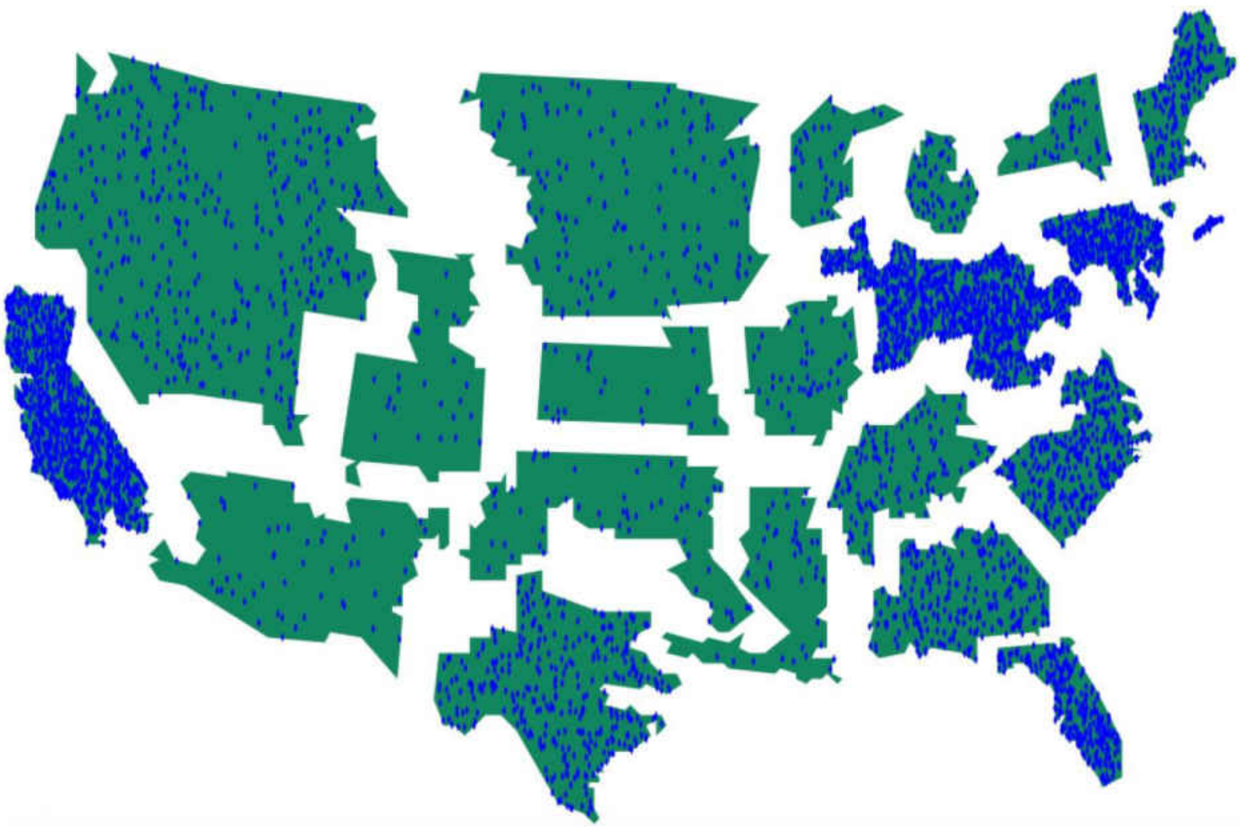


Figure 20. Configuration of agents in the ABM model **(NOTE: This illustration is for only 5,000 agents)**

The effect of different policies can be tested on the market penetration of the EVs; in this study, the effect of government subsidies was tested using the developed EVReMP model. This policy is aligned with one of the LAVE-Trans publications, in which government policies were mandated for the first 10 years [153]. As previously discussed in Section 2.4, two types of government subsidies (federal and regional) are considered in this policy, and it is assumed that the government supports EVs penetration for the first 10 years, and a randomly generated factor is used to determine whether the government offers subsidies in each year thereafter. The model is then run for 10,000 replications. The results of this analysis can be shown in any number of forms, including the average market share of all vehicle types for every replication, the changes in the market share of a particular vehicle over time, and the regional variations of the market penetration of EVs. First, the average market penetrations of the studied vehicle types are illustrated in Figure 10; compared to the base case model (Figure 4), the market shares of the EVs have increased dramatically, and approximately 26 percent of the new sales fleet will be electrified on average by the year 2030, due to the provided government subsidies.

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

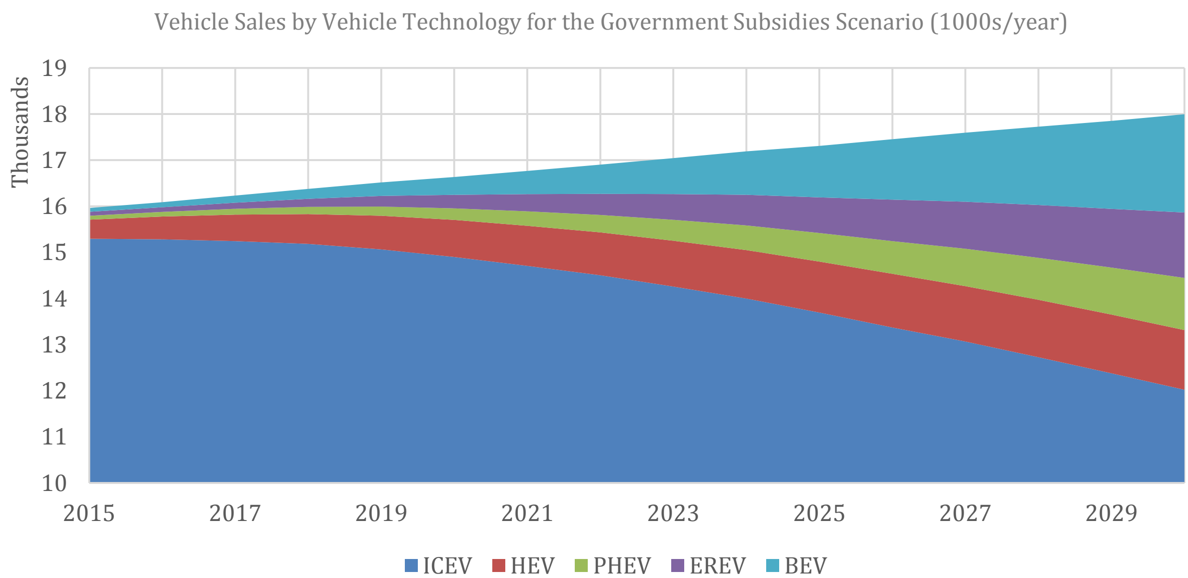


Figure 21. Vehicle Sales by Vehicle Technology for the Government Subsidies Scenario (1000/year)

Another way to look at the results is to illustrate the variations in market penetration for each vehicle type; Figure 11 shows the variations in the market penetration of the drivetrain for the first scenario. As this figure shows, the market share of the ICEV decreases while the market shares of all other alternatives increase. The variation in the results for the ICEV is lower than those for other alternatives, due to less variability in the relevant decision-making factors for purchasing an ICEV, while this variation increases over time for all other alternatives.

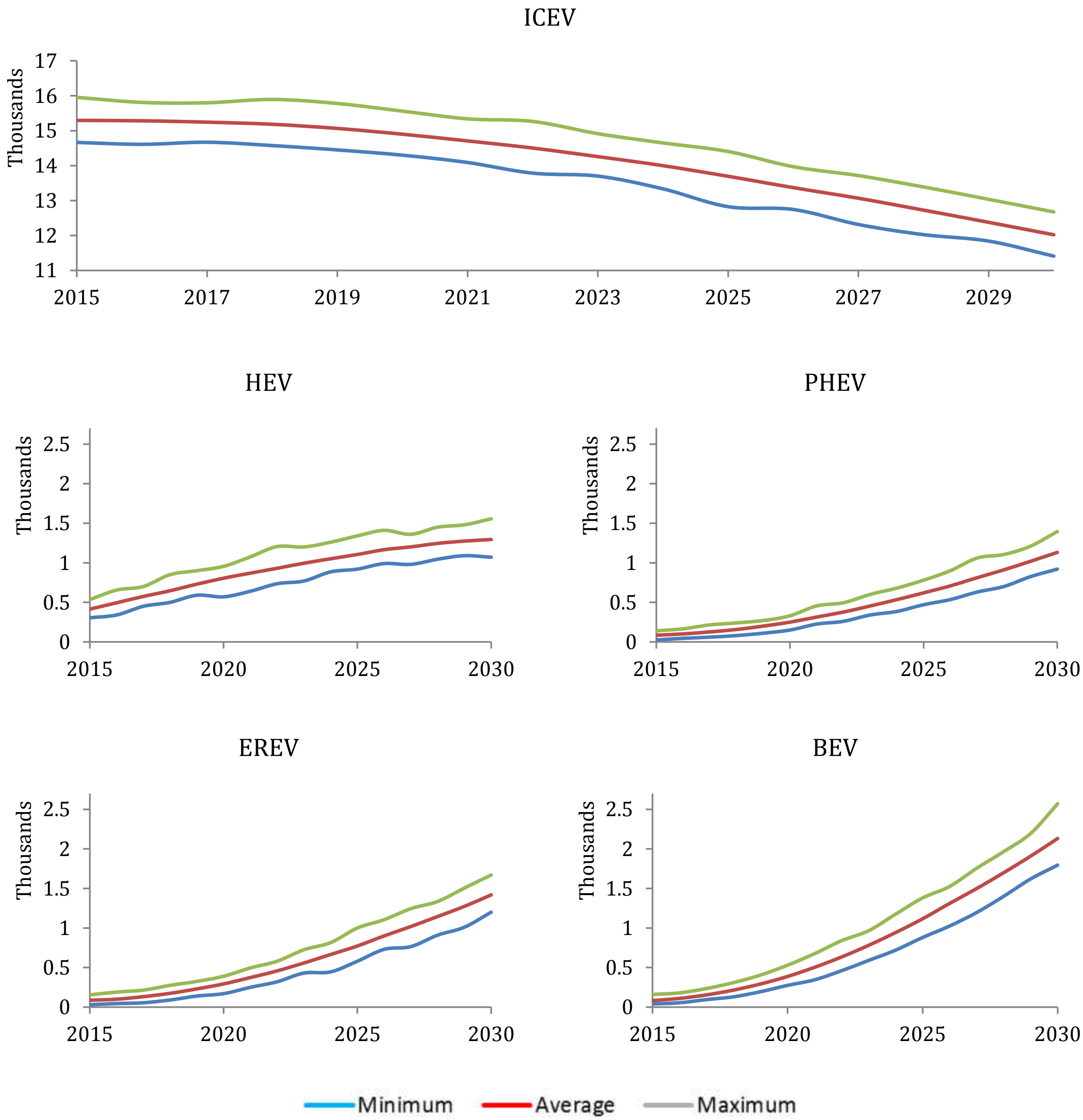


Figure 22. Variation in the Market Penetration of the studied vehicles, for government subsidies scenario (1000s/year)

The next policy analysis tests the word-of-mouth effect (or the social acceptability of the EVs) in terms of its effect(s) on EV market penetration. To this end, this policy scenario assumes that all agents are willing to consider purchasing an ICEV, meaning that the agents' willingness to purchase an ICEV is always 1. However, agents who purchase any other vehicle alternative contact other agents once a month and try to convince these other agents to purchase the non-ICEV vehicle type that they own. Whether or not the contacted agent is convinced to consider the non-ICEV vehicle type in question is simulated using a randomly generated function in which the probability of the contacted agent being convinced is 10%. Figure 12 represents the average market penetration results of the studied drivetrain under these conditions for the entire studied regions in the United States.

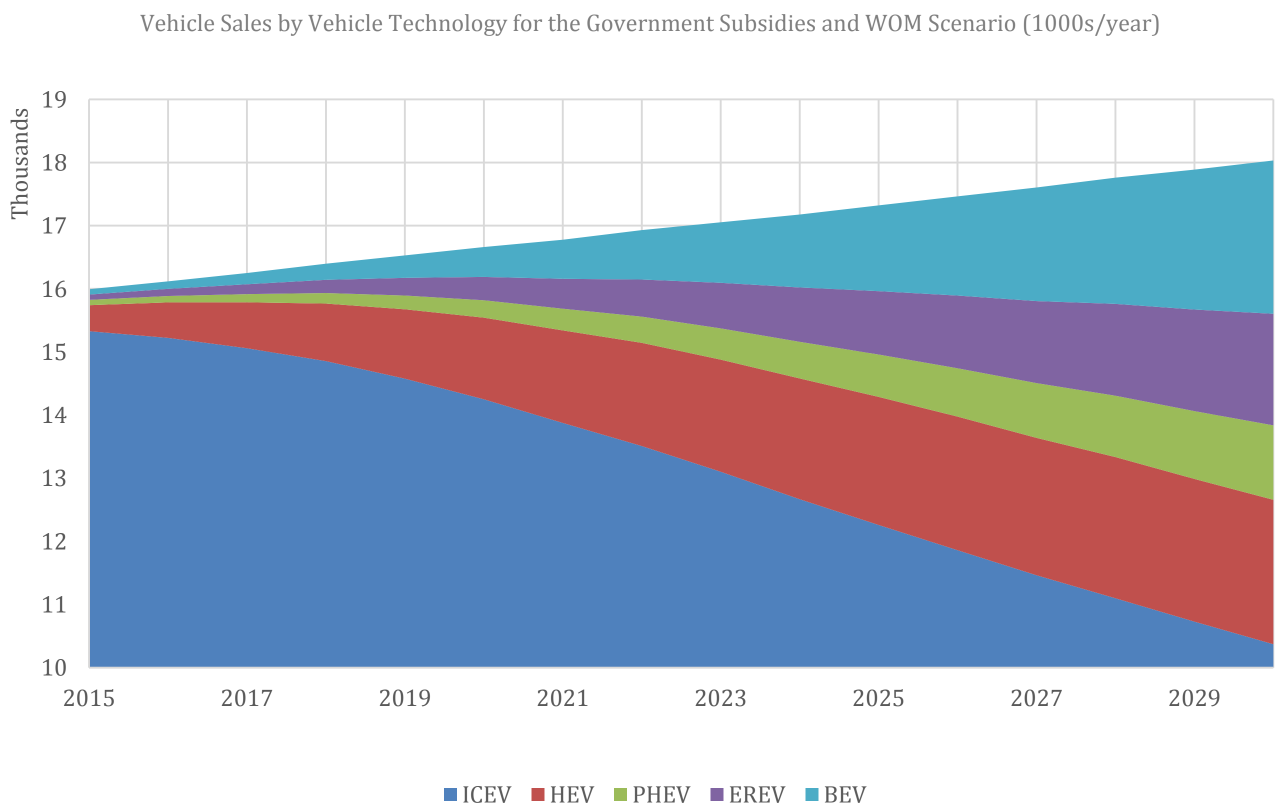


Figure 23. Vehicle Sales by Vehicle Technology for the Government Subsidies and WOM Scenario (1000/year)

As shown in the graph above, the overall market penetration of the EVs has significantly increased relative to the previous case (Figure 10), with EVs dominating approximately 30% of the total market share in 2030. The ICEV will still have the highest market penetration with a 56% market share on average, but BEVs will have the second largest market share at 14%, followed by HEVs at 13%. Conversely, the PHEV will still have the lowest market share at 6% on average.

CHAPTER FIVE: CONCLUSION AND DISCUSSION

The aim of this study was to first, develop the Electric Vehicle Regional Analyzer (EVRO) tool. This tool will enable policymakers and transportation planners to prepare our nation's transportation system for the influx of Electric Vehicles (EVs). EVRO compares EV technologies with hybrid and internal combustion gasoline vehicles using a comprehensive analysis and optimizes the drivetrain combination for the year 2030, considering the life cycle cost, environmental damage cost, and water footprint as the objective functions. Second aim of this study was to develop Electric Vehicle Regional Market Penetration (EVReMP) tool to help policy makers and transportation planners to identify the future market shares of electric vehicles in the United States. The EVReMP model compares three different EV technologies with hybrid and internal combustion gasoline vehicles using a developed agent-based model, and predicts the market share of the studied vehicles for the year 2030, accounting for agent preferences in terms of the purchase prices, maintenance and refueling costs, environmental damage costs, and water footprints of all vehicle types in the drivetrain. The purchase price is estimated using current market data, while all other vehicle attributes are estimated using data from the Electric Vehicle Regional Optimizer (EVRO) model, which estimates the variability ranges with respect to the future maintenance and refueling costs, environmental damage costs, and water footprints of the electric vehicle types. An Exploratory Modeling and Analysis (EMA) approach was then applied to the data to properly account for the inherently deep uncertainty associated with market penetration. The EMA approach was also used in tandem with the developed ABM to investigate the future market shares of the considered vehicle types in twenty-two separate electricity grid mix regions in the U.S., after which the EVReMP tool was able to generate a variety of results.

In the EVRO model, first the Life Cycle Cost (LCC), Environmental Damage Cost (EDC), and Water Footprint (WFP) of five different drivetrains were estimated. Second, an Exploratory Modeling and Analysis approach was applied to take the concept of deep uncertainty into account. Third, stochastic optimization modeling was used to find the optimal combination of drivetrains for twenty-two U.S. electricity regions. Finally, the comprehensive stochastic optimization model optimized the most appropriate fleet combination in 2030 based on different LCC, EDC, and WFP priorities. A variety of different results can be obtained from the EVRO model using different weights for the objective functions. In summary, the following conclusions are highlighted:

The Internal Combustion Engine Vehicle (ICEV) is the most cost effective vehicle type in terms of LCC, with an average LCC of $87,028 over vehicle lifetime. The lowest and highest LCC for the ICEV occurs in the Rockies and Southwest regions, respectively.

Plug-in Hybrid Electric Vehicles (PHEVs) have the highest LCC among the vehicles studied, with an average LCC of $91,487. The lowest LCC of PHEVs can be found in the Rockies region and the highest LCC happens in the Southwest region.

Movement towards electric technology reduces the EDC dramatically, with the lowest EDC (at a little less than $1 million on average) occurring for BEVs over the vehicle lifetime.

Conversely, movement towards the electric options increases the WFP dramatically. BEVs consume the highest amount of water, mainly due to upstream electricity generation and battery production water consumption. HEVs have the smallest water footprint among the alternatives because they do not rely on grid-sourced electricity and use less gasoline than ICEVs.

The EVRO model reveals that for weights of LCC = 0.4, EDC = 0.5, and WFP = 0.1, only BEVs and EREVs are in the optimal fleet composition in the year 2030.

Looking at the entire picture, by combining all of the weight combinations, EVRO predicts that an ICEV might be a good choice in very rare conditions (if policymakers weight the LCC very high, for example). HEVs dominate most of the regions since they have better fuel efficiency and less environmental impact. The HEVs are replaced with PHEVs in the regions with the cleanest electricity, and the combined share of EREV and BEV vehicles ranges between 40 to 51 percent throughout the entire U.S.

The main lesson learned from the EVRO analysis is that the ideal fleet composition will be based on a trade-off between the three types of criteria examined in this study: life cycle cost, environmental damage cost, and water footprint. How much weight is given to each of these criteria, dependent on the perspective taken (consumer, policymaker, environmentalist, oil company, car manufacturer, etc.), will determine the appropriate penetration of different vehicle technologies. Because the weighting of these various criteria will more than likely vary along regional lines (water use will be very important to the arid southwest, emissions from electricity generation will depend on how clean the generation fleet is within a region, etc.), the EVRO tool is highly suited to an analysis of the factors driving the various regions environmentally, politically, and economically.

One of the valuable lessons highlighted here is how important electricity generation fuels are to the effectiveness of BEVs in combatting climate change. In some scenarios, regions with a higher proportion of fossil fuels in the generation mix are better off with relatively more hybrid vehicles compared to regions with cleaner electricity. If the policy goal is to reduce GHG emissions, a transition to an electrified fleet must be coupled with the incorporation of renewables into the generation mix. Rethinking and redesigning the energy system is required to integrate renewable energy sources and replace fossil fuels, both on the generation and consumption sides [165].

Ultimately, this analysis shows that movement away from ICEVs is desirable from an environmental and water footprint perspective, and that even when focusing on life cycle costs alone, ICEVs are only barely less costly than the alternatives. Moreover, small increases in oil price can make the BEVs and EREVs more cost-effective compared to ICEVs. Hybrid and electrified vehicles make sense from many perspectives.

Most recently, investigations into actual driving behavior have been carried out, examining some of the design and use assumptions commonly made about EVs. For example, the National Household Travel Survey has traditionally captured the behavior of ICEV drivers, when there is reason to believe that consumers will change their driving behavior once they introduce a PHEV or EV into their household [47]. Moreover, whether EVs are charged on peak or off peak will directly influence their associated emissions [45]. If an EV is charged on peak it will require increased use of marginal generators, which often have the highest emissions. If, on the other hand, they can be used to even out peak loads through smart grid technologies, they could actually create efficiencies that benefit the grid.

There are some limitations to the work presented in the EVRO model, including those associated with incorporating marginal electricity generation mix. Projecting marginal electricity can be very problematic, since the applied identification of marginal technologies is more difficult [166]. In addition, the time of day that drivers charge their electric vehicles plays a large role in determining the marginal load that is placed on the power grid. For a fuller analysis, it is critical to understand when drivers will typically charge their vehicles, and to associate these charging times with the corresponding power grid mix profiles. Another area for improvement is that surrounding renewable generation costs. Regions have a disproportionate penetration of a particular renewable technology due to favorable conditions for that technology, meaning that regional costs do and will continue to diverge. Due to data availability issues, all renewable generation was lumped into a single value for EVRO, even though there are varying costs and environmental impacts associated with each type of renewable. Moreover, there is not a single technology that can solve the problem of climate change -there have to be many initiatives to have sustainable transport [167]. In addition, we assumed all of the variables in EVRO model are mutually exclusive, meaning a change in one factor does not cause any change in another. In reality, changes in some of the assumed variables affect others as well.

More alternative fuel options can be evaluated in future EVRO model extensions. Additionally, the optimization results presented here are recommendations for policy makers. Consumers are often not rational in their decision-making. In this regard, a market penetration evaluation study using consumer choice models would be a worthwhile future analysis. The possibility for technological advancement, mass production, and participation in energy markets, and provision of ancillary grid services should also be explored. Future cost reduction of EVs through better design and production processes, as well as the potential for vehicle owners to earn money or reduce costs through smart integration of vehicles with the electric grid, would change the modeling results. For instance, in the future, EVs could provide energy storage, demand response functions, and generate power during outages. For further development of the EVRO model, these and other factors can be incorporated as more EVs are on the road, more studies specifically addressing marginal electricity and EV grid integration potential are carried out, and more data becomes available.

EVReMP is able to generate a variety of the results. In summary, the following conclusions are highlighted:

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

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

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

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

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

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

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

Corporation/West (FRCW) region) could potentially increase the social acceptability of EV and thereby improve the market penetration of EVs.

Limitations to the work presented in the EVReMP model include the absence of the influence of manufacturers on EV market penetration; in addition to the policy initiatives previously discussed, EV manufacturers can also compete with each other in each analysis year and ultimately yield accelerated improvement in EV technology, resulting in an overall positive impact on EV market penetration. Governments can also enforce the Corporate Average Fuel Economy (CAFE) regulations and thereby influence the manufacturers' benefits in terms of EV market shares; since manufacturers were not considered as an agent in this study, these potential benefits were not taken into account. In addition to the incentives previously discussed, some utility companies offer special discounts for EV consumers to charge their vehicles during off-peak hours and/or during the evening, so the effect of lower electricity rates for the owners of EVs could be considered as a scenario in the analysis. Moreover, the time of day when an EV is charged has a considerable effect on the marginal load that is placed on the power grid; consequently, as more EVs are introduced to the market, the electricity market will most likely face a change in demand levels during on-peak and off-peak hours, which is likely to effect the rate structure of electricity, in turn eventually impacting the refueling costs of EVs. Thus, for a more thorough analysis, the times of day when EVs are charged should be also taken into account. Moreover, in the validation of the model, other approaches could be used as proposed in [168].

APPENDIX: ACRONYM LIST

ABM	Agent Based Modeling
AFLEET	Alternative Fuel Life-Cycle Environmental and Economic Transportation
ANL	Argonne National Laboratory
ASCM	Automotive System Cost Model
BEV	All-Electric Vehicle
CO_2	Carbon Dioxide
CO	Carbon Monoxide
EDC	Environmental Damage Cost
eGrid	Emissions & Generation Resource Integrated Database
EIA	Energy Information Agency
EMA	Exploratory Modeling and Analysis
EREV	Gasoline Extended Range Electric Vehicle
EV	Electric Vehicle
EVRO	Electric Vehicles Regional Optimizer
EVReMP	Electric Vehicle Regional Market Penetration
GHG	Green House Gas
GREET	Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation
HEV	Gasoline Hybrid Electric Vehicle
ICEV	Internal Combustion Engine Vehicle
LCA	Life Cycle Analysis
LCC	Life Cycle Cost
LCCA	Life Cycle Cost Analysis
LCEE	Life Cycle Environmental Emissions
LCOE	Levelized Cost of Energy

NEMS	National Energy Modeling System (see Figure 3 for region acronyms and locations)
NO_x	Oxides of Nitrogen
PADD	Petroleum Administration for Defense District
PHEV	Gasoline Plug-in Hybrid Electric Vehicle
PM10	Particulate Matter $\leq 10\ \mu m$
PSAT	Powertrain System Analysis Toolkit
SO_x	Oxides of Sulfur
TCO	Total Cost of Ownership
VMT	Vehicle Miles Traveled
VOC	Volatile Organic Compounds
WFP	Water Footprint

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